AN INVESTIGATION ON HYPERSPECTRAL IMAGE CLASSIFIERS FOR REMOTE SENSING

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OKAN BİLGE ÖZDEMİR

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AN INVESTIGATION ON HYPERSPECTRAL IMAGE CLASSIFIERS FOR REMOTE SENSING

Submitted by **Okan Bilge Özdemir** in partial fulfillment of the requirements for the degree of **Master of Science in Information Systems, Middle East Technical University** by,

Prof. Dr. Nazife Baykal
Director, **Informatics Institute**

Prof. Dr. Yasemin Yardımcı Çetin
Head of Department, **Information Systems**

Prof. Dr. Yasemin Yardımcı Çetin
Supervisor, **Information Systems, METU**

Examining Committee Members:

Prof. Dr. H. Şebnem Düzgün
Department of Mining Engineering, METU

Prof. Dr. Yasemin Yardımcı Çetin
Information Systems, METU

Asst. Prof. Dr. Erhan Eren
Information Systems, METU

Asst. Prof. Dr. Banu Günel
Information Systems, METU

Asst. Prof. Dr. Alptekin Temizel
Work Based Learning, METU

Date: 19.06.2013

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Name, Last name: **Okan Bilge Özdemir**

Signature : ___________________

ABSTRACT

AN INVESTIGATION ON HYPERSPECTRAL IMAGE CLASSIFIERS FOR REMOTE SENSING

Özdemir, Okan Bilge

MS., Department of Information Systems

Supervisor: Prof. Dr. Yasemin Yardımcı Çetin

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Hyperspectral image processing is improved by the capabilities of multispectral image processing with high spectral resolution. In this thesis, we explored hyperspectral classification with Support Vector Machines (SVM), Maximum Likelihood (ML) and K-Nearest Neighborhood algorithms. We analyzed the effect of training data on classification accuracy. For this purpose, we implemented three different training data selection methods; first N sample selection, randomly N sample selection and uniformly N sample selection methods. We employed Principal Component Analysis (PCA) as pre-processing method and conducted experiments with different number of principal components for all three classification algorithms. As a post-processing method following pixelwise classification, filtering with 3x3 window and majority voting with meanshift segmentation methods are used to incorporate spatial information over spectral information.

The experiments showed that without using pre-processing and post-processing SVM procures better classification accuracies than the other algorithms for all training data sizes. ML is inferior for lower number of training data samples but improves its performance with lower number of principal components. K-NN algorithm provides almost the same accuracies for more than 10 principal components. PCA usage does not improve SVM performance but decreases classification time for larger scenes. Filtering with 3x3 window method improves the classification accuracy by 4-5%. However, spatial information usage by employing majority voting with meanshift segmentation method performs better than filtering 3x3 window. Classification with both pre-processing and post-processing improves classification accuracy and decreases classification time. The largest improvement is for the ML method with lower number of training data.

Keywords: Hyperspectral Classification, Meanshift Segmentation, Support Vector Machines, Maximum Likelihood, K-Nearest Neighborhood

ÖZ

UZAKTAN ALGILAMA İÇİN HİPERSPEKTRAL İMGE SINIFLANDIRICILARI ÜZERİNE BİR İNCELEME

Özdemir, Okan Bilge

Yüksek Lisans, Bilişim Sistemleri Bölümü

Tez Yöneticis: Prof. Dr. Yasemin Yardımcı Çetin

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Yüksek spektral bilgi sayesinde hiperspektral imge işleme, multispektral imge işlemeye göre daha fazla kapasiteye sahiptir. Bu çalışmada, Destek Vektör Makinaları (DVM), En Büyük Olabilirlik (EBO) ve K-En Yakın Komşu algoritmaları kullanılarak hiperspektral sınıflandırma algoritmaları incelenmiştir. Çalışmada ayrıca öğrenme verisinin sınıflandırma başarımına etkisi de incelenmiştir. Bunun için ilk N örneğin seçimi, rasgele N örnek seçimi ve homojen bir biçimde N örnek seçimi olarak farklı üç öğrenme verisi seçim yöntemi kullanılmıştır. Ön işleme metodu olarak Temel Bileşen Analizi (TBA) kullanılmıştır. Her üç algoritma için farklı temel bileşen sayıları ile deneyler yapılmıştır. Spektral bilgiye ek olarak yersel bilginin kullanımı için piksel bazında sınıflandırma sonrasında, son işleme olarak 3x3 pencere ile filtreleme ve ortalama kaydırmalı bölütleme ile çoğunluk oylaması yöntemleri kullanılmıştır.

Deneylerde görüldüğü üzere ön işleme ve son işleme kullanılmadığında SVM'in bütün öğrenme verisi boyutları için diğer algoritmalardan daha iyi sonuç verdiği görülmüştür. EBO yöntemi düşük öğrenme verisi ile kötü sonuçlar aldığı gözlenmiştir. Düşük sayıda temel bileşen kullanıldığında EBO yönteminin performansını artırdığı görülmüştür. K-NN algoritmasının sınıflandırma başarımı 10 temel bileşenden daha fazla kullanıldığında değişmediği tespit edilmiştir. TBA kullanımı DVM algoritmasını etkilemediği gözlenmiştir. TBA kullanımı büyük imgeler için sınıflandırma zamanını düşürdü. 3x3 pencere ile filtreleme yöntemi sınıflandırma yüzdesini %4-5 artırdığı tespit edilmiştir. Ortalama kaydırmalı bölütleme ile çoğunluk oylaması, 3x3 pencere ile filtreleme yönteminden daha iyi sonuç verdiği görülmüştür. Ön işleme ve son işleme yöntemlerinin birlikte kullanılması sınıflandırma yüzdesini artırdığı ve sınıflandırma zamanını düşürdüğü gözlendi. Düşük sayıda öğrenme verisi kullanıldığında en büyük gelişimi ML algoritmasının yaptığı görüldü.

Anahtar Kelimeler: Hiperspektral Sınıflandırma, Ortalama Kaydırmalı Bölütleme, Destek Vektör Makinaları, En Büyük Olabilirlik , K-En Yakın Komşu

To my father Mehmet Ali Özdemir

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CHAPTER 1

INTRODUCTION

1.1 Motivation

Classification is one of the most prominent research areas in hyperspectral image processing. Hyperspectral classification is used in many applications including city planning, mining and military decision support. They provide invaluable information about the composition of the object of the scene due to their high spectral resolution. The main goal of hyperspectral classification is the assignment of each pixel to the correct class. Hyperspectral classification accuracy highly depends on training data. To investigate this phenomenon, the classification methods are employed with different training data and sample size. Moreover, the improvements on classification performance by using spatial information with spectral information are also studied. The requirement of dimensionality reduction for hyperspectral image processing is also elaborated.

1.2 Scope and goal

This study is devoted to analyzing hyperspectral classification with Maximum Likelihood, Support Vector Machines, and K-Nearest Neighborhood algorithms. The first issue is determining the effect of different training data size and selection technique on classification accuracy. Another issue that is analyzed here is the effect of dimensionality reduction with Principal Component Analysis. Finally, the contribution of spatial information usage by filtering with 3x3 window and majority voting with meanshift segmentation is also analyzed and reported. Three different scenes (2 IKONOS and 1 ROSIS) are used for experimentation stage.

1.3 Outline of thesis

This thesis is organized as five chapters including background, methodology, experiments and conclusion. In Chapter 2, literature survey on hyperspectral image classification, dimensionality reduction and meanshift segmentation is presented. In Chapter 3, proposed classification models, training data selection methods, pre-processing method and post-processing methods are described. Chapter 4 presents experiments and results for each scene and classification model. Lastly, Chapter 5 presents the discussion and future work.

CHAPTER 2

Background

Remote sensing is the science that investigates and aims to improve methods to gather information about physical objects without physical contact. The sensors in this area can be classified into two categories as active and passive sensors. In the active type, sensing system sends and receives the reflected energy from the surface whereas in passive type, sensing device measures emitted energy from the surface [1].

In active remote sensing, source of energy is supplied from the remote sensing systems. Examples of these systems are RADAR (Radio Detection and Ranging), SONAR (Sound Navigation and Ranging) and LIDAR (Light Detection and Ranging). Imaging spectrometers and radiometers are examples of optical passive sensors. These sensors measure the reflected energy from the objects. Gamma rays, Xrays, UV, the visible, near infrared and short wave infrared regions are covered by optical remote sensing [2]. According to their spectral band coverage, optical remote sensing systems can be classified into three different categories. These are panchromatic imaging systems, multispectral imaging systems and hyperspectral imaging systems. One may further classify hyperspectral imaging systems as superspectral imaging systems, hyperspectral imaging systems and ultraspectral imaging systems.

Panchromatic imaging systems: These systems use a single channel sensor which is sensitive to broadband wavelengths. Panchromatic imaging systems measure the brightness of the materials so the output is a monochromatic (gray level) image. SPOT, IKONOS-PAN and QuickBird PAN can be given as examples for panchromatic imaging systems.

Multispectral imaging systems: These systems use three or more channel sensors which are collecting data from several selected bandwidths. Output images contain both color and brightness information. Each of these images can be displayed in different gray scale images. LANDSAT TM, MSS and QuickBird MS can be given as examples for multispectral imaging systems.

Superspectral imaging systems: These systems have typically more than 10 spectral channels. Superspectral imaging systems are generally used for observing land cover or vegetation regions [3]. Like multispectral imaging systems, superspectral imaging systems can be displayed separately as grayscale images. Superspectral imaging sensors acquire images in narrower bandwidth. MODIS and MERIS can be given as examples for superspectral imaging systems.

Hyperspectral imaging systems: These systems have typically more than 100 spectral bands; the difference between two neighboring spectral bands is often less than 10nm. Furthermore, the spectral bands are consecutive. Hyperspectral imaging systems also save set of images in one data set which is called “data cube”. Hyperion and EO-1 satellites can be given as example for hyperspectral imaging systems [4].

Ultraspectral imaging systems: These systems have typically more than 500 spectral bands and high resolution. Molecular absorption or emission bands can be imaged by these devices [5].

Since the early 1980s, hyperspectral image sensors have been used in order to capture spectral information. Hyperspectral cameras, also called imaging spectrometers, combine properties of digital image cameras and spectroscopy devices. These systems are used for gathering spectral characteristics of materials. Figure 1 shows an example of spectral properties of some materials.

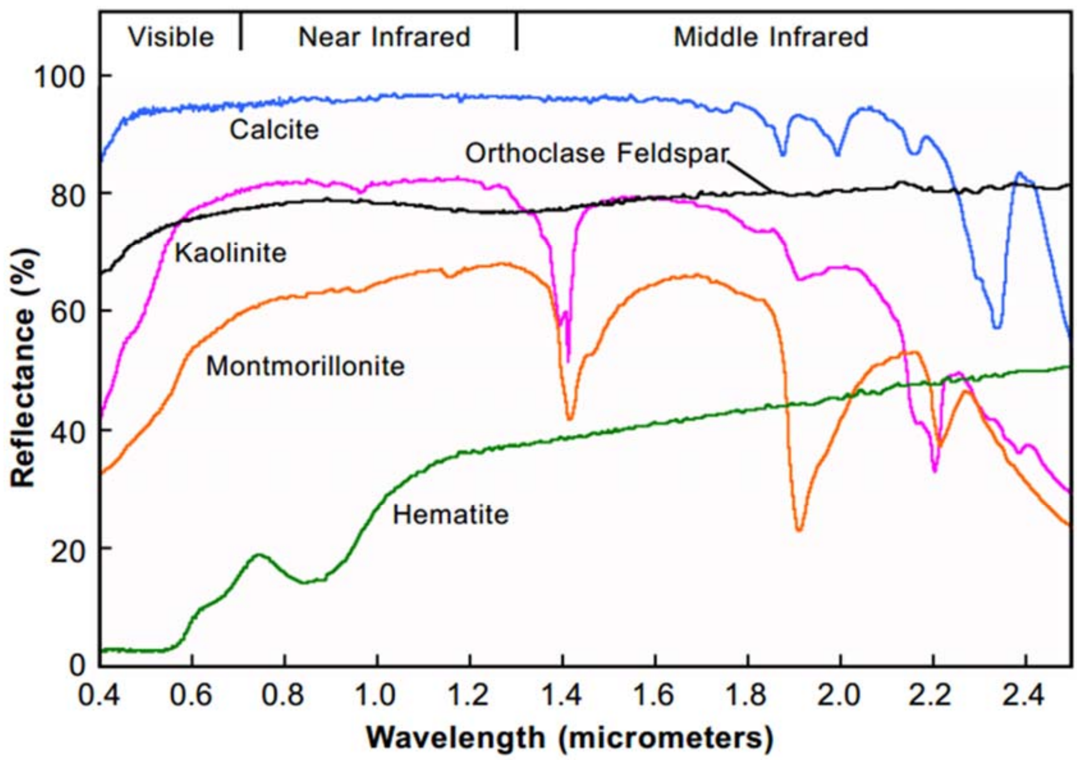

Figure 1 Reflectance spectra of some minerals adapted from [6]

There are many challenges in hyperspectral image processing. First of all due to changes in atmospheric conditions or sensor effect changes, spectral signature of the same material can vary from image to image. Secondly, since hyperspectral images have low spatial resolution and high spectral resolution one pixel may have a mixture of two or more materials' spectra. Also since hyperspectral images have a multitude of spectral bands, these images may require too much storage capacity or processing power.

These problems can be attacked by different hyperspectral image processing methods. For the high-dimension problem, dimensionality reduction techniques can be used. These methods reduce the dimension with no or little loss of information. Hyperspectral unmixing techniques can be used to solve mixed pixel problem.

2.1 Literature Survey

In this thesis hyperspectral classification methods examined and compared. As a learning algorithms Maximum Likelihood (ML), K-Nearest Neighborhood (K-NN) and Support Vector Machines (SVM) used. Post-processing and pre-processing methods used to improve hyperspectral classification accuracy. In this study, PCA used as a pre-processing method. Majority voting and filter with window (3x3) and majority voting with meanshift segmentation has been used as post-processing.

2.1.1 Dimensionality Reduction

Higher dimensional data generally increases classification accuracy. However, according to Hughes phenomenon [7, 8], the required training sample size for classification grows exponentially as the number of spectral bands increase. Applications of hyperspectral image processing may require data volume or dimensionality reduction without loss of critical information. Dimensionality reduction also improves classification time. Saldju and David in [9], increase of dimension may lower classification accuracy with limited training data size. They conducted experiments with different numbers of training data for a decision tree classifier. Results show that for 100 training data, the classification accuracy is starts to decrease after 10 features. Hyperspectral classification accuracy is mainly dependent on training data size. To reduce training data size, reduction of the number of dimensions is required. Dimensionality reduction is also required to eliminate highly correlated bands.

In the literature, dimensionality reduction can be categorized as feature selection or feature extraction [11]. Feature selection methods are primarily based on eliminating bands that do not contribute to the hyperspectral image processing task. These methods simply eliminate the irrelevant and repetitive features to reduce the dimensionality from the original dimension M to N, where (N<M). In the literature, there are different methods for feature selection ([11, 12]). These reduction techniques select features by their relevance for the task and lack of correlation between the features. They differ from each other by their feature selection methods. Feature selection is reducing dimension by eliminating highly correlated bands, the feature extraction uses maximal statistical dependency criterion to select features to eliminate.

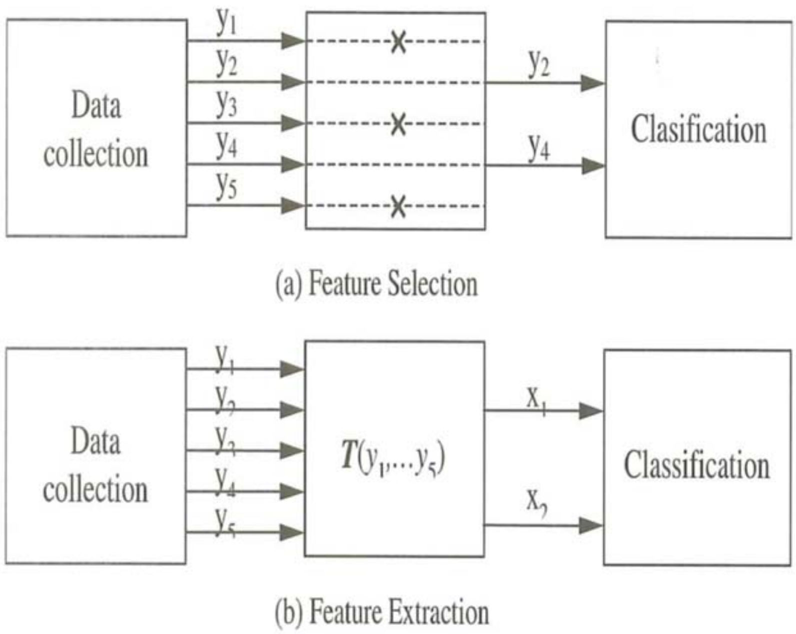

Figure 2 Dimensionality reduction diagram adapted from [12]

According to [14], feature extraction is the transformation of hyperspectral image from M dimensional space to N dimensional space where N<M. Principal Component Analysis (PCA) is one of the common feature extraction algorithms. ISOMAP, Factor Analysis, Linear Discriminant Analysis, Sammon mapping, Local Linear Embedding are other methods that are used for dimensionality reduction. Mathematical explanation of PCA is given in [15] and [16]. After applying PCA, the number of principal components can be selected using the principal values generated. These principal vectors can be used for classification. Total processing time is often significantly reduced with lower number of principal components [16].

2.1.2 Classification

Hyperspectral classification can be defined as giving a unique label class to represent each pixel by using its spectral information for every pixel vector in the hyperspectral image. In the literature, hyperspectral classification is grouped in two main categories as supervised and unsupervised classification methods. K-Mean and ISODATA [17] algorithms can be given as examples of unsupervised classification or clustering, algorithms. Clustering algorithms group or cluster the data by using their spatial and spectral properties without prior knowledge. Determining number of different classes in the image is a challenging issue. Supervised classification requires prior knowledge about data. Support Vector Machines (SVM) [18-22], K-Nearest Neighborhood (K-NN) [23-26], Gaussian Classifier (GC) [11], Maximum Likelihood [31-33] and Active Learning methods have been widely used for supervised hyperspectral classification.

2.1.2.1 Maximum Likelihood (ML)

In remote sensing Maximum Likelihood is one of the most popular methods. It has been used for many applications (remote sensing, statistics) since 1940. As a classification method it was firstly proposed by [34]. They used covariance matrices in order to derive likelihood estimate. They extend the work of [35] paper which compares two solutions of [36] and [37]. Maximum likelihood is derived from Bayes Theorem. Bayes theorem states that posterior probability that a pixel t belongs to class:

$$P(i\,|t\,) = \frac{P(\,t\,|i\,)\,P\,(i)}{P(t)}$$

Where p(t) stands for prior probability of class t and P(i) for prior information.

Maximum likelihood classification is used for multispectral data classification [38]. It is also used for hyperspectral data classification [39-40]. Both of these papers mentioned about dimensionality reduction and its necessity for better maximum likelihood classification accuracy. [39] used correlation between bands and [40] used PCA for dimensionality reduction.

2.1.2.2 K-Nearest Neighborhood (K-NN)

K-NN was introduced by [41] as a non-parametric method for pattern classification. It is very simple and easy to understand. In the literature, K-NN has been used for pattern recognition, speech recognition and remote sensing applications. The algorithm decides the class of the given pixel by majority vote of the pixels within a specific spectral distance from that pixel (in Euclidian distance determined by the k value). For every input vector, all class labels closer than maximum spectral distance is counted and the maximum numbered class is assigned for the input.

2.1.2.3 Support Vector Machines (SVM)

SVM provides high classification rates with small training datasets. In the literature SVM is used for many applications like pattern recognition [42-43], face recognition, handwritten digit recognition [44], object recognition [45, 46], fingerprint recognition [31] etc. Its formulation is presented in [47]. Since it is a very effective and simple method, SVM has been used for hyperspectral classification. SVM training algorithm tries to find the hyperplane which separates the dataset as much as possible. This is an iterative process that tries to separate training data with optimal decision boundary. Its simple form can be considered as a binary linear classifier. Every pixel in the hyperspectral image can be considered as a feature vector. Once the hyperplane is determined, SVM assigns each feature vector input to one of the classes. If the data points are not linearly separable, SVM can be used with non-linear functions named kernels. There are different kernels used in the literature: linear, polynomial, radial basis function (RBF) [48] and sigmoid are examples to that kernels. Formulations [49] of these kernels is given in (1): γ, r and d are kernel parameters.

Linear Kernel : $K(X_i, X_j) = X_i^T X_j$

Polynomial Kernel : $K(X_i, X_j) = (\gamma X_i^T X_j + r)d \ , \gamma > 0$ (1)

Radial Basis Function (RBF) : $K(X_i, X_j) = f(-\gamma \ ||X_i - X_j||^2) \ , \gamma > 0$

Sigmoid : $K(X_i, X_j) = \tanh(\gamma X_i^T X_j + r)$

2.1.3 Post-Processing Methods

In order to improve hyperspectral classification performance, spatial information may be used with spectral information [50]. Where hyperspectral classification aims to assign a unique value to each pixel, usage of spatial-spectral classification improves classification accuracy by considering neighbor pixels. The main idea is a pixel is probably same material with the neighbor pixels. One approach for using neighbor pixels is using the closest ones. Fixed window based filtering method is used in [51] and morphological profile is used in [52]. They both showed improvements on classification accuracy. Segmentation is another approach for using spatial information. [50] proposed a method for hyperspectral classification with clustering techniques. As is seen in Figure 3, pixel-wise classification results are gathered with the labeled connected components.

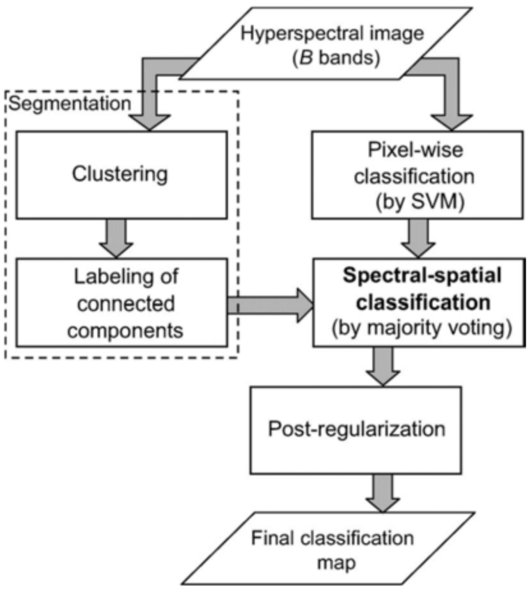

Figure 3 Flowchart of the proposed spectral–spatial classification scheme from [50]

CHAPTER 3

METHODOLOGY

3.1 Data

In this study, one high resolution and two low resolution hyperspectral images are used. Pavia University Scene is acquired by ROSIS sensor. Indian Pines and Salinas Scenes are acquired by AVIRIS sensor.

3.1.1 Pavia University Scene

Pavia University Scene (PUS) is acquired by ROSIS sensor which has a spectral range between 430-860nm in July 2002. This sensor has 115 spectral bands with 4nm bandwidth gap and 1.3 meter geometric resolution. PUS consists of 610x340 pixels. After discarding the image bands containing no information 103 bands are used for classification. PUS groundtruth has nine different classes. These classes and corresponding numbers of samples is presented in Table 1. The RGB image and groundtruth image can be seen in Figure 4. PUS is provided by Prof. Paulo Gamba of Pavia University.

Table 1 Pavia University Scene Groundtruth Classes and Sample Numbers

#	Class	Samples
1	Asphalt	6631
2	Meadows	18649
3	Gravel	2099
4	Trees	3064
5	Painted metal sheets	1345
6	Bare Soil	5029
7	Bitumen	1330
8	Self-Blocking Bricks	3682
9	Shadows	947

Figure 4 Pavia University Scene RGB Image(top) Groundtruth Image(bottom)(Courtesy of Prof. Paulo Gamba from Pavia University, Italy.)

3.1.2 Indian Pines Scene

Indian Pines Scene (IPS) is acquired by AVIRIS sensor which has a spectral range between 400-2500nm in 1992. It can gather images in 224 contiguous spectral channels. IPS has 145x145 pixels and 20 m spatial resolution. After water absorption bands ([108-112] and [154-167]) are removed, 200 bands are used for classification. There are 16 different classes in IPS. These classes and respective sample numbers is presented in Table 2. IPS is retrieved from Purdue University.

Table 2 Indian Pines Scene Groundtruth Classes and Sample Numbers

#	Class	Samples
1	Alfalfa	46
2	Corn-notill	1428
3	Corn-mintill	830
4	Corn	237
5	Grass-pasture	483
6	Grass-trees	730
7	Grass-pasture-mowed	28
8	Hay-windrowed	478
9	Oats	20
10	Soybean-notill	972
11	Soybean-mintill	2455
12	Soybean-clean	593
13	Wheat	205
14	Woods	1265
15	Buildings-Grass-Trees-Drives	386
16	Stone-Steel-Towers	93

Since we examined the effect of increasing the training data size on classification accuracy we do not use classes with less than 380 samples. The RGB image and groundtruth image of IPS can be seen in Figure 5.

Figure 5 Indian Pines Scene (Left) RGB Image (Right) Groundtruth Image (Retrieved from https://engineering.purdue.edu/~biehl/MultiSpec/hyperspectral.html)(accessed 06.05.2013)

3.1.3 Salinas Scene

Salinas Scene (SSC) is also acquired by AVIRIS sensor in 1998. Salinas Scene has 512x217 pixels and 3.7 meter spatial resolution. As in the IPS case water absorption bands ([108-112] and [154-167]) are removed and 204 bands are used for classification. Salinas Scene also has 16 classes in its groundtruth. These classes and respective sample number can be seen in Table 3. RGB image and groundtruth of Salinas Scene can be seen in Figure 6. SSC is retrieved from Purdue University.

Table 3 Salinas Scene Groundtruth Classes and Sample Numbers

#	Class	Samples
1	Brocoli_green_weeds_1	2009
2	Brocoli_green_weeds_2	3726
3	Fallow	1976
4	Fallow_rough_plow	1394
5	Fallow_smooth	2678
6	Stubble	3959
7	Celery	3579
8	Grapes_untrained	11271
9	Soil_vinyard_develop	6203
10	Corn_senesced_green_weeds	3278
11	Lettuce_romaine_4wk	1068
12	Lettuce_romaine_5wk	1927
13	Lettuce_romaine_6wk	916
14	Lettuce_romaine_7wk	1070
15	Vinyard_untrained	7268
16	Vinyard_vertical_trellis	1807

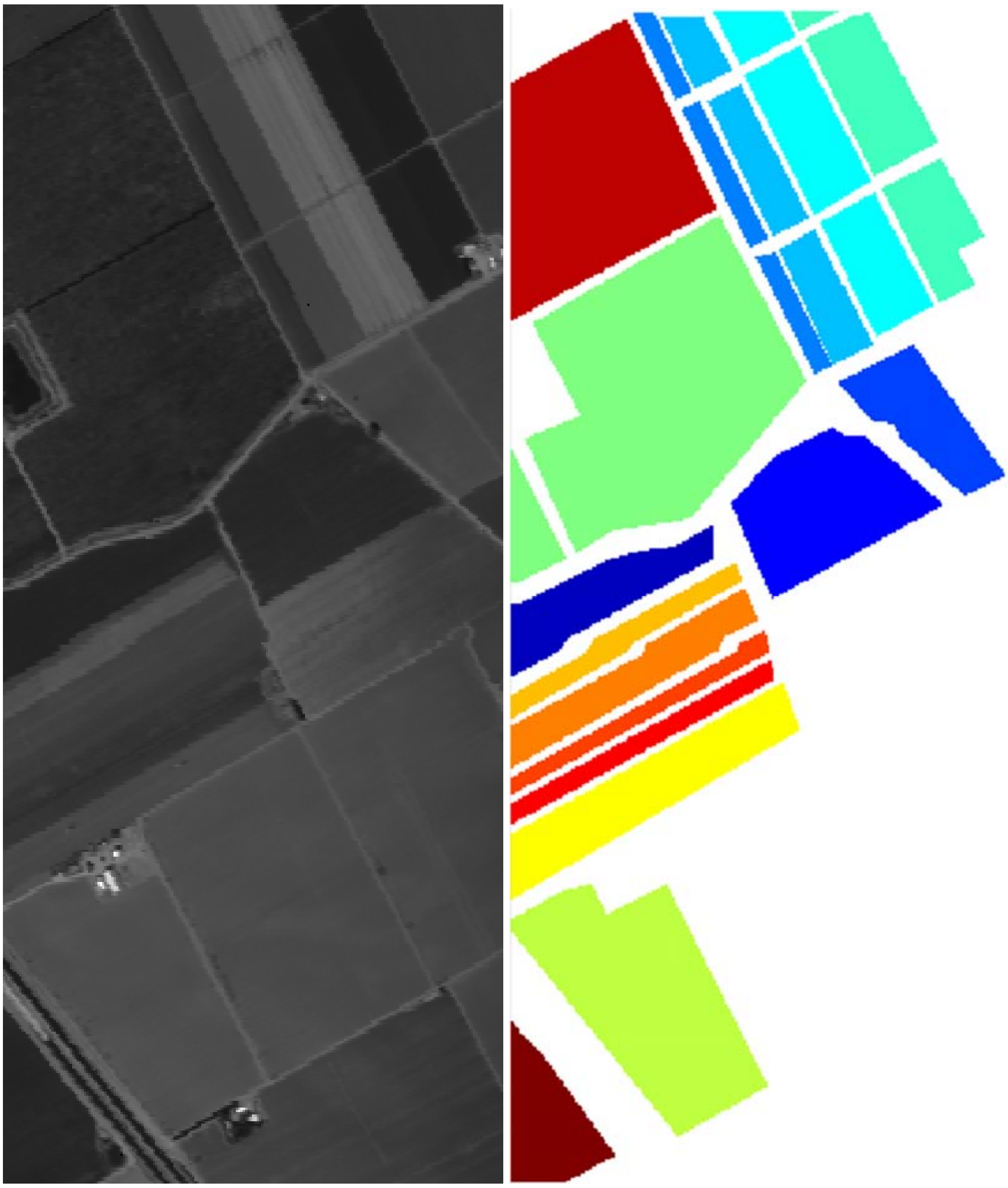

Figure 6 Salinas Scene (Left) Sample Band (Right) Groundtruth Image

3.2 Introduction

The main objective of this research is to investigate the effects of training data to supervised hyperspectral classification algorithms. In order to compare the results with the literature, training data is extracted from the image and used as external training data. Training data selection is also another aspect of this research. We tried three different train data selection methods. These methods are described in Section 3.3.

The effect of usage of pre-processing with dimensionality reduction and post-processing with filtering with 3x3 window and majority voting with meanshift segmentation methods are also examined. The experiments include the both separate and joint usage of these steps. These experiments are described in Sections 3.4 and 3.5. In this study, we used PCA for dimensionality reduction as the pre-processing stage. We also used for meanshift segmentation and filtering with window as post-processing methods.

3.3 Training Data Selection

We selected training data by using three different methods. These experiments are important to indicate the effects of training data on supervised hyperspectral classification. First we extracted first N samples for all classes. As is seen in Figure 7(top), this method extracts training data from the left columns of the image. The selected training samples are expected to have similar spectral characteristics because the closer pixels have similar spectral signatures.

Second training data selection method is extracting (N) samples from image uniformly. Selected training data with this method is expected to represent all data from the image. The selection with this method can be seen in Figure 7 (middle).

Last training data selection method is extracting (N) samples of training data randomly for each class. This selection method is very similar to uniform selection method. Nevertheless, some small parts of data may not be represented in the training data with this method. The selection with this method can be seen in Figure 7(bottom).

For all these three methods, we also wanted to observe the effect of training sample size. We used and compared the results with different values of training data size, N. For PUS we used different N values that range between 120 and 920, for IPS between 220 and 380 and for SSC ranges between 220 and 900 per class. We incremented training data size by 10 for every iteration and obtained the classification results.

Figure 7 Training Sample Selection N=700 (top)First N Samples, (middle)Uniformly Selected Samples (bottom) Randomly Selected Samples

3.4 Pre-Processing with PCA

In the context of this study, PCA implementation suggested by [53] for dimensionality reduction is employed. In this method, firstly, the hyperspectral image is normalized by subtracting its mean and the covariance matrix is calculated from the Equation (1).

$$Cov(x) = \frac{1}{N-1} X * X^T$$

Then eigendecomposition of the covariance matrix is computed from Equation (2). Let E = [e1 e2 ….en] and $\lambda = \lambda_1 \lambda_2 \ldots\ldots \lambda_n$

$Cov(x)E = Diag(\lambda)E$ (2)

The eigenvalues and eigenvectors are sorted to get the principal components of the image. We used different numbers of principal components for all three scenes. For Pavia University Scene [2,3……30,35,40,45,50,55,60,65,70,75,80,85,90,95,100,103] and for Indian Pines and Salinas Scenes [2,3,………30,35,45,55,65,75,85,95,100,120,140].

In Figure 8, flow chart of classification with Pre-processing usage can be seen. Firstly, the dimensions of hyperspectral image is reduced by PCA. After dimensionality reduction, train data extraction is performed by three different methods. By using these train data, learning step performed. Then, classification process carried out with the output of learning process and lower dimensionality image.

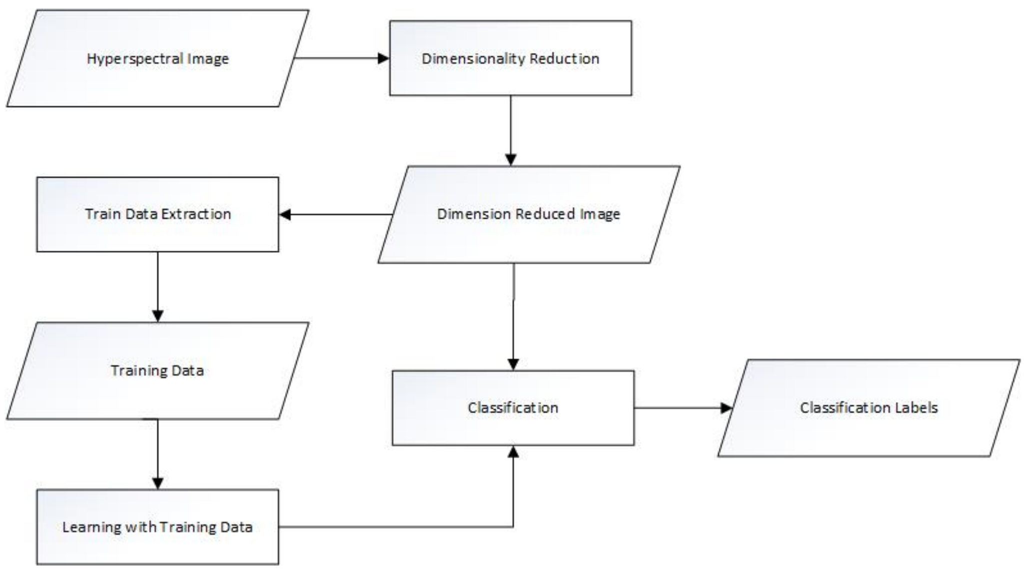

Figure 8 Flow Chart of Classification with Pre-Processing

Normal classification time for ML algorithm is 61.35 seconds. This time reduces to 7.31 seconds if two principal components are used. For SVM-LNR algorithm normal classification time 370 seconds, this time also reduces to 143 seconds. The classification time of SVM-RBF reduces from 501 seconds to 228 seconds.

3.5 Post Processing with Spatial Information

We used two different post processing methods for using spatial information with spectral information. We used majority voting with meanshift segmentation and 3x3 voting filter as post processing methods in this thesis. These methods are applied after performing pixel wise classification.

3.5.1 Filtering with 3x3 Window

We employed filtering with 3x3 window method in order to use spatial information. For every pixel, after we procured assigned class labels from classification algorithm, class labels are weighted as it is in Figure 9. We applied different weighting methods (

Figure 9).

Method 1

1	1	1
1	4	1
1	1	1

Method 2

0	1	0
1	6	1
0	1	0

Method 3

1	1	1
1	1	1
1	1	1

Method 4

0	2	0
2	4	2
0	2	0

Method 5

1	2	1
2	4	2
1	2	1

Figure 9 Weighting methods for Filtering with 3x3 Window

The overall flow of our majority voting with 3x3 window filtering method algorithms as follows;

Get the classification result

Initialize coordinate (x,y)

Define the neighbor pixels

Count the class numbers by multiplying weights

Select the most frequent and assign it as coordinate value of (x,y)

For each pixel repeat the process

In Figure 10, the classification results for these methods can be seen. Except Method-2 all of these methods improved the classification performance. Although all of them give similar results, we observed that simple averaging (Method-3) is still the best method among all.

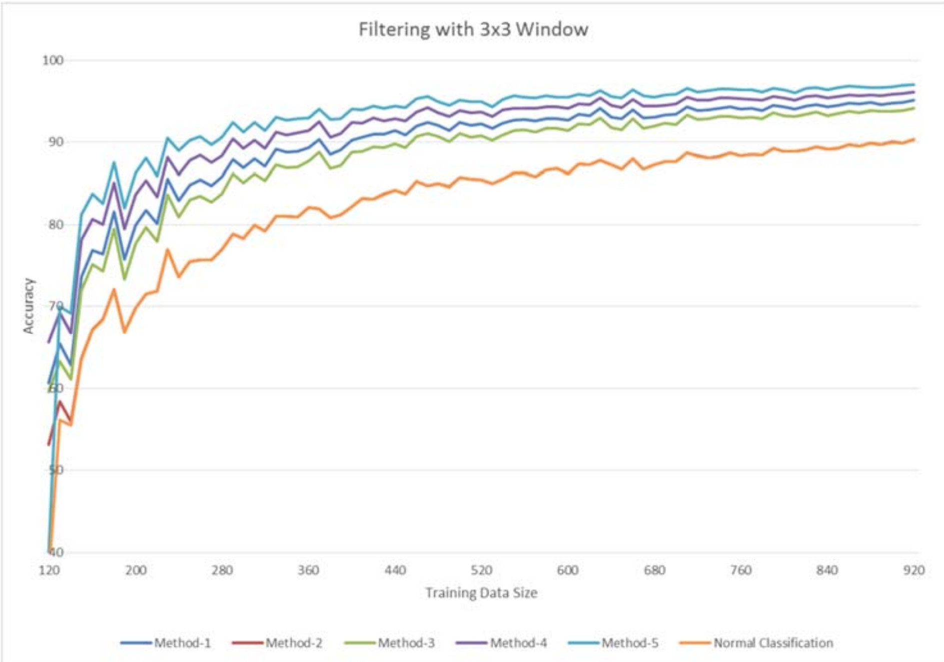

Figure 10 Different methods for filtering with 3x3 window method

3.5.2 Majority Voting with Meanshift Segmentation

We also used majority voting with meanshift segmentation. The majority voting method that we used is similar to [50]. First, we obtained the labels from meanshift segmentation. In order to achieve better segmentation results we used pattern search algorithm (Section 3.5.2.1) to find the best parameters.

The overall flow of majority voting with meanshift segmentation method algorithm as follows;

- Get the classification result
- Get segment labels from meanshift segmentation
- Count the class labels for each segment
- Select the most frequent class label and assign it to all pixels in that segment
- For each label repeat the process

The flow chart of post processing with meanshift segmentation can be seen in Figure 11.

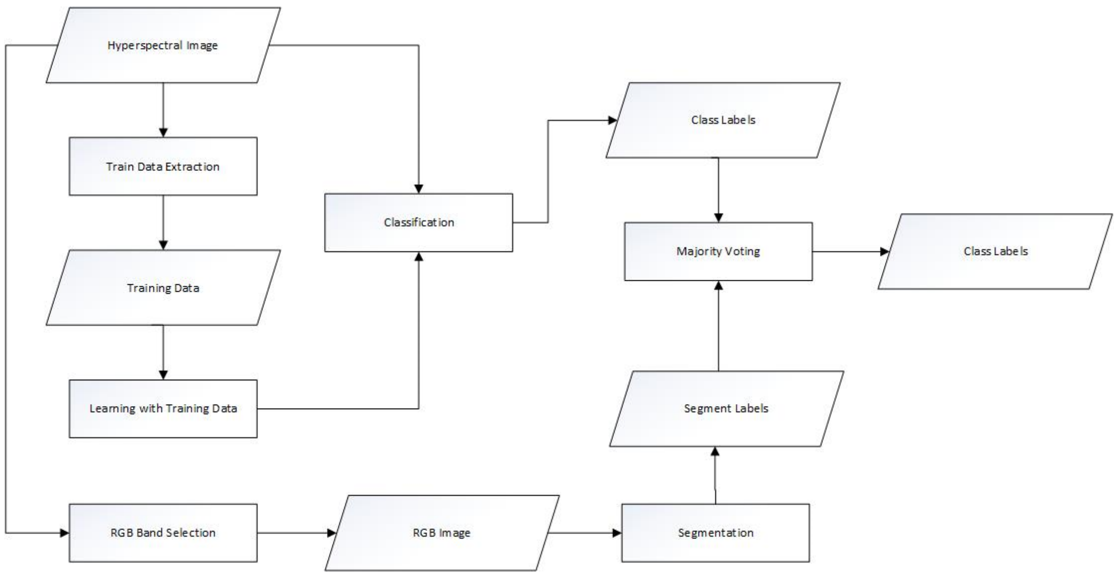

Figure 11 Post Processing with Meanshift Segmentation

For all three scenes, we also adjusted the parameters of the meanshift algorithm. Meanshift operation takes RGB image and feature function as input. Feature function has these parameters:

- SpatialBandWidth - segmentation spatial radius with default integer value 7
- RangeBandWidth - segmentation feature space radius with default float value 6.5
- MinimumRegionArea - minimum segment area with default integer value 20

We conducted experiments to set these parameters for all scenes. For PUS we used the Band 6 (462nm), Band 35 (594nm) and Band 90 (682nm). The best bands are also found by pattern search algorithm. For PUS, the best parameters are selected as "SpatialBandWidth = 18", "RangeBandWidth = 6" and "MinimumRegionArea = 9". The sample meanshift output for PUS with these parameters can be seen in Figure 12.

For IPS and SSC RGB bands are selected as 19 (620nm), 27(700nm), 33(760nm). The best parameters of meanshift for IPS are selected as "SpatialBandWidth = 1", "RangeBandWidth = 9" and "MinimumRegionArea = 13" and for SSC are selected as "SpatialBandWidth = 36", "RangeBandWidth = 57" and "MinimumRegionArea = 3". The corresponding segmentation images for IPS (b) in Figure 13 and for SSC Figure 14.

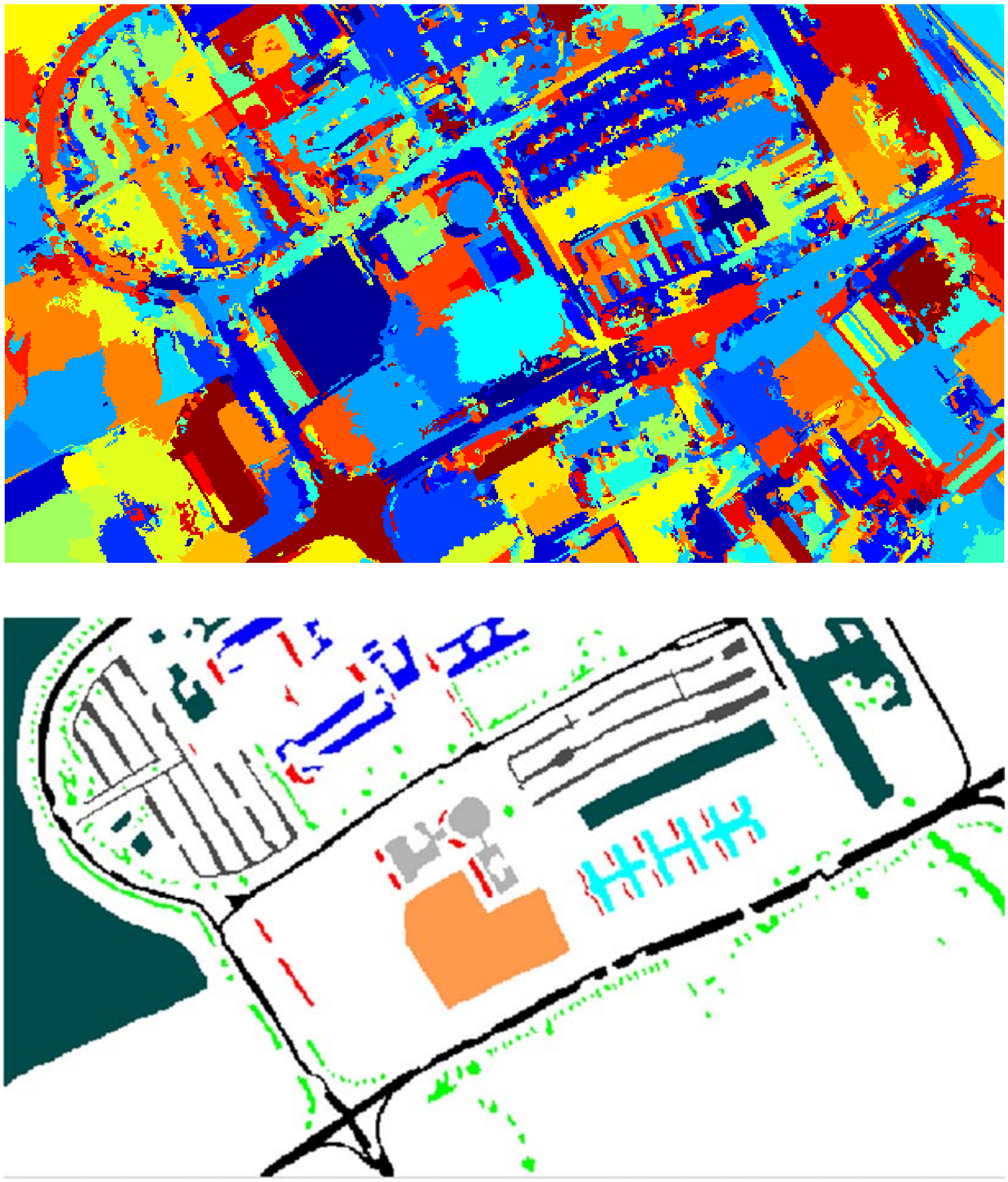

Figure 12 Pavia University Meanshift Segmentation Result (top) and Ground Truth (Bottom)

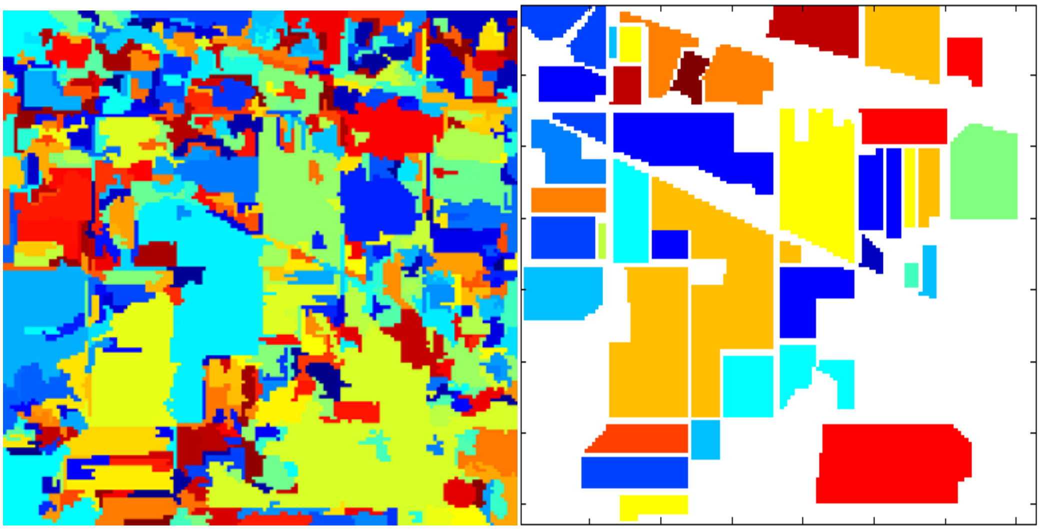

Figure 13 Segmentation Image (left) and Ground Truth (right) of Indian Pines Scene Salinas Scene

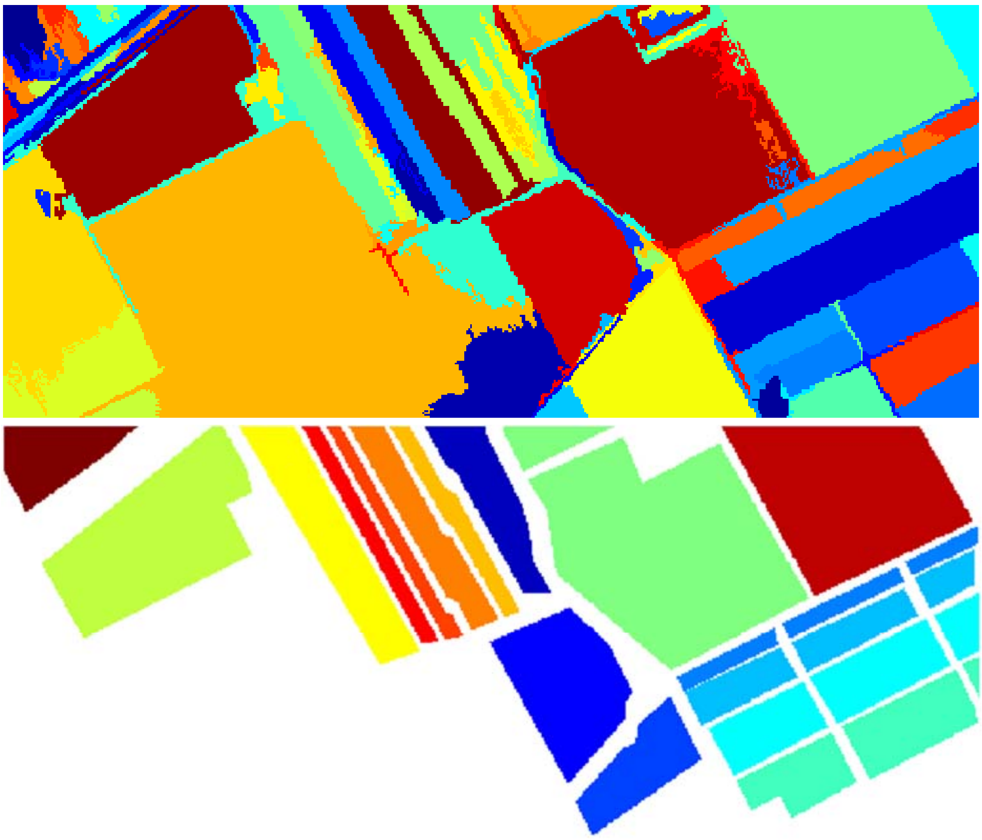

Figure 14 Segmentation Image (top) and Ground Truth (bottom) of Salinas Scene

3.5.2.1 Pattern Search

Pattern search algorithm is a method for direct search numerical optimization method proposed by Hooke and Jeeves [54]. Pattern search does not require the objective function to be continuous or differentiable. The convergence analysis of pattern search and the relation between optimality conditions and the search gradient are further detailed in the paper. [55]

Any linearly constrained optimization problem can be defined by using an objective function, $f(x)$, as given below;

$$\min_{x \in \Omega} f(x) \ , where \ f: R^n \rightarrow R$$
$$\text{and } \Omega = \{x \in R^n : \ell \leq \text{Ax} \leq \text{u}\}\ ,\text{where A} \in Q^{mxn}$$
$$and\ \ell, u \in \{R\ \}^m\ provided\ that\ \ell < \text{u}$$

The main of aim of pattern search algorithm is to minimize the objective function in the space of feasible solutions, Ω. Search space is bounded by lower and upper bounds, ℓ and u, respectively.

In the study [56], a barrier function, defined as $f_\Omega(x) = f + \psi_\Omega$, is employed instead of $f(x)$ by introducing an indicator function, ψ_Ω, for feasible solution set Ω. In other words, ψ_Ω has zero value on Ω and equal to ∞ elsewhere, which is shown below;

$$f_\Omega(x) = \begin{cases} f(x) & if\ x \in \Omega \\ \infty & otherwise \end{cases}$$

Since the pattern search is an iterative algorithm visiting instances of solutions, $\{x_n\} \in R^n$, non-increasing objective function values are required to proceed. The optimization procedure is composed of two distinct stages; SEARCH and local POLL.

In SEARCH stage, the algorithm seeks a better solution minimizing the barrier objective function. At each step the objective function is evaluated by a finite number of points on a mesh. In case of reaching a lower objective function value, $f_\Omega(x_{k+1}) < f_\Omega(x_k)$, an improved mesh point is obtained. Otherwise, the algorithm steps into POLL stage in which an optimum solution is searched in the neighborhood of the current mesh point. The current best solution for a mesh local optimizer is identified, unless POLL routine reaches a better solution. Then, the mesh size parameter Δ_k is updated by a pre-defined constant τ as follows;

$$\Delta_{k+1} = \tau^{wk}\Delta_k$$

As a result, the mesh about to be explored by pattern search at iteration k can be defined as;

$$M_k = \{x_k + \Delta_k D_z : z \in Z^+\}$$

In that formulation, D represents positive spanning directions in R^n.

Moreover, the gradient of the problem is not necessarily needed to reach the global minimum as it is proved in the paper[57] that pattern search algorithm holds the global convergence property.

3.6 Post-Processing and Pre-Processing

Section 3.4 and 3.5 shows the usage of post-processing and pre-processing. We also conduct experiments to see the effect of both post-processing and pre-processing usage. We used both meanshift segmentation and 3x3 voting filter as post-processing methods. The overall flow of the usage pre-processing and post-processing method together as follows;

- Apply PCA as pre-processing
- Get the classification result from principal components
- Get labels from meanshift segmentation
- Count the class labels for all 3x3 window
- Select the most frequent class labels from classification labels
- Assign it for all pixels in that segment
- For each label repeat the process

The flow chart of that process can be seen in Figure 15.

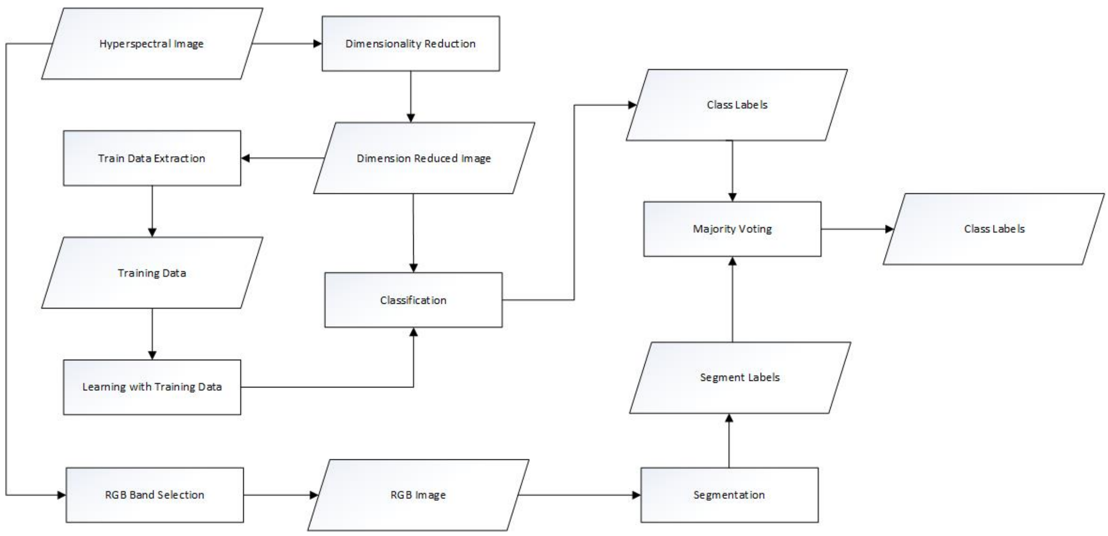

Figure 15 Flow chart of pre-processing and post-processing usage for classification

CHAPTER 4

EXPERIMENTS

In this chapter, empirical classification results are demonstrated. The effects of using pre-processing and post-processing are examined separately. In Sections 4.2, 4.3 and 4.4 the empirical results of PUS, SSC and IPS are shown. We grouped the experiments as no-pre-processing and no-post-processing, pre-processing with no-post-processing, no-pre-processing with post-processing and pre-processing with post-processing methods.

4.1 Measurement Metrics

There are several methods for assessing the performance of hyperspectral classification. In this study, we used classification accuracy as the classification metric. Classification accuracy is the fraction of truly classified data points to the total number of classified pixels. Classification error can be calculated as in equation (4.1)

$$Classification\ Accuracy\ = \frac{Number\ of\ Truly\ Classified\ Pixels}{Number\ of\ Available\ \text{Pixels}} \qquad (4.1)$$

We also calculated other indicators to assess the performance by material with precision, recall and F-Measure metrics. These indicators are;

True Positives (TP): The number of correctly labeled pixels.

True Negatives (TN): The number of correctly labeled pixels belonging to other classes.

False Positives (FP): The number of incorrectly labeled pixels belonging to class.

False Negatives (FN): The number of incorrectly classified pixels belonging to other class.

Precision is the fraction of the number of correctly labeled pixels to both correctly and incorrectly classified pixels.

$$Precision\ = \frac{TP}{TP + FP}$$

Recall is the fraction of correctly classified pixels to correctly classified pixels with incorrectly classified pixels.

$$Recall = \frac{TP}{TP + FN}$$

F-measure is the harmonic mean of precision and recall.

$$F_\beta = (1 + \beta) \frac{Precision \,.\, Recall}{\beta^2 .\, Precision + Recall}$$

The β parameter is the weight of precision and recall. The precision and recall values are deemed more important when β value is below and above 1, respectively.

4.2 Indian Pines Scene Experiments

The first objective of this section is to analyze the effect of train data on classification accuracy. We also analyzed the effect of pre- and post-processing usage on classification accuracy. Firstly, we implemented and tested all the classification algorithms that we used (ML, K-NN, SVM-LNR and SVM-RBF). Detailed explanation of this process is provided in Chapter 3. The confusion matrixes for IPS are given in Appendix A.

4.2.1 Indian Pines Scene with No Pre-Processing and No Post-Processing

We implemented different training data size for all training data selection types. In order to see the effect of training data size to classification algorithms, we conducted the experiments with different training data size. As we stated in Section 3.3, we extracted training data from the scene itself by using groundtruth. We used this extracted data as separate training data.

As the first method, we used the first N samples as the training data. With this method the average classification accuracies are between 55% and 65% for all algorithms. In Figure 16 , first N sample classification accuracies can be seen. The training data size affects ML algorithm more than the other algorithms. As the training data size increases, ML algorithms classification results are also increasing. For all algorithms that we used, training data size affected the classification accuracy in a positive manner. By using 220 training data, ML algorithms classification accuracy is 48.10%. When we increased training data size to 380, the accuracy increases to 69.33%. On the other hand, K-NN algorithm increases by approximately 8% (60.10% - 68.02%), SVM-LNR increases by %3 (66.83% - 70.90%) and SVM-RBF increases by %4 (57.71% - 67.71%). SVM-LNR obtained the highest accuracies for all training data sizes with first N sample selection method.

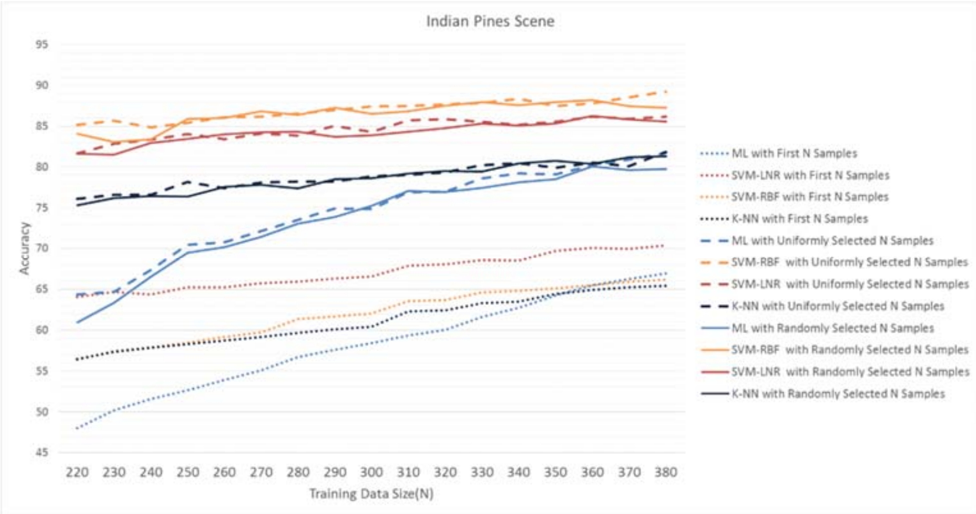

Figure 16 Indian Pines Scene Classification Accuracies

Second training data selection method for IPS is uniformly selected N samples from scene. The change of sample selection method increased the classification accuracies for all algorithms. With ML algorithm and 220 training data, the classification accuracy is 64.39%. By using 380 training data, the classification accuracy is increased to 81.73%. ML algorithm is affected by training data size like first N sample selection method, but training sample selection method change altered the classification result by 15%. Other algorithms are not affected by the increase of the training data size. K-NN algorithm increases approximately by 5% (76.06% - 81.83%), SVM-LNR increases by 3% (81.63% - 86.20%) and SVM-RBF increases by 4% (85.16% - 89.24%). However, the change of training sample selection method mostly improved the SVM-RBF algorithm. The best classification results with SVM-LNR and SVM-RBF are obtained with first N sample selection and uniformly selected N sample methods, respectively. For all training data sizes with uniformly selected N samples, SVM-RBF achieved higher classification accuracies. SVM-LNR and K-NN algorithms improved the classification accuracy approximately 20% with first N sample and randomly selected N sample methods for all training data sizes over first N sample method. The classification accuracies of randomly selected N sample method are similar to uniformly selected N sample method. The classification accuracies may differ by 1%.

In Figure 17, the classification results for ML algorithm with 380 training sample is presented. The misclassified pixels for first N sample selection method (left) generally take place on the right side of the classes as expected. Furthermore, the misclassified pixels in uniformly selected N sample selection method (right) are dispersed uniformly over the classes. First N sample selection and uniformly selected N sample selection methods acquired 66.91% and 81.74% accuracy, respectively.

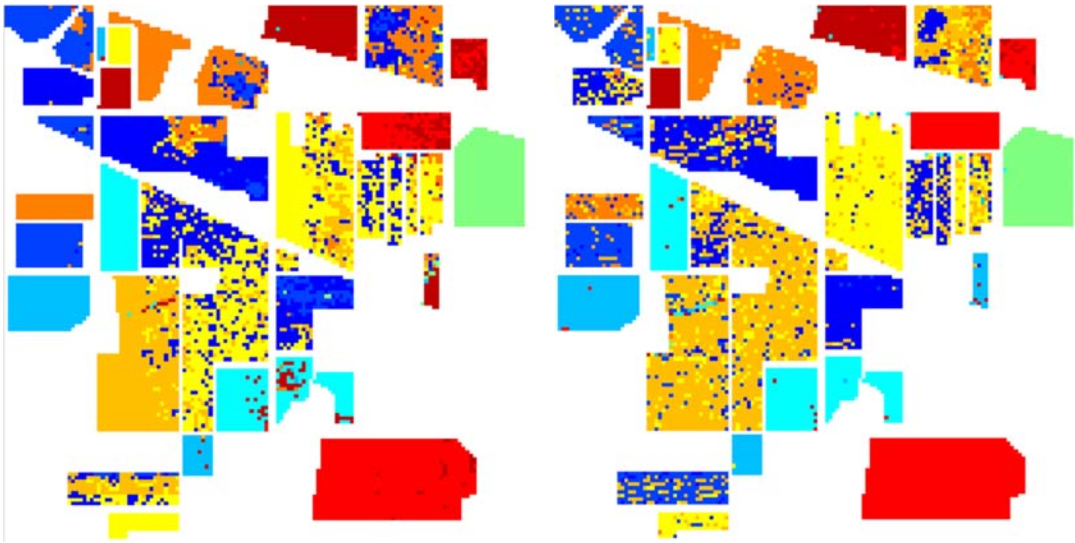

Figure 17 Indian Pines Scene (left) First N (N=380) Sample Classification Result (right) Uniformly Selected N (N=380) Sample Classification Result

4.2.2 Indian Pines Scene with Pre-Processing Only

The second stage of IPS experiments is using PCA as the pre-processing step. We used different number of principal components for classification algorithms. The aim of PCA step is to represent the data more efficiently and reduce classification time by using low number of principal components. In general, PCA usage reduces classification time, but in small scenes like IPS the difference is not significant.

The training size selection method affected the classification accuracy very similar to Section 4.2.1. The accuracies with selection of first N samples method is approximately 10% lower than both uniformly selected N samples and randomly selected N samples methods. In Figure 18, effect of training data selection method can be seen clearly.

As the number of principal components increase, ML algorithm classification accuracy is improved when training data size is increased. The difference between minimum training data size (220) and the maximum training data size (380) is approximately 4% for lower (<20) number of principal components. However this improvement is 10% for 140 principal components. As is seen in Figure 19, the classification accuracy is increasing with the number of principal components. By using ML algorithm, we obtained 50.35% classification accuracy with two principal components.

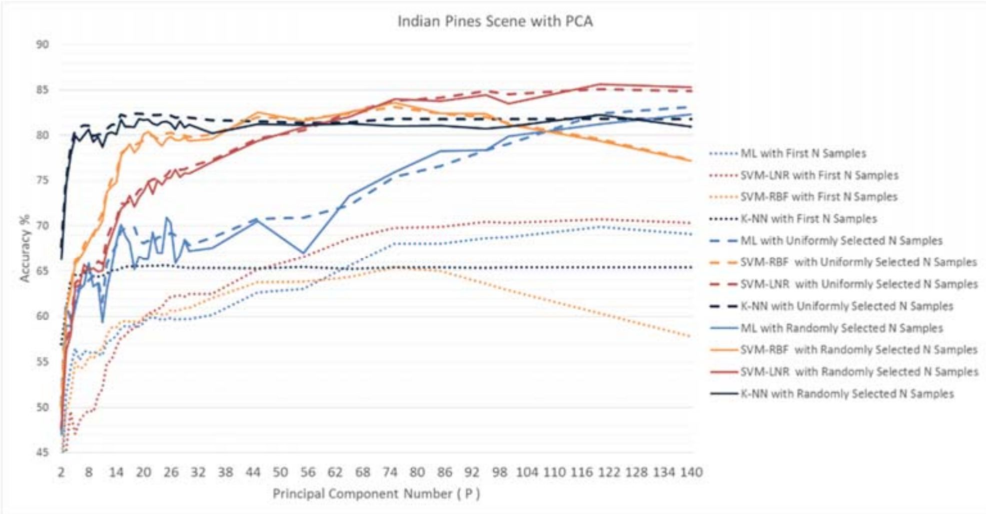

Figure 18 Indian Pines Scene classification with PCA

The accuracy with 140 principal components is 83.12%. Moreover, when we compared the classification accuracies without PCA, the classification accuracies for all training data size are improved by 2-8%. We obtained the best accuracies by using lower number of principal components with K-NN algorithm. After 18 principal components, the accuracy of the K-NN algorithm is not improved significantly with the increase of the number of principal components. In addition, K-NN gives the best results for all principal component numbers. The pre-processing usage does not affect K-NN's classification accuracy over not using pre-processing. The increase of principal component number affects SVM-LNR and SVM-RBF classification accuracy positively. Both algorithms gave better results with higher number of principal components. However, for SVM-RBF and SVM-LNR the classification accuracy for all training data sizes are decreasing if pre-processing with PCA step is used. This decrease can be defined as SVM-RBF on the average 6% and SVM-LNR on the average 2%.

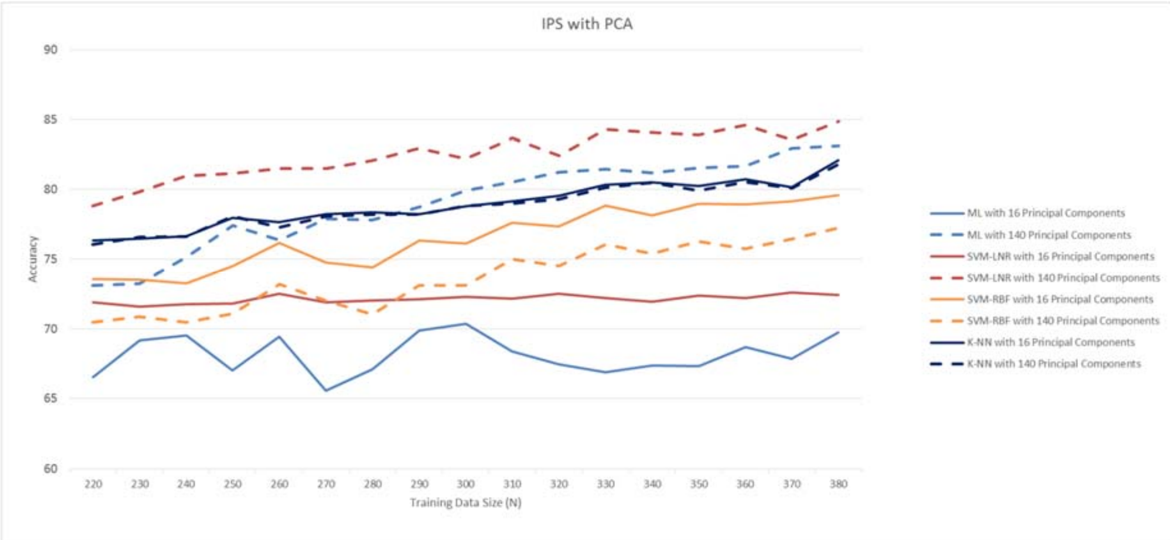

Figure 19 IPS with different number of principal components

4.2.3 Indian Pines Scene with Post-Processing Only

As we stated before, we used majority voting with meanshift segmentation (Section 3.5.2) and filtering with 3x3 window methods (Section 3.5.1) as post processing methods. The aim of this step is to improve hyperspectral classification accuracy by using spatial information. In Figure 20 the results for filtering with 3x3 window results and in Figure 21 the results for majority voting with meanshift segmentation results can be seen. The results show that both methods improve the classification accuracy.

Using majority filtering with 3x3 window as post processing method enhances the classification results for all training data sizes. The enhancement is approximately 16% for lower training data sizes and 11% for higher training data sizes. Usage of this method also enhances the classification results for other algorithms. The best result for ML algorithm is 92.54% with 360, for SVM-LNR algorithm is 93.62% with 360 training data, for SVM-RBF algorithm is 94.29% with 380 training data and for K-NN algorithm is 93.30% with 380 training data. These results show that the usage of spatial information with filtering 3x3 window improves the classification rates 10.8% for ML, 5.05% for SVM-RBF, 7.42% for SVM_LNR and 11.47% for K-NN algorithms.

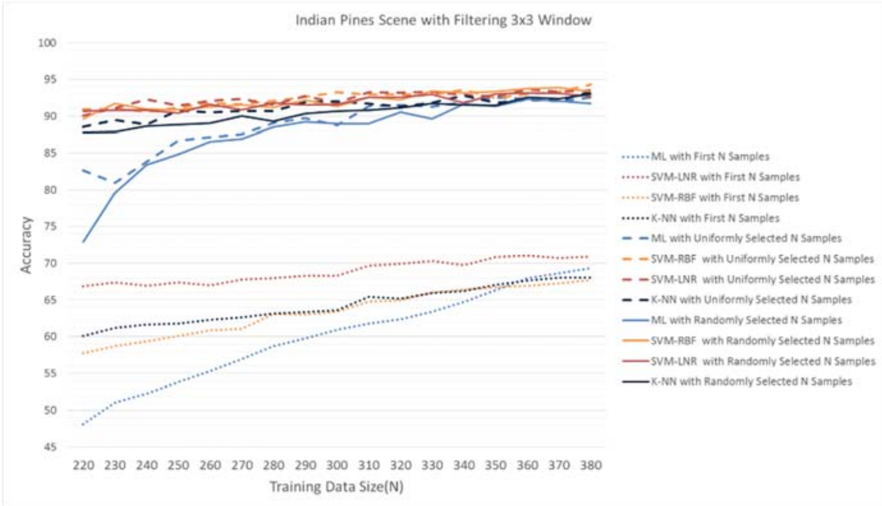

Figure 20 IPS with Filtering 3x3 Window

Moreover, the best results for IPS are obtained by using majority voting with meanshift segmentation as the post processing method. The advantage of this method is that it provides higher accuracy with lower training data size. With 220 training data size, ML algorithm classification accuracy reaches 91.92%. Spatial information usage brings not only higher accuracy but also stable classification accuracy for all number of training data. Majority voting with meanshift segmentation usage improves all algorithms classification accuracy. For example, the best classification accuracy for ML 93.18% with 340 train data, for SVM-LNR 95.05% with 310 training data, for SVM-RBF 94.36% with 370 training data and for K-NN 95.38% with 380 training data. Using this method improves the classification accuracy 11.44% for ML, 5.11% for SVM-LNR, 8.7% for SVM-RBF and 13.55% for K-NN.

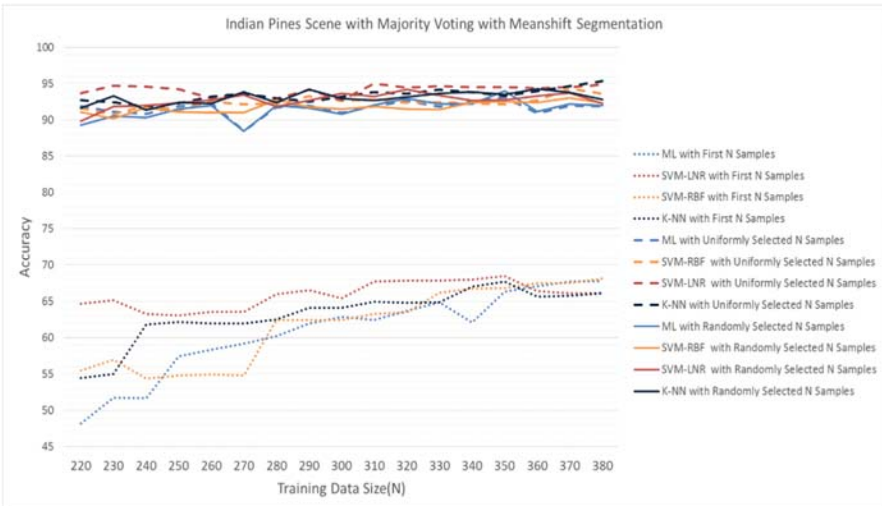

Figure 21 IPS Classification Results for Majority Voting with Meanshift Segmentation

4.2.4 Indian Pines Scene with Post-Processing and Pre-Processing

Last stage of IPS experiments is performing hyperspectral classification first pre-processing with PCA. After PCA, classification process is carried out. Lastly, filtering with 3x3 window and majority voting with meanshift segmentation as post-processing is performed. Previous experiments show that, whereas usage of the PCA reduces dimension and classification time, majority voting with meanshift segmentation is increasing classification accuracy. These experiments aim to investigate and explain the effects of pre-processing and post-processing usage for hyperspectral classification. Detailed information about this step is given in Section 3.6.

According to the experiments in Section 4.2.2., PCA usage is affecting classification algorithms differently. For SVM-LNR, SVM-RBF and ML algorithms pre-processing usage is not improving the classification accuracy. However, even with lower training data sizes, K-NN algorithm improves the classification accuracy when more than six principal components are used.

Pre-processing with PCA and post-processing as majority voting with meanshift segmentation (Figure 22) also improves the classification accuracy of classification with PCA and without post-processing method. Similarly with filtering with 3x3 window method, SVM-RBF obtained better results if PCA is not used. On the other hand, ML algorithm generally obtains better classification accuracies if PCA is not used. The usage of PCA is reducing the classification accuracy for SVM-RBF approximately by 4%. K-NN algorithm obtains similar classification accuracies with the accuracies obtained in Section 4.2.3. PCA usage affects K-NN algorithm better than other classification algorithms. The reason of that K-NN algorithm is classifying with nearest neighborhood rule so working in lower dimensional feature space provides an advantage.

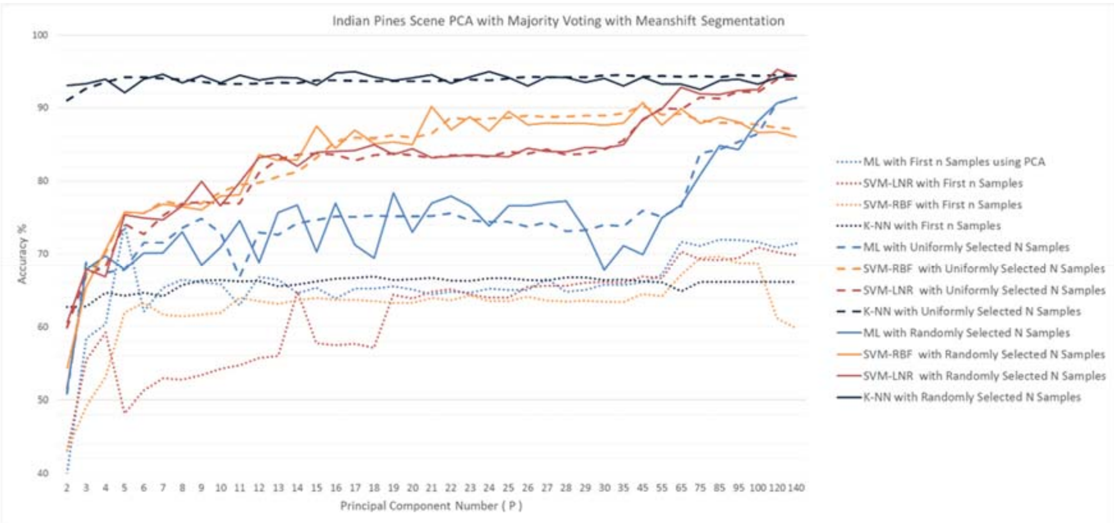

Figure 22 IPS with Majority Voting with Meanshift Segmentation

Pre-processing with PCA and post-processing as majority voting with meanshift segmentation (Figure 22) also improves the classification accuracy of classification with PCA and without post-processing method. Similarly with filtering with 3x3 window method, SVM-RBF obtained better results if PCA is not used. On the other hand, ML algorithm classification accuracies generally obtains better classification accuracies if PCA is not used. The usage of PCA is reducing the classification accuracy for SVM-RBF approximately 4%. K-NN algorithm obtains similar classification accuracies with the accuracies obtained in Section 0. PCA usage affects K-NN algorithm better than other classification algorithms. The reason of that K-NN algorithm is classifying with nearest neighborhood rule so working in lower dimensional feature space provides an advantage.

4.3 Salinas Scene Experiments

In this section we also analyze the effect of train data to classification accuracy on Salinas Scene. We also analyzed the effect of pre- and post-processing usage to classification accuracy on the same scene. Then as in Section 4.2 we implemented all the classification algorithms that we used (K-NN, ML, SVM-LNR and SVM-RBF). SSC experiments are conducted similarly with IPS experiments. SSC and IPS are acquired from same sensor but SSC is larger than IPS. We compared the results for both scenes. The confusion matrixes for SSC are given in Appendix B.

4.3.1 Salinas Scene without Pre-Processing and Post-Processing

In the same way that we conducted the experiments for IPS, the results of these experiments are analyzed by training data size and algorithm. Training data extraction methods are also same. The behaviors of each training data selection methods are examined for all algorithms.

The accuracies of the selection training data as first N samples method is around 75-80%. Training data selection method affects the Salinas data in the same way with IPS. Uniform and random selection methods acquire higher accuracies than first N sample selection method for all training data sizes. Nevertheless the accuracies obtained with first N sample training data selection method are higher than IPS. This may be due to spectral signatures of the materials in SSC being more differentiable than IPS. So, the classification results for SSC are expected to perform better than that of IPS. The Figure 23, shows that the classification accuracies can reach above 90% without pre-processing or post-processing.

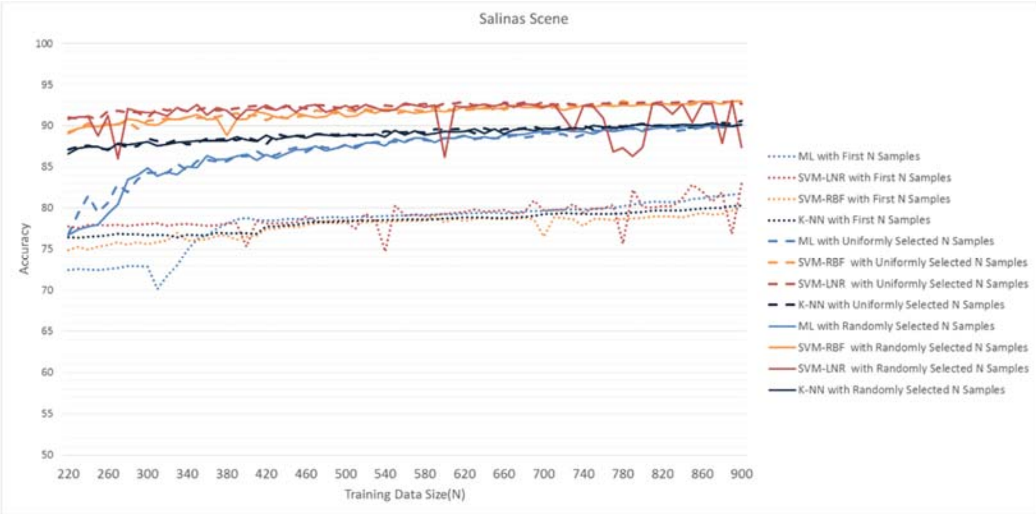

Figure 23 Salinas Scene Classification Results without Pre-Processing and Post-Processing

When we observe the results on the basis of algorithms, ML algorithm increases its classification accuracy as the training data size increases. SVM-LNR, SVM-RBF and K-NN are not affected as much from the increase of training data size. From these three algorithms, SVM-RBF obtains better classification results than others. It obtains 93.03% classification accuracy with 780 training data. On the other hand SVM-LNR obtains 92.96% classification accuracy with 890 training data. Lastly, K-NN obtains 90.62% classification accuracy with 900 training data. ML acquired lowest accuracy (90.06%) among all algorithms.

IPS and SSC have the same patterns for all classification algorithms that we applied. This situation is available for all training data selection models. Additionally the classification accuracies of SSC are better than classification accuracies of IPS. The training data selection methods also acquired similar results. First N sample selection method acquired worse results than uniformly N sample selection and randomly N sample selection methods.

Figure 24 shows the classification results for SSC uniformly selected N samples (top), first N samples from right side of the image (middle) and last N samples from left side of the image (bottom). Similar with IPS, the misclassified pixels with uniformly selected N sample selection method are dispersed through all the classes. However, right part of the 8th class denoted by green (grape-untrained) and left part of the 15th class denoted by red (vineyard-untrained) have very similar spectral characteristics. With first N sample selection method where we select training samples from left side of the classes, training samples for 15th class are very similar to samples from 8th class. As a result, the classification accuracy for 15th class decreases to 3%. Similarly, when we select training samples from right side of the classes, the accuracy of the 8th class decreases to 20%. This is the main reason for the sudden decreases of SVM-LNR with random N sample selection method in Figure 23.

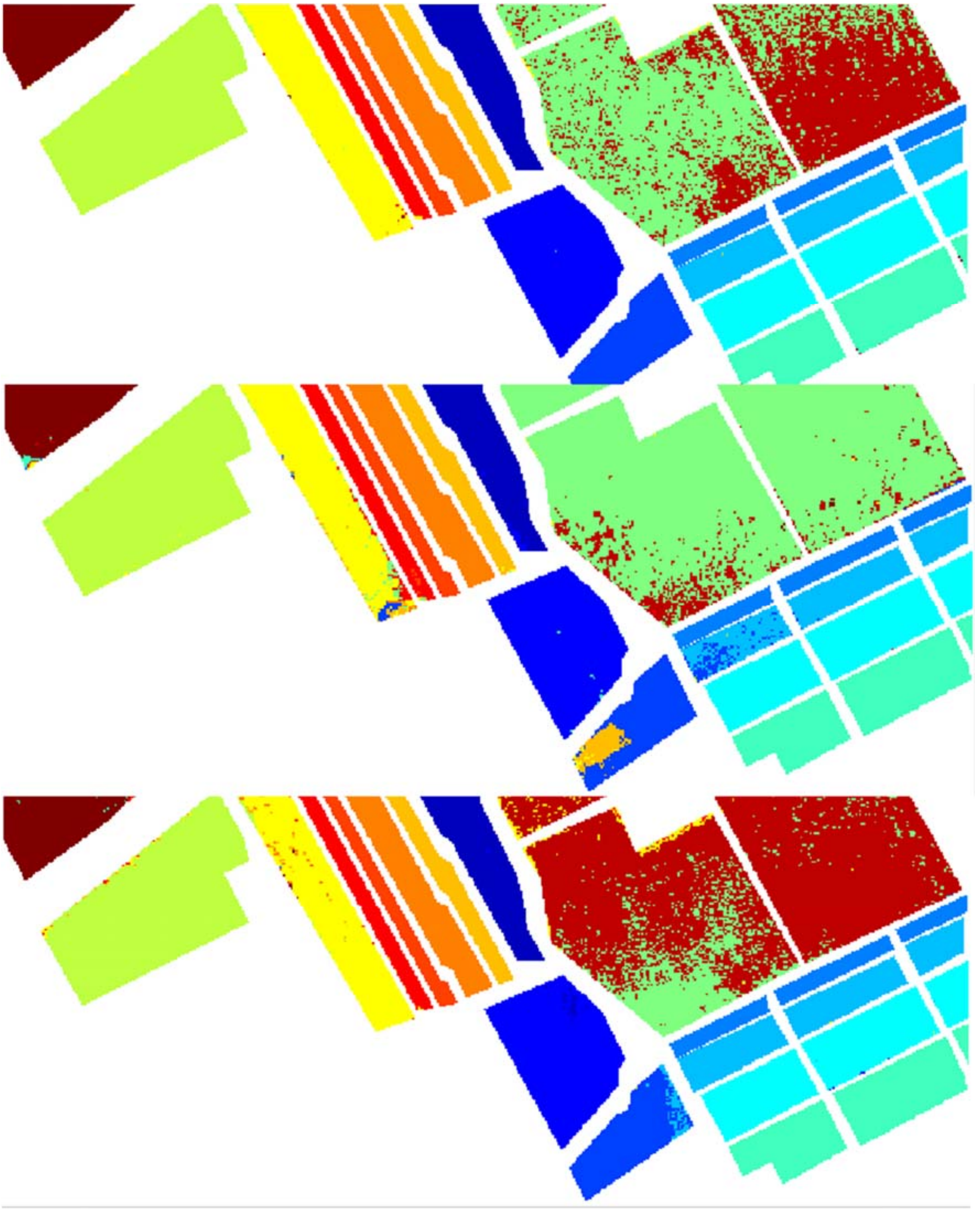

Figure 24 Salinas Scene Classification Results N=900 (top) Uniformly Selected N Samples (middle) First N Samples from right side of the image (bottom) Last N Samples from left side of the image

4.3.2 *Salinas Scene with Pre-Processing*

PCA usage as a pre-processing method does not affect IPS as classification time. However, SSC is affected by the usage of PCA as classification time when lower number of principal components is used (Figure 25). The complete classification time for ML algorithm is 44.53 seconds, however the classification time reduces to 4.68 seconds if two principal components are used for classification. Similarly, the classification time for SVM-LNR reduces from 272.9 seconds to 102.85 seconds, for SVM-RBF from 404.71 seconds to 180.15 seconds. Pre-processing usage mostly affects K-NN algorithm, the classification time of K-NN reduces from 356.6 seconds to 3.05 seconds. This may be due to the fact that K-NN algorithm directly measures the distance in feature space, so after several principal components adding new principal components does not affect the distance between neighborhoods.

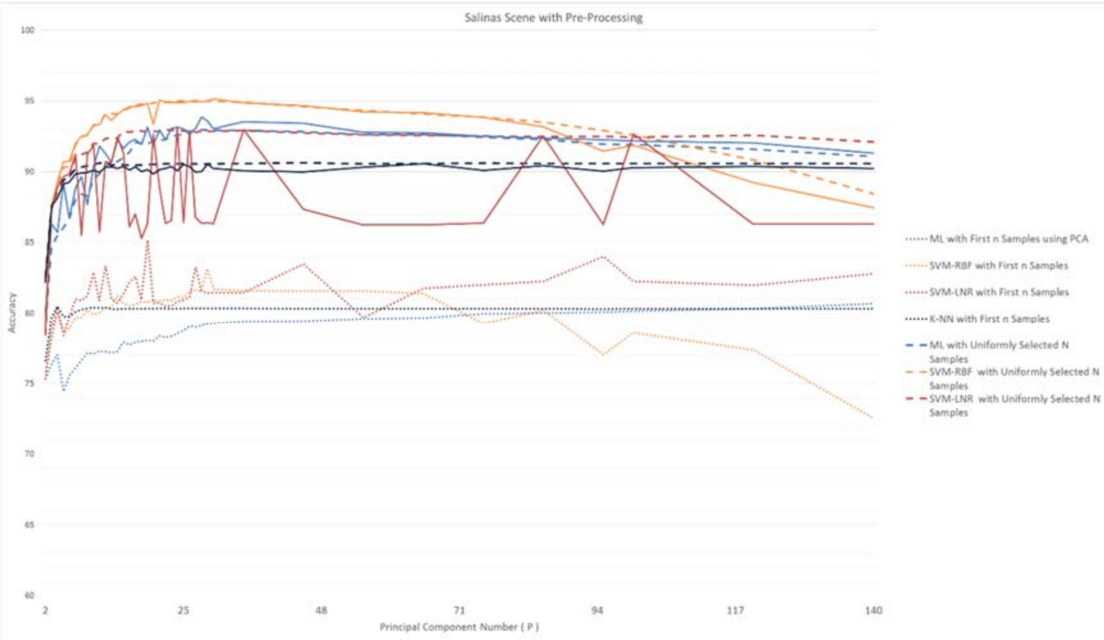

Figure 25 SSC with Pre-Processing

In IPS, the increase of the number of principal components affected classification accuracy positively. However in SSC the increase of the number of principal component decreases the classification accuracy. In Figure 26 , the dashed lines are the results with 140 principal components and the solid lines are the results for 16 principal components. These results show that using 16 principal components improves the classification accuracy by 10% for SVM-RBF, 5% for ML and SVM-LNR. K-NN results are very similar for 16 and 140 principal components.

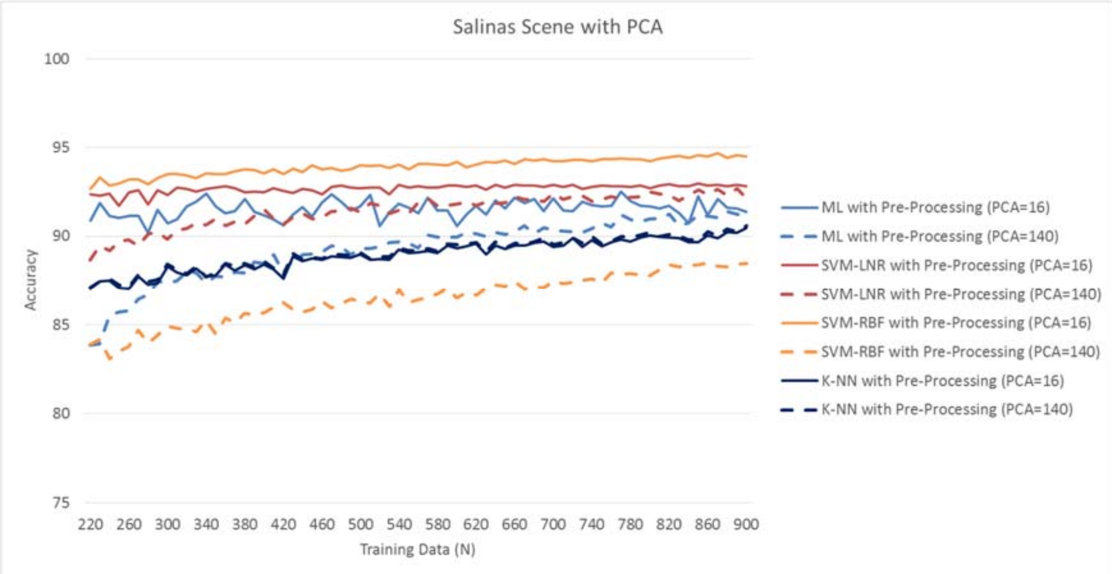

Figure 26 Salinas Scene classification with PCA results

Similarly with IPS, PCA usage also improves ML the classification accuracy. Classification accuracy for 16 principal components and 220 training data is 90.88%, whereas the classification accuracy without PCA and same number of training data is 76.78%. PCA usage provides an advantage for lower training data sizes. The difference for 900 training data size is 1.07% (PCA-91.06% and Without PCA - 89.99%). Similarly with previous experiment results, ML algorithm obtains better results with higher train data sizes for higher dimensions. When 140 principal components are used, the classification results are getting worse. Classification accuracy reduces by 10% for lower training data sizes, however, for 900 training data the classification accuracies are almost the same. The number of principal component mostly affects SVM-RBF algorithm. We obtained 92.68% classification accuracy with 16 principal components and 220 training data, whereas the classification accuracy for 140 principal components and 220 training data is 83.87%. The highest and the lowest accuracies are obtained with SVM-RBF. The classification rates of SVM-RBF increase until the 24-30 principal components, then it starts to decrease gradually. Random and uniform sample selection methods yielded similar accuracies.

Random selection method has more influence on SVM-LNR (Figure 27). Classification accuracies may change by 5%-10% for 10 training data change. SVM-LNR, SVM-RBF and K-NN acquire similar classification accuracies after 10 principal components. SVM-LNR acquires 92% with 10 principal components and 92.10% with 140 principal components. Likewise, K-NN acquires 90.51% with 10 principal components and 90.58% with 140 principal components.

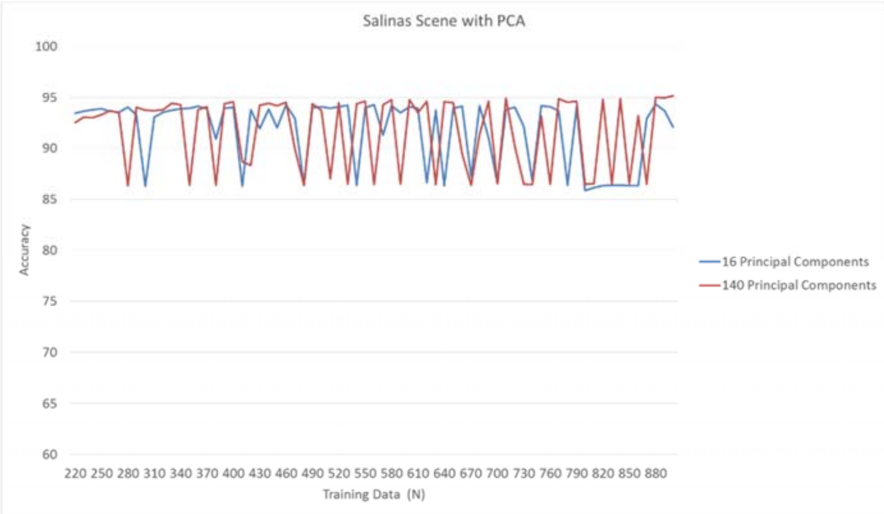

Figure 27 SVM-LNR Classification Results (Randomly Selected N Samples with PCA)

4.3.3 *Salinas Scene with Post-Processing*

Post-processing experiments aim to investigate and explain the impacts of spatial information usage to hyperspectral classification. We conducted the experiments as we stated in Section 3.5.1 for 3x3 window filtering and Section 3.5.2 for majority voting with meanshift segmentation. The results for filtering with 3x3 window results and majority voting with meanshift segmentation results can be seen in Figure 28 and Figure 29.

SSC and IPS have similar properties for classification by using post-processing as filtering with 3x3 window. This method improves the classification accuracies of the classification without post-processing for all algorithms. All the classification algorithms for SSC generally obtained better classification accuracies than IPS. Even for first N sample selection method the classification accuracies are around 75%. Similar to IPS experiments, filtering with 3x3 window increases the classification accuracy by 5-8%. When lower number of training data sizes are used, SVM-RBF and SVM-LNR algorithms obtain better classification accuracies than the other two algorithms. The accuracies are almost the same when higher training data sizes are used. The classification accuracies for 220 training data size are 93.95% for SVM-LNR, 92.60% for SVM-RBF, 91.50% for K-NN and 85.92% for ML algorithm. ML algorithm obtains the worst accuracy for lower training data sizes. However, if 900 training data used for classification, the accuracies are almost the same for SVM-LNR and SVM-RBF. The accuracies for 900 training data are 94.89% for SVM-LNR, 95.49% for SVM-RBF, 95.26% for K-NN and 94.84% for ML algorithm.

Figure 28 Salinas Scene Filtering with 3x3 Window

We obtained the best classification accuracies by using majority voting with meanshift segmentation for SSC. However, random training data selection mostly affects SVM-RBF algorithm. The main reason is that between two untrained crop fields, one dominates the other in majority voting via meanshift segmentation. Uniform training data selection ensures the classification accuracy above 90%. SVM-RBF obtained 99.29%, SVM-LNR obtained 99.33%, ML obtained 99.34% and K-NN obtained 99.38% classification accuracy.

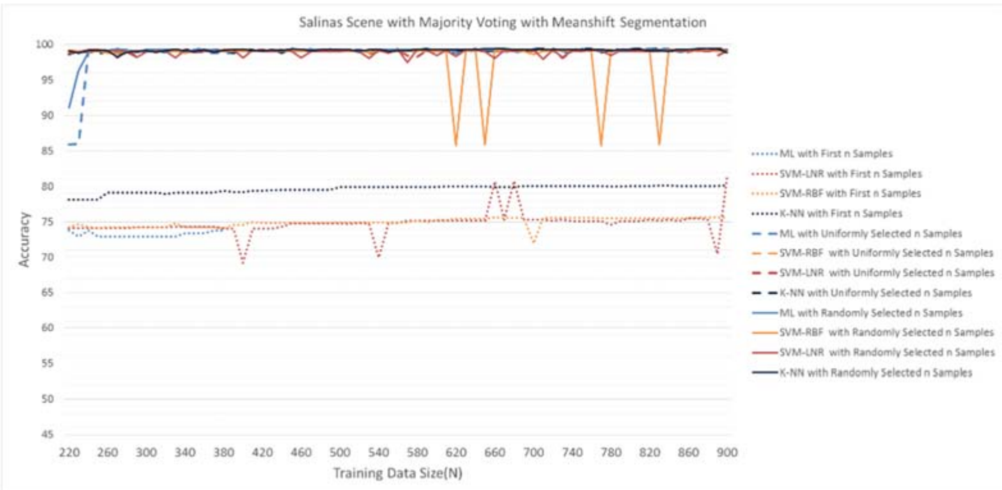

Figure 29 Salinas Scene Majority Voting with Meanshift Segmentation

4.3.4 Salinas Scene with Pre-Processing and Post-Processing

As we stated before, PCA usage reduces classification time for SSC. ML is the fastest algorithm that we used for classification. Normal classification time of ML with post-processing is 59.26 seconds, however it reduces to 18.56 seconds when joint pre-processing and post-processing is used. The classification times for all other algorithms also increased by 10-15 seconds when post-processing methods are used. However, the combination of post-processing and pre-processing usage improves classification time without reducing the classification accuracy. The classification times reduce for SVM-LNR from 293.14 to 114.98 seconds, for SVM-RBF from 419.20 to 194.65 seconds, for K-NN from 367.44 to 17.33 seconds.

Our experiments show that, in order to achieve higher accuracy rates with lower training data size, spatial information usage is necessary. For SSC experiments with post-processing, filtering with 3x3 window improves the classification accuracy by 3% to 5%, whereas majority voting with meanshift segmentation improves the classification accuracy by 5% to 20%.

In Figure 30 and Figure 31, the performance of classification algorithms can be seen. As is seen in the figures, pre-processing improves the classification accuracy, however they are still worse than the accuracies that we obtained by post-processing. The combination of pre-processing and post-processing methods improve both classification time and accuracy. Even if lower number of training data sizes used, classification accuracy that we obtained by using majority voting with meanshift segmentation is around 99%. With 12 principal components the classification accuracies with pre-processing and post-processing is very similar to the accuracies of classification with post-processing methods (Section 4.3.3).

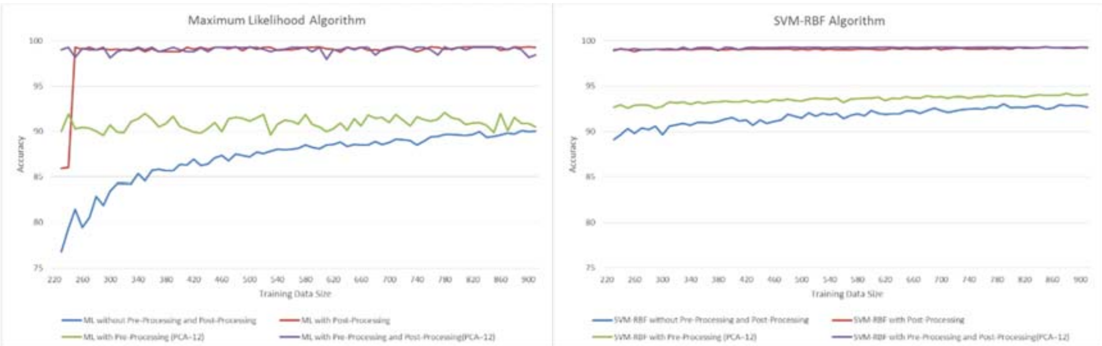

Figure 30 The Classification Accuracies for ML (left) and SVM-RBF (right)

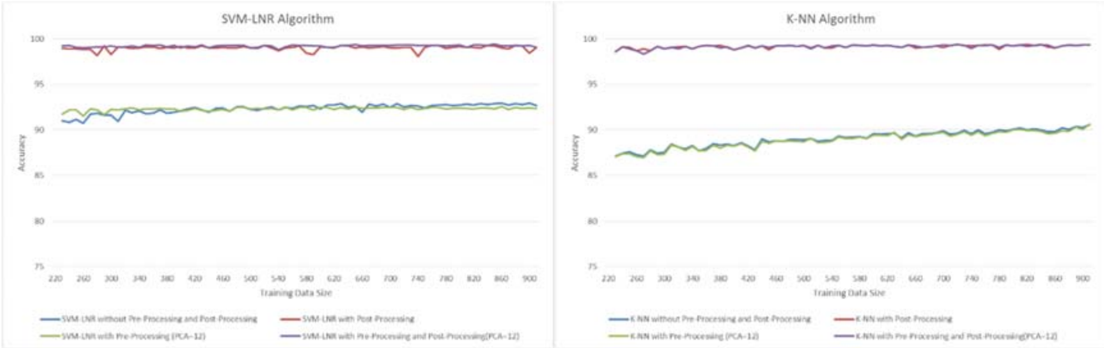

Figure 31 The Classification Accuracies for SVM-LNR (left) and K-NN (right)

Training data selection methods affect classification accuracy similar to previous experiments. First N sample selection method acquired lower results than uniformly selected N sample selection and randomly selected N sample selection methods. The accuracies that we obtain from random selection methods are also similar to the accuracies obtained from uniform selection methods. The highest accuracy that we obtained from first N sample with PCA and filtering with 3x3 window method is for ML 80.67% which is obtained with 103 principal components and 900 training data, for SVM-LNR 87.65%, for SVM-RBF 84.51 and for K-NN 81.53%. When we changed the post-processing method to meanshift segmentation most of the cases the classification accuracy is not improved for K-NN. However, SVM-LNR can reach the 96% accuracy with this selection method.

The improvements on the classification of SSC can be clearly seen in Figure 30 and Figure 31. For 12 principal components even with lowest training data sizes the accuracies are reaching 99%. Segmentation success is also an important factor for this method. Since IPS is a very small scene, majority voting after segmentation improves the accuracy up to a specific point. However, SSC is larger than IPS and majority voting with meanshift segmentation method can improve the accuracy to 99.5%. Although the classification accuracy with 10 principal components and 460 training data is 99.31%, the maximum accuracy for ML algorithm is 99.51% with 120 principal components and 280 training data. The classification accuracies for other algorithms are also similar. SVM-LNR achieves its maximum classification accuracy (99.54%) with 28 principal components and 610 training data. Average accuracy for more than 10 principal components is more than 99%. The classification accuracies of SVM-RBF and K-NN are very similar with SVM-LNR. For 12 principal components, on the average accuracy is 99.41% for SVM-RBF and 99.31% for K-NN.

4.4 Pavia University Scene Experiments

In literature, PUS is one of the most used scenes for hyperspectral classification. We conducted our experiments as we did in Section 4.2 and Section 4.3. The experiments of this chapter are aimed to investigate the differences of classification algorithms with different size of training data. Additionally, pre-processing and post processing usage with these algorithms is also investigated. The confusion matrixes for PUS are given in Appendix C.

4.4.1 Pavia University Scene without Pre-Processing and Post-Processing

As in other experiments in Section 4.2.1 for IPS and Section 4.3.1 for SSC, we conducted our experiments for PUS. The results of these experiments are analyzed for the effect of training data size to classification algorithms. This section specifically focuses on the training data size and training data selection type. We discussed our training data selection methods in Section 3.3.

Training data selection methods affect classification accuracy for all algorithms similarly with IPS and SSC. The lowest classification accuracies are acquired by the first N sample selection method for all algorithms. Besides SVM-RBF algorithm obtained better results than other classification algorithms with this method. Still the accuracies are not exceeding 71%. Figure 32 shows the classification accuracies for all algorithms with three different training data selection methods. As is seen in the figure, for uniformly selected N sample method obtained very similar accuracies with randomly selected N sample method.

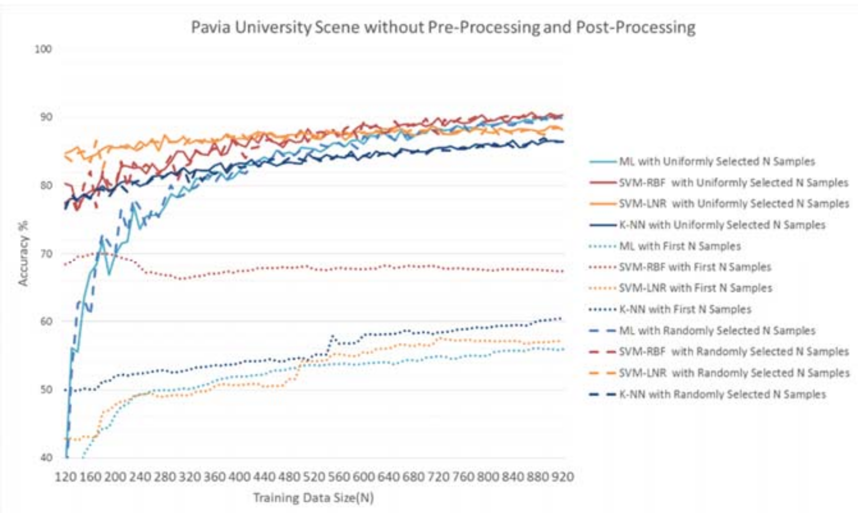

Figure 32 The Classification Results of Pavia University Scene without Pre-Processing and Post-Processing

SVM-LNR and K-NN algorithms are not much affected by training data size. However, the difference between the accuracies that procured with minimum and maximum training data size for ML is very high. On the other hand, SVM-RBF and ML procured the best accuracies with higher training data size. K-NN algorithm acquired lowest accuracies if more than 450 training data size used for learning. The best accuracies without using pre-processing or post-processing method are for ML algorithm 90.31%, for SVM-RBF algorithm 90.69%, for SVM-LNR algorithm 88.69% and for K-NN algorithm 86.66%. When we compared to the other two scenes, for PUS ML algorithm performs better. SVM-LNR and K-NN perform similar for all three scenes.

4.4.2 Pavia University Scene with Pre-Processing

The usage of pre-processing affects the classification time of PUS similar to SSC. SVM-RBF and ML algorithm both improve the accuracy and decrease the classification time. For ML algorithm classification time without pre-processing is 26.86 seconds, however the classification time with pre-processing reduces to 4.25 seconds. Other algorithms also improve both the classification time and accuracy. SVM-RBF reduces the classification time from 136.64 seconds to 112.35 seconds, SVM-LNR reduces the classification time from 113.66 seconds to 41.12 seconds and K-NN reduces the classification time from 171.27 seconds to 2.87 seconds.

In Figure 33, the improvements for ML and SVM-RBF with PCA are shown. The usage of more principal components does not give an advantage to any algorithm, although K-NN algorithm acquired almost the same accuracy for all training sizes for more than 11 principal components. On the average SVM-RBF and SVM-LNR decreased the classification accuracies if more than 45 principal components are used.

Figure 33 The Classification Accuracies of Pavia University Scene with Pre-Processing

Similar to the other two scenes, the usage of PCA improves the classification accuracy of the ML algorithms. By using 16 principal components, ML algorithm reached 92.05% on the average. Its maximum accuracy is 93.18% with 900 training data. The average classification accuracy for the ML algorithm without pre-processing is 82.18% and maximum accuracy is 90.31%. SVM-RBF algorithm also improved the classification accuracy by using 16 principal components. The average accuracy with 16 principal components is 90.35% and maximum accuracy is 92.77%. However, the average classification accuracy for SVM-RBF algorithm without pre-processing is 86.40% and maximum accuracy is 88.69%. Besides, K-NN algorithm does not improve its classification accuracy from pre-processing. Average and maximum accuracies are very similar for both cases. The average accuracy for K-NN algorithm with PCA is 83.47% while without using PCA is 83.19%. Maximum accuracy for K-NN algorithm with PCA is 86.65% whereas without using PCA is 86.34. While the usage of PCA is giving an advantage for classification of PUS, SVM-LNR decreases its classification accuracy almost 1% if pre-processing step is used. On the average its classification accuracy with PCA is 86.14% and maximum classification accuracy is 88.45%, whereas without using PCA average accuracy is 87.16% and maximum accuracy is 88.69%.

4.4.3 Pavia University Scene with Post-Processing

Similar with other two scenes, both post-processing methods that we mentioned in Section 3.5 improved the classification accuracy for all algorithms. The results for filtering with 3x3 windows can be seen in Figure 34 and the results for majority voting with meanshift segmentation results can be seen in Figure 35. The patterns for filtering with 3x3 windows method are very similar to patterns of the classification results without post-processing. The classification accuracies improved 3%-10% for all algorithms. Majority voting with meanshift segmentation also performed like other scenes. Best accuracies are obtained with the classification by using majority voting with meanshift segmentation as post-processing. Training data selection methods affected classification accuracy as it is in the without pre-processing and post-processing methods (Section 4.4.1). Randomly selected N samples method and uniformly selected N samples method achieved almost the same accuracy. Likewise, first N sample method performed worse than the other two methods.

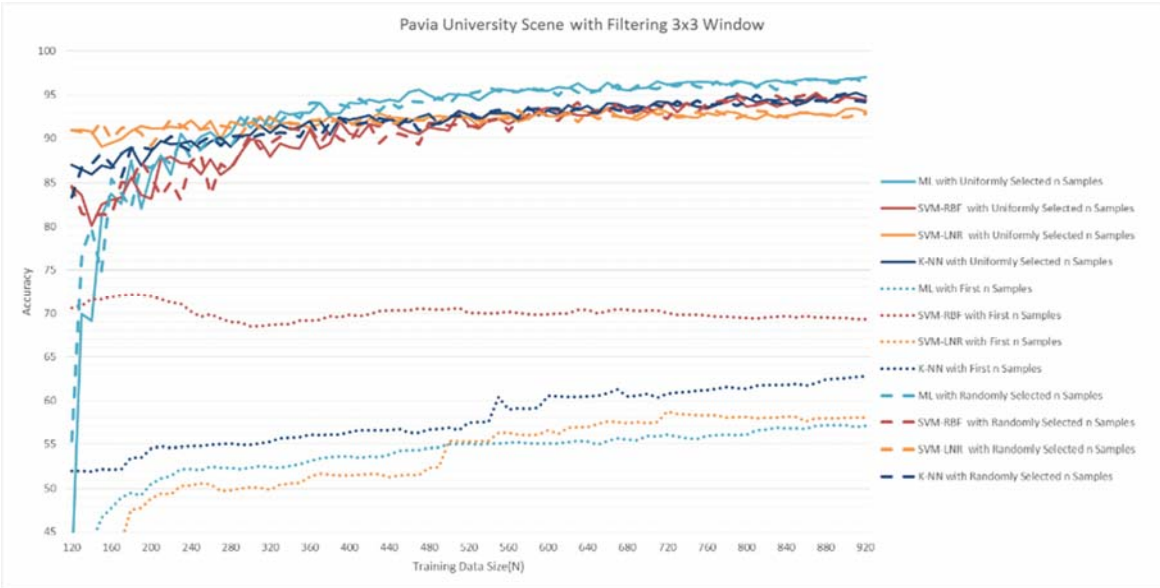

Figure 34 Pavia University Scene Results for Filtering with 3x3 Window

Filtering with 3x3 window method mostly improved the K-NN and ML algorithms. If more than 400 training data used, ML is achieving better accuracies than the other algorithms. The best accuracy that we obtained with ML algorithm is 97.04%. ML algorithm performs 92.48% on the average. On the other hand, SVM-LNR algorithm obtained at most 93.46% accuracy, however its average accuracy is 92.13. It is more robust than ML algorithm. SVM-RBF algorithm could reach 95.23% accuracy. Finally, K-NN algorithm obtained the maximum accuracy as 95.27%. Its average accuracy is 92.08%.

Majority voting with meanshift segmentation method also improves the classification accuracy as it is in other two scenes. In Figure 35, the classification results for all training data selection methods can be seen. As is seen in the figure, K-NN and ML algorithms perform better than other two algorithms for more than 360 training data. Their classification accuracies are almost 99% for K-NN and ML. SVM-LNR and SVM-RBF also perform very similarly. First N sample selection method's performance is very similar to IPS and SSC. Randomly selected N sample method and uniformly selected N sample methods obtained similar accuracies for the same training data. Selection method mostly changed SVM-LNR algorithm's accuracy.

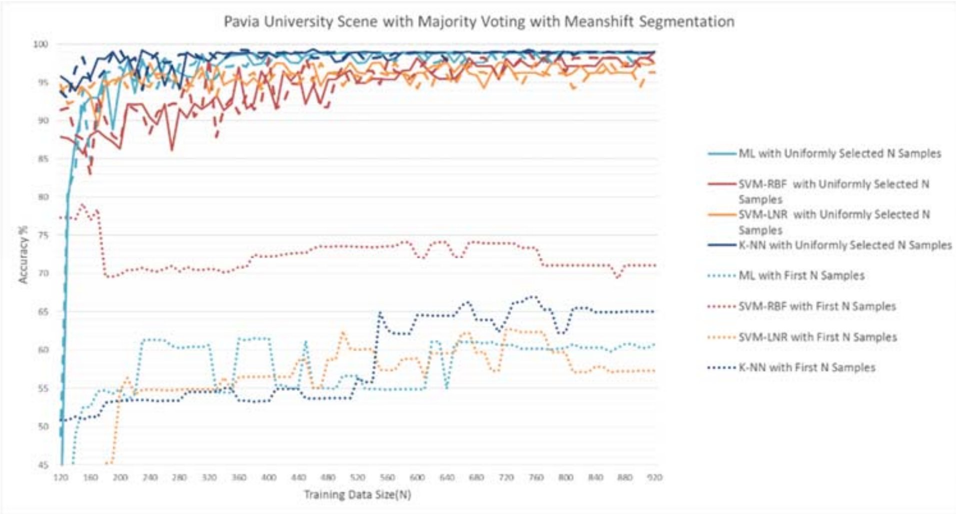

Figure 35 Pavia University Scene Results for Majority Voting with Meanshift Segmentation

Average and maximum accuracies are also increased when majority voting with meanshift segmentation method are used. For the SVM-LNR algorithm, highest accuracy achieved with majority voting with meanshift segmentation is 97.64% with 640 training samples. Average accuracy of SVM-LNR algorithm is 96.02%. SVM-RBF achieved 98.97% with 900 training data, however its average accuracy (94.42%) is lower than SVM-LNR. ML algorithm performs better than SVM-LNR and SVM-RBF algorithms. It achieves 98.99% accuracy with 750 training data. On the average ML algorithm achieves 96.74%. The average classification rate increases to 98.55% when 360 or more training data used. The best classification accuracies with this method are achieved with K-NN algorithm for PUS. K-NN algorithm achieves 99.34% with 460 training data and average accuracy for K-NN algorithm is 98.39%.

4.4.4 Pavia University Scene with Pre-Processing and Post-Processing

We mentioned about the classification time aspect of pre-processing in Section 4.4.2. Post-processing usage is slightly affecting the classification time of PCA. Post-processing step requires 10 (filtering with 3x3 window) and 15 (majority voting with meanshift segmentation) seconds to process. The classification process with filtering with 3x3 window takes 38.5 seconds. If PCA is used for filtering with 3x3 window the classification time reduces to 17.09 seconds. Required time for PCA and majority voting with meanshift segmentation is also reducing from 40.48 seconds to 18.4 seconds. The classification time for SVM-RBF reduces from 146.51 seconds to 123.56 seconds for filtering with 3x3 window and 147.38 seconds to 127.78 seconds for majority voting with meanshift segmentation, for SVM-LNR reduces from 125.53 seconds to 54.36 seconds for filtering with 3x3 window and 115.40 seconds to 55.80 seconds for majority voting with meanshift segmentation. Similar with the previous experiments, K-NN algorithm improves its classification time mostly with PCA. Its classification time reduces from 184.33 seconds to 15.88 seconds for filtering with 3x3 window method and 184.53 to 16.95 seconds for majority voting with meanshift segmentation.

Classification with PCA and filtering with 3x3 window method improves the classification accuracy similar to the other scenes. We mentioned about PCA reducing the duration of the classification process. The aim is getting higher classification rates with lower number of principal components. Figure 36 shows that with 16 principal components and filtering with 3x3 window method improves the classification accuracies of the classification without pre-processing and post-processing methods for all training data sizes. For SVM-RBF and ML algorithms, this method also performs better than classification with only post-processing method. The classification accuracy of PCA and without PCA methods are very similar for K-NN algorithm.

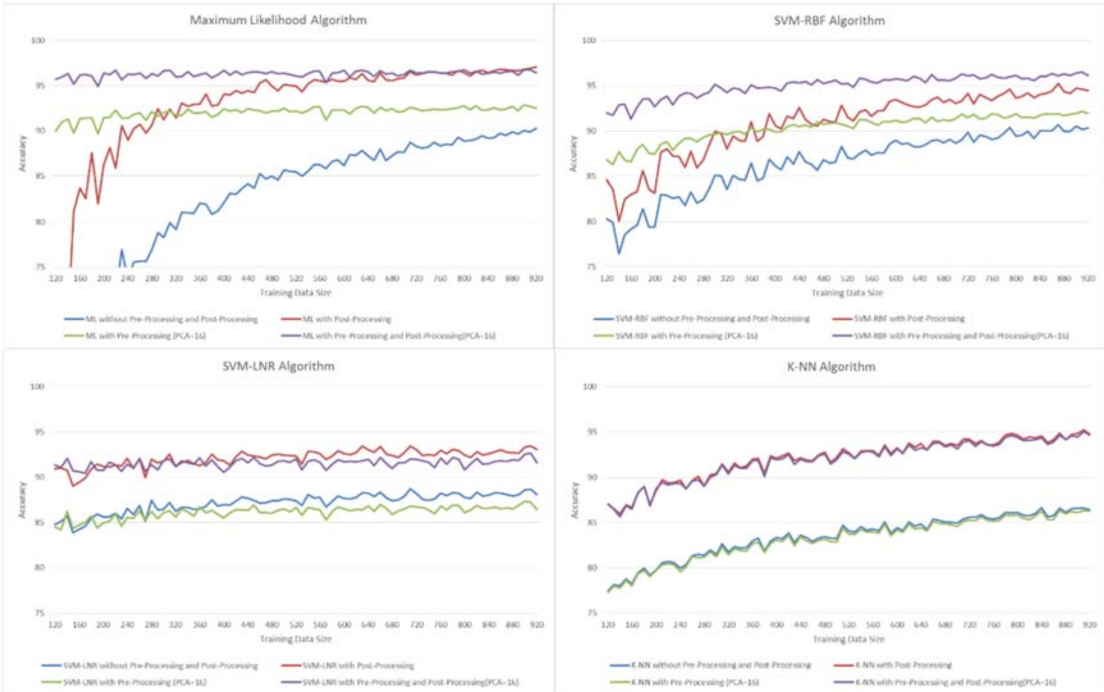

Figure 36 Pavia University Scene Classification Results for Filtering with 3x3 Window Method ML (top-left), SVM-RBF(top-right) SVM-LNR (bottom-left) and K-NN (bottom-right)

For filtering with 3x3 method, ML algorithm obtained best classification accuracy with ML with post-processing method with 97.04%. Although ML with pre-processing and post-processing method achieves 96.77%, its average accuracy (96.30%) is better than ML with post-processing method (92.48%). In Figure 36, for lower training data sizes the difference between the two methods can be seen clearly. SVM-RBF also performs better with pre-processing and post-processing method. Both its average accuracy (95.03%) and maximum accuracy (96.50%) are better than SVM-RBF with post-processing method (Average 90.81% and Maximum 95.23%). K-NN algorithm performs almost same for both methods. The average accuracies for K-NN with post-processing method are 92.08% and for K-NN with pre-processing and post-processing is 91.90%. The maximum classification accuracies are also similar. The maximum classification accuracy for K-NN with post-processing method is 95.27% and for K-NN with pre-processing and post-processing method is 95.06%.

Majority voting with meanshift segmentation results can be seen in Figure 37. When the classification process carried out without post-processing, ML and SVM-RBF performs better with pre-processing usage. On the other hand, K-NN acquires almost the same accuracies with or without using PCA. All algorithms obtained their best results with joint pre-processing and post-processing method. However, all of them obtained their best results with different number of principal components. For example, ML algorithm achieved its best result with 460 training data and 17 principal components, SVM-LNR achieves its best results with 500 training data and 75 principal components. SVM-RBF algorithm obtained its best accuracy (99.21%) with 260 training data and 27 principal components. Lastly, K-NN algorithm obtained the best results of these experiments with 99.41% with 670 training data and 13 principal components.

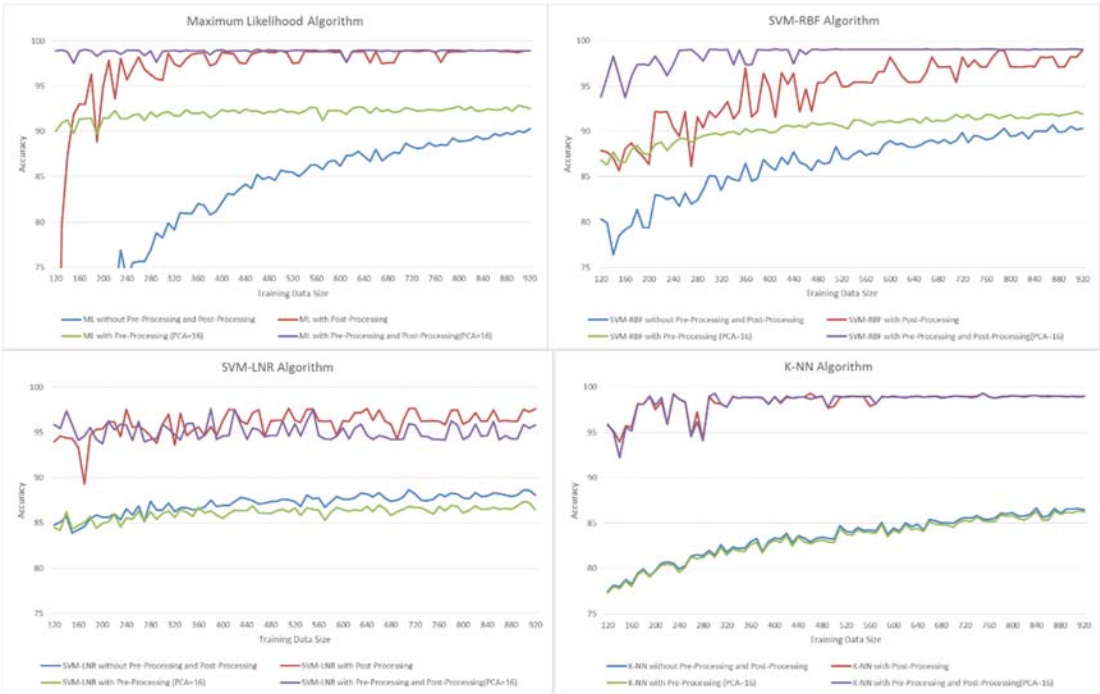

Figure 37 Pavia University Scene Classification Results for Filtering with 3x3 Window Method ML (top-left), SVM-RBF(top-right) SVM-LNR (bottom-left) and K-NN (bottom-right)

4.5 The Effects of Segregation of Training and Testing Data

In order to compare our classification results with those in the literature we extract training data from the image for training but tested on all available data. So, the same data is used both for training and testing. In this section, for SSC first we extract training data from the image. Then, we segregate the training data from testing data. Then we carried on the classification process. We observed IPS and PUS and obtained similar results with SSC. Sample groundtruth for SSC can be seen in Figure 38.

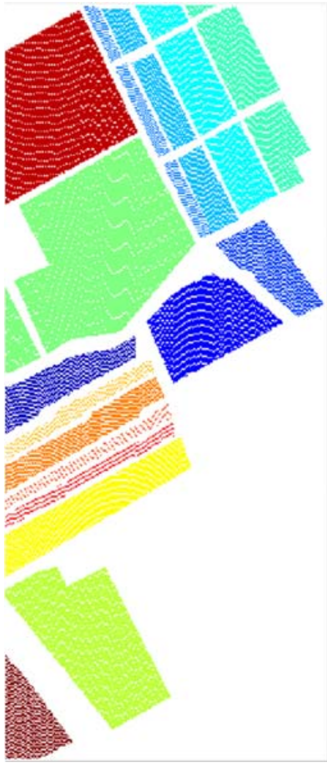

Figure 38 Sample Groundtruth for SSC (N=700)

Figure 39 shows the classification results with and without segregation training data from testing data. It is clearly seen that, the difference between two results are lower for lower number of training data and it gets higher when we increase the training data size for all classification algorithms. On the average the difference between two methods is 2.44% for ML, 1.32% for SVM-RBF, 1.13% for SVM-LNR and 2.61% for K-NN algorithm. However, the maximum classification accuracy reduces from 90.05% to 86.77% for ML algorithm, 93.02% to 91.37% for SVM-RBF algorithm, 92.96% to 91.70% for SVM-LNR algorithm and 90.59% to 87.42% for K-NN algorithm.

For all algorithms, classification accuracies do not change much after 500 training data. Especially for ML and K-NN algorithms, while the classification accuracy increase after 500 training data, when we segregate training data from testing data the accuracies do not change much.

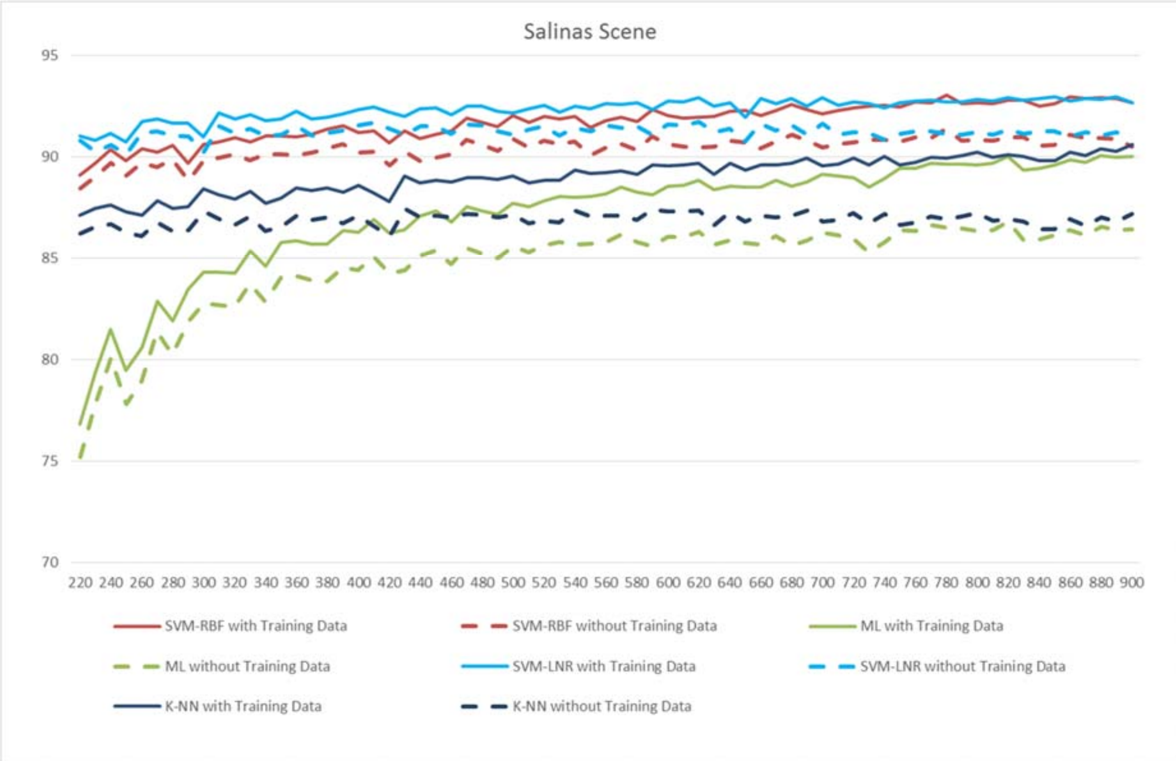

Figure 39 Classification Results for SSC with and without Segregation of Training Data

We used majority voting with meanshift segmentation method in order to use spatial information. Even though the classification accuracies for all training data sizes and algorithms reduce with segregation of train and test data, the classification accuracies are not affected when spatial information are used. After pixelwise classification, for every segment we perform majority voting to assign class labels to all pixels in that segment. The pixels that are used for training data are not counted in this process. Figure 40 shows the results for SSC with and without segregation of training data by using majority voting with meanshift segmentation method. The average and maximum accuracies for both methods are very similar. The difference for all training data sizes is not more than 0.5%. Since we need 8 neighborhood for filtering with 3x3 window method, we could not apply it to segregated groundtruth map.

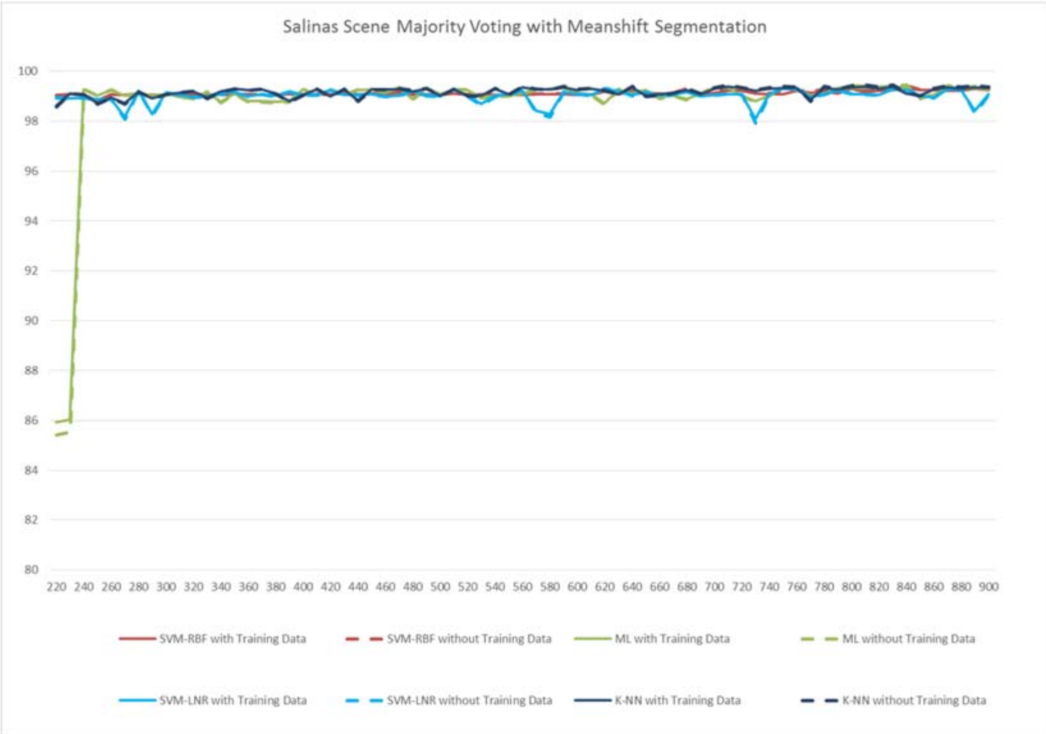

Figure 40 Classification Results for SSC with and without Segregation of Training Data by using Majority Voting with Meanshift Segmentation Method

CHAPTER 5

CONCLUSION

5.1 Summary

In this study, variations on hyperspectral image classification algorithms are analyzed. Indian Pines, Salinas and Pavia University scenes are used for classification experiments. Indian Pines and Salinas Scenes were acquired by AVIRIS sensor. Pavia University Scene was acquired by ROSIS sensor. For all scenes the bands which have no information or water absorption bands were removed. We employed ML, SVM and K-NN as supervised classification algorithms. We also implemented two different kernels for the SVM algorithm: A linear kernel and an RBF kernel. In order to show the effect of training data on hyperspectral classification, we employed three different training data selection methods: First N samples of all classes, randomly selecting N samples from groundtruth classes and uniformly selecting training data from groundtruth classes. We utilized different training data sizes for all training data selection methods. These training data sizes differ for three scenes by their band size. We also investigated the contribution of pre-processing with PCA and post-processing with spatial information from filtering with 3x3 window and majority voting with meanshift segmentation for each of the algorithms listed above.

In summary, we found out that the training data selection method and training data size are very important for hyperspectral classification. Especially ML is affected by the change of the training data size for all three scenes. PCA reduces the classification time for SSC and PUS. It also improves the classification accuracy for ML and SVM. PCA does not improve both the classification accuracy and classification time for IPS. Spatial information usage improves the classification accuracy for all IPS, SSC and PUS. For IPS, filtering with 3x3 window method improves the classification performance 5-10% for SVM-RBF, 7-11% for SVM-LNR, 10-13% for K-NN and 9-18% for ML. This method showed more improvement for smaller training data sizes. Majority voting with meanshift segmentation method obtained best results for all algorithms and scenes. All algorithms improved their classification accuracies by 5-15%. Pre-processing with PCA and post-processing usage do not affect the classification accuracies for IPS.

Almost all algorithms procured similar results for without pre-processing and post-processing method. ML algorithm increases classification accuracy more than SVM-LNR, SVM-RBF and K-NN algorithms as the training data size increases. PCA improves the classification accuracy and reduces classification time for PUS and SSC. For SSC, filtering with 3x3 window method improves the classification performance 2-5% for SVM-RBF, 2-4% for SVM-LNR, 4-5% for K-NN and 4-9% for ML. Pre-processing with PCA and post-processing usage jointly improve the classification accuracies for SSC and PUS. With this method, K-NN improves classification accuracy more than other algorithms for SSC and PUS. With lower numbers of principal components this method also lowers the classification time. Segregation of training data from test data reduces classification accuracy unless majority voting with meanshift segmentation is employed for post-processing.

Without using pre-processing and post-processing, all algorithms confuse spectrally similar materials in the Pavia University Scene (PUS). We can separate this confusion into two groups. The first group consists of asphalt, gravel, bitumen, self-blocking bricks and the second group consists of bare soil, meadow and tree. Pre-processing (PCA) method usage does not change the classification performance for all materials. The confusion within the elements in the groups still exist. When post-processing (filtering with 3x3 window) method is used for classification all algorithms reduce confusion between asphalt-bitumen-self-blocking bricks and bare soil-meadow materials. However, SVM-LNR and K-NN do not improve as much as SVM-RBF and ML. When post-processing (majority voting with meanshift segmentation) method is used for classification all algorithms reduce confusion for both groups. With this method ML, K-NN and SVM-RBF mainly confuse meadow-tree and SVM-LNR confuses meadow-bare soil materials. The confusion highly depends on the meanshift segmentation performance. When pre-processing (PCA) and post-processing (filtering with 3x3 window) method is used for classification ML confuses asphalt-self-blocking bricks and meadow-tree-bare soil materials. This method especially reduces the confusion between gravel-self-blocking bricks and asphalt-gravel for ML algorithm. SVM-RBF algorithm improves the dissociation between tree-meadow with this method. SVM-LNR and K-NN performances are not improved. When pre-processing (PCA) and post-processing (majority voting with meanshift segmentation) method is used for classification ML and K-NN perform similar to post-processing (majority voting with meanshift segmentation) method. SVM-RBF confuses asphalt-tree materials. Again this confusion is caused by the meanshift segmentation performance.

In the Salinas Scene (SSC) all algorithms confuse two untrained fields (vinyards and grapes) with each other. These classes are both grapes produced for different purposes. Hence they are very much alike spectrally. They can mainly be separated with the help of spatial information. As post-processing (majority voting with meanshift segmentation) segments the two areas (grapes and vinyards) successfully, it becomes possible to identify the classes correctly using majority voting. The other pair of classes that are confused are grapes and corn. This observation is more prominent with K-NN and SVM-RBF. This might be due to the presence of mixed pixels in the groundtruth. Such mixed pixels tend to be used for classification of pixels that are spectrally close. K-NN and SVM-RBF are likely to be affected more by this phenomenon. Grapes and corn pair is also mixed when post-processing (majority voting with meanshift segmentation) method is used. We observed that SSC has many unclassified pixels in the ground truth. These pixels are usually roads next to agricultural areas. These road areas are also segmented by meanshift segmentation however, they are not labeled in the groundtruth. The classification algorithms usually classify these roads as corn fields. When these segments overlap with agricultural areas, as a result of majority voting some pixels in the agricultural areas are also labeled as corn. When we used pre-processing (PCA) and post-processing (majority voting with meanshift segmentation) these classification errors are reduced for all algorithms.

For the Indian Pines Scene (IPS) all algorithms confuse Corn (notill-mintill)-Soybean (notill-mintill) classes with each other without spatial information. However, SVM-RBF distinguishes Soybean-notill and Soybean-mintill, Soybean-notill-Corn (notill-mintill) classes better than other algorithms. The main reason for this confusion might be due to the presence of mixed pixels in the groundtruth and the lower resolution of IPS scene. Pre-processing (PCA) method usage does not change the classification performance for all algorithms. When we use spatial information with post-processing (filtering with 3x3 window) the confusion between Corn (notill-mintill) - Soybean(notill-mintill) is distinctly reduced for SVM-RBF and K-NN. ML still confuses Soybean-mintill with Soybean-notill and Corn-notill classes. K-NN only confuses Soybean (Notill-mintill) classes with each other. As it is in the other scenes with all algorithms post-processing (majority voting with meanshift segmentation) method performs better than the other methods. All algorithms confuse Soybean-mintill with Corn-notill classes more than other classes. The main reason for that confusion is that some part of Soybean-mintill class is segmented by meanshift segmentation as Corn-notill. As a result of majority voting these regions are classified as Corn-notill. This confusion is also valid for pre-processing (PCA) and post-processing (majority voting with meanshift segmentation) methods.

5.2 Comparison with the Literature and Discussion

Training data selection methods gave similar results for all scenes. First N sample selection method obtained lowest accuracies for all training data sizes because the training data samples cannot represent the whole scene. Uniform N sample selection method and randomly N sample selection method obtained similar accuracies. ML algorithm is affected most by training data size for all scenes. It needs larger train data for satisfactory performance. On the other hand, SVM-RBF, SVM-LNR and K-NN algorithms are slightly affected by training data sizes. Without pre-processing and post-processing, the performances of the algorithms are very similar.

We compare the results with literature on hyperspectral classification with IPS. Since there is no pre-determined training data set for all maps, all of them used different training data set for classification. We acquired 95.38% by using spatial information as post-processing by using almost 30% of data. [58] used Gaussian maximum likelihood classifier and leave-one-out covariance estimation method for hyperspectral classification. They selected 20% of total samples as training samples for each class. They acquired 89.1% classification rate. [59], also used SVM and composite kernels for hyperspectral classification. They used 20% of the samples as training set. They obtained 96.53% classification accuracy with spectral and contextual kernels. [60] obtained 96.5% overall accuracy for IPS by using spatial information based SVM. They used randomly selected %10 of the samples as training samples. [61] used linear discriminant analysis to for dimensionality reduction. They also employed Markov Random Fields concept to incorporate the spatial information of the image. They also investigated the effect of training data size on accuracy by using three different training subsets and test it on randomly selected 100 samples per class. They acquired 90.78% classification rate with the best training subset.

For PUS, we obtained 99.41% by using PCA and majority voting with meanshift segmentation method and K-NN algorithm with almost 14% of data. [62] used PUS to compare the SVM-LNR, SVM-RBF, K-NN and RBF classifiers' performance. They do not use any pre-processing or post-processing methods. Their training data is not specified but they used 4757 training samples and 4588 testing samples from the image. Overall accuracy is given as 93.42% with SVM-RBF. The duration of total classification time is 2702 seconds. [63] used both supervised and unsupervised learning methods for hyperspectral classification. They used SVM for classification and fuzzy-c-means for providing segmentation maps. In order to the employ segmentation output, they used weighted majority voting rule. They repeat the classification process five times with randomly selected 50 training samples for IPS. They performed the same experiments for PUS. They obtained 91.05% accuracy for IPS and 95.99% accuracy for PUS. [64] also used majority voting over segmented image. After pixelwise classification, they employed majority voting over three different segmentation methods (Watershed, Gaussian mixture resolving and hierarchical segmentation). The results of these three majority voting process are used to assign markers to a pixel. Final part of their classification process is to group these pixels into a minimum spanning forest (MSF) and they procured spectral-spatial classification map from MSF. They obtained 97.90% overall accuracy for PUS. They used SVM-RBF for pixelwise classification with 3921 pixels for training data but there is not detailed information about the specific numbers for classes. The overall accuracy for IPS with the same method is 92.32%. [65] also used spatial information to improve pixelwise classification of hyperspectral images. They used morphological operators following pixelwise classification to incorporate spatial information. They specify different training sample size for classes and used 718 training samples. They obtained 95.57% classification accuracy.

[65] has used a model with pre-processing and post-processing methods. As a pre-processing method they used PCA. They also used morphological profiles to improve classification accuracy. They randomly selected 2% of the pixels from all classes. They perform experiments on morphological operators' number effect on classification accuracy. They acquired 95.03% accuracy for SSC. [66] used PCA for dimensionality reduction. They used synergetic theory which is founded by [67]. They classify SSC and obtained 90% average accuracy for the whole scene.

We obtained the best results by using majority voting with meanshift segmentation method. The performances of our methods mainly depend on the performance of meanshift segmentation. Except SVM-LNR, all three algorithms perform above 99% classification accuracies. Specifically on PUS, K-NN performs 99.33% classification accuracy with 460 training sample for each class. The improvement of K-NN algorithm is 16.40%. It acquired 99.22% with 220 training samples and 99.01% with 190 training samples from each class. On the other hand SVM-RBF and ML algorithms perform better with PCA. When we used 16 principal components, we obtained 99% classification accuracy by using SVM-RBF with 260 training samples from each class and 99.05% classification accuracy by using ML with 170 training samples from each class. We also observed that K-NN algorithm is not affected by the increase of the number of principal components after N=15. With lower number of principal components K-NN algorithm performs better than the other three algorithms.

Segregation of training data from test data experiments are also conducted in this study. It is observed that the average classification accuracies decrease by 4-5% when training data is segregated from test data. ML and K-NN algorithms are mostly affected by segregation process. We have not provided detailed tables with segregated data because it is not the practice within the remote sensing community. Spatial information usage with segregation of training data from test data experiments showed that the average classification accuracies are not changed with majority voting with meanshift segmentation method. For all training data sizes, the classification accuracies are almost the same with or without segregating training data.

5.3 Future Work

We used supervised classification algorithms for three remote sensing images. Although the obtained results are very promising, experiments with other images should also be conducted to generalize these results. We also showed that the performance of supervised classification algorithms mainly depend on training data. The minimum training sample set consisted of 120 samples for each class. This number might be considered excessively high for some applications. One possible future work is to improve classification performance with even lower training data sizes.

We show that spatial information usage by filtering with 3x3 window and majority voting with meanshift segmentation improves classification accuracy. Further experiments with other segmentation methods should also be conducted.

Hyperspectral images have high spectral resolution and low spectral resolution whereas multispectral images may have high spatial resolution but low spectral resolution. In order to improve hyperspectral classification accuracy, fusion of a high resolution multispectral image and a hyperspectral image may be considered.

We also noted that the imperfections in the groundtruth has negative effects on the classification accuracy. To combat the degrading effect of these imperfections of the groundtruth, the samples that are typical of the given class may be employed for training. Another approach could be to assign weights on training samples depending on their impurity. These issues will be investigated in future studies.

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APPENDICES

APPENDIX-A INDIAN PINES SCENE RESULTS

First N Sample without Pre-Processing or Post Processing

Table 4 IPS - ML -First N Sample without Pre-Processing or Post Processing

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	981	123	0	0	1	0	0	0	210	19	88	0	0	6	0	981	1428	68,70%	54,71%	60,91%
Corn-mintill	0	83	539	0	0	0	0	0	0	91	82	33	0	0	2	0	539	830	64,94%	68,14%	66,50%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	4	2	0	418	0	0	5	0	1	2	7	0	0	44	0	418	483	86,54%	99,05%	92,38%
Grass-trees	0	0	0	0	2	600	0	0	0	1	0	4	0	2	121	0	600	730	82,19%	99,50%	90,02%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	98,96%	99,48%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	110	3	0	0	0	0	0	0	695	127	27	0	0	10	0	695	972	71,50%	40,43%	51,65%
Soybean-mintill	0	586	71	0	0	1	0	0	0	716	801	261	0	0	19	0	801	2455	32,63%	77,54%	45,93%
Soybean-clean	0	29	53	0	1	0	0	0	0	5	2	501	0	0	2	0	501	593	84,49%	54,40%	66,18%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	1	1	0	0	0	0	0	0	0	1038	225	0	1038	1265	82,06%	99,81%	90,07%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	47,36%	64,28%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					66,91%

Table 5 IPS - SVM-RBF - First N Sample without Pre-Processing or Post Processing

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	934	133	0	2	2	0	1	0	133	16	192	0	0	15	0	934	1428	65,41%	46,58%	54,41%
Corn-mintill	0	84	513	0	1	0	0	0	0	48	132	50	0	0	2	0	513	830	61,81%	67,59%	64,57%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	432	0	0	4	0	1	1	4	0	0	41	0	432	483	89,44%	88,16%	88,80%
Grass-trees	0	0	0	0	24	656	0	0	0	1	0	0	0	0	49	0	656	730	89,86%	99,09%	94,25%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	98,96%	99,48%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	250	2	0	6	0	0	0	0	641	49	23	0	0	1	0	641	972	65,95%	50,16%	56,98%
Soybean-mintill	0	701	74	0	7	3	0	0	0	441	916	301	0	0	12	0	916	2455	37,31%	80,78%	51,04%
Soybean-clean	0	36	37	0	12	0	0	0	0	13	20	471	0	0	4	0	471	593	79,43%	45,24%	57,65%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	4	0	0	0	0	0	0	0	0	944	317	0	944	1265	74,62%	99,79%	85,39%
Buildings-Grass-Trees-Drives	0	0	0	0	2	1	0	0	0	0	0	0	0	2	381	0	381	386	98,70%	46,35%	63,08%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					66,17%

Table 6 IPS - SVM-LNR - First N Sample without Pre-Processing or Post Processing

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	868	35	0	6	1	0	1	0	303	213	1	0	0	0	0	868	1428	60,78%	72,82%	66,26%
Corn-mintill	0	16	567	0	1	0	0	0	0	91	145	10	0	0	0	0	567	830	68,31%	83,26%	75,05%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	449	0	0	2	0	2	15	2	0	0	13	0	449	483	92,96%	92,39%	92,67%
Grass-trees	0	0	0	0	7	689	0	0	0	11	0	0	0	1	22	0	689	730	94,38%	99,71%	96,97%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	99,38%	99,69%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	33	1	0	4	0	0	0	0	906	25	3	0	0	0	0	906	972	93,21%	39,82%	55,81%
Soybean-mintill	0	269	38	0	6	1	0	0	0	961	862	317	0	0	1	0	862	2455	35,11%	67,98%	46,31%
Soybean-clean	0	6	40	0	11	0	0	0	0	1	8	524	0	0	3	0	524	593	88,36%	61,14%	72,28%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	2	0	0	0	0	0	0	0	0	1039	224	0	1039	1265	82,13%	99,90%	90,15%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	59,48%	74,59%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					70,35%

Table 7 IPS – K-NN - First N Sample without Pre-Processing or Post Processing

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	792	350	0	14	3	0	0	0	81	28	159	0	0	1	0	792	1428	55,46%	46,62%	50,66%
Corn-mintill	0	97	537	0	0	1	0	0	0	69	92	33	0	0	1	0	537	830	64,70%	42,52%	51,31%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	2	0	434	1	0	14	0	0	10	1	0	0	21	0	434	483	89,86%	79,78%	84,52%
Grass-trees	0	0	0	0	17	665	0	0	0	0	1	0	0	4	43	0	665	730	91,10%	98,37%	94,59%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	97,15%	98,56%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	132	60	0	5	1	0	0	0	646	80	47	0	0	1	0	646	972	66,46%	55,79%	60,66%
Soybean-mintill	0	628	251	0	25	3	0	0	0	348	957	238	0	0	5	0	957	2455	38,98%	80,96%	52,63%
Soybean-clean	0	50	63	0	20	1	0	0	0	14	13	432	0	0	0	0	432	593	72,85%	47,47%	57,49%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	28	1	0	0	0	0	1	0	0	970	265	0	970	1265	76,68%	99,28%	86,53%
Buildings-Grass-Trees-Drives	0	0	0	0	1	0	0	0	0	0	0	0	0	3	382	0	382	386	98,96%	53,13%	69,14%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					65,42%

First N Sample with Pre-Processing (PCA)

Table 8 IPS – ML - First N Sample with Pre-Processing (PCA)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	998	118	0	0	2	0	4	0	191	29	81	0	0	5	0	998	1428	69,89%	61,64%	65,51%
Corn-mintill	0	59	544	0	0	0	0	0	0	71	125	29	0	0	2	0	544	830	65,54%	70,93%	68,13%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	3	2	0	422	0	0	8	0	1	3	7	0	0	37	0	422	483	87,37%	99,06%	92,85%
Grass-trees	0	0	0	0	3	680	0	0	0	0	0	3	0	2	42	0	680	730	93,15%	98,69%	95,84%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	97,55%	98,76%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	70	2	0	0	1	0	0	0	707	159	26	0	0	7	0	707	972	72,74%	40,06%	51,66%
Soybean-mintill	0	453	59	0	0	2	0	0	0	794	896	234	0	0	17	0	896	2455	36,50%	72,96%	48,66%
Soybean-clean	0	36	42	0	1	0	0	0	0	1	16	495	0	0	2	0	495	593	83,47%	56,57%	67,44%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	1	0	0	0	0	0	0	0	1126	138	0	1126	1265	89,01%	99,12%	93,79%
Buildings-Grass-Trees-Drives	0	0	0	0	0	3	0	0	0	0	0	0	0	8	375	0	375	386	97,15%	60,00%	74,18%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					69,86%

Table 9 IPS – SVM-RBF - First N Sample with Pre-Processing (PCA)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	965	80	0	0	0	0	54	0	117	4	200	0	0	8	0	965	1428	67,58%	62,18%	64,77%
Corn-mintill	0	56	513	0	0	0	0	2	0	95	103	60	0	0	1	0	513	830	61,81%	72,15%	66,58%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	1	0	0	412	2	0	20	0	0	4	8	0	0	36	0	412	483	85,30%	93,00%	88,98%
Grass-trees	0	0	0	0	11	659	0	3	0	0	0	2	0	3	52	0	659	730	90,27%	99,55%	94,68%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	83,28%	90,87%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	126	10	0	5	0	0	2	0	649	79	93	0	0	8	0	649	972	66,77%	39,03%	49,26%
Soybean-mintill	0	380	60	0	10	1	0	3	0	798	801	383	0	0	19	0	801	2455	32,63%	80,26%	46,39%
Soybean-clean	0	24	48	0	3	0	0	3	0	4	7	500	0	0	4	0	500	593	84,32%	38,40%	52,77%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	2	0	0	9	0	0	0	56	0	930	268	0	930	1265	73,52%	99,57%	84,58%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	1	385	0	385	386	99,74%	49,30%	65,98%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					65,41%

Table 10 IPS – SVM-LNR - First N Sample with Pre-Processing (PCA)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	932	47	0	8	16	0	0	0	289	126	5	0	0	5	0	932	1428	65,27%	74,32%	69,50%
Corn-mintill	0	21	559	0	0	0	0	0	0	93	146	11	0	0	0	0	559	830	67,35%	75,95%	71,39%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	1	0	443	21	0	0	0	4	9	1	0	0	4	0	443	483	91,72%	91,15%	91,43%
Grass-trees	0	0	0	0	7	702	0	0	0	2	4	0	0	2	13	0	702	730	96,16%	92,49%	94,29%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	50	1	0	4	5	0	0	0	869	40	2	0	0	1	0	869	972	89,40%	39,36%	54,65%
Soybean-mintill	0	248	89	0	10	8	0	0	0	951	897	246	0	0	6	0	897	2455	36,54%	73,28%	48,76%
Soybean-clean	0	2	39	0	7	3	0	0	0	0	0	538	0	0	4	0	538	593	90,73%	67,00%	77,08%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	1	0	0	7	4	0	0	0	0	2	0	0	1015	236	0	1015	1265	80,24%	99,51%	88,84%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	3	383	0	383	386	99,22%	58,74%	73,80%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					70,85%

Table 11 IPS – K-NN - First N Sample with Pre-Processing (PCA)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	790	358	0	11	3	0	0	0	62	34	169	0	0	1	0	790	1428	55,32%	46,91%	50,77%
Corn-mintill	0	87	543	0	0	1	0	0	0	71	96	32	0	0	0	0	543	830	65,42%	43,34%	52,14%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	2	0	437	1	0	13	0	0	9	1	0	0	20	0	437	483	90,48%	81,53%	85,77%
Grass-trees	0	0	0	0	13	679	0	0	0	0	1	0	0	4	33	0	679	730	93,01%	98,55%	95,70%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	96,96%	98,46%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	128	60	0	5	1	0	0	0	638	75	64	0	0	1	0	638	972	65,64%	56,56%	60,76%
Soybean-mintill	0	634	217	0	21	2	0	2	0	340	968	268	0	0	3	0	968	2455	39,43%	81,07%	53,06%
Soybean-clean	0	45	73	0	17	1	0	0	0	17	10	430	0	0	0	0	430	593	72,51%	44,61%	55,23%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	31	1	0	0	0	0	1	0	0	970	262	0	970	1265	76,68%	99,39%	86,57%
Buildings-Grass-Trees-Drives	0	0	0	0	1	0	0	0	0	0	0	0	0	2	383	0	383	386	99,22%	54,48%	70,34%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					65,65%

First N Sample with Post-Processing (Filtering with 3x3 window)

Table 12 IPS - ML - First N Sample with Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1004	104	0	0	0	0	0	0	196	9	103	0	0	12	0	1004	1428	70,31%	64,48%	67,27%
Corn-mintill	0	37	558	0	0	0	0	0	0	95	106	24	0	1	9	0	558	830	67,23%	74,90%	70,86%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	421	0	0	2	0	0	1	6	0	0	53	0	421	483	87,16%	100,00%	93,14%
Grass-trees	0	0	0	0	0	629	0	0	0	0	0	0	0	0	101	0	629	730	86,16%	100,00%	92,57%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	99,58%	99,79%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	32	0	0	0	0	0	0	0	781	119	17	0	0	23	0	781	972	80,35%	41,99%	55,16%
Soybean-mintill	0	480	39	0	0	0	0	0	0	788	838	280	0	3	27	0	838	2455	34,13%	78,10%	47,51%
Soybean-clean	0	4	44	0	0	0	0	0	0	0	0	537	0	0	8	0	537	593	90,56%	55,53%	68,85%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	1038	227	0	1038	1265	82,06%	99,62%	89,99%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	45,63%	62,66%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					69,33%

Table 13 IPS - SVM-RBF - First N Sample with Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	956	119	0	1	0	0	0	0	108	7	216	0	0	21	0	956	1428	66,95%	47,42%	55,52%
Corn-mintill	0	52	515	0	0	0	0	0	0	45	183	29	0	4	2	0	515	830	62,05%	72,84%	67,01%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	426	0	0	0	0	0	0	2	0	0	55	0	426	483	88,20%	92,81%	90,45%
Grass-trees	0	0	0	0	20	678	0	0	0	0	0	0	0	0	32	0	678	730	92,88%	99,85%	96,24%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	477	0	0	0	0	0	0	1	0	477	478	99,79%	100,00%	99,90%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	269	0	0	0	0	0	0	0	643	33	14	0	0	13	0	643	972	66,15%	54,63%	59,84%
Soybean-mintill	0	724	58	0	1	1	0	0	0	380	950	320	0	4	17	0	950	2455	38,70%	80,51%	52,27%
Soybean-clean	0	15	15	0	11	0	0	0	0	1	7	531	0	0	13	0	531	593	89,54%	47,75%	62,29%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	952	313	0	952	1265	75,26%	99,17%	85,57%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	45,25%	62,31%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					67,71%

Table 14 IPS - SVM-LNR - First N Sample with Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	839	4	0	0	0	0	0	0	355	218	0	0	1	11	0	839	1428	58,75%	87,76%	70,39%
Corn-mintill	0	0	563	0	0	0	0	0	0	92	171	2	0	0	2	0	563	830	67,83%	91,99%	78,09%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	439	0	0	0	0	2	18	0	0	0	24	0	439	483	90,89%	97,56%	94,11%
Grass-trees	0	0	0	0	0	716	0	0	0	1	0	0	0	1	12	0	716	730	98,08%	100,00%	99,03%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	1	0	0	0	0	0	0	0	954	11	0	0	0	6	0	954	972	98,15%	38,88%	55,69%
Soybean-mintill	0	116	16	0	2	0	0	0	0	1050	891	379	0	0	1	0	891	2455	36,29%	67,76%	47,27%
Soybean-clean	0	0	29	0	9	0	0	0	0	0	6	540	0	0	9	0	540	593	91,06%	58,63%	71,33%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	1026	239	0	1026	1265	81,11%	99,81%	89,49%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	55,94%	71,75%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					71,02%

Table 15 IPS - K-NN - First N Sample with Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	823	357	0	9	0	0	1	0	76	12	133	0	0	17	0	823	1428	57,63%	50,65%	53,91%
Corn-mintill	0	65	541	0	0	0	0	0	0	62	136	17	0	0	9	0	541	830	65,18%	43,77%	52,37%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	424	0	0	17	0	0	6	0	0	0	36	0	424	483	87,78%	90,21%	88,98%
Grass-trees	0	0	0	0	0	696	0	0	0	0	0	0	0	0	34	0	696	730	95,34%	98,58%	96,94%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	96,37%	98,15%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	74	47	0	0	1	0	0	0	710	99	32	0	0	9	0	710	972	73,05%	60,84%	66,39%
Soybean-mintill	0	608	223	0	16	5	0	0	0	317	1069	196	0	5	16	0	1069	2455	43,54%	80,44%	56,50%
Soybean-clean	0	55	68	0	21	4	0	0	0	2	7	435	0	0	1	0	435	593	73,36%	53,51%	61,88%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	985	280	0	985	1265	77,87%	99,49%	87,36%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	48,98%	65,76%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					68,06%

First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

Table 16 IPS - ML - First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1040	0	0	0	0	0	0	0	274	0	103	0	0	11	0	1040	1428	72,83%	84,35%	78,17%
Corn-mintill	0	4	520	0	1	0	0	0	0	163	103	16	0	0	23	0	520	830	62,65%	84,97%	72,12%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	381	9	0	5	0	2	1	5	0	0	77	0	381	483	78,88%	99,74%	88,09%
Grass-trees	0	0	0	0	0	556	0	0	0	0	0	0	0	5	169	0	556	730	76,16%	98,23%	85,80%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	98,96%	99,48%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	1	0	0	0	0	0	0	0	932	0	29	0	0	10	0	932	972	95,88%	37,46%	53,87%
Soybean-mintill	0	183	25	0	0	1	0	0	0	1106	819	285	0	0	36	0	819	2455	33,36%	88,73%	48,49%
Soybean-clean	0	0	64	0	0	0	0	0	0	7	0	514	0	0	8	0	514	593	86,68%	53,49%	66,15%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	0	0	0	0	0	0	0	4	0	6	0	904	349	0	904	1265	71,46%	99,45%	83,16%
Buildings-Grass-Trees-Drives	0	3	0	0	0	0	0	0	0	0	0	3	0	0	380	0	380	386	98,45%	35,75%	52,45%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					67,82%

Table 17 IPS - SVM-RBF - First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	**Corn-notill**	**Corn-mintill**	**Corn**	**Grass-pasture**	**Grass-trees**	**Grass-pasture-mowed**	**Hay-windrowed**	**Oats**	**Soybean-notill**	**Soybean-mintill**	**Soybean-clean**	**Wheat**	**Woods**	**Buildings-Grass-Trees-Drives**	**Stone-Steel-Towers**	**Correctly Classified**	**Ground Truth**	**Recall**	**Precision**	**F-Measure**
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1074	0	0	0	0	0	0	0	109	0	234	0	0	11	0	1074	1428	75,21%	47,54%	58,26%
Corn-mintill	0	28	496	0	1	0	0	0	0	0	266	16	0	0	23	0	496	830	59,76%	86,41%	70,66%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	386	9	0	5	0	2	1	0	0	0	77	0	386	483	79,92%	93,01%	85,97%
Grass-trees	0	0	0	0	21	657	0	0	0	0	0	0	0	5	47	0	657	730	90,00%	98,50%	94,06%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	98,96%	99,48%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	89	0	0	3	0	0	0	0	844	0	26	0	0	10	0	844	972	86,83%	77,15%	81,70%
Soybean-mintill	0	1061	67	0	0	1	0	0	0	130	819	341	0	0	36	0	819	2455	33,36%	75,41%	46,26%
Soybean-clean	0	0	3	0	4	0	0	0	0	7	0	515	0	0	64	0	515	593	86,85%	45,45%	59,68%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	6	5	0	0	0	0	0	0	0	0	1	0	904	349	0	904	1265	71,46%	99,45%	83,16%
Buildings-Grass-Trees-Drives	0	1	0	0	0	0	0	0	0	2	0	0	0	0	383	0	383	386	99,22%	38,30%	55,27%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					68,15%

Table 18 IPS - SVM-LNR - First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	**Corn-notill**	**Corn-mintill**	**Corn**	**Grass-pasture**	**Grass-trees**	**Grass-pasture-mowed**	**Hay-windrowed**	**Oats**	**Soybean-notill**	**Soybean-mintill**	**Soybean-clean**	**Wheat**	**Woods**	**Buildings-Grass-Trees-Drives**	**Stone-Steel-Towers**	**Correctly Classified**	**Ground Truth**	**Recall**	**Precision**	**F-Measure**
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	755	7	0	0	0	0	0	0	365	272	0	0	5	24	0	755	1428	52,87%	97,17%	68,48%
Corn-mintill	0	4	524	0	8	0	0	0	0	163	103	0	0	0	28	0	524	830	63,13%	95,80%	76,11%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	386	9	0	0	0	2	22	0	0	0	61	0	386	483	79,92%	95,54%	87,03%
Grass-trees	0	0	0	0	0	665	0	0	0	21	0	0	0	5	39	0	665	730	91,10%	98,52%	94,66%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	0	0	0	3	0	0	0	0	933	0	26	0	6	4	0	933	972	95,99%	34,85%	51,14%
Soybean-mintill	0	6	8	0	0	1	0	0	0	1181	819	404	0	20	16	0	819	2455	33,36%	66,86%	44,51%
Soybean-clean	0	9	0	0	7	0	0	0	0	8	9	504	0	0	56	0	504	593	84,99%	53,79%	65,88%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	5	0	0	0	0	0	0	4	0	1	0	1141	112	0	1141	1265	90,20%	96,94%	93,45%
Buildings-Grass-Trees-Drives	0	1	0	0	0	0	0	0	0	0	0	2	0	0	383	0	383	386	99,22%	52,97%	69,07%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					68,48%

Table 19 IPS - K-NN - First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	896	294	0	0	0	0	0	0	153	0	74	0	5	6	0	896	1428	62,75%	39,18%	48,24%
Corn-mintill	0	4	535	0	3	0	0	0	0	163	103	11	0	0	11	0	535	830	64,46%	43,43%	51,89%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	386	9	0	21	0	2	1	0	0	0	61	0	386	483	79,92%	95,07%	86,84%
Grass-trees	0	0	0	0	0	705	0	0	0	0	0	0	0	5	20	0	705	730	96,58%	98,60%	97,58%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	95,79%	97,85%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	0	104	0	3	0	0	0	0	829	0	26	0	6	4	0	829	972	85,29%	63,92%	73,07%
Soybean-mintill	0	1314	156	0	0	1	0	0	0	140	818	0	0	20	6	0	818	2455	33,32%	87,86%	48,32%
Soybean-clean	0	67	128	0	4	0	0	0	0	8	9	359	0	0	18	0	359	593	60,54%	76,38%	67,54%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	10	0	0	0	0	0	0	0	0	0	0	1141	112	0	1141	1265	90,20%	96,94%	93,45%
Buildings-Grass-Trees-Drives	0	4	2	0	10	0	0	0	0	2	0	0	0	0	368	0	368	386	95,34%	60,73%	74,19%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					67,72%

First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

Table 20 IPS - ML - First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1014	105	0	0	0	0	0	0	186	12	102	0	2	7	0	1014	1428	71,01%	70,61%	70,81%
Corn-mintill	0	29	550	0	0	0	0	0	0	65	158	22	0	1	5	0	550	830	66,27%	76,07%	70,83%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	421	0	0	7	0	0	2	6	0	0	47	0	421	483	87,16%	100,00%	93,14%
Grass-trees	0	0	0	0	0	701	0	0	0	1	0	0	0	1	27	0	701	730	96,03%	100,00%	97,97%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	98,56%	99,27%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	23	0	0	0	0	0	0	0	768	146	22	0	2	11	0	768	972	79,01%	40,53%	53,58%
Soybean-mintill	0	357	35	0	0	0	0	0	0	875	909	254	0	1	24	0	909	2455	37,03%	74,08%	49,38%
Soybean-clean	0	13	33	0	0	0	0	0	0	0	0	541	0	0	6	0	541	593	91,23%	57,13%	70,26%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	1142	123	0	1142	1265	90,28%	99,30%	94,58%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	1	385	0	385	386	99,74%	60,63%	75,42%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					71,82%

Table 21 IPS – SVM-RBF - First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Alfalfa	**Corn-notill**	**Corn-mintill**	**Corn**	**Grass-pasture**	**Grass-trees**	**Grass-pasture-mowed**	**Hay-windrowed**	**Oats**	**Soybean-notill**	**Soybean-mintill**	**Soybean-clean**	**Wheat**	**Woods**	**Buildings-Grass-Trees-Drives**	**Stone-Steel-Towers**	**Correctly Classified**	**Ground Truth**	**Recall**	**Precision**	**F-Measure**
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1077	65	0	0	0	0	25	0	87	0	165	0	0	9	0	1077	1428	75,42%	74,53%	74,97%
Corn-mintill	0	16	532	0	0	0	0	0	0	109	137	30	0	1	5	0	532	830	64,10%	78,93%	70,74%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	414	0	0	20	0	0	0	4	0	0	45	0	414	483	85,71%	99,52%	92,10%
Grass-trees	0	0	0	0	0	673	0	0	0	0	0	0	0	1	56	0	673	730	92,19%	100,00%	95,94%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	477	0	0	0	0	0	0	1	0	477	478	99,79%	91,38%	95,40%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	68	1	0	1	0	0	0	0	701	76	110	0	0	15	0	701	972	72,12%	39,34%	50,91%
Soybean-mintill	0	280	43	0	1	0	0	0	0	884	811	411	0	3	22	0	811	2455	33,03%	79,20%	46,62%
Soybean-clean	0	4	33	0	0	0	0	0	0	1	0	551	0	0	4	0	551	593	92,92%	42,09%	57,94%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	38	0	947	280	0	947	1265	74,86%	99,47%	85,43%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	46,90%	63,85%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					68,28%

Table 22 IPS – SVM-LNR - First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Alfalfa	**Corn-notill**	**Corn-mintill**	**Corn**	**Grass-pasture**	**Grass-trees**	**Grass-pasture-mowed**	**Hay-windrowed**	**Oats**	**Soybean-notill**	**Soybean-mintill**	**Soybean-clean**	**Wheat**	**Woods**	**Buildings-Grass-Trees-Drives**	**Stone-Steel-Towers**	**Correctly Classified**	**Ground Truth**	**Recall**	**Precision**	**F-Measure**
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1018	15	0	1	10	0	0	0	246	124	1	0	2	11	0	1018	1428	71,29%	64,92%	67,96%
Corn-mintill	0	51	559	0	1	0	0	0	0	34	175	7	0	2	1	0	559	830	67,35%	90,89%	77,37%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	444	30	0	0	0	1	6	0	0	2	0	0	444	483	91,93%	95,28%	93,57%
Grass-trees	0	0	0	0	0	724	0	0	0	0	0	0	0	1	5	0	724	730	99,18%	93,54%	96,28%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	99,17%	99,58%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	77	0	0	1	6	0	0	0	827	56	1	0	0	4	0	827	972	85,08%	46,20%	59,88%
Soybean-mintill	0	422	19	0	3	4	0	4	0	682	1012	295	0	8	6	0	1012	2455	41,22%	73,71%	52,87%
Soybean-clean	0	0	22	0	16	0	0	0	0	0	0	549	0	0	6	0	549	593	92,58%	64,36%	75,93%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	997	268	0	997	1265	78,81%	98,52%	87,57%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	56,19%	71,95%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					72,70%

Table 23 IPS – K-NN - First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	819	364	0	8	0	0	1	0	43	16	161	0	0	16	0	819	1428	57,35%	50,52%	53,72%
Corn-mintill	0	36	558	0	0	0	0	0	0	75	145	10	0	1	5	0	558	830	67,23%	45,51%	54,28%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	423	0	0	16	0	0	6	0	0	0	38	0	423	483	87,58%	91,16%	89,33%
Grass-trees	0	0	0	0	5	700	0	0	0	0	0	0	0	0	25	0	700	730	95,89%	99,01%	97,43%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	96,57%	98,25%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	87	41	0	1	0	0	0	0	707	78	49	0	0	9	0	707	972	72,74%	62,73%	67,37%
Soybean-mintill	0	632	187	0	8	3	0	0	0	299	1083	226	0	5	12	0	1083	2455	44,11%	81,25%	57,18%
Soybean-clean	0	47	76	0	19	4	0	0	0	3	5	437	0	0	2	0	437	593	73,69%	49,49%	59,21%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	979	286	0	979	1265	77,39%	99,39%	87,02%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	49,55%	66,27%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					68,30%

First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

Table 23 IPS - ML - First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	**Corn-notill**	**Corn-mintill**	**Corn**	**Grass-pasture**	**Grass-trees**	**Grass-pasture-mowed**	**Hay-windrowed**	**Oats**	**Soybean-notill**	**Soybean-mintill**	**Soybean-clean**	**Wheat**	**Woods**	**Buildings-Grass-Trees-Drives**	**Stone-Steel-Towers**	**Correctly Classified**	**Ground Truth**	**Recall**	**Precision**	**F-Measure**
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	544	452	0	0	0	0	0	0	70	98	253	0	5	6	0	544	1428	38,10%	80,24%	51,66%
Corn-mintill	0	0	553	0	1	0	0	0	0	0	235	15	0	0	26	0	553	830	66,63%	48,51%	56,14%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	386	9	0	0	0	0	1	2	0	0	82	0	386	483	79,92%	82,13%	81,01%
Grass-trees	0	0	0	0	35	664	0	0	0	0	0	0	0	5	26	0	664	730	90,96%	98,52%	94,59%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	0	0	0	3	0	0	0	0	798	0	161	0	6	4	0	798	972	82,10%	84,98%	83,52%
Soybean-mintill	0	123	0	0	0	1	0	0	0	71	1867	357	0	20	16	0	1867	2455	76,05%	82,83%	79,29%
Soybean-clean	0	9	132	0	4	0	0	0	0	0	41	351	0	0	56	0	351	593	59,19%	30,52%	40,28%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	0	0	0	0	0	0	0	0	0	10	0	1141	112	0	1141	1265	90,20%	96,94%	93,45%
Buildings-Grass-Trees-Drives	0	0	0	0	41	0	0	0	0	0	12	1	0	0	332	0	332	386	86,01%	50,30%	63,48%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					73,95%

Table 24 IPS – SVM-RBF - First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1175	0	0	0	0	0	0	0	139	0	103	0	0	11	0	1175	1428	82,28%	95,14%	88,25%
Corn-mintill	0	4	520	0	1	0	0	0	0	166	103	16	0	0	20	0	520	830	62,65%	94,37%	75,31%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	381	9	0	21	0	2	1	5	0	0	61	0	381	483	78,88%	99,74%	88,09%
Grass-trees	0	0	0	0	0	665	0	0	0	0	0	0	0	5	60	0	665	730	91,10%	98,52%	94,66%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	95,79%	97,85%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	1	0	0	0	0	0	0	0	836	0	125	0	0	10	0	836	972	86,01%	36,94%	51,68%
Soybean-mintill	0	52	25	0	0	1	0	0	0	1113	819	409	0	0	36	0	819	2455	33,36%	88,73%	48,49%
Soybean-clean	0	0	3	0	0	0	0	0	0	7	0	575	0	0	8	0	575	593	96,96%	44,82%	61,30%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	0	0	0	0	0	0	0	0	0	45	0	869	349	0	869	1265	68,70%	99,43%	81,25%
Buildings-Grass-Trees-Drives	0	1	0	0	0	0	0	0	0	0	0	5	0	0	380	0	380	386	98,45%	40,64%	57,53%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					69,63%

Table 25 IPS – SVM-LNR - First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1120	7	0	0	3	0	0	0	198	92	0	0	5	3	0	1120	1428	78,43%	98,59%	87,36%
Corn-mintill	0	4	531	0	1	0	0	0	0	3	267	5	0	0	19	0	531	830	63,98%	90,61%	75,00%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	318	133	0	0	0	2	11	5	0	3	8	0	318	483	65,84%	99,69%	79,30%
Grass-trees	0	0	0	0	0	728	0	0	0	0	0	0	0	2	0	0	728	730	99,73%	84,16%	91,29%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	1	0	0	0	0	0	0	0	932	0	29	0	6	4	0	932	972	95,88%	39,97%	56,42%
Soybean-mintill	0	7	33	0	0	1	0	0	0	1185	829	374	0	20	6	0	829	2455	33,77%	69,14%	45,37%
Soybean-clean	0	0	12	0	0	0	0	0	0	8	0	524	0	0	49	0	524	593	88,36%	55,33%	68,05%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	3	0	0	0	0	0	0	0	4	0	5	0	1141	112	0	1141	1265	90,20%	96,94%	93,45%
Buildings-Grass-Trees-Drives	0	1	0	0	0	0	0	0	0	0	0	5	0	0	380	0	380	386	98,45%	65,40%	78,59%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					72,57%

Table 26 IPS – K-NN - First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	896	294	0	0	0	0	0	0	153	0	74	0	5	6	0	896	1428	62,75%	39,18%	48,24%
Corn-mintill	0	4	535	0	3	0	0	0	0	163	103	11	0	0	11	0	535	830	64,46%	43,43%	51,89%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	386	9	0	21	0	2	1	0	0	0	61	0	386	483	79,92%	95,07%	86,84%
Grass-trees	0	0	0	0	0	705	0	0	0	0	0	0	0	5	20	0	705	730	96,58%	98,60%	97,58%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	95,79%	97,85%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	0	104	0	3	0	0	0	0	829	0	26	0	6	4	0	829	972	85,29%	63,92%	73,07%
Soybean-mintill	0	1314	156	0	0	1	0	0	0	140	818	0	0	20	6	0	818	2455	33,32%	87,86%	48,32%
Soybean-clean	0	67	128	0	4	0	0	0	0	8	9	359	0	0	18	0	359	593	60,54%	76,38%	67,54%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	10	0	0	0	0	0	0	0	0	0	0	1141	112	0	1141	1265	90,20%	96,94%	93,45%
Buildings-Grass-Trees-Drives	0	4	2	0	10	0	0	0	0	2	0	0	0	0	368	0	368	386	95,34%	60,73%	74,19%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					67,72%

Randomly Selected N Sample without Pre-Processing or Post Processing

Table 27 IPS - ML -Randomly Selected N Sample without Pre-Processing or Post Processing

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1128	57	0	1	3	0	0	0	79	129	29	0	0	2	0	1128	1428	78,99%	66,71%	72,33%
Corn-mintill	0	64	639	0	0	0	0	0	0	21	67	38	0	0	1	0	639	830	76,99%	69,38%	72,99%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	2	0	0	463	3	0	0	0	0	5	2	0	2	6	0	463	483	95,86%	98,93%	97,37%
Grass-trees	0	0	0	0	2	703	0	0	0	0	0	0	0	1	24	0	703	730	96,30%	98,05%	97,17%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	99,79%	99,90%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	87	16	0	0	3	0	0	0	753	97	15	0	0	1	0	753	972	77,47%	64,30%	70,28%
Soybean-mintill	0	384	199	0	2	4	0	1	0	311	1449	97	0	0	8	0	1449	2455	59,02%	81,73%	68,54%
Soybean-clean	0	26	10	0	0	0	0	0	0	6	26	523	0	0	2	0	523	593	88,20%	74,29%	80,65%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	1	0	0	0	0	0	0	0	1189	75	0	1189	1265	93,99%	99,25%	96,55%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	1	0	0	0	6	379	0	379	386	98,19%	76,10%	85,75%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					80,08%

Table 28 IPS – SVM-RBF -Randomly Selected N Sample without Pre-Processing or Post Processing

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1152	16	0	4	2	0	0	0	87	99	68	0	0	0	0	1152	1428	80,67%	87,01%	83,72%
Corn-mintill	0	18	721	0	0	0	0	0	0	3	47	41	0	0	0	0	721	830	86,87%	83,64%	85,22%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	467	1	0	1	0	1	0	10	0	0	3	0	467	483	96,69%	93,78%	95,21%
Grass-trees	0	0	0	0	0	712	0	0	0	1	0	0	0	0	17	0	712	730	97,53%	98,34%	97,94%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	2	0	0	476	0	0	0	0	0	0	0	0	476	478	99,58%	99,58%	99,58%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	12	5	0	2	3	0	0	0	910	21	18	0	0	1	0	910	972	93,62%	78,58%	85,45%
Soybean-mintill	0	140	112	0	13	3	0	1	0	152	1929	92	0	0	13	0	1929	2455	78,57%	91,86%	84,70%
Soybean-clean	0	2	8	0	0	0	0	0	0	4	4	573	0	0	2	0	573	593	96,63%	71,45%	82,15%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	9	1	0	0	0	0	0	0	0	1171	84	0	1171	1265	92,57%	99,07%	95,71%
Buildings-Grass-Trees-Drives	0	0	0	0	1	2	0	0	0	0	0	0	0	11	372	0	372	386	96,37%	75,61%	84,74%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					88,18%

Table 29 IPS – SVM-LNR -Randomly Selected N Sample without Pre-Processing or Post Processing

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1160	69	0	1	1	0	0	0	67	122	6	0	0	2	0	1160	1428	81,23%	86,57%	83,82%
Corn-mintill	0	20	692	0	0	0	0	0	0	3	68	47	0	0	0	0	692	830	83,37%	74,41%	78,64%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	1	0	474	0	0	0	0	2	0	1	0	1	4	0	474	483	98,14%	95,37%	96,73%
Grass-trees	0	0	0	0	0	722	0	0	0	2	0	0	0	0	6	0	722	730	98,90%	99,04%	98,97%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	99,79%	99,90%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	14	10	0	3	1	0	0	0	841	103	0	0	0	0	0	841	972	86,52%	75,83%	80,83%
Soybean-mintill	0	146	152	0	10	2	0	1	0	193	1803	141	0	0	7	0	1803	2455	73,44%	85,73%	79,11%
Soybean-clean	0	0	6	0	3	0	0	0	0	1	7	573	0	0	3	0	573	593	96,63%	74,61%	84,20%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	5	3	0	0	0	0	0	0	0	1174	83	0	1174	1265	92,81%	99,41%	95,99%
Buildings-Grass-Trees-Drives	0	0	0	0	1	0	0	0	0	0	0	0	0	6	379	0	379	386	98,19%	78,31%	87,13%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					86,24%

Table 30 IPS – K-NN -Randomly Selected N Sample without Pre-Processing or Post Processing

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1002	104	0	3	1	0	0	0	78	128	112	0	0	0	0	1002	1428	70,17%	72,93%	71,52%
Corn-mintill	0	38	676	0	0	0	0	0	0	28	34	54	0	0	0	0	676	830	81,45%	65,44%	72,57%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	1	0	0	472	1	0	1	0	1	2	1	0	2	2	0	472	483	97,72%	89,90%	93,65%
Grass-trees	0	0	0	0	1	713	0	0	0	1	0	0	0	1	14	0	713	730	97,67%	98,21%	97,94%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	99,58%	99,79%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	34	21	0	3	2	0	0	0	845	44	23	0	0	0	0	845	972	86,93%	69,66%	77,35%
Soybean-mintill	0	273	218	0	13	5	0	1	0	247	1612	78	0	0	8	0	1612	2455	65,66%	88,04%	75,22%
Soybean-clean	0	26	14	0	1	0	0	0	0	13	11	526	0	0	2	0	526	593	88,70%	66,25%	75,85%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	32	4	0	0	0	0	0	0	0	1114	115	0	1114	1265	88,06%	99,55%	93,46%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	2	384	0	384	386	99,48%	73,14%	84,30%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					81,31%

Randomly Selected N Sample with Pre-Processing (PCA)

Table 31 IPS – ML - Randomly Selected N Sample with Pre-Processing (PCA)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	961	60	0	1	5	0	0	0	161	200	39	0	0	1	0	961	1428	67,30%	82,21%	74,01%
Corn-mintill	0	37	670	0	0	0	0	0	0	18	88	16	0	0	1	0	670	830	80,72%	79,86%	80,29%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	465	2	0	0	0	2	1	3	0	4	6	0	465	483	96,27%	98,52%	97,38%
Grass-trees	0	0	0	0	1	717	0	0	0	1	0	0	0	4	7	0	717	730	98,22%	96,24%	97,22%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	2	0	475	0	0	0	1	0	0	0	0	475	478	99,37%	99,79%	99,58%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	13	5	0	0	3	0	0	0	862	83	6	0	0	0	0	862	972	88,68%	63,80%	74,21%
Soybean-mintill	0	143	73	0	4	9	0	1	0	285	1814	116	0	0	10	0	1814	2455	73,89%	81,13%	77,34%
Soybean-clean	0	15	31	0	0	1	0	0	0	22	50	473	0	0	1	0	473	593	79,76%	72,32%	75,86%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	2	0	0	0	0	0	0	0	1224	39	0	1224	1265	96,76%	96,68%	96,72%
Buildings-Grass-Trees-Drives	0	0	0	0	1	4	0	0	0	0	0	0	0	34	347	0	347	386	89,90%	84,22%	86,97%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					83,24%

Table 32 IPS – SVM-RBF - Randomly Selected N Sample with Pre-Processing (PCA)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1135	24	0	0	0	0	5	0	74	80	107	0	0	3	0	1135	1428	79,48%	84,01%	81,68%
Corn-mintill	0	22	673	0	0	0	0	0	0	7	62	66	0	0	0	0	673	830	81,08%	80,12%	80,60%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	473	0	0	3	0	0	0	6	0	0	1	0	473	483	97,93%	92,20%	94,98%
Grass-trees	0	0	0	0	12	682	0	2	0	0	0	2	0	3	29	0	682	730	93,42%	99,56%	96,40%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	96,96%	98,46%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	18	6	0	8	0	0	1	0	842	39	55	0	0	3	0	842	972	86,63%	77,39%	81,75%
Soybean-mintill	0	168	126	0	18	2	0	3	0	163	1674	292	0	0	9	0	1674	2455	68,19%	90,00%	77,59%
Soybean-clean	0	8	11	0	1	0	0	1	0	2	5	564	0	0	1	0	564	593	95,11%	49,60%	65,20%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	1	1	0	0	0	0	0	45	0	1141	77	0	1141	1265	90,20%	99,48%	94,61%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	3	383	0	383	386	99,22%	75,69%	85,87%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					83,63%

Table 33 IPS – SVM-LNR - Randomly Selected N Sample with Pre-Processing (PCA)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1140	79	0	2	8	0	0	0	53	130	14	0	0	2	0	1140	1428	79,83%	86,76%	83,15%
Corn-mintill	0	36	668	0	0	0	0	0	0	8	60	58	0	0	0	0	668	830	80,48%	69,37%	74,51%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	481	0	0	0	0	1	0	1	0	0	0	0	481	483	99,59%	95,82%	97,66%
Grass-trees	0	0	0	0	0	727	0	0	0	0	0	0	0	0	3	0	727	730	99,59%	96,93%	98,24%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	22	11	0	1	6	0	0	0	823	107	1	0	0	1	0	823	972	84,67%	77,86%	81,12%
Soybean-mintill	0	116	198	0	14	3	0	0	0	171	1810	133	0	0	10	0	1810	2455	73,73%	85,70%	79,26%
Soybean-clean	0	0	7	0	0	0	0	0	0	1	5	579	0	0	1	0	579	593	97,64%	73,66%	83,97%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	4	6	0	0	0	0	0	0	0	1148	107	0	1148	1265	90,75%	99,83%	95,07%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	2	384	0	384	386	99,48%	75,59%	85,91%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					85,63%

Table 34 IPS – K-NN - Randomly Selected N Sample with Pre-Processing (PCA)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1017	92	0	6	4	0	0	0	66	144	98	0	0	1	0	1017	1428	71,22%	78,41%	74,64%
Corn-mintill	0	38	692	0	0	0	0	0	0	27	32	41	0	0	0	0	692	830	83,37%	67,84%	74,81%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	1	0	0	477	1	0	0	0	1	0	1	0	1	1	0	477	483	98,76%	88,50%	93,35%
Grass-trees	0	0	0	0	2	702	0	0	0	0	0	0	0	1	25	0	702	730	96,16%	97,77%	96,96%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	27	21	0	6	3	0	0	0	866	33	15	0	0	1	0	866	972	89,09%	69,67%	78,19%
Soybean-mintill	0	195	200	0	18	3	0	0	0	264	1681	86	0	0	8	0	1681	2455	68,47%	88,29%	77,13%
Soybean-clean	0	19	15	0	1	0	0	0	0	18	14	525	0	0	1	0	525	593	88,53%	68,54%	77,26%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	29	4	0	0	0	0	0	0	0	1092	140	0	1092	1265	86,32%	99,73%	92,54%
Buildings-Grass-Trees-Drives	0	0	0	0	0	1	0	0	0	1	0	0	0	1	383	0	383	386	99,22%	68,39%	80,97%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					82,26%

Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

Table 35 IPS - ML - Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1242	16	0	0	1	0	0	0	39	70	50	0	4	6	0	1242	1428	86,97%	90,20%	88,56%
Corn-mintill	0	13	771	0	0	0	0	0	0	0	25	14	0	3	4	0	771	830	92,89%	94,60%	93,74%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	476	3	0	0	0	0	0	1	0	0	3	0	476	483	98,55%	100,00%	99,27%
Grass-trees	0	0	0	0	0	725	0	0	0	0	0	0	0	1	4	0	725	730	99,32%	99,04%	99,18%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	2	0	0	0	0	0	0	0	904	47	5	0	2	12	0	904	972	93,00%	87,77%	90,31%
Soybean-mintill	0	114	28	0	0	3	0	0	0	87	2087	110	0	3	23	0	2087	2455	85,01%	93,63%	89,11%
Soybean-clean	0	6	0	0	0	0	0	0	0	0	0	585	0	0	2	0	585	593	98,65%	76,47%	86,16%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	1224	41	0	1224	1265	96,76%	98,95%	97,84%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	80,25%	89,04%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					92,29%

Table 36 IPS – SVM-RBF - Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1232	2	0	4	1	0	0	0	87	45	46	0	4	7	0	1232	1428	86,27%	94,19%	90,06%
Corn-mintill	0	0	779	0	1	1	0	0	0	0	7	40	0	1	1	0	779	830	93,86%	96,65%	95,23%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	475	3	0	0	0	0	0	4	0	0	1	0	475	483	98,34%	98,34%	98,34%
Grass-trees	0	0	0	0	0	722	0	0	0	0	0	0	0	0	8	0	722	730	98,90%	99,31%	99,11%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	0	0	0	1	0	0	0	0	944	14	2	0	3	8	0	944	972	97,12%	86,29%	91,38%
Soybean-mintill	0	76	25	0	2	0	0	0	0	63	2215	57	0	1	16	0	2215	2455	90,22%	97,11%	93,54%
Soybean-clean	0	0	0	0	0	0	0	0	0	0	0	591	0	0	2	0	591	593	99,66%	79,86%	88,67%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	1216	49	0	1216	1265	96,13%	98,86%	97,47%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	5	381	0	381	386	98,70%	80,55%	88,71%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					93,90%

Table 37 IPS – SVM-LNR - Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1267	14	0	7	0	0	0	0	48	79	6	0	4	3	0	1267	1428	88,73%	96,94%	92,65%
Corn-mintill	0	10	771	0	4	0	0	0	0	8	12	18	0	4	3	0	771	830	92,89%	93,00%	92,95%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	483	0	0	0	0	0	0	0	0	0	0	0	483	483	100,00%	95,45%	97,67%
Grass-trees	0	0	0	0	0	729	0	0	0	1	0	0	0	0	0	0	729	730	99,86%	99,59%	99,73%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	1	0	0	1	1	0	0	0	943	20	0	0	2	4	0	943	972	97,02%	84,35%	90,24%
Soybean-mintill	0	29	44	0	11	2	0	0	0	118	2091	150	0	1	9	0	2091	2455	85,17%	94,92%	89,78%
Soybean-clean	0	0	0	0	0	0	0	0	0	0	1	591	0	0	1	0	591	593	99,66%	77,25%	87,04%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	1224	41	0	1224	1265	96,76%	99,11%	97,92%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	86,35%	92,68%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					93,17%

Table 38 IPS – K-NN - Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1219	22	0	0	1	0	0	0	71	61	37	0	0	17	0	1219	1428	85,36%	93,20%	89,11%
Corn-mintill	0	4	798	0	0	0	0	0	0	0	8	13	0	6	1	0	798	830	96,14%	91,41%	93,72%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	481	1	0	0	0	0	0	1	0	0	0	0	481	483	99,59%	99,18%	99,38%
Grass-trees	0	0	0	0	0	726	0	0	0	0	0	0	0	0	4	0	726	730	99,45%	98,78%	99,11%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	6	0	0	1	1	0	0	0	930	13	18	0	0	3	0	930	972	95,68%	82,16%	88,40%
Soybean-mintill	0	79	51	0	2	5	0	0	0	131	2148	18	0	5	16	0	2148	2455	87,49%	96,32%	91,70%
Soybean-clean	0	0	2	0	0	0	0	0	0	0	0	591	0	0	0	0	591	593	99,66%	87,17%	93,00%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	1	1	0	0	0	0	0	0	0	1191	72	0	1191	1265	94,15%	99,08%	96,55%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	77,35%	87,23%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					93,01%

Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

Table 39 IPS - ML - Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1298	0	0	0	2	0	0	0	12	39	68	0	5	4	0	1298	1428	90,90%	88,48%	89,67%
Corn-mintill	0	0	797	0	1	0	0	0	0	0	10	20	0	0	2	0	797	830	96,02%	99,13%	97,55%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	452	9	0	0	0	2	1	5	0	0	11	0	452	483	93,58%	99,78%	96,58%
Grass-trees	0	0	0	0	0	717	0	0	0	2	0	0	0	5	6	0	717	730	98,22%	98,22%	98,22%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	53	0	0	0	0	0	0	0	875	4	29	0	6	5	0	875	972	90,02%	94,80%	92,35%
Soybean-mintill	0	113	0	0	0	1	0	0	0	25	2246	44	0	3	23	0	2246	2455	91,49%	97,52%	94,41%
Soybean-clean	0	0	3	0	0	0	0	0	0	7	3	569	0	0	11	0	569	593	95,95%	76,58%	85,18%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	1	0	0	1	0	0	0	0	0	5	0	1231	25	0	1231	1265	97,31%	98,48%	97,89%
Buildings-Grass-Trees-Drives	0	1	0	0	0	0	0	0	0	0	0	3	0	0	382	0	382	386	98,96%	81,45%	89,36%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					94,02%

Table 40 IPS – SVM-RBF - Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1139	0	0	0	0	0	0	0	235	36	7	0	5	6	0	1139	1428	79,76%	98,53%	88,16%
Corn-mintill	0	0	786	0	1	0	0	0	0	4	0	16	0	0	23	0	786	830	94,70%	97,40%	96,03%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	442	9	0	0	0	2	1	5	0	0	21	0	442	483	91,51%	99,77%	95,46%
Grass-trees	0	0	0	0	0	705	0	0	0	0	0	0	0	5	20	0	705	730	96,58%	98,60%	97,58%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	8	0	0	0	0	0	0	0	925	0	29	0	6	4	0	925	972	95,16%	72,32%	82,19%
Soybean-mintill	0	6	9	0	0	1	0	0	0	101	2277	25	0	20	16	0	2277	2455	92,75%	98,32%	95,45%
Soybean-clean	0	1	3	0	0	0	0	0	0	7	0	565	0	0	17	0	565	593	95,28%	86,92%	90,91%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	6	0	0	0	0	0	0	4	0	0	0	1253	0	0	1253	1265	99,05%	97,21%	98,12%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	1	2	3	0	0	380	0	380	386	98,45%	78,03%	87,06%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					93,04%

Table 41 IPS – SVM-LNR - Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1238	7	0	0	3	0	0	0	70	77	7	0	5	21	0	1238	1428	86,69%	98,65%	92,28%
Corn-mintill	0	0	790	0	12	0	0	0	0	0	0	9	0	0	19	0	790	830	95,18%	96,93%	96,05%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	452	9	0	0	0	2	1	5	0	0	11	0	452	483	93,58%	95,16%	94,36%
Grass-trees	0	0	0	0	8	717	0	0	0	0	0	0	0	5	0	0	717	730	98,22%	97,42%	97,82%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	8	0	0	0	0	0	0	0	925	0	29	0	6	4	0	925	972	95,16%	83,41%	88,90%
Soybean-mintill	0	6	15	0	0	7	0	0	0	101	2262	34	0	20	10	0	2262	2455	92,14%	96,63%	94,33%
Soybean-clean	0	1	0	0	3	0	0	0	0	7	0	565	0	0	17	0	565	593	95,28%	86,00%	90,40%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	0	0	0	0	0	0	0	4	0	6	0	1253	0	0	1253	1265	99,05%	97,21%	98,12%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	1	2	0	0	383	0	383	386	99,22%	82,37%	90,01%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					94,21%

Table 42 IPS – K-NN - Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1264	14	0	0	0	0	0	0	5	116	0	0	5	24	0	1264	1428	88,52%	94,54%	91,43%
Corn-mintill	0	0	809	0	3	0	0	0	0	0	0	12	0	0	6	0	809	830	97,47%	97,47%	97,47%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	437	9	0	5	0	2	1	5	0	0	21	0	437	483	90,48%	97,11%	93,68%
Grass-trees	0	0	0	0	0	719	0	0	0	0	0	0	0	5	6	0	719	730	98,49%	98,63%	98,56%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	98,96%	99,48%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	8	0	0	0	0	0	0	0	880	45	29	0	6	4	0	880	972	90,53%	91,48%	91,00%
Soybean-mintill	0	49	1	0	0	1	0	0	0	55	2305	0	0	20	24	0	2305	2455	93,89%	93,36%	93,62%
Soybean-clean	0	10	0	0	0	0	0	0	0	16	0	559	0	0	8	0	559	593	94,27%	92,40%	93,32%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	1	0	0	0	0	0	0	4	0	0	0	1253	5	0	1253	1265	99,05%	97,21%	98,12%
Buildings-Grass-Trees-Drives	0	4	2	0	10	0	0	0	0	0	2	0	0	0	368	0	368	386	95,34%	78,97%	86,38%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					94,30%

Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

Table 43 IPS - ML - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1257	7	0	1	0	0	0	0	59	55	39	0	1	9	0	1257	1428	88,03%	90,37%	89,18%
Corn-mintill	0	12	770	0	1	0	0	0	0	2	14	24	0	3	4	0	770	830	92,77%	97,84%	95,24%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	472	4	0	0	0	0	0	7	0	0	0	0	472	483	97,72%	99,58%	98,64%
Grass-trees	0	0	0	0	0	726	0	0	0	0	0	0	0	1	3	0	726	730	99,45%	99,32%	99,38%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	0	0	0	0	0	0	0	0	950	13	5	0	1	3	0	950	972	97,74%	84,15%	90,43%
Soybean-mintill	0	120	6	0	0	0	0	0	0	118	2100	89	0	6	16	0	2100	2455	85,54%	95,93%	90,44%
Soybean-clean	0	2	4	0	0	0	0	0	0	0	7	577	0	0	3	0	577	593	97,30%	77,87%	86,51%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	1	0	0	0	0	0	0	0	1239	25	0	1239	1265	97,94%	99,04%	98,49%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	85,97%	92,46%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					93,09%

Table 44 IPS – SVM-RBF - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1266	1	0	0	0	0	0	0	43	25	82	0	3	8	0	1266	1428	88,66%	96,35%	92,34%
Corn-mintill	0	2	722	0	0	0	0	0	0	1	56	38	0	6	5	0	722	830	86,99%	97,96%	92,15%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	477	1	0	0	0	0	0	3	0	0	2	0	477	483	98,76%	99,58%	99,17%
Grass-trees	0	0	0	0	0	729	0	0	0	0	0	0	0	0	1	0	729	730	99,86%	99,86%	99,86%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	1	1	0	1	0	0	0	0	891	25	44	0	3	6	0	891	972	91,67%	89,64%	90,64%
Soybean-mintill	0	45	13	0	1	0	0	0	0	59	1873	443	0	4	17	0	1873	2455	76,29%	94,64%	84,48%
Soybean-clean	0	0	0	0	0	0	0	0	0	0	0	591	0	0	2	0	591	593	99,66%	48,76%	65,48%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	11	0	1220	34	0	1220	1265	96,44%	98,71%	97,56%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	83,73%	91,15%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					89,74%

Table 45 IPS – SVM-LNR - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1286	19	0	0	0	0	0	0	41	61	9	0	2	10	0	1286	1428	90,06%	97,94%	93,83%
Corn-mintill	0	10	794	0	0	0	0	0	0	8	11	7	0	0	0	0	794	830	95,66%	92,54%	94,08%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	481	0	0	0	0	0	0	1	0	1	0	0	481	483	99,59%	99,38%	99,48%
Grass-trees	0	0	0	0	0	729	0	0	0	1	0	0	0	0	0	0	729	730	99,86%	99,59%	99,73%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	99,79%	99,90%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	1	2	0	0	1	0	0	0	932	33	0	0	2	1	0	932	972	95,88%	88,59%	92,09%
Soybean-mintill	0	16	43	0	3	2	0	1	0	70	2166	130	0	8	16	0	2166	2455	88,23%	95,38%	91,66%
Soybean-clean	0	0	0	0	0	0	0	0	0	0	0	591	0	0	2	0	591	593	99,66%	80,08%	88,81%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	1226	39	0	1226	1265	96,92%	98,95%	97,92%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	85,02%	91,90%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					94,27%

Table 46 IPS – K-NN - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1217	3	0	3	0	0	0	0	68	71	50	0	2	14	0	1217	1428	85,22%	91,85%	88,41%
Corn-mintill	0	4	791	0	0	0	0	0	0	4	11	9	0	8	3	0	791	830	95,30%	94,05%	94,67%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	483	0	0	0	0	0	0	0	0	0	0	0	483	483	100,00%	97,58%	98,77%
Grass-trees	0	0	0	0	0	725	0	0	0	0	0	0	0	0	5	0	725	730	99,32%	99,59%	99,45%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	0	0	0	2	1	0	0	0	956	3	6	0	0	4	0	956	972	98,35%	84,75%	91,05%
Soybean-mintill	0	101	47	0	4	2	0	0	0	100	2164	18	0	2	17	0	2164	2455	88,15%	96,22%	92,01%
Soybean-clean	0	3	0	0	0	0	0	0	0	0	0	589	0	0	1	0	589	593	99,33%	87,65%	93,12%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	3	0	0	0	0	0	0	0	0	1218	44	0	1218	1265	96,28%	99,02%	97,64%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	81,43%	89,77%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					93,63%

Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

Table 47 IPS - ML - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1209	0	0	0	3	0	0	0	53	130	7	0	5	21	0	1209	1428	84,66%	94,09%	89,13%
Corn-mintill	0	0	786	0	1	0	0	0	0	4	0	16	0	0	23	0	786	830	94,70%	99,24%	96,92%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	442	9	0	0	0	2	1	5	0	0	21	0	442	483	91,51%	99,77%	95,46%
Grass-trees	0	0	0	0	0	719	0	0	0	0	0	0	0	5	6	0	719	730	98,49%	98,22%	98,36%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	8	0	0	0	0	0	0	0	872	53	29	0	8	2	0	872	972	89,71%	87,64%	88,66%
Soybean-mintill	0	65	0	0	0	1	0	0	0	46	2219	88	0	20	16	0	2219	2455	90,39%	92,27%	91,32%
Soybean-clean	0	1	3	0	0	0	0	0	0	7	0	574	0	0	8	0	574	593	96,80%	79,50%	87,30%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	0	0	0	0	0	0	0	10	0	0	0	1253	0	0	1253	1265	99,05%	97,06%	98,04%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	1	2	3	0	0	380	0	380	386	98,45%	79,66%	88,06%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					92,85%

Table 48 IPS – SVM-RBF - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1151	0	0	0	0	0	0	0	163	89	14	0	5	6	0	1151	1428	80,60%	83,41%	81,98%
Corn-mintill	0	0	786	0	1	0	0	0	0	0	0	20	0	0	23	0	786	830	94,70%	99,24%	96,92%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	437	9	0	5	0	0	1	7	0	0	21	0	437	483	90,48%	99,77%	94,90%
Grass-trees	0	0	0	0	0	678	0	0	0	0	0	0	0	5	47	0	678	730	92,88%	98,55%	95,63%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	98,96%	99,48%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	53	0	0	0	0	0	0	0	841	8	60	0	6	4	0	841	972	86,52%	80,87%	83,60%
Soybean-mintill	0	173	0	0	0	1	0	0	0	30	2152	29	0	20	50	0	2152	2455	87,66%	95,64%	91,48%
Soybean-clean	0	1	3	0	0	0	0	0	0	0	0	569	0	0	20	0	569	593	95,95%	80,59%	87,61%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	0	0	0	0	0	0	0	5	0	5	0	1253	0	0	1253	1265	99,05%	97,21%	98,12%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	1	0	2	0	0	383	0	383	386	99,22%	69,13%	81,49%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					90,73%

Table 49 IPS – SVM-LNR - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1297	7	0	0	0	0	0	0	70	36	0	0	5	13	0	1297	1428	90,83%	98,63%	94,57%
Corn-mintill	0	0	797	0	2	0	0	0	0	3	0	5	0	0	23	0	797	830	96,02%	98,40%	97,20%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	452	9	0	0	0	2	1	5	0	3	8	0	452	483	93,58%	97,41%	95,46%
Grass-trees	0	0	0	0	0	728	0	0	0	0	0	0	0	2	0	0	728	730	99,73%	97,59%	98,64%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	8	0	0	0	2	0	0	0	925	0	29	0	6	2	0	925	972	95,16%	83,18%	88,77%
Soybean-mintill	0	6	0	0	10	7	0	0	0	101	2302	9	0	20	0	0	2302	2455	93,77%	98,42%	96,04%
Soybean-clean	0	1	3	0	0	0	0	0	0	7	0	574	0	0	8	0	574	593	96,80%	91,11%	93,87%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	0	0	0	0	0	0	0	4	0	6	0	1253	0	0	1253	1265	99,05%	97,21%	98,12%
Buildings-Grass-Trees-Drives	0	1	0	0	0	0	0	0	0	0	0	2	0	0	383	0	383	386	99,22%	87,64%	93,07%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					95,52%

Table 50 IPS – K-NN - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1297	7	0	0	0	0	0	0	70	36	7	0	5	6	0	1297	1428	90,83%	98,78%	94,64%
Corn-mintill	0	0	805	0	4	0	0	0	0	0	0	16	0	0	5	0	805	830	96,99%	95,61%	96,29%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	447	9	0	5	0	7	1	0	0	0	11	0	447	483	92,55%	96,96%	94,70%
Grass-trees	0	0	0	0	0	719	0	0	0	0	0	0	0	5	6	0	719	730	98,49%	98,63%	98,56%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	98,96%	99,48%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	8	0	0	0	0	0	0	0	920	8	26	0	6	4	0	920	972	94,65%	82,66%	88,25%
Soybean-mintill	0	6	13	0	0	1	0	0	0	96	2303	0	0	20	16	0	2303	2455	93,81%	98,00%	95,86%
Soybean-clean	0	1	6	0	0	0	0	0	0	11	0	567	0	0	8	0	567	593	95,62%	92,05%	93,80%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	6	0	0	0	0	0	0	4	2	0	0	1232	21	0	1232	1265	97,39%	97,16%	97,28%
Buildings-Grass-Trees-Drives	0	1	2	0	10	0	0	0	0	5	0	0	0	0	368	0	368	386	95,34%	82,70%	88,57%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					94,97%

Uniformly Selected N Sample without Pre-Processing or Post Processing

Table 51 IPS - ML - Uniformly Selected N Sample without Pre-Processing or Post Processing

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1059	53	0	2	3	0	0	0	98	170	43	0	0	0	0	1059	1428	74,16%	73,24%	73,70%
Corn-mintill	0	62	615	0	0	0	0	0	0	21	101	31	0	0	0	0	615	830	74,10%	73,39%	73,74%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	3	0	0	466	2	0	0	0	1	0	1	0	6	4	0	466	483	96,48%	97,90%	97,18%
Grass-trees	0	0	0	0	0	705	0	0	0	0	0	1	0	3	21	0	705	730	96,58%	97,92%	97,24%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	1	0	477	0	0	0	0	0	0	0	0	477	478	99,79%	99,79%	99,79%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	29	14	0	2	1	0	0	0	824	91	10	0	0	1	0	824	972	84,77%	64,93%	73,54%
Soybean-mintill	0	283	145	0	5	6	0	1	0	312	1574	121	0	0	8	0	1574	2455	64,11%	80,43%	71,35%
Soybean-clean	0	10	11	0	0	0	0	0	0	13	21	538	0	0	0	0	538	593	90,73%	72,21%	80,42%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	1	2	0	0	0	0	0	0	0	1221	41	0	1221	1265	96,52%	99,11%	97,80%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	2	384	0	384	386	99,48%	83,66%	90,89%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					81,74%

Table 52 IPS – SVM-RBF - Uniformly Selected N Sample without Pre-Processing or Post Processing

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1171	19	0	2	2	0	1	0	97	78	57	0	0	1	0	1171	1428	82,00%	88,05%	84,92%
Corn-mintill	0	15	722	0	0	0	0	0	0	3	39	51	0	0	0	0	722	830	86,99%	85,55%	86,26%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	471	0	0	1	0	2	0	6	0	2	1	0	471	483	97,52%	94,58%	96,02%
Grass-trees	0	0	0	0	1	721	0	0	0	1	0	0	0	0	7	0	721	730	98,77%	98,36%	98,56%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	99,38%	99,69%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	13	7	0	2	4	0	0	0	904	29	12	0	0	1	0	904	972	93,00%	79,30%	85,61%
Soybean-mintill	0	127	89	0	15	3	0	1	0	129	1981	97	0	0	13	0	1981	2455	80,69%	93,05%	86,43%
Soybean-clean	0	4	7	0	0	0	0	0	0	4	2	574	0	0	2	0	574	593	96,80%	72,02%	82,59%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	6	1	0	0	0	0	0	0	0	1197	61	0	1197	1265	94,62%	98,44%	96,49%
Buildings-Grass-Trees-Drives	0	0	0	0	1	2	0	0	0	0	0	0	0	17	366	0	366	386	94,82%	80,97%	87,35%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					89,24%

Table 53 IPS – SVM-LNR - Uniformly Selected N Sample without Pre-Processing or Post Processing

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1173	53	0	3	1	0	0	0	53	134	10	0	0	1	0	1173	1428	82,14%	85,12%	83,61%
Corn-mintill	0	37	689	0	0	0	0	0	0	3	52	49	0	0	0	0	689	830	83,01%	71,40%	76,77%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	1	0	478	1	0	0	0	1	0	1	0	0	1	0	478	483	98,96%	95,03%	96,96%
Grass-trees	0	0	0	0	2	722	0	0	0	2	0	0	0	0	4	0	722	730	98,90%	98,90%	98,90%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	99,79%	99,90%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	19	14	0	2	1	0	0	0	843	92	0	0	0	1	0	843	972	86,73%	79,08%	82,73%
Soybean-mintill	0	147	203	0	13	2	0	1	0	164	1778	141	0	0	6	0	1778	2455	72,42%	86,06%	78,66%
Soybean-clean	0	2	5	0	0	0	0	0	0	0	10	574	0	0	2	0	574	593	96,80%	74,06%	83,92%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	5	2	0	0	0	0	0	0	0	1181	77	0	1181	1265	93,36%	99,24%	96,21%
Buildings-Grass-Trees-Drives	0	0	0	0	0	1	0	0	0	0	0	0	0	9	376	0	376	386	97,41%	80,34%	88,06%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					86,20%

Table 54 IPS – K-NN - Uniformly Selected N Sample without Pre-Processing or Post Processing

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	996	94	0	6	1	0	0	0	79	137	114	0	0	1	0	996	1428	69,75%	75,17%	72,36%
Corn-mintill	0	46	678	0	2	0	0	0	0	22	40	42	0	0	0	0	678	830	81,69%	67,33%	73,82%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	479	1	0	1	0	0	0	0	0	1	1	0	479	483	99,17%	89,03%	93,83%
Grass-trees	0	0	0	0	2	708	0	0	0	2	0	0	0	1	17	0	708	730	96,99%	98,61%	97,79%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	1	0	0	477	0	0	0	0	0	0	0	0	477	478	99,79%	99,58%	99,69%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	35	19	0	4	0	0	0	0	837	47	29	0	0	1	0	837	972	86,11%	70,04%	77,25%
Soybean-mintill	0	227	195	0	16	2	0	1	0	243	1673	87	0	0	11	0	1673	2455	68,15%	87,50%	76,62%
Soybean-clean	0	21	21	0	2	0	0	0	0	11	15	522	0	0	1	0	522	593	88,03%	65,74%	75,27%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	26	5	0	0	0	0	0	0	0	1120	114	0	1120	1265	88,54%	99,64%	93,76%
Buildings-Grass-Trees-Drives	0	0	0	0	0	1	0	0	0	1	0	0	0	2	382	0	382	386	98,96%	72,35%	83,59%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					81,83%

Uniformly Selected N Sample with Pre-Processing (PCA)

Table 55 IPS – ML - Uniformly Selected N Sample with Pre-Processing (PCA)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1048	43	0	2	3	0	0	0	127	166	39	0	0	0	0	1048	1428	73,39%	80,31%	76,69%
Corn-mintill	0	46	635	0	0	0	0	0	0	26	96	27	0	0	0	0	635	830	76,51%	77,34%	76,92%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	1	0	0	470	1	0	0	0	2	1	1	0	3	4	0	470	483	97,31%	97,71%	97,51%
Grass-trees	0	0	0	0	1	719	0	0	0	0	0	1	0	2	7	0	719	730	98,49%	97,43%	97,96%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	1	0	477	0	0	0	0	0	0	0	0	477	478	99,79%	99,79%	99,79%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	16	10	0	1	2	0	0	0	859	74	10	0	0	0	0	859	972	88,37%	61,53%	72,55%
Soybean-mintill	0	177	113	0	7	8	0	1	0	367	1676	100	0	0	6	0	1676	2455	68,27%	81,68%	74,37%
Soybean-clean	0	17	20	0	0	0	0	0	0	15	39	502	0	0	0	0	502	593	84,65%	73,82%	78,87%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	2	0	0	0	0	0	0	0	1242	21	0	1242	1265	98,18%	98,42%	98,30%
Buildings-Grass-Trees-Drives	0	0	0	0	0	2	0	0	0	0	0	0	0	15	369	0	369	386	95,60%	90,66%	93,06%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					83,13%

Table 56 IPS – SVM-RBF - Uniformly Selected N Sample with Pre-Processing (PCA)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1133	24	0	1	0	0	2	0	60	80	126	0	0	2	0	1133	1428	79,34%	83,93%	81,57%
Corn-mintill	0	28	634	0	0	0	0	0	0	6	75	87	0	0	0	0	634	830	76,39%	80,66%	78,47%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	1	0	465	0	0	3	0	1	0	7	0	2	4	0	465	483	96,27%	94,90%	95,58%
Grass-trees	0	0	0	0	4	708	0	0	0	0	0	3	0	0	15	0	708	730	96,99%	99,30%	98,13%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	1	0	0	477	0	0	0	0	0	0	0	0	477	478	99,79%	98,76%	99,27%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	17	12	0	6	1	0	0	0	823	51	60	0	0	2	0	823	972	84,67%	80,53%	82,55%
Soybean-mintill	0	171	101	0	13	2	0	1	0	130	1694	334	0	0	9	0	1694	2455	69,00%	88,92%	77,71%
Soybean-clean	0	1	14	0	0	0	0	0	0	2	5	570	0	0	1	0	570	593	96,12%	45,78%	62,02%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	1	0	0	0	0	0	58	0	1116	90	0	1116	1265	88,22%	99,29%	93,43%
Buildings-Grass-Trees-Drives	0	0	0	0	0	1	0	0	0	0	0	0	0	6	379	0	379	386	98,19%	75,50%	85,36%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					83,15%

Table 57 IPS – SVM-LNR - Uniformly Selected N Sample with Pre-Processing (PCA)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1123	70	0	6	2	0	0	0	71	143	7	0	0	6	0	1123	1428	78,64%	84,75%	81,58%
Corn-mintill	0	41	669	0	0	3	0	0	0	13	57	47	0	0	0	0	669	830	80,60%	69,91%	74,87%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	1	0	479	0	0	0	0	0	0	1	0	1	1	0	479	483	99,17%	95,23%	97,16%
Grass-trees	0	0	0	0	1	722	0	0	0	0	0	0	0	1	6	0	722	730	98,90%	96,91%	97,90%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	27	2	0	2	4	0	0	0	831	105	0	0	0	1	0	831	972	85,49%	76,94%	80,99%
Soybean-mintill	0	134	211	0	11	8	0	0	0	165	1765	154	0	2	5	0	1765	2455	71,89%	84,94%	77,87%
Soybean-clean	0	0	4	0	1	0	0	0	0	0	8	577	0	0	3	0	577	593	97,30%	73,32%	83,62%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	3	5	0	0	0	0	0	0	0	1168	89	0	1168	1265	92,33%	99,15%	95,62%
Buildings-Grass-Trees-Drives	0	0	0	0	0	1	0	0	0	0	0	1	0	6	378	0	378	386	97,93%	77,30%	86,40%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					85,14%

Table 58 IPS – K-NN - Uniformly Selected N Sample with Pre-Processing (PCA)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1014	91	0	6	1	0	0	0	62	135	118	0	0	1	0	1014	1428	71,01%	76,18%	73,50%
Corn-mintill	0	46	678	0	2	0	0	0	0	26	46	32	0	0	0	0	678	830	81,69%	68,90%	74,75%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	478	1	0	1	0	0	0	1	0	1	1	0	478	483	98,96%	89,51%	94,00%
Grass-trees	0	0	0	0	1	712	0	0	0	1	0	0	0	1	15	0	712	730	97,53%	98,89%	98,21%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	99,38%	99,69%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	33	23	0	4	1	0	0	0	839	46	25	0	0	1	0	839	972	86,32%	71,40%	78,16%
Soybean-mintill	0	219	176	0	15	1	0	2	0	233	1708	89	0	0	12	0	1708	2455	69,57%	87,59%	77,55%
Soybean-clean	0	19	16	0	2	0	0	0	0	14	15	526	0	0	1	0	526	593	88,70%	66,50%	76,01%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	26	3	0	0	0	0	0	0	0	1111	125	0	1111	1265	87,83%	99,64%	93,36%
Buildings-Grass-Trees-Drives	0	0	0	0	0	1	0	0	0	0	0	0	0	2	383	0	383	386	99,22%	71,06%	82,81%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					82,40%

Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

Table 59 IPS - ML - Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1239	3	0	0	0	0	0	0	39	86	53	0	5	3	0	1239	1428	86,76%	91,04%	88,85%
Corn-mintill	0	17	751	0	0	0	0	0	0	1	30	22	0	3	6	0	751	830	90,48%	98,17%	94,17%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	474	0	0	0	0	0	0	4	0	4	1	0	474	483	98,14%	99,79%	98,96%
Grass-trees	0	0	0	0	0	728	0	0	0	0	0	0	0	1	1	0	728	730	99,73%	99,73%	99,73%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	0	0	0	0	0	0	0	0	947	13	4	0	1	7	0	947	972	97,43%	86,72%	91,76%
Soybean-mintill	0	104	11	0	1	2	0	0	0	105	2064	141	0	6	21	0	2064	2455	84,07%	94,12%	88,81%
Soybean-clean	0	1	0	0	0	0	0	0	0	0	0	592	0	0	0	0	592	593	99,83%	72,55%	84,03%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	1243	22	0	1243	1265	98,26%	98,42%	98,34%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	86,35%	92,68%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					92,54%

Table 60 IPS – SVM-RBF - Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1234	4	0	5	0	0	0	0	108	23	46	0	4	4	0	1234	1428	86,41%	97,17%	91,48%
Corn-mintill	0	1	784	0	1	0	0	0	0	2	8	25	0	3	6	0	784	830	94,46%	96,43%	95,44%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	1	0	477	1	0	0	0	0	0	3	0	0	1	0	477	483	98,76%	97,75%	98,25%
Grass-trees	0	0	0	0	0	726	0	0	0	0	0	0	0	0	4	0	726	730	99,45%	99,73%	99,59%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	2	0	0	2	0	0	0	0	956	2	2	0	2	6	0	956	972	98,35%	83,13%	90,10%
Soybean-mintill	0	33	22	0	3	1	0	0	0	84	2233	50	0	1	28	0	2233	2455	90,96%	98,54%	94,60%
Soybean-clean	0	0	2	0	0	0	0	0	0	0	0	586	0	0	5	0	586	593	98,82%	82,30%	89,81%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	1222	43	0	1222	1265	96,60%	98,31%	97,45%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	11	375	0	375	386	97,15%	79,45%	87,41%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					94,29%

Table 61 IPS – SVM-LNR - Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1306	8	0	6	1	0	0	0	40	55	8	0	2	2	0	1306	1428	91,46%	96,03%	93,69%
Corn-mintill	0	16	765	0	5	0	0	0	0	3	16	22	0	1	2	0	765	830	92,17%	94,68%	93,41%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	483	0	0	0	0	0	0	0	0	0	0	0	483	483	100,00%	96,41%	98,17%
Grass-trees	0	0	0	0	0	726	0	0	0	0	0	0	0	0	4	0	726	730	99,45%	99,45%	99,45%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	1	0	0	2	1	0	0	0	932	29	1	0	3	3	0	932	972	95,88%	89,70%	92,69%
Soybean-mintill	0	37	35	0	5	2	0	0	0	64	2115	183	0	8	6	0	2115	2455	86,15%	95,49%	90,58%
Soybean-clean	0	0	0	0	0	0	0	0	0	0	0	592	0	0	1	0	592	593	99,83%	73,45%	84,63%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	1223	42	0	1223	1265	96,68%	98,87%	97,76%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	86,55%	92,79%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					93,62%

Table 62 IPS – K-NN - Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1214	27	0	8	0	0	0	0	63	66	34	0	0	16	0	1214	1428	85,01%	96,12%	90,23%
Corn-mintill	0	7	802	0	0	0	0	0	0	3	8	3	0	6	1	0	802	830	96,63%	89,61%	92,99%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	480	2	0	0	0	0	0	0	0	1	0	0	480	483	99,38%	96,77%	98,06%
Grass-trees	0	0	0	0	0	724	0	0	0	0	0	0	0	1	5	0	724	730	99,18%	99,31%	99,25%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	0	1	0	4	1	0	0	0	960	0	1	0	0	5	0	960	972	98,77%	81,56%	89,34%
Soybean-mintill	0	42	62	0	4	2	0	0	0	150	2128	42	0	2	23	0	2128	2455	86,68%	96,64%	91,39%
Soybean-clean	0	0	3	0	0	0	0	0	0	1	0	588	0	0	1	0	588	593	99,16%	88,02%	93,26%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	1216	49	0	1216	1265	96,13%	99,18%	97,63%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	79,42%	88,53%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					93,31%

Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

Table 63 IPS - ML - Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1229	0	0	0	0	0	0	0	5	101	82	0	5	6	0	1229	1428	86,06%	94,18%	89,94%
Corn-mintill	0	0	786	0	1	0	0	0	0	0	0	20	0	0	23	0	786	830	94,70%	99,24%	96,92%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	442	9	0	0	0	2	1	5	0	0	21	0	442	483	91,51%	99,77%	95,46%
Grass-trees	0	0	0	0	0	711	0	0	0	0	0	0	0	5	14	0	711	730	97,40%	98,61%	98,00%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	8	0	0	0	0	0	0	0	880	45	29	0	6	4	0	880	972	90,53%	91,95%	91,24%
Soybean-mintill	0	65	0	0	0	1	0	0	0	59	2260	34	0	20	16	0	2260	2455	92,06%	93,47%	92,76%
Soybean-clean	0	0	3	0	0	0	0	0	0	7	9	566	0	0	8	0	566	593	95,45%	75,97%	84,60%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	0	0	0	0	0	0	0	4	0	6	0	1232	21	0	1232	1265	97,39%	97,16%	97,28%
Buildings-Grass-Trees-Drives	0	1	0	0	0	0	0	0	0	0	2	3	0	0	380	0	380	386	98,45%	77,08%	86,46%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					93,18%

Table 64 IPS – SVM-RBF - Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1294	0	0	0	0	0	0	0	39	30	48	0	5	12	0	1294	1428	90,62%	89,18%	89,89%
Corn-mintill	0	0	793	0	1	0	0	0	0	0	14	20	0	0	2	0	793	830	95,54%	99,00%	97,24%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	452	9	0	0	0	2	1	5	0	0	11	0	452	483	93,58%	99,34%	96,38%
Grass-trees	0	0	0	0	2	717	0	0	0	0	0	0	0	5	6	0	717	730	98,22%	98,62%	98,42%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	53	0	0	0	0	0	0	0	879	0	29	0	6	5	0	879	972	90,43%	93,21%	91,80%
Soybean-mintill	0	101	1	0	0	1	0	0	0	15	2277	33	0	3	24	0	2277	2455	92,75%	98,06%	95,33%
Soybean-clean	0	1	3	0	0	0	0	0	0	7	0	571	0	0	11	0	571	593	96,29%	80,31%	87,58%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	1	0	0	0	0	0	0	0	0	5	0	1231	26	0	1231	1265	97,31%	98,48%	97,89%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	1	0	0	0	0	385	0	385	386	99,74%	79,88%	88,71%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					94,36%

Table 65 IPS – SVM-LNR - Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1342	10	0	7	2	0	0	0	28	30	0	0	5	4	0	1342	1428	93,98%	91,29%	92,62%
Corn-mintill	0	0	816	0	8	0	0	0	0	4	0	0	0	0	2	0	816	830	98,31%	95,77%	97,03%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	457	9	0	0	0	2	1	0	0	0	11	0	457	483	94,62%	94,62%	94,62%
Grass-trees	0	0	0	0	0	723	0	0	0	2	0	0	0	5	0	0	723	730	99,04%	97,97%	98,50%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	53	0	0	3	0	0	0	0	879	0	26	0	6	5	0	879	972	90,43%	93,41%	91,90%
Soybean-mintill	0	71	16	0	1	3	0	0	0	19	2247	66	0	3	29	0	2247	2455	91,53%	98,64%	94,95%
Soybean-clean	0	1	6	0	7	0	0	0	0	7	0	561	0	0	11	0	561	593	94,60%	85,91%	90,05%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	1	0	0	1	0	0	0	0	0	0	0	1256	5	0	1256	1265	99,29%	98,51%	98,90%
Buildings-Grass-Trees-Drives	0	1	0	0	0	0	0	0	0	0	0	0	0	0	385	0	385	386	99,74%	85,18%	91,89%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					95,05%

Table 66 IPS – K-NN - Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1339	34	0	6	0	0	0	0	5	33	0	0	5	6	0	1339	1428	93,77%	91,40%	92,57%
Corn-mintill	0	0	826	0	4	0	0	0	0	0	0	0	0	0	0	0	826	830	99,52%	95,16%	97,29%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	5	3	0	455	9	0	5	0	2	1	0	0	0	3	0	455	483	94,20%	93,24%	93,72%
Grass-trees	0	0	0	0	0	708	0	0	0	2	0	0	0	5	15	0	708	730	96,99%	98,20%	97,59%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	98,96%	99,48%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	56	0	0	0	0	0	0	0	879	0	26	0	6	5	0	879	972	90,43%	91,85%	91,14%
Soybean-mintill	0	54	1	0	4	3	0	0	0	57	2312	0	0	3	21	0	2312	2455	94,18%	98,42%	96,25%
Soybean-clean	0	8	3	0	0	0	0	0	0	7	0	564	0	0	11	0	564	593	95,11%	95,59%	95,35%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	1	0	0	1	0	0	0	5	0	0	0	1252	4	0	1252	1265	98,97%	98,51%	98,74%
Buildings-Grass-Trees-Drives	0	1	0	0	19	0	0	0	0	0	3	0	0	0	363	0	363	386	94,04%	84,81%	89,19%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					95,38%

Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

Table 67 IPS - ML - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1188	6	0	0	0	0	0	0	78	73	69	0	4	10	0	1188	1428	83,19%	92,81%	87,74%
Corn-mintill	0	9	759	0	0	0	0	0	0	2	42	12	0	3	3	0	759	830	91,45%	98,06%	94,64%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	473	0	0	0	0	0	0	3	0	2	5	0	473	483	97,93%	100,00%	98,95%
Grass-trees	0	0	0	0	0	725	0	0	0	0	0	0	0	1	4	0	725	730	99,32%	99,86%	99,59%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	1	0	0	0	0	0	0	0	945	12	7	0	3	4	0	945	972	97,22%	84,91%	90,65%
Soybean-mintill	0	82	9	0	0	1	0	0	0	88	2098	155	0	7	15	0	2098	2455	85,46%	94,21%	89,62%
Soybean-clean	0	0	0	0	0	0	0	0	0	0	2	590	0	0	1	0	590	593	99,49%	70,57%	82,58%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	1246	19	0	1246	1265	98,50%	98,03%	98,26%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	5	381	0	381	386	98,70%	86,20%	92,03%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					92,34%

Table 68 IPS – SVM-RBF - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1211	0	0	1	0	0	0	0	63	40	104	0	6	3	0	1211	1428	84,80%	95,58%	89,87%
Corn-mintill	0	6	733	0	0	0	0	0	0	1	51	31	0	4	4	0	733	830	88,31%	97,09%	92,49%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	479	0	0	0	0	0	0	4	0	0	0	0	479	483	99,17%	99,38%	99,27%
Grass-trees	0	0	0	0	0	724	0	0	0	0	0	0	0	0	6	0	724	730	99,18%	100,00%	99,59%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	0	0	0	1	0	0	0	0	893	17	52	0	1	8	0	893	972	91,87%	88,50%	90,16%
Soybean-mintill	0	50	21	0	1	0	0	0	0	52	1909	395	0	6	21	0	1909	2455	77,76%	94,65%	85,38%
Soybean-clean	0	0	1	0	0	0	0	0	0	0	0	590	0	0	2	0	590	593	99,49%	50,13%	66,67%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	1	0	1231	33	0	1231	1265	97,31%	98,64%	97,97%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	83,37%	90,93%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					89,75%

Table 69 IPS – SVM-LNR - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1282	24	0	0	1	0	0	0	40	60	7	0	4	10	0	1282	1428	89,78%	98,54%	93,95%
Corn-mintill	0	4	780	0	0	0	0	0	0	9	12	18	0	7	0	0	780	830	93,98%	91,55%	92,75%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	480	0	0	0	0	0	0	2	0	1	0	0	480	483	99,38%	97,76%	98,56%
Grass-trees	0	0	0	0	0	729	0	0	0	1	0	0	0	0	0	0	729	730	99,86%	99,59%	99,73%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	99,79%	99,90%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	2	0	0	2	2	0	0	0	926	40	0	0	0	0	0	926	972	95,27%	87,44%	91,19%
Soybean-mintill	0	13	48	0	9	0	0	1	0	83	2150	136	0	7	8	0	2150	2455	87,58%	95,05%	91,16%
Soybean-clean	0	0	0	0	0	0	0	0	0	0	0	592	0	0	1	0	592	593	99,83%	78,41%	87,83%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	0	0	0	0	0	0	0	0	0	1231	34	0	1231	1265	97,31%	98,48%	97,89%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	87,93%	93,58%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					93,91%

Table 70 IPS – K-NN - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1235	28	0	9	0	0	0	0	56	45	39	0	0	16	0	1235	1428	86,48%	95,44%	90,74%
Corn-mintill	0	6	804	0	1	0	0	0	0	4	8	0	0	5	2	0	804	830	96,87%	89,04%	92,79%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	0	0	482	0	0	0	0	0	0	0	0	1	0	0	482	483	99,79%	96,21%	97,97%
Grass-trees	0	0	0	0	0	726	0	0	0	0	0	0	0	1	3	0	726	730	99,45%	99,73%	99,59%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	0	1	0	4	1	0	0	0	953	3	4	0	0	6	0	953	972	98,05%	84,19%	90,59%
Soybean-mintill	0	53	67	0	4	1	0	0	0	118	2161	29	0	2	20	0	2161	2455	88,02%	97,43%	92,49%
Soybean-clean	0	0	3	0	0	0	0	0	0	1	1	588	0	0	0	0	588	593	99,16%	89,09%	93,85%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	0	0	0	1	0	0	0	0	0	0	0	0	1215	49	0	1215	1265	96,05%	99,26%	97,63%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	0	0	0	0	0	386	0	386	386	100,00%	80,08%	88,94%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					93,85%

Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

Table 71 IPS - ML - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	**Corn-notill**	**Corn-mintill**	**Corn**	**Grass-pasture**	**Grass-trees**	**Grass-pasture-mowed**	**Hay-windrowed**	**Oats**	**Soybean-notill**	**Soybean-mintill**	**Soybean-clean**	**Wheat**	**Woods**	**Buildings-Grass-Trees-Drives**	**Stone-Steel-Towers**	**Correctly Classified**	**Ground Truth**	**Recall**	**Precision**	**F-Measure**
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1146	0	0	0	0	0	0	0	111	60	85	0	5	21	0	1146	1428	80,25%	94,24%	86,69%
Corn-mintill	0	0	769	0	9	0	0	0	0	13	0	35	0	0	4	0	769	830	92,65%	99,61%	96,00%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	452	9	0	0	0	0	1	7	0	0	11	0	452	483	93,58%	97,41%	95,46%
Grass-trees	0	0	0	0	0	719	0	0	0	0	0	0	0	5	6	0	719	730	98,49%	98,63%	98,56%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	1	0	0	0	0	0	0	0	886	15	62	0	6	2	0	886	972	91,15%	81,28%	85,94%
Soybean-mintill	0	65	0	0	0	1	0	0	0	75	2181	89	0	20	24	0	2181	2455	88,84%	96,63%	92,57%
Soybean-clean	0	0	0	0	3	0	0	0	0	0	0	582	0	0	8	0	582	593	98,15%	67,21%	79,78%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	0	0	0	0	0	0	0	4	0	1	0	1253	5	0	1253	1265	99,05%	97,21%	98,12%
Buildings-Grass-Trees-Drives	0	2	0	0	0	0	0	0	0	1	0	5	0	0	378	0	378	386	97,93%	82,35%	89,47%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					91,93%

Table 72 IPS – SVM-RBF - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1151	0	0	0	0	0	0	0	163	89	14	0	5	6	0	1151	1428	80,60%	81,98%	81,29%
Corn-mintill	0	24	762	0	1	0	0	0	0	0	0	20	0	0	23	0	762	830	91,81%	99,22%	95,37%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	437	9	0	5	0	0	1	7	0	0	21	0	437	483	90,48%	99,77%	94,90%
Grass-trees	0	0	0	0	0	705	0	0	0	0	0	0	0	2	23	0	705	730	96,58%	98,60%	97,58%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	98,96%	99,48%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	53	0	0	0	0	0	0	0	849	0	60	0	6	4	0	849	972	87,35%	79,05%	82,99%
Soybean-mintill	0	173	0	0	0	1	0	0	0	56	2093	96	0	20	16	0	2093	2455	85,25%	95,88%	90,25%
Soybean-clean	0	1	3	0	0	0	0	0	0	0	0	572	0	0	17	0	572	593	96,46%	73,71%	83,56%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	0	0	0	0	0	0	0	5	0	5	0	1253	0	0	1253	1265	99,05%	97,43%	98,24%
Buildings-Grass-Trees-Drives	0	0	0	0	0	0	0	0	0	1	0	2	0	0	383	0	383	386	99,22%	77,69%	87,14%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					90,26%

Table 73 IPS – SVM-LNR - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1279	0	0	0	0	0	0	0	70	36	14	0	5	24	0	1279	1428	89,57%	98,61%	93,87%
Corn-mintill	0	0	786	0	2	0	0	0	0	3	0	20	0	0	19	0	786	830	94,70%	99,24%	96,92%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	0	3	0	452	9	0	0	0	2	1	5	0	3	8	0	452	483	93,58%	98,26%	95,86%
Grass-trees	0	0	0	0	6	719	0	0	0	0	0	0	0	5	0	0	719	730	98,49%	97,82%	98,16%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	100,00%	100,00%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	8	0	0	0	0	0	0	0	925	0	29	0	6	4	0	925	972	95,16%	83,18%	88,77%
Soybean-mintill	0	6	0	0	0	7	0	0	0	101	2302	9	0	20	10	0	2302	2455	93,77%	98,42%	96,04%
Soybean-clean	0	1	3	0	0	0	0	0	0	7	0	574	0	0	8	0	574	593	96,80%	87,10%	91,69%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	0	0	0	0	0	0	0	4	0	6	0	1232	21	0	1232	1265	97,39%	96,93%	97,16%
Buildings-Grass-Trees-Drives	0	1	0	0	0	0	0	0	0	0	0	2	0	0	383	0	383	386	99,22%	80,29%	88,76%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					94,91%

Table 74 IPS – K-NN - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Alfalfa	Corn-notill	Corn-mintill	Corn	Grass-pasture	Grass-trees	Grass-pasture-mowed	Hay-windrowed	Oats	Soybean-notill	Soybean-mintill	Soybean-clean	Wheat	Woods	Buildings-Grass-Trees-Drives	Stone-Steel-Towers	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn-notill	0	1241	14	0	0	0	0	0	0	61	101	0	0	5	6	0	1241	1428	86,90%	97,72%	91,99%
Corn-mintill	0	0	816	0	4	0	0	0	0	0	0	5	0	0	5	0	816	830	98,31%	96,68%	97,49%
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Grass-pasture	0	5	3	0	447	9	0	5	0	2	1	0	0	0	11	0	447	483	92,55%	96,96%	94,70%
Grass-trees	0	0	0	0	0	719	0	0	0	0	0	0	0	5	6	0	719	730	98,49%	98,63%	98,56%
Grass-pasture-mowed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hay-windrowed	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	478	478	100,00%	98,96%	99,48%
Oats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Soybean-notill	0	11	0	0	0	0	0	0	0	872	53	26	0	6	4	0	872	972	89,71%	88,26%	88,98%
Soybean-mintill	0	6	5	0	0	1	0	0	0	33	2374	0	0	20	16	0	2374	2455	96,70%	93,80%	95,23%
Soybean-clean	0	5	3	0	0	0	0	0	0	7	0	570	0	0	8	0	570	593	96,12%	94,84%	95,48%
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Woods	0	2	1	0	0	0	0	0	0	9	0	0	0	1253	0	0	1253	1265	99,05%	97,21%	98,12%
Buildings-Grass-Trees-Drives	0	0	2	0	10	0	0	0	0	4	2	0	0	0	368	0	368	386	95,34%	86,79%	90,86%
Stone-Steel-Towers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
																					94,99%

APPENDIX-B: SALINAS SCENE RESULTS

First N Sample without Pre-Processing or Post Processing

Table 75 SSC - ML -First N Sample without Pre-Processing or Post Processing

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1865	144	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1865	2009	92,83%	100,00%	96,28%
Brocoli Green Weeds 2	0	3699	0	0	0	0	0	3	0	0	0	0	0	24	0	0	3699	3726	99,28%	96,25%	97,74%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	76,21%	86,50%
Fallow Rough Plow	0	0	2	1392	0	0	0	0	0	0	0	0	0	0	0	0	1392	1394	99,86%	98,58%	99,22%
Fallow Smooth	0	0	608	20	2044	4	0	1	0	1	0	0	0	0	0	0	2044	2678	76,33%	100,00%	86,57%
Stubble	0	0	0	0	0	3953	0	6	0	0	0	0	0	0	0	0	3953	3959	99,85%	99,90%	99,87%
Celery	0	0	0	0	0	0	3573	6	0	0	0	0	0	0	0	0	3573	3579	99,83%	100,00%	99,92%
Grapes Untrained	0	0	0	0	0	0	0	3990	0	4	0	0	0	0	7276	1	3990	11271	35,40%	75,35%	48,17%
Soil Vinyard Develop	0	0	0	0	0	0	0	14	5804	371	2	12	0	0	0	0	5804	6203	93,57%	99,95%	96,65%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	163	3	3081	24	0	0	6	0	1	3081	3278	93,99%	87,65%	90,71%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	1	1067	0	0	0	0	0	1067	1068	99,91%	97,62%	98,75%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	19	0	1902	6	0	0	0	1902	1927	98,70%	99,37%	99,04%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	914	2	0	0	914	916	99,78%	98,92%	99,35%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	2	0	9	0	0	4	1055	0	0	1055	1070	98,60%	97,06%	97,82%
Vinyard Untrained	0	0	7	0	0	0	0	1108	0	0	0	0	0	0	6153	0	6153	7268	84,66%	45,82%	59,46%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	2	0	29	0	0	0	0	0	1776	1776	1807	98,28%	99,89%	99,08%
																					81,74%

Table 76 SSC - SVM-RBF -First N Sample without Pre-Processing or Post Processing

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1966	41	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1966	2009	97,86%	99,95%	98,89%
Brocoli Green Weeds 2	1	3632	0	0	0	0	0	79	0	0	0	0	0	0	0	14	3632	3726	97,48%	98,88%	98,18%
Fallow	0	0	1591	0	0	0	0	0	0	148	213	24	0	0	0	0	1591	1976	80,52%	69,69%	74,71%
Fallow Rough Plow	0	0	2	1391	1	0	0	0	0	0	0	0	0	0	0	0	1391	1394	99,78%	99,29%	99,53%
Fallow Smooth	0	0	633	9	2015	4	0	9	0	7	1	0	0	0	0	0	2015	2678	75,24%	99,95%	85,85%
Stubble	0	0	0	0	0	3942	0	17	0	0	0	0	0	0	0	0	3942	3959	99,57%	99,87%	99,72%
Celery	0	0	0	0	0	0	3540	12	0	0	0	0	0	0	0	27	3540	3579	98,91%	100,00%	99,45%
Grapes Untrained	0	0	0	0	0	0	0	2491	0	163	2	0	0	0	8600	15	2491	11271	22,10%	80,41%	34,67%
Soil Vinyard Develop	0	0	0	0	0	0	0	9	6160	17	17	0	0	0	0	0	6160	6203	99,31%	99,61%	99,46%
Corn Senesced Green Weeds	0	0	54	1	0	1	0	144	24	2920	79	20	0	0	35	0	2920	3278	89,08%	86,42%	87,73%
Lettuce Romaine 4wk	0	0	2	0	0	0	0	0	0	7	1059	0	0	0	0	0	1059	1068	99,16%	77,24%	86,84%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	97,77%	98,87%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	914	2	0	0	914	916	99,78%	97,55%	98,65%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	17	0	1	0	0	23	1028	1	0	1028	1070	96,07%	99,81%	97,90%
Vinyard Untrained	0	0	1	0	0	0	0	268	0	103	0	0	0	0	6874	22	6874	7268	94,58%	44,31%	60,35%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	51	0	13	0	0	0	0	2	1741	1741	1807	96,35%	95,66%	96,00%
																					79,79%

Table 77 SSC - SVM-LNR -First N Sample without Pre-Processing or Post Processing

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1947	62	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1947	2009	96,91%	100,00%	98,43%
Brocoli Green Weeds 2	0	3714	0	0	0	0	12	0	0	0	0	0	0	0	0	0	3714	3726	99,68%	98,36%	99,01%
Fallow	0	0	1616	0	0	0	0	0	0	29	330	1	0	0	0	0	1616	1976	81,78%	84,52%	83,13%
Fallow Rough Plow	0	0	0	1392	2	0	0	0	0	0	0	0	0	0	0	0	1392	1394	99,86%	98,65%	99,25%
Fallow Smooth	0	0	225	14	2433	1	0	0	4	0	1	0	0	0	0	0	2433	2678	90,85%	99,47%	94,96%
Stubble	0	0	0	0	0	3958	0	0	0	0	0	0	0	1	0	0	3958	3959	99,97%	99,95%	99,96%
Celery	0	0	0	0	1	0	3578	0	0	0	0	0	0	0	0	0	3578	3579	99,97%	98,87%	99,42%
Grapes Untrained	0	0	0	0	0	0	1	10270	0	11	0	0	0	3	977	9	10270	11271	91,12%	59,36%	71,89%
Soil Vinyard Develop	0	0	0	0	0	0	0	1	6185	16	1	0	0	0	0	0	6185	6203	99,71%	99,60%	99,65%
Corn Senesced Green Weeds	0	0	56	2	2	0	0	93	20	2914	67	27	0	88	6	3	2914	3278	88,90%	97,20%	92,86%
Lettuce Romaine 4wk	0	0	0	0	0	1	0	0	0	6	1061	0	0	0	0	0	1061	1068	99,34%	72,57%	83,87%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	98,52%	99,25%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	97,86%	98,87%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	4	1	2	2	0	20	1041	0	0	1041	1070	97,29%	91,56%	94,34%
Vinyard Untrained	0	0	15	1	7	0	1	6933	0	10	0	1	0	1	262	37	262	7268	3,60%	20,79%	6,14%
Vinyard Vertical Trellis	0	0	0	2	1	0	27	0	0	10	0	0	0	2	15	1750	1750	1807	96,85%	97,28%	97,06%
																					83,07%

Table 78 SSC - K-NN -First N Sample without Pre-Processing or Post Processing

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1949	60	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1949	2009	97,01%	99,54%	98,26%
Brocoli Green Weeds 2	9	3662	0	0	0	0	9	0	0	0	0	0	0	15	0	31	3662	3726	98,28%	98,39%	98,34%
Fallow	0	0	1596	0	0	0	0	0	0	60	320	0	0	0	0	0	1596	1976	80,77%	74,93%	77,74%
Fallow Rough Plow	0	0	0	1391	3	0	0	0	0	0	0	0	0	0	0	0	1391	1394	99,78%	98,93%	99,36%
Fallow Smooth	0	0	472	7	2190	4	0	0	2	0	3	0	0	0	0	0	2190	2678	81,78%	99,55%	89,79%
Stubble	0	0	0	0	0	3945	0	8	0	0	0	0	0	6	0	0	3945	3959	99,65%	99,85%	99,75%
Celery	0	0	0	0	0	1	3562	4	0	1	0	0	1	3	1	6	3562	3579	99,53%	99,41%	99,47%
Grapes Untrained	0	0	0	0	0	0	11	3087	6	173	6	1	1	16	7962	8	3087	11271	27,39%	81,07%	40,94%
Soil Vinyard Develop	0	0	0	0	0	1	0	8	5951	145	97	0	0	1	0	0	5951	6203	95,94%	99,23%	97,56%
Corn Senesced Green Weeds	0	0	56	2	1	0	0	89	27	2925	69	23	0	31	53	2	2925	3278	89,23%	86,08%	87,63%
Lettuce Romaine 4wk	0	0	3	0	0	0	0	0	0	4	1059	2	0	0	0	0	1059	1068	99,16%	67,97%	80,65%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	98,07%	99,02%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	95,91%	97,86%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	8	6	1	0	0	37	1017	1	0	1017	1070	95,05%	92,88%	93,95%
Vinyard Untrained	0	0	3	1	0	0	1	604	5	71	4	9	0	5	6547	18	6547	7268	90,08%	44,87%	59,90%
Vinyard Vertical Trellis	0	0	0	5	6	0	0	0	0	18	0	3	0	0	28	1747	1747	1807	96,68%	96,41%	96,55%
																					80,31%

First N Sample with Pre-Processing (PCA)

Table 79 SSC – ML - First N Sample with Pre-Processing (PCA)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1875	126	0	0	0	0	0	0	0	0	0	0	0	0	0	8	1875	2009	93,33%	100,00%	96,55%
Brocoli Green Weeds 2	0	3656	0	0	0	0	0	0	0	0	0	0	0	0	0	70	3656	3726	98,12%	96,67%	97,39%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	58,95%	74,17%
Fallow Rough Plow	0	0	18	1374	2	0	0	0	0	0	0	0	0	0	0	0	1374	1394	98,57%	99,42%	98,99%
Fallow Smooth	0	0	1355	8	1290	0	0	0	0	0	0	0	0	0	0	25	1290	2678	48,17%	99,85%	64,99%
Stubble	0	0	0	0	0	3904	0	0	0	0	0	0	0	0	0	55	3904	3959	98,61%	100,00%	99,30%
Celery	0	0	0	0	0	0	3571	0	0	0	0	0	0	0	0	8	3571	3579	99,78%	100,00%	99,89%
Grapes Untrained	0	0	0	0	0	0	0	2070	0	12	0	0	0	0	9149	40	2070	11271	18,37%	90,63%	30,54%
Soil Vinyard Develop	0	0	0	0	0	0	0	10	5607	574	9	0	0	0	0	3	5607	6203	90,39%	99,84%	94,88%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	40	9	2861	14	0	0	0	37	317	2861	3278	87,28%	82,81%	84,98%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	1	1060	0	0	0	0	7	1060	1068	99,25%	97,88%	98,56%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	5	0	1908	13	0	0	1	1908	1927	99,01%	100,00%	99,50%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	894	20	0	2	894	916	97,60%	97,39%	97,49%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	10	0	1	0	0	11	1016	3	29	1016	1070	94,95%	98,07%	96,49%
Vinyard Untrained	0	0	3	0	0	0	0	152	0	0	0	0	0	0	7089	24	7089	7268	97,54%	43,55%	60,21%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	2	0	1	0	0	0	0	0	1804	1804	1807	99,83%	75,39%	85,90%
																					77,51%

Table 80 SSC – SVM-RBF - First N Sample with Pre-Processing (PCA)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1899	104	0	0	0	0	0	1	0	0	0	0	0	0	1	4	1899	2009	94,52%	100,00%	97,19%
Brocoli Green Weeds 2	0	3657	0	0	0	0	5	13	0	0	0	0	0	0	0	51	3657	3726	98,15%	97,23%	97,69%
Fallow	0	0	1937	0	0	0	0	0	0	2	24	0	0	0	7	6	1937	1976	98,03%	69,48%	81,32%
Fallow Rough Plow	0	0	1	1374	19	0	0	0	0	0	0	0	0	0	0	0	1374	1394	98,57%	99,71%	99,13%
Fallow Smooth	0	0	811	4	1858	0	0	0	0	0	0	0	0	0	0	5	1858	2678	69,38%	98,20%	81,31%
Stubble	0	0	3	0	0	3932	1	4	0	0	0	0	0	0	1	18	3932	3959	99,32%	100,00%	99,66%
Celery	0	0	0	0	1	0	3569	0	0	0	0	0	0	0	0	9	3569	3579	99,72%	99,64%	99,68%
Grapes Untrained	0	0	0	0	0	0	0	2981	0	65	0	0	0	0	8175	50	2981	11271	26,45%	86,78%	40,54%
Soil Vinyard Develop	0	0	0	0	0	0	0	5	6189	6	2	1	0	0	0	0	6189	6203	99,77%	99,71%	99,74%
Corn Senesced Green Weeds	0	0	36	0	0	0	0	78	18	2987	105	2	0	0	12	40	2987	3278	91,12%	96,82%	93,89%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1066	1	0	0	0	1	1066	1068	99,81%	88,39%	93,76%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	2	1925	0	0	0	0	1925	1927	99,90%	98,92%	99,41%
Lettuce Romaine 6wk	0	0	0	0	0	0	3	2	0	0	0	12	894	5	0	0	894	916	97,60%	96,34%	96,96%
Lettuce Romaine 7wk	0	0	0	0	0	0	4	15	0	16	3	5	34	982	5	6	982	1070	91,78%	99,49%	95,48%
Vinyard Untrained	0	0	0	0	14	0	0	336	0	2	0	0	0	0	6889	27	6889	7268	94,79%	45,65%	61,62%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	7	4	0	0	0	1	1795	1795	1807	99,34%	89,21%	94,00%
																					81,17%

Table 81 SSC – SVM-LNR - First N Sample with Pre-Processing (PCA)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1987	21	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1987	2009	98,90%	100,00%	99,45%
Brocoli Green Weeds 2	0	3655	0	0	0	1	2	0	0	0	0	0	0	64	0	4	3655	3726	98,09%	99,43%	98,76%
Fallow	0	0	1435	0	0	0	0	0	0	10	501	30	0	0	0	0	1435	1976	72,62%	74,74%	73,67%
Fallow Rough Plow	0	0	2	1388	4	0	0	0	0	0	0	0	0	0	0	0	1388	1394	99,57%	99,07%	99,32%
Fallow Smooth	0	0	414	11	2248	0	0	0	3	1	1	0	0	0	0	0	2248	2678	83,94%	98,94%	90,83%
Stubble	0	0	3	0	0	3949	1	3	0	0	0	0	0	3	0	0	3949	3959	99,75%	99,70%	99,72%
Celery	0	0	0	0	1	0	3578	0	0	0	0	0	0	0	0	0	3578	3579	99,97%	99,50%	99,74%
Grapes Untrained	0	0	0	0	0	0	0	6344	18	207	31	1	0	3	4666	1	6344	11271	56,29%	77,73%	65,29%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6092	15	40	56	0	0	0	0	6092	6203	98,21%	99,06%	98,63%
Corn Senesced Green Weeds	0	0	42	0	5	8	0	117	37	2833	148	45	0	2	41	0	2833	3278	86,42%	89,14%	87,76%
Lettuce Romaine 4wk	0	0	1	0	0	1	0	0	0	5	1058	3	0	0	0	0	1058	1068	99,06%	59,07%	74,01%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	1	1926	0	0	0	0	1926	1927	99,95%	92,86%	96,28%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	910	6	0	0	910	916	99,34%	97,95%	98,64%
Lettuce Romaine 7wk	0	0	0	0	0	2	0	1	0	6	2	10	19	1022	8	0	1022	1070	95,51%	92,82%	94,15%
Vinyard Untrained	0	0	20	0	1	0	8	1697	0	101	1	3	0	0	5432	5	5432	7268	74,74%	53,39%	62,28%
Vinyard Vertical Trellis	0	0	3	2	13	0	7	0	0	0	8	0	0	0	28	1746	1746	1807	96,62%	99,43%	98,01%
																					84,25%

Table 82 SSC – K-NN - First N Sample with Pre-Processing (PCA)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1852	157	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1852	2009	92,19%	100,00%	95,93%
Brocoli Green Weeds 2	0	3637	0	0	0	0	11	0	0	0	0	0	0	9	0	69	3637	3726	97,61%	95,86%	96,73%
Fallow	0	0	1454	0	0	0	0	0	0	93	425	4	0	0	0	0	1454	1976	73,58%	65,32%	69,21%
Fallow Rough Plow	0	0	1	1388	5	0	0	0	0	0	0	0	0	0	0	0	1388	1394	99,57%	99,36%	99,46%
Fallow Smooth	0	0	710	7	1948	0	0	0	2	0	4	7	0	0	0	0	1948	2678	72,74%	98,43%	83,66%
Stubble	0	0	1	0	0	3923	0	22	4	1	0	2	0	6	0	0	3923	3959	99,09%	99,95%	99,52%
Celery	0	0	1	0	0	0	3550	0	0	0	0	0	2	0	2	24	3550	3579	99,19%	98,69%	98,94%
Grapes Untrained	0	0	0	0	0	1	9	3167	52	135	21	5	15	7	7840	19	3167	11271	28,10%	74,94%	40,87%
Soil Vinyard Develop	0	0	1	0	0	0	0	0	5818	222	161	0	0	1	0	0	5818	6203	93,79%	97,58%	95,65%
Corn Senesced Green Weeds	0	0	47	1	5	1	0	134	68	2558	100	51	7	7	299	0	2558	3278	78,04%	83,54%	80,69%
Lettuce Romaine 4wk	0	0	6	0	1	0	0	0	5	5	1049	2	0	0	0	0	1049	1068	98,22%	59,40%	74,03%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	1	5	1921	0	0	0	0	1921	1927	99,69%	95,29%	97,44%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	893	23	0	0	893	916	97,49%	93,12%	95,25%
Lettuce Romaine 7wk	0	0	0	0	0	0	26	3	7	3	0	0	42	973	16	0	973	1070	90,93%	94,83%	92,84%
Vinyard Untrained	0	0	5	1	1	0	1	900	6	38	1	15	0	0	6298	2	6298	7268	86,65%	42,87%	57,36%
Vinyard Vertical Trellis	0	0	0	0	19	0	0	0	0	6	0	9	0	0	237	1536	1536	1807	85,00%	93,09%	88,86%
																					77,53%

First N Sample with Post-Processing (Filtering with 3x3 window)

Table 83 SSC - ML - First N Sample with Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1866	143	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1866	2009	92,88%	100,00%	96,31%
Brocoli Green Weeds 2	0	3718	0	0	0	0	0	0	0	0	0	0	0	8	0	0	3718	3726	99,79%	96,30%	98,01%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	76,06%	86,40%
Fallow Rough Plow	0	0	2	1392	0	0	0	0	0	0	0	0	0	0	0	0	1392	1394	99,86%	98,24%	99,04%
Fallow Smooth	0	0	614	25	2033	6	0	0	0	0	0	0	0	0	0	0	2033	2678	75,91%	100,00%	86,31%
Stubble	0	0	0	0	0	3957	1	1	0	0	0	0	0	0	0	0	3957	3959	99,95%	99,85%	99,90%
Celery	0	0	0	0	0	0	3575	4	0	0	0	0	0	0	0	0	3575	3579	99,89%	99,97%	99,93%
Grapes Untrained	0	0	0	0	0	0	0	3252	0	2	0	0	0	0	8017	0	3252	11271	28,85%	85,11%	43,10%
Soil Vinyard Develop	0	0	0	0	0	0	0	2	5998	203	0	0	0	0	0	0	5998	6203	96,70%	99,98%	98,31%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	101	1	3163	9	0	0	4	0	0	3163	3278	96,49%	92,84%	94,63%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	1	1067	0	0	0	0	0	1067	1068	99,91%	99,16%	99,53%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1925	2	0	0	0	1925	1927	99,90%	100,00%	99,95%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	99,78%	99,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	7	0	0	0	1063	0	0	1063	1070	99,35%	98,79%	99,07%
Vinyard Untrained	0	0	6	0	0	0	0	461	0	0	0	0	0	0	6801	0	6801	7268	93,57%	45,90%	61,59%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	31	0	0	0	0	0	1776	1776	1807	98,28%	100,00%	99,13%
																					82,17%

Table 84 SSC - SVM-RBF - First N Sample with Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1994	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1994	2009	99,25%	100,00%	99,63%
Brocoli Green Weeds 2	0	3670	0	0	0	0	0	53	0	0	0	0	0	0	0	3	3670	3726	98,50%	99,59%	99,04%
Fallow	0	0	1599	0	0	0	0	0	0	151	222	4	0	0	0	0	1599	1976	80,92%	70,47%	75,34%
Fallow Rough Plow	0	0	2	1392	0	0	0	0	0	0	0	0	0	0	0	0	1392	1394	99,86%	99,00%	99,43%
Fallow Smooth	0	0	616	14	2035	8	0	0	0	5	0	0	0	0	0	0	2035	2678	75,99%	100,00%	86,36%
Stubble	0	0	0	0	0	3946	0	13	0	0	0	0	0	0	0	0	3946	3959	99,67%	99,80%	99,73%
Celery	0	0	0	0	0	0	3548	23	0	0	0	0	0	0	0	8	3548	3579	99,13%	100,00%	99,57%
Grapes Untrained	0	0	0	0	0	0	0	2097	0	146	0	0	0	0	9028	0	2097	11271	18,61%	86,47%	30,62%
Soil Vinyard Develop	0	0	0	0	0	0	0	2	6199	1	1	0	0	0	0	0	6199	6203	99,94%	99,68%	99,81%
Corn Senesced Green Weeds	0	0	52	0	0	0	0	113	20	3014	50	10	0	0	19	0	3014	3278	91,95%	88,62%	90,25%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	6	1062	0	0	0	0	0	1062	1068	99,44%	79,55%	88,39%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	99,28%	99,64%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	916	0	0	0	916	916	100,00%	98,49%	99,24%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	15	0	0	0	0	14	1041	0	0	1041	1070	97,29%	100,00%	98,63%
Vinyard Untrained	0	0	0	0	0	0	0	71	0	66	0	0	0	0	7128	3	7128	7268	98,07%	44,07%	60,81%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	38	0	12	0	0	0	0	0	1757	1757	1807	97,23%	99,21%	98,21%
																					80,04%

Table 85 SSC - SVM-LNR - First N Sample with Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1925	84	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1925	2009	95,82%	100,00%	97,86%
Brocoli Green Weeds 2	0	3725	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3725	3726	99,97%	97,79%	98,87%
Fallow	0	0	1440	0	0	0	0	0	0	0	536	0	0	0	0	0	1440	1976	72,87%	85,21%	78,56%
Fallow Rough Plow	0	0	1	1392	1	0	0	0	0	0	0	0	0	0	0	0	1392	1394	99,86%	98,93%	99,39%
Fallow Smooth	0	0	178	14	2480	3	0	0	3	0	0	0	0	0	0	0	2480	2678	92,61%	99,88%	96,11%
Stubble	0	0	0	0	0	3957	1	0	0	0	0	0	0	1	0	0	3957	3959	99,95%	99,90%	99,92%
Celery	0	0	0	0	1	0	3578	0	0	0	0	0	0	0	0	0	3578	3579	99,97%	99,94%	99,96%
Grapes Untrained	0	0	0	0	0	0	0	4435	0	13	0	0	0	0	6823	0	4435	11271	39,35%	87,82%	54,35%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6203	100,00%	99,57%	99,78%
Corn Senesced Green Weeds	0	0	58	0	0	0	0	21	24	2965	64	32	0	104	7	3	2965	3278	90,45%	99,30%	94,67%
Lettuce Romaine 4wk	0	0	0	1	0	1	0	0	0	0	1066	0	0	0	0	0	1066	1068	99,81%	63,99%	77,98%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	98,22%	99,10%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	916	0	0	0	916	916	100,00%	97,03%	98,49%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	6	0	0	0	0	28	1036	0	0	1036	1070	96,82%	90,80%	93,71%
Vinyard Untrained	0	0	13	0	0	0	0	588	0	0	0	0	0	0	6664	3	6664	7268	91,69%	49,07%	63,93%
Vinyard Vertical Trellis	0	0	0	0	1	0	0	0	0	8	0	3	0	0	86	1709	1709	1807	94,58%	99,65%	97,05%
																					83,91%

Table 86 SSC - K-NN - First N Sample with Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1968	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1968	2009	97,96%	99,90%	98,92%
Brocoli Green Weeds 2	2	3696	0	0	0	0	3	0	0	0	0	0	0	11	0	14	3696	3726	99,19%	98,90%	99,05%
Fallow	0	0	1598	0	0	0	0	0	0	35	343	0	0	0	0	0	1598	1976	80,87%	75,95%	78,33%
Fallow Rough Plow	0	0	0	1393	1	0	0	0	0	0	0	0	0	0	0	0	1393	1394	99,93%	99,57%	99,75%
Fallow Smooth	0	0	435	6	2224	11	0	0	1	0	1	0	0	0	0	0	2224	2678	83,05%	99,78%	90,65%
Stubble	0	0	0	0	0	3956	0	0	0	0	0	0	0	3	0	0	3956	3959	99,92%	99,72%	99,82%
Celery	0	0	0	0	0	0	3576	0	0	0	0	1	1	1	0	0	3576	3579	99,92%	99,89%	99,90%
Grapes Untrained	0	0	0	0	0	0	1	2589	0	173	1	0	0	0	8507	0	2589	11271	22,97%	89,96%	36,60%
Soil Vinyard Develop	0	0	0	0	0	0	0	3	6112	20	68	0	0	0	0	0	6112	6203	98,53%	99,56%	99,04%
Corn Senesced Green Weeds	0	0	65	0	0	0	0	50	18	3049	39	12	0	8	35	2	3049	3278	93,01%	91,73%	92,37%
Lettuce Romaine 4wk	0	0	0	0	1	0	0	0	0	2	1063	2	0	0	0	0	1063	1068	99,53%	70,12%	82,28%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	99,18%	99,59%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	916	0	0	0	916	916	100,00%	96,83%	98,39%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	6	5	0	0	0	29	1030	0	0	1030	1070	96,26%	97,82%	97,03%
Vinyard Untrained	0	0	6	0	0	0	0	230	3	22	1	1	0	0	6989	16	6989	7268	96,16%	44,97%	61,28%
Vinyard Vertical Trellis	0	0	0	0	3	0	0	0	0	23	0	0	0	0	12	1769	1769	1807	97,90%	98,22%	98,06%
																					81,02%

First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

Table 87 SSC - ML - First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3713	0	0	0	0	0	0	0	0	0	0	0	13	0	0	3713	3726	99,65%	99,97%	99,81%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	82,13%	90,19%
Fallow Rough Plow	0	0	2	1382	10	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	96,11%	97,60%
Fallow Smooth	0	0	352	25	2300	1	0	0	0	0	0	0	0	0	0	0	2300	2678	85,88%	99,27%	92,09%
Stubble	0	0	2	0	0	3952	4	0	0	0	0	0	1	0	0	0	3952	3959	99,82%	99,62%	99,72%
Celery	0	1	2	0	0	0	3572	0	0	0	0	0	4	0	0	0	3572	3579	99,80%	97,76%	98,77%
Grapes Untrained	0	0	1	0	0	14	0	1205	0	23	104	1	0	0	9923	0	1205	11271	10,69%	88,93%	19,09%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6200	0	3	0	0	0	0	0	6200	6203	99,95%	98,87%	99,41%
Corn Senesced Green Weeds	0	0	71	0	0	0	0	149	33	470	2239	0	280	36	0	0	470	3278	14,34%	95,33%	24,93%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	29,61%	45,01%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,64%	98,29%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	75,85%	85,40%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	1	0	0	20	0	0	1049	0	0	1049	1070	98,04%	93,74%	95,84%
Vinyard Untrained	0	0	0	14	7	0	0	0	38	0	1	0	0	0	7208	0	7208	7268	99,17%	40,68%	57,70%
Vinyard Vertical Trellis	0	0	0	17	0	0	78	0	0	0	15	0	0	0	587	1110	1110	1807	61,43%	100,00%	76,11%
																					73,84%

Table 88 SSC - SVM-RBF - First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,95%	99,97%
Fallow Rough Plow	0	0	0	1383	11	0	0	0	0	0	0	0	0	0	0	0	1383	1394	99,21%	97,46%	98,33%
Fallow Smooth	0	0	0	36	2638	4	0	0	0	0	0	0	0	0	0	0	2638	2678	98,51%	98,32%	98,41%
Stubble	0	0	0	0	0	3957	0	2	0	0	0	0	0	0	0	0	3957	3959	99,95%	99,90%	99,92%
Celery	0	0	0	0	0	0	3574	5	0	0	0	0	0	0	0	0	3574	3579	99,86%	100,00%	99,93%
Grapes Untrained	0	0	1	0	0	0	0	870	0	0	0	0	0	0	10400	0	870	11271	7,72%	94,57%	14,27%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6203	100,00%	72,55%	84,09%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	1	2347	800	105	0	0	25	0	0	800	3278	24,41%	97,92%	39,07%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	988	80	0	0	0	0	988	1068	92,51%	89,17%	90,81%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,01%	97,97%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	901	15	0	0	901	916	98,36%	100,00%	99,17%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	16	15	0	0	1039	0	0	1039	1070	97,10%	96,29%	96,70%
Vinyard Untrained	0	0	0	0	34	0	0	1	0	1	0	0	0	0	7232	0	7232	7268	99,50%	41,02%	58,09%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	1766	1766	1807	97,73%	100,00%	98,85%
																					75,72%

Table 89 SSC - SVM-LNR - First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,95%	99,97%
Fallow Rough Plow	0	0	0	1383	11	0	0	0	0	0	0	0	0	0	0	0	1383	1394	99,21%	95,71%	97,43%
Fallow Smooth	0	0	0	36	2638	4	0	0	0	0	0	0	0	0	0	0	2638	2678	98,51%	98,25%	98,38%
Stubble	0	0	0	0	0	3957	2	0	0	0	0	0	0	0	0	0	3957	3959	99,95%	99,90%	99,92%
Celery	0	0	0	0	2	0	3577	0	0	0	0	0	0	0	0	0	3577	3579	99,94%	99,94%	99,94%
Grapes Untrained	0	0	1	0	0	0	0	11188	0	82	0	0	0	0	0	0	11188	11271	99,26%	60,36%	75,07%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6203	100,00%	72,41%	84,00%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	112	2348	688	105	0	0	25	0	0	688	3278	20,99%	87,76%	33,87%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	988	80	0	0	0	0	988	1068	92,51%	89,17%	90,81%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,01%	97,97%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	901	15	0	0	901	916	98,36%	100,00%	99,17%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	3	0	13	15	0	0	1039	0	0	1039	1070	97,10%	96,29%	96,70%
Vinyard Untrained	0	0	0	0	34	0	0	7232	0	1	0	0	0	0	0	1	0	7268	0,00%	#DIV/0!	#DIV/0!
Vinyard Vertical Trellis	0	0	0	26	0	0	0	0	15	0	0	0	0	0	0	1766	1766	1807	97,73%	99,94%	98,82%
																					81,22%

Table 90 SSC - K-NN - First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	94,14%	96,98%
Fallow Rough Plow	0	0	0	1383	11	0	0	0	0	0	0	0	0	0	0	0	1383	1394	99,21%	95,71%	97,43%
Fallow Smooth	0	0	0	36	2638	4	0	0	0	0	0	0	0	0	0	0	2638	2678	98,51%	98,32%	98,41%
Stubble	0	0	0	0	0	3957	2	0	0	0	0	0	0	0	0	0	3957	3959	99,95%	99,90%	99,92%
Celery	0	0	2	0	0	0	3576	0	0	0	0	0	0	1	0	0	3576	3579	99,92%	99,94%	99,93%
Grapes Untrained	0	0	1	0	0	0	0	807	0	374	0	0	0	0	10089	0	807	11271	7,16%	98,06%	13,35%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6203	100,00%	72,55%	84,09%
Corn Senesced Green Weeds	0	0	105	0	0	0	0	1	2347	800	0	0	0	25	0	0	800	3278	24,41%	67,17%	35,80%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	988	80	0	0	0	0	988	1068	92,51%	100,00%	96,11%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,01%	97,97%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	901	15	0	0	901	916	98,36%	100,00%	99,17%
Lettuce Romaine 7wk	0	0	15	0	0	0	0	0	0	16	0	0	0	1039	0	0	1039	1070	97,10%	96,20%	96,65%
Vinyard Untrained	0	0	0	0	34	0	0	0	0	1	0	0	0	0	7232	1	7232	7268	99,50%	41,75%	58,82%
Vinyard Vertical Trellis	0	0	0	26	0	0	0	15	0	0	0	0	0	0	0	1766	1766	1807	97,73%	99,94%	98,82%
																					75,61%

First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

Table 91 SSC - ML - First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1874	133	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1874	2009	93,28%	100,00%	96,52%
Brocoli Green Weeds 2	0	3676	0	0	0	0	0	0	0	0	0	0	0	0	0	50	3676	3726	98,66%	96,51%	97,57%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	58,91%	74,15%
Fallow Rough Plow	0	0	13	1379	2	0	0	0	0	0	0	0	0	0	0	0	1379	1394	98,92%	98,99%	98,96%
Fallow Smooth	0	0	1363	14	1277	0	0	0	0	0	0	0	0	0	0	24	1277	2678	47,68%	99,84%	64,54%
Stubble	0	0	0	0	0	3909	0	0	0	0	0	0	0	0	0	50	3909	3959	98,74%	100,00%	99,36%
Celery	0	0	0	0	0	0	3571	0	0	0	0	0	0	0	0	8	3571	3579	99,78%	100,00%	99,89%
Grapes Untrained	0	0	0	0	0	0	0	1676	0	14	0	0	0	0	9546	35	1676	11271	14,87%	98,24%	25,83%
Soil Vinyard Develop	0	0	0	0	0	0	0	3	5850	347	1	0	0	0	0	2	5850	6203	94,31%	99,86%	97,01%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	6	8	2943	4	0	0	0	8	309	2943	3278	89,78%	89,05%	89,41%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1061	0	0	0	0	7	1061	1068	99,34%	99,53%	99,44%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1923	4	0	0	0	1923	1927	99,79%	100,00%	99,90%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	900	16	0	0	900	916	98,25%	99,34%	98,79%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	0	0	2	1038	0	29	1038	1070	97,01%	98,48%	97,74%
Vinyard Untrained	0	0	2	0	0	0	0	21	0	0	0	0	0	0	7228	17	7228	7268	99,45%	43,07%	60,11%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1807	1807	1807	100,00%	77,22%	87,15%
																					77,75%

Table 92 SSC - SVM-RBF - First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1889	116	0	0	0	0	0	4	0	0	0	0	0	0	0	0	1889	2009	94,03%	100,00%	96,92%
Brocoli Green Weeds 2	0	3693	0	0	0	0	0	14	0	0	0	0	0	2	0	17	3693	3726	99,11%	96,95%	98,02%
Fallow	0	0	1873	0	0	0	0	44	0	0	59	0	0	0	0	0	1873	1976	94,79%	78,47%	85,86%
Fallow Rough Plow	0	0	0	1393	0	0	0	1	0	0	0	0	0	0	0	0	1393	1394	99,93%	99,57%	99,75%
Fallow Smooth	0	0	476	6	2191	0	0	5	0	0	0	0	0	0	0	0	2191	2678	81,81%	100,00%	90,00%
Stubble	0	0	0	0	0	3953	1	2	0	0	0	0	0	0	0	3	3953	3959	99,85%	100,00%	99,92%
Celery	0	0	0	0	0	0	3567	12	0	0	0	0	0	0	0	0	3567	3579	99,66%	99,97%	99,82%
Grapes Untrained	0	0	0	0	0	0	0	2065	0	10	0	0	0	0	9196	0	2065	11271	18,32%	91,17%	30,51%
Soil Vinyard Develop	0	0	0	0	0	0	0	2	6200	1	0	0	0	0	0	0	6200	6203	99,95%	99,71%	99,83%
Corn Senesced Green Weeds	0	0	38	0	0	0	0	63	18	3109	35	1	0	5	6	3	3109	3278	94,84%	99,36%	97,05%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	5	0	0	1063	0	0	0	0	0	1063	1068	99,53%	91,80%	95,51%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	99,95%	99,97%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	916	0	0	0	916	916	100,00%	93,66%	96,73%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	15	0	0	0	0	62	993	0	0	993	1070	92,80%	99,30%	95,94%
Vinyard Untrained	0	0	0	0	0	0	0	30	0	0	0	0	0	0	7236	2	7236	7268	99,56%	44,02%	61,05%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	3	0	9	1	0	0	0	0	1794	1794	1807	99,28%	98,63%	98,95%
																					81,03%

Table 93 SSC - SVM-LNR - First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2008	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2008	2009	99,95%	100,00%	99,98%
Brocoli Green Weeds 2	0	3699	0	0	0	0	0	0	0	0	0	0	0	23	0	4	3699	3726	99,28%	99,97%	99,62%
Fallow	0	0	1390	0	0	0	0	0	0	2	477	107	0	0	0	0	1390	1976	70,34%	76,46%	73,27%
Fallow Rough Plow	0	0	2	1390	2	0	0	0	0	0	0	0	0	0	0	0	1390	1394	99,71%	98,93%	99,32%
Fallow Smooth	0	0	396	15	2261	1	0	0	0	5	0	0	0	0	0	0	2261	2678	84,43%	99,56%	91,37%
Stubble	0	0	0	0	0	3956	2	1	0	0	0	0	0	0	0	0	3956	3959	99,92%	99,57%	99,75%
Celery	0	0	0	0	0	0	3579	0	0	0	0	0	0	0	0	0	3579	3579	100,00%	99,42%	99,71%
Grapes Untrained	0	0	0	0	0	0	0	8509	4	174	3	0	0	0	2581	0	8509	11271	75,49%	68,95%	72,08%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6172	5	19	7	0	0	0	0	6172	6203	99,50%	99,55%	99,52%
Corn Senesced Green Weeds	0	0	24	0	5	11	0	81	24	2973	104	42	0	4	10	0	2973	3278	90,70%	92,53%	91,60%
Lettuce Romaine 4wk	0	0	0	0	0	2	0	0	0	0	1066	0	0	0	0	0	1066	1068	99,81%	63,34%	77,50%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	5	1922	0	0	0	0	1922	1927	99,74%	92,36%	95,91%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	100,00%	99,95%
Lettuce Romaine 7wk	0	0	0	0	0	2	0	0	0	3	0	3	0	1062	0	0	1062	1070	99,25%	97,43%	98,33%
Vinyard Untrained	0	0	6	0	0	0	5	3749	0	51	0	0	0	0	3457	0	3457	7268	47,56%	56,91%	51,82%
Vinyard Vertical Trellis	0	0	0	0	3	1	14	0	0	0	9	0	0	0	26	1754	1754	1807	97,07%	99,77%	98,40%
																					85,19%

Table 94 SSC - K-NN - First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1892	117	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1892	2009	94,18%	100,00%	97,00%
Brocoli Green Weeds 2	0	3682	0	0	0	0	11	0	0	0	0	0	0	2	0	31	3682	3726	98,82%	96,92%	97,86%
Fallow	0	0	1456	0	0	0	0	0	0	58	461	1	0	0	0	0	1456	1976	73,68%	66,21%	69,75%
Fallow Rough Plow	0	0	0	1362	32	0	0	0	0	0	0	0	0	0	0	0	1362	1394	97,70%	99,63%	98,66%
Fallow Smooth	0	0	679	5	1987	1	0	0	1	1	3	1	0	0	0	0	1987	2678	74,20%	97,83%	84,39%
Stubble	0	0	0	0	0	3948	0	5	0	0	0	1	0	5	0	0	3948	3959	99,72%	99,97%	99,85%
Celery	0	0	0	0	0	0	3572	0	0	0	0	1	1	0	0	5	3572	3579	99,80%	99,64%	99,72%
Grapes Untrained	0	0	0	0	0	0	0	2634	38	113	37	5	4	1	8435	4	2634	11271	23,37%	87,22%	36,86%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6055	34	114	0	0	0	0	0	6055	6203	97,61%	98,55%	98,08%
Corn Senesced Green Weeds	0	0	53	0	0	0	0	132	43	2634	109	19	4	6	278	0	2634	3278	80,35%	92,29%	85,91%
Lettuce Romaine 4wk	0	0	0	0	2	0	0	0	0	0	1063	3	0	0	0	0	1063	1068	99,53%	59,49%	74,47%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	97,67%	98,82%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	900	16	0	0	900	916	98,25%	94,94%	96,57%
Lettuce Romaine 7wk	0	0	0	0	0	0	2	5	7	3	0	0	39	1008	6	0	1008	1070	94,21%	97,11%	95,64%
Vinyard Untrained	0	0	11	0	0	0	0	244	0	8	0	4	0	0	7001	0	7001	7268	96,33%	43,90%	60,31%
Vinyard Vertical Trellis	0	0	0	0	10	0	0	0	0	3	0	11	0	0	228	1555	1555	1807	86,05%	97,49%	91,42%
																					78,84%

First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

Table 95 SSC - ML - First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1880	129	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1880	2009	93,58%	100,00%	96,68%
Brocoli Green Weeds 2	0	3684	1	0	1	0	0	12	0	1	2	1	0	24	0	0	3684	3726	98,87%	96,54%	97,69%
Fallow	0	0	1744	0	0	0	0	2	0	212	18	0	0	0	0	0	1744	1976	88,26%	65,84%	75,42%
Fallow Rough Plow	0	0	9	1338	35	0	0	0	0	4	0	3	0	0	5	0	1338	1394	95,98%	96,26%	96,12%
Fallow Smooth	0	0	878	45	1718	26	0	0	0	11	0	0	0	0	0	0	1718	2678	64,15%	97,78%	77,47%
Stubble	0	0	6	0	0	3942	4	4	0	3	0	0	0	0	0	0	3942	3959	99,57%	99,34%	99,46%
Celery	0	3	0	0	0	0	3500	16	0	3	0	0	0	3	0	54	3500	3579	97,79%	99,89%	98,83%
Grapes Untrained	0	0	0	0	0	0	0	2943	0	255	5	12	0	0	7775	281	2943	11271	26,11%	75,08%	38,75%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6043	160	0	0	0	0	0	0	6043	6203	97,42%	99,16%	98,28%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	645	49	2544	12	0	0	28	0	0	2544	3278	77,61%	77,75%	77,68%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	1	0	0	987	80	0	0	0	0	987	1068	92,42%	94,81%	93,60%
Lettuce Romaine 5wk	0	0	11	0	0	0	0	0	0	6	17	1872	21	0	0	0	1872	1927	97,15%	93,32%	95,19%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	27	0	25	804	60	0	0	804	916	87,77%	91,68%	89,68%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	154	0	33	0	0	52	831	0	0	831	1070	77,66%	87,84%	82,44%
Vinyard Untrained	0	0	0	7	3	0	0	143	2	11	0	13	0	0	6980	109	6980	7268	96,04%	47,14%	63,24%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	2	0	0	0	0	48	1757	1757	1807	97,23%	79,83%	87,67%
																					78,64%

Table 96 SSC - SVM-RBF - First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

t_PCA	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3709	1	0	2	0	0	0	0	0	2	0	0	12	0	0	3709	3726	99,54%	99,84%	99,69%
Fallow	0	0	1930	0	8	0	0	0	6	0	32	0	0	0	0	0	1930	1976	97,67%	80,28%	88,13%
Fallow Rough Plow	0	0	8	1352	25	0	0	0	4	0	0	0	0	0	5	0	1352	1394	96,99%	96,23%	96,61%
Fallow Smooth	0	0	435	45	2161	26	0	0	11	0	0	0	0	0	0	0	2161	2678	80,69%	97,08%	88,13%
Stubble	0	0	6	0	0	3946	4	0	3	0	0	0	0	0	0	0	3946	3959	99,67%	99,10%	99,38%
Celery	0	6	0	0	0	0	3541	7	1	2	0	0	0	0	0	22	3541	3579	98,94%	99,89%	99,41%
Grapes Untrained	0	0	0	0	0	0	0	4537	6	104	66	42	56	0	5987	473	4537	11271	40,25%	77,45%	52,97%
Soil Vinyard Develop	0	0	0	0	0	10	0	0	6065	22	106	0	0	0	0	0	6065	6203	97,78%	98,20%	97,99%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	473	77	2541	49	14	24	100	0	0	2541	3278	77,52%	93,08%	84,59%
Lettuce Romaine 4wk	0	0	0	0	1	0	0	0	0	0	987	80	0	0	0	0	987	1068	92,42%	78,33%	84,79%
Lettuce Romaine 5wk	0	0	11	0	0	0	0	0	0	0	17	1878	21	0	0	0	1878	1927	97,46%	92,06%	94,68%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	27	0	25	804	60	0	0	804	916	87,77%	83,84%	85,76%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	103	0	34	0	0	54	879	0	0	879	1070	82,15%	83,63%	82,89%
Vinyard Untrained	0	0	13	7	3	0	0	738	2	0	1	0	0	0	6387	117	6387	7268	87,88%	50,70%	64,30%
Vinyard Vertical Trellis	0	0	0	1	26	0	0	0	1	0	0	1	0	0	219	1559	1559	1807	86,28%	71,81%	78,38%
																					81,81%

Table 97 SSC - SVM-LNR - First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	80,52%	89,21%
Fallow Rough Plow	0	0	2	1382	10	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	352	25	2300	1	0	0	0	0	0	0	0	0	0	0	2300	2678	85,88%	98,54%	91,78%
Stubble	0	0	2	0	0	3952	5	0	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	0	2	0	0	0	3576	0	0	0	0	0	0	0	0	1	3576	3579	99,92%	99,86%	99,89%
Grapes Untrained	0	0	11	0	0	0	0	10882	0	38	94	0	0	0	246	0	10882	11271	96,55%	99,67%	98,08%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6203	100,00%	99,42%	99,71%
Corn Senesced Green Weeds	0	0	71	0	0	0	0	36	36	3035	100	0	0	0	0	0	3035	3278	92,59%	98,73%	95,56%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	82,33%	87,70%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	20	0	0	1049	0	0	1049	1070	98,04%	98,04%	98,04%
Vinyard Untrained	0	0	38	0	7	0	0	0	0	0	1	0	0	0	7208	14	7208	7268	99,17%	96,51%	97,82%
Vinyard Vertical Trellis	0	0	0	0	17	0	0	0	0	0	0	0	0	0	15	1775	1775	1807	98,23%	99,16%	98,69%
																					97,72%

Table 98 SSC - K-NN - First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1868	141	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1868	2009	92,98%	100,00%	96,36%
Brocoli Green Weeds 2	0	3713	0	0	0	0	13	0	0	0	0	0	0	0	0	0	3713	3726	99,65%	96,32%	97,96%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	80,72%	89,33%
Fallow Rough Plow	0	0	2	1382	10	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	97,05%	98,08%
Fallow Smooth	0	0	352	25	2300	1	0	0	0	0	0	0	0	0	0	0	2300	2678	85,88%	99,27%	92,09%
Stubble	0	0	2	0	0	3952	5	0	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	1	6	0	0	0	3572	0	0	0	0	0	0	0	0	0	3572	3579	99,80%	99,50%	99,65%
Grapes Untrained	0	0	1	0	0	0	0	773	2	92	10	24	0	0	10369	0	773	11271	6,86%	94,85%	12,79%
Soil Vinyard Develop	0	0	0	0	0	0	0	3	6200	0	0	0	0	0	0	0	6200	6203	99,95%	99,44%	99,69%
Corn Senesced Green Weeds	0	0	71	0	0	0	0	39	33	2606	100	0	0	0	429	0	2606	3278	79,50%	96,55%	87,20%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	88,52%	91,09%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	94,83%	97,35%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	0	20	0	0	1049	1	0	1049	1070	98,04%	98,04%	98,04%
Vinyard Untrained	0	0	38	0	7	0	0	0	0	1	0	0	0	0	7222	0	7222	7268	99,37%	39,74%	56,78%
Vinyard Vertical Trellis	0	0	0	17	0	0	0	0	0	0	0	15	0	0	150	1625	1625	1807	89,93%	100,00%	94,70%
																					77,71%

Randomly Selected N Sample without Pre-Processing or Post Processing

Table 99 SSC - ML -Randomly Selected N Sample without Pre-Processing or Post Processing

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2005	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2005	2009	99,80%	100,00%	99,90%
Brocoli Green Weeds 2	0	3724	0	0	0	0	0	0	0	0	0	0	0	2	0	0	3724	3726	99,95%	99,89%	99,92%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	98,75%	99,37%
Fallow Rough Plow	0	0	0	1393	1	0	0	0	0	0	0	0	0	0	0	0	1393	1394	99,93%	99,43%	99,68%
Fallow Smooth	0	0	25	8	2639	2	0	0	0	2	0	0	0	0	2	0	2639	2678	98,54%	99,96%	99,25%
Stubble	0	0	0	0	0	3959	0	0	0	0	0	0	0	0	0	0	3959	3959	100,00%	99,95%	99,97%
Celery	0	0	0	0	0	0	3571	2	0	6	0	0	0	0	0	0	3571	3579	99,78%	100,00%	99,89%
Grapes Untrained	0	0	0	0	0	0	0	8369	0	71	0	0	0	0	2831	0	8369	11271	74,25%	78,57%	76,35%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6138	65	0	0	0	0	0	0	6138	6203	98,95%	99,87%	99,41%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	3	8	3262	0	2	0	1	0	2	3262	3278	99,51%	95,16%	97,29%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	3	1065	0	0	0	0	0	1065	1068	99,72%	100,00%	99,86%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	4	0	1921	0	2	0	0	1921	1927	99,69%	99,90%	99,79%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	100,00%	99,95%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	2	0	0	0	1068	0	0	1068	1070	99,81%	99,44%	99,63%
Vinyard Untrained	0	0	0	0	0	0	0	2278	0	6	0	0	0	0	4984	0	4984	7268	68,57%	63,76%	66,08%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	1800	1800	1807	99,61%	99,89%	99,75%
																					90,13%

Table 100 SSC - SVM-RBF -Randomly Selected N Sample without Pre-Processing or Post Processing

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2001	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2001	2009	99,60%	100,00%	99,80%
Brocoli Green Weeds 2	0	3718	0	0	0	0	0	4	0	1	0	0	0	0	0	3	3718	3726	99,79%	99,79%	99,79%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	97,68%	98,82%
Fallow Rough Plow	0	0	0	1389	5	0	0	0	0	0	0	0	0	0	0	0	1389	1394	99,64%	99,36%	99,50%
Fallow Smooth	0	0	3	8	2662	1	0	0	0	4	0	0	0	0	0	0	2662	2678	99,40%	99,78%	99,59%
Stubble	0	0	0	0	1	3957	0	0	0	1	0	0	0	0	0	0	3957	3959	99,95%	99,97%	99,96%
Celery	0	0	0	0	0	0	3560	12	0	0	0	0	0	1	1	5	3560	3579	99,47%	100,00%	99,73%
Grapes Untrained	0	0	0	0	0	0	0	9355	0	217	2	0	0	6	1684	7	9355	11271	83,00%	85,69%	84,32%
Soil Vinyard Develop	0	0	0	0	0	0	0	2	6177	18	5	0	0	1	0	0	6177	6203	99,58%	99,56%	99,57%
Corn Senesced Green Weeds	0	0	44	1	0	0	0	2	27	3159	21	15	0	3	4	2	3159	3278	96,37%	91,14%	93,68%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	97,45%	98,71%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	99,23%	99,61%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	914	2	0	0	914	916	99,78%	100,00%	99,89%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	4	0	0	0	1066	0	0	1066	1070	99,63%	98,80%	99,21%
Vinyard Untrained	0	0	0	0	0	0	0	1541	0	56	0	0	0	0	5639	32	5639	7268	77,59%	76,93%	77,26%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	1	0	6	0	0	0	0	2	1798	1798	1807	99,50%	97,35%	98,41%
																					93,05%

Table 101 SSC - SVM-LNR -Randomly Selected N Sample without Pre-Processing or Post Processing

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2008	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2008	2009	99,95%	99,95%	99,95%
Brocoli Green Weeds 2	1	3723	0	0	0	0	2	0	0	0	0	0	0	0	0	0	3723	3726	99,92%	99,97%	99,95%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,95%	99,97%
Fallow Rough Plow	0	0	1	1390	3	0	0	0	0	0	0	0	0	0	0	0	1390	1394	99,71%	99,14%	99,43%
Fallow Smooth	0	0	0	11	2664	1	0	0	1	0	1	0	0	0	0	0	2664	2678	99,48%	99,63%	99,55%
Stubble	0	0	0	0	1	3958	0	0	0	0	0	0	0	0	0	0	3958	3959	99,97%	99,97%	99,97%
Celery	0	0	0	0	1	0	3578	0	0	0	0	0	0	0	0	0	3578	3579	99,97%	99,94%	99,96%
Grapes Untrained	0	0	0	0	0	0	0	9141	6	65	0	0	0	0	2059	0	9141	11271	81,10%	85,68%	83,33%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6195	5	0	0	0	3	0	0	6195	6203	99,87%	99,44%	99,65%
Corn Senesced Green Weeds	0	0	0	0	2	0	0	0	28	3224	0	1	0	22	1	0	3224	3278	98,35%	97,64%	97,99%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	99,91%	99,95%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	99,95%	99,97%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	100,00%	99,95%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	5	0	0	0	1065	0	0	1065	1070	99,53%	97,53%	98,52%
Vinyard Untrained	0	0	0	1	3	0	0	1528	0	1	0	0	0	0	5733	2	5733	7268	78,88%	73,57%	76,13%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	2	0	0	0	1	0	1804	1804	1807	99,83%	99,89%	99,86%
																					93,05%

Table 102 SSC - K-NN -Randomly Selected N Sample without Pre-Processing or Post Processing

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2004	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2004	2009	99,75%	100,00%	99,88%
Brocoli Green Weeds 2	0	3721	0	0	0	0	0	0	0	0	0	0	0	4	0	1	3721	3726	99,87%	99,87%	99,87%
Fallow	0	0	1973	0	2	0	0	0	0	1	0	0	0	0	0	0	1973	1976	99,85%	97,77%	98,80%
Fallow Rough Plow	0	0	0	1391	3	0	0	0	0	0	0	0	0	0	0	0	1391	1394	99,78%	99,50%	99,64%
Fallow Smooth	0	0	22	7	2643	1	0	0	2	2	1	0	0	0	0	0	2643	2678	98,69%	99,66%	99,17%
Stubble	0	0	0	0	1	3952	0	0	0	0	0	0	0	6	0	0	3952	3959	99,82%	99,92%	99,87%
Celery	0	0	0	0	1	0	3567	4	0	0	0	0	1	4	1	1	3567	3579	99,66%	99,86%	99,76%
Grapes Untrained	0	0	0	0	0	2	5	8061	13	194	5	0	1	18	2967	5	8061	11271	71,52%	82,43%	76,59%
Soil Vinyard Develop	0	0	0	0	0	0	0	3	6156	17	16	0	0	11	0	0	6156	6203	99,24%	99,34%	99,29%
Corn Senesced Green Weeds	0	0	17	0	2	0	0	6	26	3180	15	9	0	7	6	10	3180	3278	97,01%	91,85%	94,36%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	96,65%	98,30%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	2	0	1925	0	0	0	0	1925	1927	99,90%	99,53%	99,72%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	99,78%	99,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	0	0	0	1069	0	0	1069	1070	99,91%	95,19%	97,49%
Vinyard Untrained	0	0	6	0	0	0	0	1705	0	62	0	0	0	3	5478	14	5478	7268	75,37%	64,80%	69,69%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	3	0	0	0	0	2	1802	1802	1807	99,72%	98,31%	99,01%
																					90,35%

Randomly Selected N Sample with Pre-Processing (PCA)

Table 103 SSC – ML - Randomly Selected N Sample with Pre-Processing (PCA)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2004	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2004	2009	99,75%	100,00%	99,88%
Brocoli Green Weeds 2	0	3719	0	0	0	0	0	0	0	4	0	0	0	3	0	0	3719	3726	99,81%	99,87%	99,84%
Fallow	0	0	1969	0	1	0	0	2	0	4	0	0	0	0	0	0	1969	1976	99,65%	97,48%	98,55%
Fallow Rough Plow	0	0	1	1389	4	0	0	0	0	0	0	0	0	0	0	0	1389	1394	99,64%	99,00%	99,32%
Fallow Smooth	0	0	50	14	2605	1	0	0	0	6	0	0	0	0	1	1	2605	2678	97,27%	99,81%	98,52%
Stubble	0	0	0	0	0	3959	0	0	0	0	0	0	0	0	0	0	3959	3959	100,00%	99,97%	99,99%
Celery	0	0	0	0	0	0	3571	0	0	1	0	0	0	0	4	3	3571	3579	99,78%	100,00%	99,89%
Grapes Untrained	0	0	0	0	0	0	0	9484	0	66	0	0	0	0	1721	0	9484	11271	84,15%	87,60%	85,84%
Soil Vinyard Develop	0	0	0	0	0	0	0	1	6136	66	0	0	0	0	0	0	6136	6203	98,92%	99,64%	99,28%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	2	22	3237	2	6	0	6	1	2	3237	3278	98,75%	95,04%	96,86%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	99,81%	99,91%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	1	0	1926	0	0	0	0	1926	1927	99,95%	99,69%	99,82%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	906	10	0	0	906	916	98,91%	100,00%	99,45%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	12	0	0	0	1058	0	0	1058	1070	98,88%	98,24%	98,56%
Vinyard Untrained	0	0	0	0	0	0	0	1338	0	0	0	0	0	0	5930	0	5930	7268	81,59%	77,45%	79,46%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	1798	1798	1807	99,50%	99,67%	99,58%
																					93,77%

Table 104 SSC – SVM-RBF - Randomly Selected N Sample with Pre-Processing (PCA)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3715	0	0	0	0	0	0	0	1	0	0	0	7	0	3	3715	3726	99,70%	100,00%	99,85%
Fallow	0	0	1970	0	0	0	0	0	0	2	0	0	0	0	0	4	1970	1976	99,70%	99,75%	99,72%
Fallow Rough Plow	0	0	0	1390	4	0	0	0	0	0	0	0	0	0	0	0	1390	1394	99,71%	99,64%	99,68%
Fallow Smooth	0	0	4	5	2661	0	0	1	0	5	0	0	0	0	0	2	2661	2678	99,37%	99,78%	99,57%
Stubble	0	0	1	0	0	3956	0	0	0	2	0	0	0	0	0	0	3956	3959	99,92%	100,00%	99,96%
Celery	0	0	0	0	0	0	3572	2	0	4	0	0	0	0	0	1	3572	3579	99,80%	100,00%	99,90%
Grapes Untrained	0	0	0	0	0	0	0	10504	0	39	0	0	0	2	726	0	10504	11271	93,19%	82,46%	87,50%
Soil Vinyard Develop	0	0	0	0	0	0	0	3	6192	7	0	0	0	1	0	0	6192	6203	99,82%	99,53%	99,68%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	1	29	3234	3	4	0	3	0	4	3234	3278	98,66%	97,67%	98,16%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	99,72%	99,86%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	99,79%	99,90%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	100,00%	99,95%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	5	0	0	0	1065	0	0	1065	1070	99,53%	98,70%	99,12%
Vinyard Untrained	0	0	0	0	2	0	0	2227	0	8	0	0	0	0	5029	2	5029	7268	69,19%	87,38%	77,23%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	1803	1803	1807	99,78%	99,12%	99,45%
																					94,24%

Table 105 SSC – SVM-LNR - Randomly Selected N Sample with Pre-Processing (PCA)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2005	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2005	2009	99,80%	100,00%	99,90%
Brocoli Green Weeds 2	0	3724	0	0	0	0	0	1	0	0	0	0	0	1	0	0	3724	3726	99,95%	99,79%	99,87%
Fallow	0	0	1964	0	12	0	0	0	0	0	0	0	0	0	0	0	1964	1976	99,39%	99,39%	99,39%
Fallow Rough Plow	0	0	0	1389	5	0	0	0	0	0	0	0	0	0	0	0	1389	1394	99,64%	99,36%	99,50%
Fallow Smooth	0	0	10	8	2658	1	0	0	1	0	0	0	0	0	0	0	2658	2678	99,25%	99,14%	99,20%
Stubble	0	4	0	0	3	3951	0	0	0	0	0	0	0	1	0	0	3951	3959	99,80%	99,97%	99,89%
Celery	0	0	0	0	0	0	3579	0	0	0	0	0	0	0	0	0	3579	3579	100,00%	100,00%	100,00%
Grapes Untrained	0	0	0	0	0	0	0	9660	5	34	0	0	0	1	1570	1	9660	11271	85,71%	83,01%	84,34%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6202	1	0	0	0	0	0	0	6202	6203	99,98%	99,34%	99,66%
Corn Senesced Green Weeds	0	0	2	1	3	0	0	3	35	3163	34	8	0	15	6	8	3163	3278	96,49%	98,26%	97,37%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1067	1	0	0	0	0	1067	1068	99,91%	96,56%	98,21%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	4	1923	0	0	0	0	1923	1927	99,79%	99,53%	99,66%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	916	0	0	0	916	916	100,00%	94,73%	97,29%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	11	0	0	50	1009	0	0	1009	1070	94,30%	98,15%	96,19%
Vinyard Untrained	0	0	0	0	0	0	0	1973	0	4	0	0	0	0	5289	2	5289	7268	72,77%	77,04%	74,85%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	6	0	0	1	1	0	1799	1799	1807	99,56%	99,39%	99,47%
																					92,92%

Table 106 SSC – K-NN - Randomly Selected N Sample with Pre-Processing (PCA)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	1996	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1996	2010	99,35%	99,80%	99,58%
Brocoli Green Weeds 2	4	3716	0	0	0	0	0	0	0	0	0	0	0	4	0	2	3716	3727	99,73%	99,57%	99,65%
Fallow	0	0	1967	2	5	0	0	0	0	0	2	0	0	0	0	0	1967	1977	99,54%	96,80%	98,15%
Fallow Rough Plow	0	0	0	1389	5	0	0	0	0	0	0	0	0	0	0	0	1389	1395	99,64%	98,93%	99,29%
Fallow Smooth	0	0	28	13	2627	3	0	0	2	0	3	0	0	1	0	1	2627	2679	98,10%	99,51%	98,80%
Stubble	0	0	0	0	0	3950	0	0	0	6	1	0	0	2	0	0	3950	3960	99,77%	99,72%	99,75%
Celery	0	0	0	0	0	1	3567	1	0	0	0	0	1	7	1	1	3567	3580	99,66%	99,78%	99,72%
Grapes Untrained	0	0	0	0	0	5	6	7810	37	251	12	2	2	26	3117	3	7810	11272	69,29%	78,84%	73,76%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6082	41	75	0	0	5	0	0	6082	6204	98,05%	98,81%	98,43%
Corn Senesced Green Weeds	0	0	37	0	3	2	0	11	32	3066	58	15	0	20	14	20	3066	3279	93,53%	88,84%	91,13%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	3	1064	1	0	0	0	0	1064	1069	99,63%	87,36%	93,09%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	1	3	1923	0	0	0	0	1923	1928	99,79%	98,92%	99,35%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	913	3	0	0	913	917	99,67%	98,81%	99,24%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	2	1	4	0	0	8	1055	0	0	1055	1071	98,60%	93,86%	96,17%
Vinyard Untrained	0	0	0	0	0	0	0	2082	1	74	0	1	0	1	5096	13	5096	7269	70,12%	61,92%	65,76%
Vinyard Vertical Trellis	0	3	0	0	0	0	2	0	0	5	0	2	0	0	2	1793	1793	1808	99,23%	97,82%	98,52%
																					88,68%

Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

Table 107 SSC - ML - Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1391	3	0	0	0	0	0	0	0	0	0	0	0	1391	1394	99,78%	99,36%	99,57%
Fallow Smooth	0	0	0	9	2666	2	0	0	0	0	0	0	0	0	1	0	2666	2678	99,55%	99,89%	99,72%
Stubble	0	0	0	0	0	3959	0	0	0	0	0	0	0	0	0	0	3959	3959	100,00%	99,95%	99,97%
Celery	0	0	0	0	0	0	3576	1	0	1	0	0	0	0	1	0	3576	3579	99,92%	100,00%	99,96%
Grapes Untrained	0	0	0	0	0	0	0	9846	0	34	0	0	0	0	1391	0	9846	11271	87,36%	88,94%	88,14%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6196	7	0	0	0	0	0	0	6196	6203	99,89%	99,65%	99,77%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	2	22	3254	0	0	0	0	0	0	3254	3278	99,27%	98,67%	98,97%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	100,00%	100,00%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	100,00%	100,00%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	100,00%	99,95%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	0	0	0	1069	0	0	1069	1070	99,91%	99,91%	99,91%
Vinyard Untrained	0	0	0	0	0	0	0	1222	0	0	0	0	0	0	6046	0	6046	7268	83,19%	81,27%	82,22%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1806	1806	1807	99,94%	100,00%	99,97%
																					95,01%

Table 108 SSC - SVM-RBF - Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3723	0	0	0	0	0	1	0	2	0	0	0	0	0	0	3723	3726	99,92%	100,00%	99,96%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,40%	99,70%
Fallow Rough Plow	0	0	0	1391	3	0	0	0	0	0	0	0	0	0	0	0	1391	1394	99,78%	98,93%	99,36%
Fallow Smooth	0	0	0	15	2663	0	0	0	0	0	0	0	0	0	0	0	2663	2678	99,44%	99,89%	99,66%
Stubble	0	0	0	0	0	3955	0	0	0	3	0	0	0	0	0	1	3955	3959	99,90%	100,00%	99,95%
Celery	0	0	0	0	0	0	3572	4	0	3	0	0	0	0	0	0	3572	3579	99,80%	100,00%	99,90%
Grapes Untrained	0	0	0	0	0	0	0	9991	0	232	0	0	0	1	1047	0	9991	11271	88,64%	90,98%	89,79%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6197	6	0	0	0	0	0	0	6197	6203	99,90%	99,57%	99,73%
Corn Senesced Green Weeds	0	0	12	0	0	0	0	2	27	3232	3	2	0	0	0	0	3232	3278	98,60%	91,20%	94,75%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	99,72%	99,86%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	99,90%	99,95%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	914	2	0	0	914	916	99,78%	100,00%	99,89%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	0	0	0	0	1070	0	0	1070	1070	100,00%	99,72%	99,86%
Vinyard Untrained	0	0	0	0	0	0	0	984	0	57	0	0	0	0	6224	3	6224	7268	85,64%	85,60%	85,62%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	1798	1798	1807	99,50%	99,78%	99,64%
																					95,53%

Table 109 SSC - SVM-LNR - Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,95%	99,97%
Fallow Rough Plow	0	0	0	1392	2	0	0	0	0	0	0	0	0	0	0	0	1392	1394	99,86%	99,64%	99,75%
Fallow Smooth	0	0	0	5	2673	0	0	0	0	0	0	0	0	0	0	0	2673	2678	99,81%	99,89%	99,85%
Stubble	0	0	0	0	0	3959	0	0	0	0	0	0	0	0	0	0	3959	3959	100,00%	100,00%	100,00%
Celery	0	0	0	0	1	0	3578	0	0	0	0	0	0	0	0	0	3578	3579	99,97%	100,00%	99,99%
Grapes Untrained	0	0	0	0	0	0	0	10073	0	58	0	0	0	3	1137	0	10073	11271	89,37%	86,96%	88,15%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6202	1	0	0	0	0	0	0	6202	6203	99,98%	99,76%	99,87%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	15	3244	0	0	0	14	0	5	3244	3278	98,96%	98,18%	98,57%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	100,00%	100,00%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	100,00%	100,00%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	100,00%	99,95%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	0	0	0	1069	0	0	1069	1070	99,91%	98,34%	99,12%
Vinyard Untrained	0	0	1	0	0	0	0	1510	0	0	0	0	0	0	5756	1	5756	7268	79,20%	83,51%	81,29%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1807	1807	1807	100,00%	99,67%	99,83%
																					94,91%

Table 110 SSC - K-NN - Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3718	0	0	0	0	2	0	0	0	0	0	0	6	0	0	3718	3726	99,79%	100,00%	99,89%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,65%	99,82%
Fallow Rough Plow	0	0	0	1392	2	0	0	0	0	0	0	0	0	0	0	0	1392	1394	99,86%	99,57%	99,71%
Fallow Smooth	0	0	6	5	2664	0	0	0	0	0	3	0	0	0	0	0	2664	2678	99,48%	99,89%	99,68%
Stubble	0	0	0	0	0	3959	0	0	0	0	0	0	0	0	0	0	3959	3959	100,00%	99,97%	99,99%
Celery	0	0	0	0	1	0	3577	0	0	0	0	0	0	1	0	0	3577	3579	99,94%	99,94%	99,94%
Grapes Untrained	0	0	0	0	0	1	0	9737	0	162	12	0	0	7	1350	2	9737	11271	86,39%	91,89%	89,06%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6192	4	3	0	0	4	0	0	6192	6203	99,82%	99,74%	99,78%
Corn Senesced Green Weeds	0	0	1	0	0	0	0	1	16	3243	7	2	0	5	2	1	3243	3278	98,93%	94,44%	96,63%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	97,71%	98,84%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	99,90%	99,95%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	916	0	0	0	916	916	100,00%	100,00%	100,00%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	0	0	0	0	1070	0	0	1070	1070	100,00%	97,90%	98,94%
Vinyard Untrained	0	0	0	0	0	0	0	858	0	24	0	0	0	0	6385	1	6385	7268	87,85%	82,53%	85,10%
Vinyard Vertical Trellis	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1805	1805	1807	99,89%	99,78%	99,83%
																					95,40%

Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

Table 111 SSC - ML - Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	99,10%	99,07%
Stubble	0	0	0	0	2	3952	4	1	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	0	0	0	2	0	3572	4	0	0	0	0	0	0	0	1	3572	3579	99,80%	99,89%	99,85%
Grapes Untrained	0	0	0	0	1	0	0	11128	0	142	0	0	0	0	0	0	11128	11271	98,73%	99,96%	99,34%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6200	3	0	0	0	0	0	0	6200	6203	99,95%	100,00%	99,98%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	0	3278	0	0	0	0	0	0	3278	3278	100,00%	94,74%	97,30%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	100,00%	96,81%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	21	0	0	0	1049	0	0	1049	1070	98,04%	98,04%	98,04%
Vinyard Untrained	0	0	0	0	7	0	0	0	0	1	0	0	0	0	7260	0	7260	7268	99,89%	100,00%	99,94%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	1792	1792	1807	99,17%	99,94%	99,56%
																					99,39%

Table 112 SSC - SVM-RBF - Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	99,10%	99,07%
Stubble	0	0	0	0	2	3952	4	1	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	0	0	0	2	0	3572	5	0	0	0	0	0	0	0	0	3572	3579	99,80%	99,89%	99,85%
Grapes Untrained	0	0	0	0	1	0	0	11188	0	82	0	0	0	0	0	0	11188	11271	99,26%	99,67%	99,47%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6200	3	0	0	0	0	0	0	6200	6203	99,95%	99,47%	99,71%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	33	3244	1	0	0	0	0	0	3244	3278	98,96%	95,86%	97,39%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	97,95%	95,84%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	20	0	0	1049	0	0	1049	1070	98,04%	98,04%	98,04%
Vinyard Untrained	0	0	0	0	7	0	0	14	0	39	0	0	0	0	7208	0	7208	7268	99,17%	100,00%	99,59%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	17	0	15	0	0	0	0	0	1775	1775	1807	98,23%	100,00%	99,11%
																					99,31%

Table 113 SSC - SVM-LNR - Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	99,97%	99,99%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	98,96%	98,99%
Stubble	0	0	0	0	2	3952	5	0	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,72%	99,77%
Celery	0	1	0	0	6	0	3572	0	0	0	0	0	0	0	0	0	3572	3579	99,80%	99,86%	99,83%
Grapes Untrained	0	0	0	0	1	10	0	11128	0	131	0	0	0	0	1	0	11128	11271	98,73%	100,00%	99,36%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6203	100,00%	99,50%	99,75%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	31	3246	1	0	0	0	0	0	3246	3278	99,02%	96,06%	97,52%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	97,95%	95,84%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	20	0	0	1049	0	0	1049	1070	98,04%	98,04%	98,04%
Vinyard Untrained	0	0	0	0	7	0	0	0	0	1	0	0	0	0	7260	0	7260	7268	99,89%	99,99%	99,94%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1807	1807	1807	100,00%	100,00%	100,00%
																					99,37%

Table 114 SSC - K-NN - Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	99,97%	99,99%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,75%	99,87%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	98,59%	98,81%
Stubble	0	0	0	0	2	3952	4	0	0	0	0	0	0	1	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	1	0	0	6	0	3572	0	0	0	0	0	0	0	0	0	3572	3579	99,80%	99,89%	99,85%
Grapes Untrained	0	0	0	0	11	0	0	11142	0	118	0	0	0	0	0	0	11142	11271	98,86%	100,00%	99,42%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6200	3	0	0	0	0	0	0	6200	6203	99,95%	99,55%	99,75%
Corn Senesced Green Weeds	0	0	5	0	0	0	0	0	28	3244	1	0	0	0	0	0	3244	3278	98,96%	96,35%	97,64%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	97,95%	95,84%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	20	0	0	1049	0	0	1049	1070	98,04%	97,95%	97,99%
Vinyard Untrained	0	0	0	0	7	0	0	0	0	1	0	0	0	0	7260	0	7260	7268	99,89%	100,00%	99,94%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1807	1807	1807	100,00%	100,00%	100,00%
																					99,38%

Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

Table 115 SSC - ML - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1391	3	0	0	0	0	0	0	0	0	0	0	0	1391	1394	99,78%	99,36%	99,57%
Fallow Smooth	0	0	0	9	2666	2	0	0	0	0	0	0	0	0	1	0	2666	2678	99,55%	99,89%	99,72%
Stubble	0	0	0	0	0	3959	0	0	0	0	0	0	0	0	0	0	3959	3959	100,00%	99,95%	99,97%
Celery	0	0	0	0	0	0	3576	1	0	1	0	0	0	0	1	0	3576	3579	99,92%	100,00%	99,96%
Grapes Untrained	0	0	0	0	0	0	0	9846	0	34	0	0	0	0	1391	0	9846	11271	87,36%	88,94%	88,14%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6196	7	0	0	0	0	0	0	6196	6203	99,89%	99,65%	99,77%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	2	22	3254	0	0	0	0	0	0	3254	3278	99,27%	98,67%	98,97%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	100,00%	100,00%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	100,00%	100,00%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	100,00%	99,95%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	0	0	0	1069	0	0	1069	1070	99,91%	99,91%	99,91%
Vinyard Untrained	0	0	0	0	0	0	0	1222	0	0	0	0	0	0	6046	0	6046	7268	83,19%	81,27%	82,22%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1806	1806	1807	99,94%	100,00%	99,97%
																					95,01%

Table 116 SSC - SVM-RBF - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1391	2	0	0	1	0	0	0	0	0	0	0	0	1391	1394	99,78%	99,57%	99,68%
Fallow Smooth	0	0	0	6	2672	0	0	0	0	0	0	0	0	0	0	0	2672	2678	99,78%	99,89%	99,83%
Stubble	0	0	0	0	0	3959	0	0	0	0	0	0	0	0	0	0	3959	3959	100,00%	100,00%	100,00%
Celery	0	0	0	0	0	0	3568	0	0	1	0	0	0	0	0	10	3568	3579	99,69%	100,00%	99,85%
Grapes Untrained	0	0	0	0	0	0	0	10288	0	56	0	0	0	0	927	0	10288	11271	91,28%	91,74%	91,51%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6199	1	0	0	0	3	0	0	6199	6203	99,94%	99,60%	99,77%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	25	3248	1	0	0	0	0	4	3248	3278	99,08%	97,63%	98,35%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1067	1	0	0	0	0	1067	1068	99,91%	99,91%	99,91%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	99,95%	99,97%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	914	2	0	0	914	916	99,78%	100,00%	99,89%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	6	0	0	0	1064	0	0	1064	1070	99,44%	99,53%	99,49%
Vinyard Untrained	0	0	0	0	1	0	0	925	0	11	0	0	0	0	6319	12	6319	7268	86,94%	87,21%	87,07%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	1803	1803	1807	99,78%	98,58%	99,17%
																					96,31%

Table 117 SSC - SVM-LNR - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1392	2	0	0	0	0	0	0	0	0	0	0	0	1392	1394	99,86%	99,36%	99,61%
Fallow Smooth	0	0	0	9	2669	0	0	0	0	0	0	0	0	0	0	0	2669	2678	99,66%	99,63%	99,65%
Stubble	0	0	0	0	0	3958	0	0	0	1	0	0	0	0	0	0	3958	3959	99,97%	100,00%	99,99%
Celery	0	0	0	0	1	0	3578	0	0	0	0	0	0	0	0	0	3578	3579	99,97%	100,00%	99,99%
Grapes Untrained	0	0	0	0	0	0	0	9570	0	23	0	0	0	0	1678	0	9570	11271	84,91%	89,56%	87,17%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6202	1	0	0	0	0	0	0	6202	6203	99,98%	99,73%	99,86%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	17	3234	0	3	0	24	0	0	3234	3278	98,66%	98,99%	98,82%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	100,00%	100,00%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	99,84%	99,92%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	914	2	0	0	914	916	99,78%	100,00%	99,89%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	3	0	0	0	1067	0	0	1067	1070	99,72%	97,62%	98,66%
Vinyard Untrained	0	0	0	0	7	0	0	1116	0	0	0	0	0	0	6145	0	6145	7268	84,55%	78,55%	81,44%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	1802	1802	1807	99,72%	100,00%	99,86%
																					94,66%

Table 118 SSC - K-NN - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2007	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2007	2010	99,90%	100,00%	99,95%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3727	100,00%	99,89%	99,95%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1977	100,00%	97,97%	98,97%
Fallow Rough Plow	0	0	0	1390	4	0	0	0	0	0	0	0	0	0	0	0	1390	1395	99,71%	99,14%	99,43%
Fallow Smooth	0	0	11	12	2654	1	0	0	0	0	0	0	0	0	0	0	2654	2679	99,10%	99,85%	99,48%
Stubble	0	0	0	0	0	3959	0	0	0	0	0	0	0	0	0	0	3959	3960	100,00%	99,92%	99,96%
Celery	0	0	0	0	0	1	3577	0	0	0	0	0	0	1	0	0	3577	3580	99,94%	100,00%	99,97%
Grapes Untrained	0	0	0	0	0	1	0	9224	4	241	26	0	0	14	1753	8	9224	11272	81,84%	87,73%	84,68%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6168	9	26	0	0	0	0	0	6168	6204	99,44%	99,55%	99,49%
Corn Senesced Green Weeds	0	0	30	0	0	0	0	0	24	3172	40	3	0	1	2	6	3172	3279	96,77%	92,26%	94,46%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1069	100,00%	92,07%	95,87%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1928	100,00%	99,84%	99,92%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	916	0	0	0	916	917	100,00%	100,00%	100,00%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	3	0	0	0	1067	0	0	1067	1071	99,72%	98,52%	99,12%
Vinyard Untrained	0	0	0	0	0	0	0	1290	0	13	0	0	0	0	5962	3	5962	7269	82,03%	77,26%	79,57%
Vinyard Vertical Trellis	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1805	1805	1808	99,89%	99,07%	99,48%
																					93,45%

Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

Table 119 SSC - ML - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	99,10%	99,07%
Stubble	0	0	0	0	2	3952	4	1	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	0	0	0	2	0	3572	4	0	0	0	0	0	0	0	1	3572	3579	99,80%	99,89%	99,85%
Grapes Untrained	0	0	0	0	1	0	0	11223	0	47	0	0	0	0	0	0	11223	11271	99,57%	99,49%	99,53%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6203	100,00%	99,50%	99,75%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	31	3247	0	0	0	0	0	0	3247	3278	99,05%	97,51%	98,27%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	100,00%	96,81%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	21	0	0	0	1049	0	0	1049	1070	98,04%	98,04%	98,04%
Vinyard Untrained	0	0	0	0	7	0	0	53	0	0	0	0	0	0	7208	0	7208	7268	99,17%	100,00%	99,59%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	1792	1792	1807	99,17%	99,94%	99,56%
																					99,42%

Table 120 SSC - SVM-RBF - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	99,10%	99,07%
Stubble	0	0	0	0	2	3952	5	0	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	0	0	0	2	0	3572	0	0	0	0	0	0	0	0	5	3572	3579	99,80%	99,86%	99,83%
Grapes Untrained	0	0	0	0	1	0	0	11208	0	48	0	0	0	0	0	14	11208	11271	99,44%	99,99%	99,72%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6203	100,00%	99,42%	99,71%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	36	3242	0	0	0	0	0	0	3242	3278	98,90%	97,92%	98,41%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	100,00%	96,81%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	21	0	0	0	1049	0	0	1049	1070	98,04%	98,04%	98,04%
Vinyard Untrained	0	0	0	0	7	0	0	1	0	0	0	0	0	0	7246	14	7246	7268	99,70%	100,00%	99,85%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1807	1807	1807	100,00%	98,21%	99,10%
																					99,48%

Table 121 SSC - SVM-LNR - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,80%	99,90%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	99,10%	99,07%
Stubble	0	0	0	0	2	3952	5	0	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	0	4	0	2	0	3573	0	0	0	0	0	0	0	0	0	3573	3579	99,83%	99,86%	99,85%
Grapes Untrained	0	0	0	0	1	0	0	11222	0	48	0	0	0	0	0	0	11222	11271	99,57%	99,83%	99,70%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6203	100,00%	99,42%	99,71%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	18	36	3224	0	0	0	0	0	0	3224	3278	98,35%	97,90%	98,13%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	100,00%	96,81%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	21	0	0	0	1049	0	0	1049	1070	98,04%	98,04%	98,04%
Vinyard Untrained	0	0	0	0	7	0	0	1	0	0	0	0	0	0	7260	0	7260	7268	99,89%	100,00%	99,94%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1807	1807	1807	100,00%	100,00%	100,00%
																					99,50%

Table 122 SSC - K-NN - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2010	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3727	100,00%	99,97%	99,99%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1977	100,00%	99,75%	99,87%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1395	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2679	99,03%	98,55%	98,79%
Stubble	0	0	0	0	2	3952	4	0	0	0	0	0	0	1	0	0	3952	3960	99,82%	99,97%	99,90%
Celery	0	1	0	0	6	0	3572	0	0	0	0	0	0	0	0	0	3572	3580	99,80%	99,89%	99,85%
Grapes Untrained	0	0	0	0	12	0	0	11151	0	108	0	0	0	0	0	0	11151	11272	98,94%	100,00%	99,46%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6200	3	0	0	0	0	0	0	6200	6204	99,95%	99,55%	99,75%
Corn Senesced Green Weeds	0	0	5	0	0	0	0	0	28	3244	1	0	0	0	0	0	3244	3279	98,96%	96,63%	97,78%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1069	93,82%	97,95%	95,84%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1928	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	917	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	20	0	0	1049	0	0	1049	1071	98,04%	97,95%	97,99%
Vinyard Untrained	0	0	0	0	7	0	0	0	0	1	0	0	0	0	7246	14	7246	7269	99,70%	100,00%	99,85%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1807	1807	1808	100,00%	99,23%	99,61%
																					99,34%

Uniformly Selected N Sample without Pre-Processing or Post Processing

Table 123 SSC - ML - Uniformly Selected N Sample without Pre-Processing or Post Processing

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2004	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2004	2009	99,75%	99,95%	99,85%
Brocoli Green Weeds 2	1	3718	0	0	0	0	0	0	0	4	0	0	0	3	0	0	3718	3726	99,79%	99,87%	99,83%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,10%	99,55%
Fallow Rough Plow	0	0	0	1394	0	0	0	0	0	0	0	0	0	0	0	0	1394	1394	100,00%	99,43%	99,71%
Fallow Smooth	0	0	18	8	2650	1	0	0	0	1	0	0	0	0	0	0	2650	2678	98,95%	99,96%	99,46%
Stubble	0	0	0	0	0	3958	0	1	0	0	0	0	0	0	0	0	3958	3959	99,97%	99,97%	99,97%
Celery	0	0	0	0	0	0	3573	2	0	4	0	0	0	0	0	0	3573	3579	99,83%	100,00%	99,92%
Grapes Untrained	0	0	0	0	0	0	0	8157	0	53	0	0	0	0	3061	0	8157	11271	72,37%	79,41%	75,73%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6144	59	0	0	0	0	0	0	6144	6203	99,05%	99,77%	99,41%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	1	14	3262	0	1	0	0	0	0	3262	3278	99,51%	95,58%	97,50%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	100,00%	100,00%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	4	0	1923	0	0	0	0	1923	1927	99,79%	99,95%	99,87%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	913	3	0	0	913	916	99,67%	100,00%	99,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	4	0	0	0	1066	0	0	1066	1070	99,63%	99,44%	99,53%
Vinyard Untrained	0	0	0	0	1	0	0	2111	0	14	0	0	0	0	5142	0	5142	7268	70,75%	62,68%	66,47%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	1799	1799	1807	99,56%	100,00%	99,78%
																					90,06%

Table 124 SSC - SVM-RBF - Uniformly Selected N Sample without Pre-Processing or Post Processing

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2001	7	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2001	2009	99,60%	100,00%	99,80%
Brocoli Green Weeds 2	0	3722	0	0	0	0	0	2	0	0	0	0	0	0	0	2	3722	3726	99,89%	99,81%	99,85%
Fallow	0	0	1971	0	1	0	0	0	0	4	0	0	0	0	0	0	1971	1976	99,75%	98,55%	99,14%
Fallow Rough Plow	0	0	0	1389	5	0	0	0	0	0	0	0	0	0	0	0	1389	1394	99,64%	98,93%	99,29%
Fallow Smooth	0	0	0	14	2659	0	0	0	0	5	0	0	0	0	0	0	2659	2678	99,29%	99,59%	99,44%
Stubble	0	0	0	0	1	3954	0	0	0	4	0	0	0	0	0	0	3954	3959	99,87%	100,00%	99,94%
Celery	0	0	0	0	1	0	3563	9	0	0	0	0	0	3	0	3	3563	3579	99,55%	100,00%	99,78%
Grapes Untrained	0	0	0	0	0	0	0	9309	0	232	2	0	0	3	1718	7	9309	11271	82,59%	85,88%	84,21%
Soil Vinyard Develop	0	0	0	0	0	0	0	4	6179	19	0	0	0	1	0	0	6179	6203	99,61%	99,56%	99,59%
Corn Senesced Green Weeds	0	0	29	1	3	0	0	6	27	3162	27	12	0	3	6	2	3162	3278	96,46%	90,09%	93,16%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	97,36%	98,66%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	2	0	1925	0	0	0	0	1925	1927	99,90%	99,38%	99,64%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	912	4	0	0	912	916	99,56%	100,00%	99,78%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	1	0	7	0	0	0	1061	1	0	1061	1070	99,16%	98,70%	98,93%
Vinyard Untrained	0	0	0	0	0	0	0	1506	0	66	0	0	0	0	5686	10	5686	7268	78,23%	76,69%	77,46%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	2	0	9	0	0	0	0	3	1793	1793	1807	99,23%	98,62%	98,92%
																					93,03%

Table 125 SSC - SVM-LNR - Uniformly Selected N Sample without Pre-Processing or Post Processing

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2008	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2008	2009	99,95%	100,00%	99,98%
Brocoli Green Weeds 2	0	3725	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3725	3726	99,97%	99,97%	99,97%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,80%	99,90%
Fallow Rough Plow	0	0	2	1387	5	0	0	0	0	0	0	0	0	0	0	0	1387	1394	99,50%	99,71%	99,61%
Fallow Smooth	0	0	2	4	2670	1	0	0	0	0	1	0	0	0	0	0	2670	2678	99,70%	99,70%	99,70%
Stubble	0	0	0	0	1	3958	0	0	0	0	0	0	0	0	0	0	3958	3959	99,97%	99,97%	99,97%
Celery	0	0	0	0	0	0	3578	0	0	0	0	0	0	0	0	1	3578	3579	99,97%	99,97%	99,97%
Grapes Untrained	0	0	0	0	0	0	0	9294	0	60	0	0	0	0	1917	0	9294	11271	82,46%	84,29%	83,37%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6188	11	0	1	0	3	0	0	6188	6203	99,76%	99,66%	99,71%
Corn Senesced Green Weeds	0	0	0	0	1	0	0	0	21	3229	0	7	0	18	2	0	3229	3278	98,51%	97,52%	98,01%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	99,81%	99,91%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	1	1926	0	0	0	0	1926	1927	99,95%	99,59%	99,77%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	916	0	0	0	916	916	100,00%	100,00%	100,00%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	9	0	0	0	1061	0	0	1061	1070	99,16%	98,06%	98,61%
Vinyard Untrained	0	0	0	0	1	0	0	1732	0	0	0	0	0	0	5532	3	5532	7268	76,11%	74,25%	75,17%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1805	1805	1807	99,89%	99,78%	99,83%
																					92,96%

Table 126 SSC - K-NN - Uniformly Selected N Sample without Pre-Processing or Post Processing

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2002	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2002	2009	99,65%	100,00%	99,83%
Brocoli Green Weeds 2	0	3719	0	0	0	0	0	0	0	0	0	0	0	5	0	2	3719	3726	99,81%	99,81%	99,81%
Fallow	0	0	1972	0	2	0	0	0	0	2	0	0	0	0	0	0	1972	1976	99,80%	98,06%	98,92%
Fallow Rough Plow	0	0	0	1393	1	0	0	0	0	0	0	0	0	0	0	0	1393	1394	99,93%	99,36%	99,64%
Fallow Smooth	0	0	23	9	2642	1	0	0	2	1	0	0	0	0	0	0	2642	2678	98,66%	99,70%	99,17%
Stubble	0	0	0	0	2	3956	0	0	0	1	0	0	0	0	0	0	3956	3959	99,92%	99,92%	99,92%
Celery	0	0	0	0	1	0	3567	0	0	0	0	0	2	6	1	2	3567	3579	99,66%	99,94%	99,80%
Grapes Untrained	0	0	0	0	0	2	2	8147	9	182	12	1	1	16	2891	8	8147	11271	72,28%	83,18%	77,35%
Soil Vinyard Develop	0	0	0	0	0	0	0	1	6143	27	30	0	0	2	0	0	6143	6203	99,03%	99,53%	99,28%
Corn Senesced Green Weeds	0	0	16	0	1	0	0	9	17	3181	34	5	0	2	4	9	3181	3278	97,04%	92,34%	94,63%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	93,36%	96,56%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	99,69%	99,84%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	99,67%	99,78%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	2	1	0	0	0	0	1067	0	0	1067	1070	99,72%	96,74%	98,21%
Vinyard Untrained	0	0	0	0	0	0	0	1636	0	51	0	0	0	4	5546	31	5546	7268	76,31%	65,69%	70,60%
Vinyard Vertical Trellis	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1805	1805	1807	99,89%	97,20%	98,53%
																					90,62%

Uniformly Selected N Sample with Pre-Processing (PCA)

Table 127 SSC – ML - Uniformly Selected N Sample with Pre-Processing (PCA)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2003	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2003	2010	99,70%	100,00%	99,85%
Brocoli Green Weeds 2	0	3725	0	0	0	0	0	0	0	0	0	0	0	1	0	0	3725	3727	99,97%	99,84%	99,91%
Fallow	0	0	1971	0	0	0	0	0	0	5	0	0	0	0	0	0	1971	1977	99,75%	99,70%	99,72%
Fallow Rough Plow	0	0	1	1389	4	0	0	0	0	0	0	0	0	0	0	0	1389	1395	99,64%	99,14%	99,39%
Fallow Smooth	0	0	5	12	2656	1	0	0	0	2	0	0	0	0	0	2	2656	2679	99,18%	99,85%	99,51%
Stubble	0	0	0	0	0	3959	0	0	0	0	0	0	0	0	0	0	3959	3960	100,00%	99,97%	99,99%
Celery	0	0	0	0	0	0	3570	0	0	5	0	0	0	0	0	4	3570	3580	99,75%	100,00%	99,87%
Grapes Untrained	0	0	0	0	0	0	0	9161	0	90	0	0	0	0	2020	0	9161	11272	81,28%	87,21%	84,14%
Soil Vinyard Develop	0	0	0	0	0	0	0	4	6140	57	1	0	0	1	0	0	6140	6204	98,98%	99,66%	99,32%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	8	21	3239	2	2	0	3	1	2	3239	3279	98,81%	94,18%	96,44%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1069	100,00%	99,72%	99,86%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	2	0	1925	0	0	0	0	1925	1928	99,90%	99,90%	99,90%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	908	8	0	0	908	917	99,13%	100,00%	99,56%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	11	0	0	0	1059	0	0	1059	1071	98,97%	98,79%	98,88%
Vinyard Untrained	0	0	0	0	0	0	0	1331	0	18	0	0	0	0	5919	0	5919	7269	81,44%	74,55%	77,84%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	1797	1797	1808	99,45%	99,56%	99,50%
																					93,25%

Table 128 SSC – SVM-RBF - Uniformly Selected N Sample with Pre-Processing (PCA)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2010	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3727	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1977	100,00%	99,90%	99,95%
Fallow Rough Plow	0	0	0	1390	4	0	0	0	0	0	0	0	0	0	0	0	1390	1395	99,71%	99,43%	99,57%
Fallow Smooth	0	0	2	8	2668	0	0	0	0	0	0	0	0	0	0	0	2668	2679	99,63%	99,22%	99,42%
Stubble	0	0	0	0	2	3956	0	0	0	1	0	0	0	0	0	0	3956	3960	99,92%	100,00%	99,96%
Celery	0	0	0	0	1	0	3578	0	0	0	0	0	0	0	0	0	3578	3580	99,97%	100,00%	99,99%
Grapes Untrained	0	0	0	0	0	0	0	9417	0	23	0	0	0	1	1830	0	9417	11272	83,55%	83,48%	83,52%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6187	15	1	0	0	0	0	0	6187	6204	99,74%	99,69%	99,72%
Corn Senesced Green Weeds	0	0	0	0	3	0	0	1	19	3221	3	12	0	15	2	2	3221	3279	98,26%	98,53%	98,40%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	2	1066	0	0	0	0	0	1066	1069	99,81%	99,63%	99,72%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1928	100,00%	99,38%	99,69%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	917	99,89%	99,89%	99,89%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	4	0	0	1	1065	0	0	1065	1071	99,53%	98,34%	98,93%
Vinyard Untrained	0	0	0	0	11	0	0	1862	0	2	0	0	0	0	5393	0	5393	7269	74,20%	74,64%	74,42%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1805	1805	1808	99,89%	99,89%	99,89%
																					92,90%

Table 129 SSC – SVM-LNR - Uniformly Selected N Sample with Pre-Processing (PCA)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2010	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3727	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1977	100,00%	99,90%	99,95%
Fallow Rough Plow	0	0	0	1390	4	0	0	0	0	0	0	0	0	0	0	0	1390	1395	99,71%	99,43%	99,57%
Fallow Smooth	0	0	2	8	2668	0	0	0	0	0	0	0	0	0	0	0	2668	2679	99,63%	99,22%	99,42%
Stubble	0	0	0	0	2	3956	0	0	0	1	0	0	0	0	0	0	3956	3960	99,92%	100,00%	99,96%
Celery	0	0	0	0	1	0	3578	0	0	0	0	0	0	0	0	0	3578	3580	99,97%	100,00%	99,99%
Grapes Untrained	0	0	0	0	0	0	0	9417	0	23	0	0	0	1	1830	0	9417	11272	83,55%	83,48%	83,52%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6187	15	1	0	0	0	0	0	6187	6204	99,74%	99,69%	99,72%
Corn Senesced Green Weeds	0	0	0	0	3	0	0	1	19	3221	3	12	0	15	2	2	3221	3279	98,26%	98,53%	98,40%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	2	1066	0	0	0	0	0	1066	1069	99,81%	99,63%	99,72%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1928	100,00%	99,38%	99,69%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	917	99,89%	99,89%	99,89%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	4	0	0	1	1065	0	0	1065	1071	99,53%	98,34%	98,93%
Vinyard Untrained	0	0	0	0	11	0	0	1862	0	2	0	0	0	0	5393	0	5393	7269	74,20%	74,64%	74,42%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1805	1805	1808	99,89%	99,89%	99,89%
																					92,90%

Table 130 SSC – K-NN - Uniformly Selected N Sample with Pre-Processing (PCA)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2000	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2000	2010	99,55%	100,00%	99,78%
Brocoli Green Weeds 2	0	3717	0	0	0	0	0	0	0	0	0	0	0	9	0	0	3717	3727	99,76%	99,70%	99,73%
Fallow	0	0	1969	0	6	0	0	0	0	0	1	0	0	0	0	0	1969	1977	99,65%	96,52%	98,06%
Fallow Rough Plow	0	0	0	1388	6	0	0	0	0	0	0	0	0	0	0	0	1388	1395	99,57%	98,86%	99,21%
Fallow Smooth	0	0	30	16	2626	0	0	0	2	0	3	0	0	1	0	0	2626	2679	98,06%	99,09%	98,57%
Stubble	0	0	0	0	2	3952	0	0	0	0	0	0	0	5	0	0	3952	3960	99,82%	99,87%	99,85%
Celery	0	0	0	0	1	0	3552	1	0	0	0	0	2	8	4	11	3552	3580	99,25%	99,36%	99,30%
Grapes Untrained	0	0	0	0	0	2	19	7760	5	219	14	1	2	16	3230	3	7760	11272	68,85%	78,10%	73,18%
Soil Vinyard Develop	0	0	0	0	0	0	0	12	6082	28	59	0	0	22	0	0	6082	6204	98,05%	99,38%	98,71%
Corn Senesced Green Weeds	0	1	40	0	5	3	0	27	28	3091	41	15	0	12	8	7	3091	3279	94,30%	90,41%	92,31%
Lettuce Romaine 4wk	0	0	0	0	1	0	0	0	0	2	1064	1	0	0	0	0	1064	1069	99,63%	90,02%	94,58%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	2	0	1925	0	0	0	0	1925	1928	99,90%	99,02%	99,46%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	913	3	0	0	913	917	99,67%	98,70%	99,19%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	2	2	2	0	0	8	1054	2	0	1054	1071	98,50%	92,95%	95,64%
Vinyard Untrained	0	0	1	0	1	0	2	2134	1	68	0	2	0	4	5029	26	5029	7269	69,19%	60,77%	64,71%
Vinyard Vertical Trellis	0	1	0	0	2	0	2	0	0	7	0	0	0	0	2	1793	1793	1808	99,23%	97,45%	98,33%
																					88,49%

Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

Table 131 SSC - ML - Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1393	1	0	0	0	0	0	0	0	0	0	0	0	1393	1394	99,93%	99,43%	99,68%
Fallow Smooth	0	0	0	8	2668	2	0	0	0	0	0	0	0	0	0	0	2668	2678	99,63%	99,93%	99,78%
Stubble	0	0	0	0	0	3959	0	0	0	0	0	0	0	0	0	0	3959	3959	100,00%	99,95%	99,97%
Celery	0	0	0	0	0	0	3574	0	0	5	0	0	0	0	0	0	3574	3579	99,86%	100,00%	99,93%
Grapes Untrained	0	0	0	0	0	0	0	9693	0	53	0	0	0	0	1525	0	9693	11271	86,00%	90,50%	88,19%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6162	41	0	0	0	0	0	0	6162	6203	99,34%	99,77%	99,56%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	14	3264	0	0	0	0	0	0	3264	3278	99,57%	96,57%	98,05%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	100,00%	100,00%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	100,00%	100,00%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	100,00%	99,95%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	2	0	0	0	1068	0	0	1068	1070	99,81%	99,91%	99,86%
Vinyard Untrained	0	0	0	0	1	0	0	1018	0	8	0	0	0	0	6241	0	6241	7268	85,87%	80,36%	83,03%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	1800	1800	1807	99,61%	100,00%	99,81%
																					95,04%

Table 132 SSC - SVM-RBF - Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,05%	99,52%
Fallow Rough Plow	0	0	0	1390	2	0	0	0	0	2	0	0	0	0	0	0	1390	1394	99,71%	99,21%	99,46%
Fallow Smooth	0	0	0	11	2661	1	0	0	0	5	0	0	0	0	0	0	2661	2678	99,37%	99,89%	99,63%
Stubble	0	0	0	0	0	3958	0	0	0	1	0	0	0	0	0	0	3958	3959	99,97%	99,97%	99,97%
Celery	0	0	0	0	1	0	3568	9	0	1	0	0	0	0	0	0	3568	3579	99,69%	100,00%	99,85%
Grapes Untrained	0	0	0	0	0	0	0	10055	0	191	0	0	0	0	1025	0	10055	11271	89,21%	91,19%	90,19%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6184	17	2	0	0	0	0	0	6184	6203	99,69%	99,58%	99,64%
Corn Senesced Green Weeds	0	0	19	0	0	0	0	0	26	3219	5	9	0	0	0	0	3219	3278	98,20%	92,82%	95,43%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	99,35%	99,67%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	99,54%	99,77%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	100,00%	99,95%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	0	0	0	1069	0	0	1069	1070	99,91%	99,91%	99,91%
Vinyard Untrained	0	0	0	0	0	0	0	963	0	23	0	0	0	0	6275	7	6275	7268	86,34%	85,96%	86,15%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	1799	1799	1807	99,56%	99,61%	99,58%
																					95,70%

Table 133 SSC - SVM-LNR - Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,95%	99,97%
Fallow Rough Plow	0	0	0	1390	4	0	0	0	0	0	0	0	0	0	0	0	1390	1394	99,71%	99,78%	99,75%
Fallow Smooth	0	0	0	3	2674	1	0	0	0	0	0	0	0	0	0	0	2674	2678	99,85%	99,85%	99,85%
Stubble	0	0	0	0	0	3959	0	0	0	0	0	0	0	0	0	0	3959	3959	100,00%	99,97%	99,99%
Celery	0	0	0	0	0	0	3579	0	0	0	0	0	0	0	0	0	3579	3579	100,00%	100,00%	100,00%
Grapes Untrained	0	0	0	0	0	0	0	9986	0	58	0	0	0	2	1225	0	9986	11271	88,60%	88,07%	88,33%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6203	100,00%	99,65%	99,82%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	22	3255	0	0	0	1	0	0	3255	3278	99,30%	97,14%	98,20%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	100,00%	100,00%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	100,00%	100,00%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	916	99,89%	100,00%	99,95%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	36	0	0	0	1034	0	0	1034	1070	96,64%	99,61%	98,10%
Vinyard Untrained	0	0	1	0	0	0	0	1353	0	1	0	0	0	0	5913	0	5913	7268	81,36%	82,84%	82,09%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1806	1806	1807	99,94%	100,00%	99,97%
																					95,00%

Table 134 SSC - K-NN - Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,60%	99,80%
Fallow Rough Plow	0	0	0	1393	1	0	0	0	0	0	0	0	0	0	0	0	1393	1394	99,93%	99,43%	99,68%
Fallow Smooth	0	0	1	8	2667	1	0	0	1	0	0	0	0	0	0	0	2667	2678	99,59%	99,89%	99,74%
Stubble	0	0	0	0	0	3959	0	0	0	0	0	0	0	0	0	0	3959	3959	100,00%	99,95%	99,97%
Celery	0	0	0	0	1	0	3574	1	0	0	0	0	0	2	0	1	3574	3579	99,86%	100,00%	99,93%
Grapes Untrained	0	0	0	0	0	1	0	9576	0	173	6	0	0	4	1507	4	9576	11271	84,96%	92,58%	88,61%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6195	2	6	0	0	0	0	0	6195	6203	99,87%	99,76%	99,81%
Corn Senesced Green Weeds	0	0	7	0	0	0	0	0	14	3251	5	0	0	1	0	0	3251	3278	99,18%	94,20%	96,63%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1068	100,00%	98,43%	99,21%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	100,00%	100,00%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	916	0	0	0	916	916	100,00%	100,00%	100,00%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	0	0	0	0	1070	0	0	1070	1070	100,00%	99,35%	99,67%
Vinyard Untrained	0	0	0	0	1	0	0	766	0	24	0	0	0	0	6477	0	6477	7268	89,12%	81,12%	84,93%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1806	1806	1807	99,94%	99,72%	99,83%
																					95,31%

Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

Table 135 SSC - ML - Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	99,10%	99,07%
Stubble	0	0	0	0	2	3952	4	1	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	0	0	0	2	0	3572	0	0	4	0	0	0	0	0	1	3572	3579	99,80%	99,89%	99,85%
Grapes Untrained	0	0	0	0	1	0	0	11128	0	142	0	0	0	0	0	0	11128	11271	98,73%	99,99%	99,36%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6200	3	0	0	0	0	0	0	6200	6203	99,95%	99,55%	99,75%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	28	3250	0	0	0	0	0	0	3250	3278	99,15%	94,59%	96,81%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	100,00%	96,81%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	21	0	0	0	1049	0	0	1049	1070	98,04%	98,04%	98,04%
Vinyard Untrained	0	0	0	0	7	0	0	0	0	1	0	0	0	0	7260	0	7260	7268	99,89%	100,00%	99,94%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	1792	1792	1807	99,17%	99,94%	99,56%
																					99,34%

Table 136 SSC - SVM-RBF - Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,75%	99,87%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	99,10%	99,07%
Stubble	0	0	0	0	2	3952	4	1	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	0	0	0	2	0	3572	0	0	4	0	0	0	0	0	1	3572	3579	99,80%	99,89%	99,85%
Grapes Untrained	0	0	0	0	1	0	0	11143	0	127	0	0	0	0	0	0	11143	11271	98,86%	99,99%	99,42%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6200	3	0	0	0	0	0	0	6200	6203	99,95%	99,55%	99,75%
Corn Senesced Green Weeds	0	0	5	0	0	0	0	0	28	3244	1	0	0	0	0	0	3244	3278	98,96%	95,16%	97,02%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	97,95%	95,84%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	20	0	0	1049	0	0	1049	1070	98,04%	98,04%	98,04%
Vinyard Untrained	0	0	0	0	7	0	0	0	0	15	0	0	0	0	7246	0	7246	7268	99,70%	100,00%	99,85%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	1792	1792	1807	99,17%	99,94%	99,56%
																					99,33%

Table 137 SSC - SVM-LNR - Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	99,97%	99,99%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	98,96%	98,99%
Stubble	0	0	0	0	2	3952	4	0	0	0	0	0	0	1	0	0	3952	3959	99,82%	99,72%	99,77%
Celery	0	1	0	0	6	0	3572	0	0	0	0	0	0	0	0	0	3572	3579	99,80%	99,89%	99,85%
Grapes Untrained	0	0	0	0	1	10	0	11088	0	131	0	0	0	0	41	0	11088	11271	98,38%	100,00%	99,18%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6203	100,00%	99,50%	99,75%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	31	3246	1	0	0	0	0	0	3246	3278	99,02%	96,06%	97,52%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	97,95%	95,84%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	20	0	0	1049	0	0	1049	1070	98,04%	97,95%	97,99%
Vinyard Untrained	0	0	0	0	7	0	0	0	0	1	0	0	0	0	7260	0	7260	7268	99,89%	99,44%	99,66%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1807	1807	1807	100,00%	100,00%	100,00%
																					99,29%

Table 138 SSC - K-NN - Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	99,97%	99,99%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	98,59%	98,81%
Stubble	0	0	0	0	2	3952	4	0	0	0	0	0	0	1	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	1	0	0	6	0	3572	0	0	0	0	0	0	0	0	0	3572	3579	99,80%	99,89%	99,85%
Grapes Untrained	0	0	0	0	11	0	0	11142	0	118	0	0	0	0	0	0	11142	11271	98,86%	100,00%	99,42%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6200	3	0	0	0	0	0	0	6200	6203	99,95%	99,47%	99,71%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	33	3244	1	0	0	0	0	0	3244	3278	98,96%	96,35%	97,64%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	97,95%	95,84%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	20	0	0	1049	0	0	1049	1070	98,04%	97,95%	97,99%
Vinyard Untrained	0	0	0	0	7	0	0	0	0	1	0	0	0	0	7260	0	7260	7268	99,89%	100,00%	99,94%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1807	1807	1807	100,00%	100,00%	100,00%
																					99,38%

Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

Table 139 SSC - ML - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2010	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3727	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1977	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1390	4	0	0	0	0	0	0	0	0	0	0	0	1390	1395	99,71%	99,29%	99,50%
Fallow Smooth	0	0	0	10	2664	1	0	0	0	2	0	0	0	0	1	0	2664	2679	99,48%	99,85%	99,66%
Stubble	0	0	0	0	0	3957	1	1	0	0	0	0	0	0	0	0	3957	3960	99,95%	99,97%	99,96%
Celery	0	0	0	0	0	0	3577	0	0	2	0	0	0	0	0	0	3577	3580	99,94%	99,97%	99,96%
Grapes Untrained	0	0	0	0	0	0	0	10150	0	96	0	0	0	0	1025	0	10150	11272	90,05%	93,68%	91,83%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6156	47	0	0	0	0	0	0	6156	6204	99,24%	99,66%	99,45%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	21	3257	0	0	0	0	0	0	3257	3279	99,36%	95,07%	97,17%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1069	100,00%	100,00%	100,00%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1928	100,00%	100,00%	100,00%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	908	8	0	0	908	917	99,13%	100,00%	99,56%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	7	0	0	0	1063	0	0	1063	1071	99,35%	99,25%	99,30%
Vinyard Untrained	0	0	0	0	0	0	0	684	0	0	0	0	0	0	6584	0	6584	7269	90,59%	86,52%	88,51%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	1792	1792	1808	99,17%	100,00%	99,58%
																					96,42%

Table 140 SSC - SVM-RBF - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2010	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3727	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1977	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1392	2	0	0	0	0	0	0	0	0	0	0	0	1392	1395	99,86%	99,57%	99,71%
Fallow Smooth	0	0	0	6	2668	0	0	0	0	4	0	0	0	0	0	0	2668	2679	99,63%	99,93%	99,78%
Stubble	0	0	0	0	0	3956	0	0	0	1	0	0	0	0	0	2	3956	3960	99,92%	100,00%	99,96%
Celery	0	0	0	0	0	0	3575	0	0	2	0	0	0	0	1	1	3575	3580	99,89%	100,00%	99,94%
Grapes Untrained	0	0	0	0	0	0	0	10132	0	66	0	0	0	0	1073	0	10132	11272	89,89%	91,22%	90,55%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6202	1	0	0	0	0	0	0	6202	6204	99,98%	99,60%	99,79%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	25	3253	0	0	0	0	0	0	3253	3279	99,24%	97,34%	98,28%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1069	100,00%	100,00%	100,00%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1928	100,00%	100,00%	100,00%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	915	1	0	0	915	917	99,89%	100,00%	99,95%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	4	0	0	0	1066	0	0	1066	1071	99,63%	99,91%	99,77%
Vinyard Untrained	0	0	0	0	0	0	0	975	0	2	0	0	0	0	6281	10	6281	7269	86,42%	85,40%	85,91%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	1798	1798	1808	99,50%	99,28%	99,39%
																					95,93%

Table 141 SSC - SVM-LNR - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2010	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3727	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1977	100,00%	99,90%	99,95%
Fallow Rough Plow	0	0	0	1391	3	0	0	0	0	0	0	0	0	0	0	0	1391	1395	99,78%	99,64%	99,71%
Fallow Smooth	0	0	2	5	2671	0	0	0	0	0	0	0	0	0	0	0	2671	2679	99,74%	99,89%	99,81%
Stubble	0	0	0	0	0	3959	0	0	0	0	0	0	0	0	0	0	3959	3960	100,00%	100,00%	100,00%
Celery	0	0	0	0	0	0	3579	0	0	0	0	0	0	0	0	0	3579	3580	100,00%	100,00%	100,00%
Grapes Untrained	0	0	0	0	0	0	0	9901	3	42	0	0	0	2	1323	0	9901	11272	87,84%	86,88%	87,36%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6204	100,00%	99,66%	99,83%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	18	3254	0	0	0	6	0	0	3254	3279	99,27%	98,70%	98,98%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1068	0	0	0	0	0	1068	1069	100,00%	100,00%	100,00%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1928	100,00%	100,00%	100,00%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	916	0	0	0	916	917	100,00%	100,00%	100,00%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	0	0	0	1069	0	0	1069	1071	99,91%	99,26%	99,58%
Vinyard Untrained	0	0	0	0	0	0	0	1495	0	0	0	0	0	0	5773	0	5773	7269	79,43%	81,36%	80,38%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1807	1807	1808	100,00%	100,00%	100,00%
																					94,61%

Table 142 SSC – K-NN - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2008	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2008	2010	99,95%	100,00%	99,98%
Brocoli Green Weeds 2	0	3724	0	0	0	0	0	0	0	0	0	0	0	2	0	0	3724	3727	99,95%	99,97%	99,96%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1977	100,00%	97,34%	98,65%
Fallow Rough Plow	0	0	0	1393	1	0	0	0	0	0	0	0	0	0	0	0	1393	1395	99,93%	99,08%	99,50%
Fallow Smooth	0	0	17	13	2643	1	0	0	2	2	0	0	0	0	0	0	2643	2679	98,69%	99,92%	99,30%
Stubble	0	0	0	0	1	3956	0	0	0	0	0	0	0	2	0	0	3956	3960	99,92%	99,95%	99,94%
Celery	0	0	0	0	0	0	3576	0	0	0	0	0	1	1	1	0	3576	3580	99,92%	99,94%	99,93%
Grapes Untrained	0	0	0	0	0	1	0	9208	2	216	9	2	0	6	1824	3	9208	11272	81,70%	87,32%	84,42%
Soil Vinyard Develop	0	0	0	0	0	0	0	2	6172	21	7	0	0	1	0	0	6172	6204	99,50%	99,48%	99,49%
Corn Senesced Green Weeds	0	0	37	0	0	0	0	0	28	3196	4	10	0	0	0	3	3196	3279	97,50%	92,50%	94,94%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1066	2	0	0	0	0	1066	1069	99,81%	98,16%	98,98%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1928	100,00%	99,28%	99,64%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	912	4	0	0	912	917	99,56%	99,89%	99,73%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	3	0	0	0	1067	0	0	1067	1071	99,72%	98,52%	99,12%
Vinyard Untrained	0	0	0	0	0	0	0	1335	0	17	0	0	0	0	5867	49	5867	7269	80,72%	76,27%	78,44%
Vinyard Vertical Trellis	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	1805	1805	1808	99,89%	97,04%	98,45%
																					93,26%

Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

Table 143 SSC - ML - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	99,10%	99,07%
Stubble	0	0	0	0	2	3952	4	1	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	0	0	0	2	0	3572	0	0	4	0	0	0	0	0	1	3572	3579	99,80%	99,89%	99,85%
Grapes Untrained	0	0	0	0	1	0	0	11223	0	47	0	0	0	0	0	0	11223	11271	99,57%	99,98%	99,78%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6200	3	0	0	0	0	0	0	6200	6203	99,95%	99,55%	99,75%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	28	3249	1	0	0	0	0	0	3249	3278	99,12%	97,89%	98,50%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	97,95%	95,84%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	20	0	0	1049	0	0	1049	1070	98,04%	98,04%	98,04%
Vinyard Untrained	0	0	0	0	7	0	0	1	0	0	0	0	0	0	7260	0	7260	7268	99,89%	100,00%	99,94%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	1792	1792	1807	99,17%	99,94%	99,56%
																					99,51%

Table 144 SSC - SVM-RBF - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	99,10%	99,07%
Stubble	0	0	0	0	2	3952	5	0	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	0	0	0	2	0	3572	0	0	4	0	0	0	0	0	1	3572	3579	99,80%	99,86%	99,83%
Grapes Untrained	0	0	0	0	1	0	0	11222	0	48	0	0	0	0	0	0	11222	11271	99,57%	99,99%	99,78%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6203	100,00%	99,42%	99,71%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	36	3241	1	0	0	0	0	0	3241	3278	98,87%	96,83%	97,84%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	97,95%	95,84%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	20	0	0	1049	0	0	1049	1070	98,04%	98,04%	98,04%
Vinyard Untrained	0	0	0	0	7	0	0	1	0	38	0	0	0	0	7208	14	7208	7268	99,17%	100,00%	99,59%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	1792	1792	1807	99,17%	99,17%	99,17%
																					99,41%

Table 145 SSC - SVM-LNR - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3726	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3726	3726	100,00%	100,00%	100,00%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	100,00%	100,00%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	99,10%	99,07%
Stubble	0	0	0	0	2	3952	5	0	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	0	0	0	2	0	3573	0	0	0	0	0	0	0	4	0	3573	3579	99,83%	99,86%	99,85%
Grapes Untrained	0	0	0	0	1	0	0	11222	0	47	0	0	0	0	1	0	11222	11271	99,57%	99,99%	99,78%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6203	0	0	0	0	0	0	0	6203	6203	100,00%	99,42%	99,71%
Corn Senesced Green Weeds	0	0	0	0	0	0	0	0	36	3241	1	0	0	0	0	0	3241	3278	98,87%	98,09%	98,48%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	97,95%	95,84%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	20	0	0	1049	0	0	1049	1070	98,04%	98,04%	98,04%
Vinyard Untrained	0	0	0	0	7	0	0	1	0	0	0	0	0	0	7260	0	7260	7268	99,89%	99,93%	99,91%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	1792	1792	1807	99,17%	100,00%	99,58%
																					99,50%

Table 146 SSC – K-NN - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Brocoli Green Weeds 1	Brocoli Green Weeds 2	Fallow	Fallow Rough Plow	Fallow Smooth	Stubble	Celery	Grapes Untrained	Soil Vinyard Develop	Corn Senesced Green Weeds	Lettuce Romaine 4wk	Lettuce Romaine 5wk	Lettuce Romaine 6wk	Lettuce Romaine 7wk	Vinyard Untrained	Vinyard Vertical Trellis	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Brocoli Green Weeds 1	2009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2009	2009	100,00%	100,00%	100,00%
Brocoli Green Weeds 2	0	3713	0	0	0	0	0	0	0	0	0	0	0	13	0	0	3713	3726	99,65%	99,97%	99,81%
Fallow	0	0	1976	0	0	0	0	0	0	0	0	0	0	0	0	0	1976	1976	100,00%	99,75%	99,87%
Fallow Rough Plow	0	0	0	1382	12	0	0	0	0	0	0	0	0	0	0	0	1382	1394	99,14%	98,22%	98,68%
Fallow Smooth	0	0	0	25	2652	1	0	0	0	0	0	0	0	0	0	0	2652	2678	99,03%	99,10%	99,07%
Stubble	0	0	0	0	2	3952	5	0	0	0	0	0	0	0	0	0	3952	3959	99,82%	99,97%	99,90%
Celery	0	1	0	0	2	0	3572	0	0	0	0	0	0	4	0	0	3572	3579	99,80%	99,86%	99,83%
Grapes Untrained	0	0	0	0	1	0	0	11128	0	142	0	0	0	0	0	0	11128	11271	98,73%	100,00%	99,36%
Soil Vinyard Develop	0	0	0	0	0	0	0	0	6200	3	0	0	0	0	0	0	6200	6203	99,95%	99,55%	99,75%
Corn Senesced Green Weeds	0	0	5	0	0	0	0	0	28	3244	1	0	0	0	0	0	3244	3278	98,96%	95,66%	97,29%
Lettuce Romaine 4wk	0	0	0	0	0	0	0	0	0	0	1002	66	0	0	0	0	1002	1068	93,82%	97,95%	95,84%
Lettuce Romaine 5wk	0	0	0	0	0	0	0	0	0	0	0	1927	0	0	0	0	1927	1927	100,00%	96,69%	98,32%
Lettuce Romaine 6wk	0	0	0	0	0	0	0	0	0	0	0	0	895	21	0	0	895	916	97,71%	100,00%	98,84%
Lettuce Romaine 7wk	0	0	0	0	0	0	0	0	0	1	20	0	0	1049	0	0	1049	1070	98,04%	96,50%	97,26%
Vinyard Untrained	0	0	0	0	7	0	0	0	0	1	0	0	0	0	7246	14	7246	7268	99,70%	100,00%	99,85%
Vinyard Vertical Trellis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1807	1807	1807	100,00%	99,23%	99,61%
																					99,31%

APPENDIX-C: PAVIA UNIVERSITY SCENE RESULTS

First N Sample without Pre-Processing or Post Processing

Table 147 PUS - ML -First N Sample without Pre-Processing or Post Processing

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	4487	1	562	2	22	12	788	751	6	4487	6631	67,67%	95,55%	79,23%
Meadows	10	5281	1	8193	0	4186	0	978	0	5281	18649	28,32%	95,76%	43,71%
Gravel	2	0	2070	1	1	0	1	24	0	2070	2099	98,62%	46,70%	63,38%
Trees	0	0	0	3046	0	8	0	0	10	3046	3064	99,41%	26,73%	42,13%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	98,10%	99,04%
Bare Soil	172	233	1	154	0	3698	0	766	5	3698	5029	73,53%	46,76%	57,17%
Bitumen	14	0	27	0	0	0	1219	70	0	1219	1330	91,65%	60,65%	72,99%
Self-Blocking Bricks	7	0	1772	0	1	4	2	1896	0	1896	3682	51,49%	42,27%	46,43%
Shadows	4	0	0	0	2	0	0	0	941	941	947	99,37%	97,82%	98,59%
														56,07%

Table 148 PUS - SVM-RBF -First N Sample without Pre-Processing or Post Processing

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5427	1	146	0	10	11	695	339	2	5427	6631	81,84%	73,68%	77,55%
Meadows	457	6723	0	3134	0	8103	0	232	0	6723	18649	36,05%	91,57%	51,73%
Gravel	246	0	1751	0	0	2	28	72	0	1751	2099	83,42%	55,96%	66,99%
Trees	11	6	0	3040	1	5	0	0	1	3040	3064	99,22%	48,93%	65,54%
Painted Metal Sheets	1	0	0	0	1344	0	0	0	0	1344	1345	99,93%	98,68%	99,30%
Bare Soil	982	611	0	39	7	3199	0	191	0	3199	5029	63,61%	28,25%	39,13%
Bitumen	113	0	6	0	0	0	1199	12	0	1199	1330	90,15%	62,25%	73,65%
Self-Blocking Bricks	129	1	1226	0	0	2	4	2320	0	2320	3682	63,01%	73,28%	67,76%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,68%	99,84%
														60,66%

Table 149 PUS - SVM-LNR -First N Sample without Pre-Processing or Post Processing

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	2658	1	360	0	2	7	2763	838	2	2658	6631	40,08%	99,36%	57,12%
Meadows	0	8381	5	2532	0	6713	0	1018	0	8381	18649	44,94%	94,78%	60,97%
Gravel	0	0	2071	0	0	1	5	22	0	2071	2099	98,67%	46,47%	63,18%
Trees	0	57	0	2936	2	67	0	1	1	2936	3064	95,82%	53,28%	68,48%
Painted Metal Sheets	0	0	0	0	1342	1	2	0	0	1342	1345	99,78%	98,60%	99,19%
Bare Soil	0	403	0	43	15	3355	0	1213	0	3355	5029	66,71%	33,07%	44,22%
Bitumen	16	0	11	0	0	0	1290	13	0	1290	1330	96,99%	31,74%	47,83%
Self-Blocking Bricks	1	1	2010	0	0	2	4	1664	0	1664	3682	45,19%	34,89%	39,38%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,68%	99,84%
														57,61%

Table 150 PUS - K-NN -First N Sample without Pre-Processing or Post Processing

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5161	15	204	0	14	11	746	478	2	5161	6631	77,83%	76,15%	76,98%
Meadows	332	7095	0	2895	0	8059	0	268	0	7095	18649	38,04%	87,40%	53,01%
Gravel	231	0	1666	0	0	1	59	142	0	1666	2099	79,37%	56,65%	66,11%
Trees	6	6	0	3037	3	12	0	0	0	3037	3064	99,12%	50,96%	67,31%
Painted Metal Sheets	1	0	0	0	1344	0	0	0	0	1344	1345	99,93%	97,75%	98,82%
Bare Soil	771	1000	4	28	14	2950	0	262	0	2950	5029	58,66%	26,74%	36,73%
Bitumen	78	0	12	0	0	0	1232	8	0	1232	1330	92,63%	60,42%	73,14%
Self-Blocking Bricks	197	2	1055	0	0	0	2	2426	0	2426	3682	65,89%	67,69%	66,78%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,79%	99,89%
														60,45%

First N Sample with Pre-Processing (PCA)

Table 151 PUS – ML - First N Sample with Pre-Processing (PCA)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5684	0	139	1	17	18	507	264	1	5684	6631	85,72%	85,94%	85,83%
Meadows	236	6796	0	5001	0	6433	0	183	0	6796	18649	36,44%	95,14%	52,70%
Gravel	114	0	1833	0	1	2	1	148	0	1833	2099	87,33%	57,95%	69,67%
Trees	4	0	0	3045	0	14	0	0	1	3045	3064	99,38%	37,28%	54,22%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	98,10%	99,04%
Bare Soil	289	345	59	121	1	3657	0	556	1	3657	5029	72,72%	36,06%	48,21%
Bitumen	180	0	7	0	1	0	1132	10	0	1132	1330	85,11%	69,02%	76,23%
Self-Blocking Bricks	99	2	1125	0	0	18	0	2438	0	2438	3682	66,21%	67,74%	66,97%
Shadows	8	0	0	0	6	0	0	0	933	933	947	98,52%	99,68%	99,10%
														62,80%

Table 152 PUS – SVM-RBF - First N Sample with Pre-Processing (PCA)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5632	0	232	0	2	10	461	267	27	5632	6631	84,93%	90,56%	87,66%
Meadows	170	9137	1	1847	0	6635	0	859	0	9137	18649	48,99%	97,09%	65,12%
Gravel	43	0	1846	0	0	1	37	172	0	1846	2099	87,95%	56,37%	68,70%
Trees	10	44	0	2949	3	58	0	0	0	2949	3064	96,25%	61,16%	74,79%
Painted Metal Sheets	1	0	0	0	1344	0	0	0	0	1344	1345	99,93%	99,56%	99,74%
Bare Soil	212	228	71	26	0	3551	0	939	2	3551	5029	70,61%	34,59%	46,43%
Bitumen	109	0	8	0	0	0	1192	21	0	1192	1330	89,62%	70,24%	78,76%
Self-Blocking Bricks	42	2	1117	0	1	11	7	2502	0	2502	3682	67,95%	52,56%	59,28%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	97,03%	98,49%
														68,03%

Table 153 PUS – SVM-LNR - First N Sample with Pre-Processing (PCA)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	3277	44	1108	1	126	184	417	1457	17	3277	6631	49,42%	83,58%	62,11%
Meadows	21	13064	10	2143	0	3234	0	176	1	13064	18649	70,05%	89,91%	78,75%
Gravel	96	4	1317	0	0	6	4	671	1	1317	2099	62,74%	38,24%	47,52%
Trees	0	324	0	2708	0	15	0	0	17	2708	3064	88,38%	54,55%	67,46%
Painted Metal Sheets	0	0	0	0	1344	0	0	0	1	1344	1345	99,93%	78,18%	87,73%
Bare Soil	11	1067	10	42	0	3770	0	118	11	3770	5029	74,97%	51,57%	61,10%
Bitumen	284	2	147	0	2	5	671	219	0	671	1330	50,45%	60,89%	55,18%
Self-Blocking Bricks	203	25	850	0	0	97	10	2495	2	2495	3682	67,76%	48,58%	56,59%
Shadows	29	0	2	70	247	0	0	0	599	599	947	63,25%	92,30%	75,06%
														68,37%

Table 154 PUS – K-NN - First N Sample with Pre-Processing (PCA)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5164	15	205	0	14	11	747	473	2	5164	6631	77,88%	76,09%	76,97%
Meadows	333	7111	0	2896	0	8040	0	269	0	7111	18649	38,13%	87,47%	53,11%
Gravel	227	0	1666	0	0	1	64	141	0	1666	2099	79,37%	56,67%	66,12%
Trees	6	6	0	3037	3	12	0	0	0	3037	3064	99,12%	50,95%	67,30%
Painted Metal Sheets	1	0	0	0	1344	0	0	0	0	1344	1345	99,93%	97,75%	98,82%
Bare Soil	772	996	4	28	14	2953	0	262	0	2953	5029	58,72%	26,80%	36,81%
Bitumen	81	0	12	0	0	0	1229	8	0	1229	1330	92,41%	60,19%	72,89%
Self-Blocking Bricks	203	2	1053	0	0	0	2	2422	0	2422	3682	65,78%	67,75%	66,75%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,79%	99,89%
														60,48%

First N Sample with Post-Processing (Filtering with 3x3 window)

Table 155 PUS - ML - First N Sample with Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	4904	0	622	3	4	5	438	652	3	4904	6631	73,96%	97,48%	84,10%
Meadows	2	4997	0	8753	0	4025	0	872	0	4997	18649	26,80%	99,15%	42,19%
Gravel	0	0	2096	0	0	0	0	3	0	2096	2099	99,86%	46,36%	63,32%
Trees	0	0	0	3047	0	4	0	0	13	3047	3064	99,45%	25,71%	40,86%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,56%	99,78%
Bare Soil	124	43	0	47	0	3971	0	844	0	3971	5029	78,96%	49,59%	60,92%
Bitumen	1	0	4	0	0	0	1263	62	0	1263	1330	94,96%	74,25%	83,34%
Self-Blocking Bricks	0	0	1799	0	0	2	0	1881	0	1881	3682	51,09%	43,60%	47,05%
Shadows	0	0	0	0	2	0	0	0	945	945	947	99,79%	98,34%	99,06%
														57,16%

Table 156 PUS - SVM-RBF - First N Sample with Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5170	25	613	2	25	115	384	297	0	5170	6631	77,97%	90,42%	83,73%
Meadows	0	12928	0	2541	0	3180	0	0	0	12928	18649	69,32%	82,28%	75,25%
Gravel	0	0	1149	0	0	7	13	930	0	1149	2099	54,74%	55,37%	55,06%
Trees	0	29	0	3023	10	2	0	0	0	3023	3064	98,66%	54,25%	70,01%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	91,12%	95,36%
Bare Soil	0	2723	0	4	95	2201	0	6	0	2201	5029	43,77%	39,92%	41,75%
Bitumen	547	0	11	0	0	0	772	0	0	772	1330	58,05%	63,38%	60,60%
Self-Blocking Bricks	1	7	302	2	0	9	49	3312	0	3312	3682	89,95%	72,87%	80,52%
Shadows	0	0	0	0	1	0	0	0	946	946	947	99,89%	100,00%	99,95%
														72,11%

Table 157 PUS - SVM-LNR - First N Sample with Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	2761	2	261	0	0	1	2782	823	1	2761	6631	41,64%	100,00%	58,79%
Meadows	0	8467	3	2560	0	6687	1	930	1	8467	18649	45,40%	96,94%	61,84%
Gravel	0	0	2098	0	0	0	0	1	0	2098	2099	99,95%	48,50%	65,31%
Trees	0	33	0	2953	2	66	0	6	4	2953	3064	96,38%	53,39%	68,71%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,85%	99,93%
Bare Soil	0	232	0	18	0	3512	0	1267	0	3512	5029	69,83%	34,20%	45,92%
Bitumen	0	0	2	0	0	0	1324	4	0	1324	1330	99,55%	32,23%	48,69%
Self-Blocking Bricks	0	0	1962	0	0	2	1	1717	0	1717	3682	46,63%	36,16%	40,74%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,37%	99,68%
														58,73%

Table 158 PUS - K-NN - First N Sample with Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5720	0	48	0	2	10	462	387	2	5720	6631	86,26%	79,72%	82,86%
Meadows	328	7047	0	2926	0	8096	7	244	1	7047	18649	37,79%	88,07%	52,88%
Gravel	229	0	1770	0	0	3	30	67	0	1770	2099	84,33%	63,69%	72,57%
Trees	1	2	0	3030	4	26	0	1	0	3030	3064	98,89%	50,80%	67,12%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,34%	99,67%
Bare Soil	766	950	0	9	2	3089	0	213	0	3089	5029	61,42%	27,52%	38,01%
Bitumen	45	0	5	0	0	0	1278	2	0	1278	1330	96,09%	71,92%	82,27%
Self-Blocking Bricks	86	3	956	0	1	1	0	2635	0	2635	3682	71,56%	74,25%	72,88%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,68%	99,84%
														62,79%

First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

Table 159 PUS - ML - First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	4901	0	454	8	0	14	268	986	0	4901	6631	73,91%	96,93%	83,87%
Meadows	0	6021	0	8357	0	3534	0	737	0	6021	18649	32,29%	100,00%	48,81%
Gravel	1	0	2098	0	0	0	0	0	0	2098	2099	99,95%	53,06%	69,32%
Trees	79	0	0	2893	0	55	0	27	10	2893	3064	94,42%	25,65%	40,35%
Painted Metal Sheets	1	0	0	0	1335	0	0	8	1	1335	1345	99,26%	99,85%	99,55%
Bare Soil	73	0	0	0	0	4153	0	803	0	4153	5029	82,58%	53,53%	64,96%
Bitumen	1	0	0	0	0	2	1327	0	0	1327	1330	99,77%	83,20%	90,74%
Self-Blocking Bricks	0	0	1402	4	0	0	0	2276	0	2276	3682	61,81%	47,05%	53,43%
Shadows	0	0	0	15	2	0	0	0	930	930	947	98,20%	98,83%	98,52%
														60,63%

Table 160 PUS - SVM-RBF - First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5987	12	23	1	0	10	406	192	0	5987	6631	90,29%	74,02%	81,35%
Meadows	718	5897	0	3157	0	8860	0	17	0	5897	18649	31,62%	92,55%	47,14%
Gravel	398	0	1701	0	0	0	0	0	0	1701	2099	81,04%	72,75%	76,67%
Trees	112	14	0	2805	0	92	0	5	36	2805	3064	91,55%	47,01%	62,12%
Painted Metal Sheets	20	0	0	0	1324	0	0	0	1	1324	1345	98,44%	99,85%	99,14%
Bare Soil	851	447	0	0	0	3706	0	25	0	3706	5029	73,69%	29,24%	41,87%
Bitumen	0	2	0	0	0	0	1327	0	1	1327	1330	99,77%	76,57%	86,65%
Self-Blocking Bricks	2	0	614	4	0	7	0	3055	0	3055	3682	82,97%	92,74%	87,59%
Shadows	0	0	0	0	2	0	0	0	945	945	947	99,79%	96,13%	97,93%
														62,53%

Table 161 PUS - SVM-LNR - First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	2951	0	610	1	0	19	1946	1104	0	2951	6631	44,50%	99,03%	61,41%
Meadows	0	8144	0	2673	0	7077	0	755	0	8144	18649	43,67%	99,95%	60,78%
Gravel	0	0	2098	0	0	0	1	0	0	2098	2099	99,95%	50,36%	66,98%
Trees	29	2	0	2659	10	178	46	33	107	2659	3064	86,78%	49,84%	63,32%
Painted Metal Sheets	0	0	0	0	1331	0	1	12	1	1331	1345	98,96%	99,11%	99,03%
Bare Soil	0	0	0	0	0	3706	0	1323	0	3706	5029	73,69%	33,75%	46,30%
Bitumen	0	2	0	0	0	0	1327	0	1	1327	1330	99,77%	39,96%	57,06%
Self-Blocking Bricks	0	0	1458	2	0	1	0	2220	1	2220	3682	60,29%	40,76%	48,64%
Shadows	0	0	0	0	2	0	0	0	945	945	947	99,79%	89,57%	94,41%
														59,33%

Table 162 PUS - K-NN - First N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6094	0	4	0	0	0	244	288	1	6094	6631	91,90%	71,06%	80,15%
Meadows	1	8657	0	2783	0	7206	0	2	0	8657	18649	46,42%	89,96%	61,24%
Gravel	419	0	1677	1	0	2	0	0	0	1677	2099	79,90%	98,19%	88,10%
Trees	7	19	0	2967	2	65	0	3	1	2967	3064	96,83%	51,56%	67,29%
Painted Metal Sheets	16	0	0	0	1329	0	0	0	0	1329	1345	98,81%	99,77%	99,29%
Bare Soil	610	947	0	2	0	3430	0	40	0	3430	5029	68,20%	32,03%	43,59%
Bitumen	0	0	0	0	0	0	1330	0	0	1330	1330	100,00%	83,60%	91,06%
Self-Blocking Bricks	1429	0	27	1	0	5	17	2201	2	2201	3682	59,78%	86,86%	70,82%
Shadows	0	0	0	0	1	0	0	0	946	946	947	99,89%	99,58%	99,74%
														66,93%

First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

Table 163 PUS - ML - First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6108	0	57	0	1	18	239	208	0	6108	6631	92,11%	88,60%	90,32%
Meadows	253	6746	0	5007	0	6493	3	147	0	6746	18649	36,17%	97,23%	52,73%
Gravel	82	0	1973	0	0	3	0	41	0	1973	2099	94,00%	67,64%	78,67%
Trees	4	0	0	3050	0	10	0	0	0	3050	3064	99,54%	37,63%	54,61%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,56%	99,78%
Bare Soil	285	192	19	48	0	3862	0	623	0	3862	5029	76,79%	37,14%	50,06%
Bitumen	131	0	0	0	0	1	1193	5	0	1193	1330	89,70%	83,14%	86,29%
Self-Blocking Bricks	25	0	868	1	1	12	0	2775	0	2775	3682	75,37%	73,05%	74,19%
Shadows	6	0	0	0	4	0	0	0	937	937	947	98,94%	100,00%	99,47%
														65,43%

Table 164 PUS - SVM-RBF - First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6267	2	49	0	3	4	66	240	0	6267	6631	94,51%	96,15%	95,32%
Meadows	58	9290	0	1882	0	6601	1	817	0	9290	18649	49,82%	98,84%	66,24%
Gravel	9	0	1996	0	0	2	26	66	0	1996	2099	95,09%	65,98%	77,91%
Trees	11	29	0	2971	2	50	0	1	0	2971	3064	96,96%	61,21%	75,04%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,63%	99,81%
Bare Soil	126	78	20	1	0	3727	0	1077	0	3727	5029	74,11%	35,86%	48,34%
Bitumen	35	0	0	0	0	0	1282	13	0	1282	1330	96,39%	93,24%	94,79%
Self-Blocking Bricks	12	0	960	0	0	8	0	2702	0	2702	3682	73,38%	54,96%	62,85%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	100,00%	100,00%
														71,36%

Table 165 PUS - SVM-LNR - First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	4673	5	181	0	0	41	1325	406	0	4673	6631	70,47%	97,56%	81,83%
Meadows	0	12665	163	3536	0	2274	0	11	0	12665	18649	67,91%	85,55%	75,72%
Gravel	16	1	1330	0	0	3	20	729	0	1330	2099	63,36%	66,73%	65,00%
Trees	0	11	0	3036	0	16	0	1	0	3036	3064	99,09%	45,55%	62,41%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	100,00%	100,00%
Bare Soil	0	2119	6	93	0	2694	0	117	0	2694	5029	53,57%	53,20%	53,38%
Bitumen	97	0	1	0	0	0	1229	3	0	1229	1330	92,41%	47,00%	62,31%
Self-Blocking Bricks	4	4	312	0	0	36	41	3285	0	3285	3682	89,22%	72,17%	79,79%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	100,00%	100,00%
														72,95%

Table 166 PUS - K-NN - First N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	4257	23	924	36	10	381	282	683	35	4257	6631	64,20%	72,60%	68,14%
Meadows	44	11650	3	4111	0	2543	0	294	4	11650	18649	62,47%	86,36%	72,50%
Gravel	287	9	1149	0	0	25	2	625	2	1149	2099	54,74%	38,17%	44,98%
Trees	0	314	0	2718	0	7	0	0	25	2718	3064	88,71%	36,44%	51,66%
Painted Metal Sheets	0	0	0	0	1333	0	0	0	12	1333	1345	99,11%	90,80%	94,77%
Bare Soil	35	1449	13	482	0	2879	0	140	31	2879	5029	57,25%	47,28%	51,79%
Bitumen	485	7	130	0	1	31	590	86	0	590	1330	44,36%	67,12%	53,42%
Self-Blocking Bricks	536	37	787	2	0	210	5	2098	7	2098	3682	56,98%	53,44%	55,15%
Shadows	220	1	4	110	124	13	0	0	475	475	947	50,16%	80,37%	61,77%
														63,47%

First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

Table 167 PUS - ML - First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	**Meadows**	**Gravel**	**Trees**	**Painted Metal Sheets**	**Bare Soil**	**Bitumen**	**Self-Blocking Bricks**	**Shadows**	**Correctly Classified**	**Ground Truth**	**Recall**	**Precision**	**F-Measure**
Asphalt	6397	0	0	1	0	50	0	183	0	6397	6631	96,47%	93,26%	94,84%
Meadows	0	7260	0	4871	0	6518	0	0	0	7260	18649	38,93%	100,00%	56,04%
Gravel	180	0	1919	0	0	0	0	0	0	1919	2099	91,42%	96,34%	93,82%
Trees	111	0	0	2859	0	89	0	5	0	2859	3064	93,31%	36,89%	52,88%
Painted Metal Sheets	5	0	0	0	1335	0	0	4	1	1335	1345	99,26%	99,85%	99,55%
Bare Soil	134	0	0	0	0	4154	0	741	0	4154	5029	82,60%	38,39%	52,42%
Bitumen	1	0	0	0	0	2	1327	0	0	1327	1330	99,77%	100,00%	99,89%
Self-Blocking Bricks	2	0	73	4	0	7	0	3596	0	3596	3682	97,66%	79,40%	87,59%
Shadows	29	0	0	15	2	0	0	0	901	901	947	95,14%	99,89%	97,46%
														69,54%

Table 168 PUS - SVM-RBF - First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6334	0	18	1	0	19	0	259	0	6334	6631	95,52%	96,51%	96,01%
Meadows	3	10021	0	2274	0	5616	0	735	0	10021	18649	53,73%	99,79%	69,85%
Gravel	31	0	2068	0	0	0	0	0	0	2068	2099	98,52%	76,59%	86,18%
Trees	112	19	0	2744	0	141	0	13	35	2744	3064	89,56%	54,63%	67,86%
Painted Metal Sheets	7	0	0	0	1330	0	0	7	1	1330	1345	98,88%	99,85%	99,36%
Bare Soil	73	0	0	0	0	3868	0	1088	0	3868	5029	76,91%	40,08%	52,70%
Bitumen	1	2	0	0	0	0	1327	0	0	1327	1330	99,77%	100,00%	99,89%
Self-Blocking Bricks	2	0	614	4	0	7	0	3055	0	3055	3682	82,97%	59,24%	69,13%
Shadows	0	0	0	0	2	0	0	0	945	945	947	99,79%	96,33%	98,03%
														74,09%

Table 169 PUS - SVM-LNR - First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	4469	16	1032	12	17	96	339	646	4	4469	6631	67,40%	81,27%	73,69%
Meadows	110	13389	0	2828	0	2154	0	168	0	13389	18649	71,79%	92,55%	80,86%
Gravel	110	3	1471	0	0	0	0	515	0	1471	2099	70,08%	42,95%	53,26%
Trees	0	124	0	2920	0	9	0	0	11	2920	3064	95,30%	48,87%	64,61%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	97,61%	98,79%
Bare Soil	58	912	9	195	0	3803	0	51	1	3803	5029	75,62%	62,10%	68,20%
Bitumen	300	0	115	0	1	1	829	84	0	829	1330	62,33%	70,85%	66,32%
Self-Blocking Bricks	333	22	798	7	0	61	2	2459	0	2459	3682	66,78%	62,68%	64,67%
Shadows	119	0	0	13	15	0	0	0	800	800	947	84,48%	98,04%	90,75%
														73,60%

Table 170 PUS - K-NN - First N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	3975	46	1362	50	6	142	351	649	50	3975	6631	59,95%	76,60%	67,26%
Meadows	89	12906	0	3252	0	2258	0	141	3	12906	18649	69,20%	88,32%	77,60%
Gravel	161	3	1259	1	0	0	0	674	1	1259	2099	59,98%	32,12%	41,83%
Trees	0	272	0	2774	0	4	0	0	14	2774	3064	90,54%	42,76%	58,08%
Painted Metal Sheets	0	0	0	0	1338	0	0	0	7	1338	1345	99,48%	87,68%	93,21%
Bare Soil	44	1355	31	297	0	3186	0	80	36	3186	5029	63,35%	56,16%	59,54%
Bitumen	395	1	244	0	1	2	581	106	0	581	1330	43,68%	62,21%	51,33%
Self-Blocking Bricks	435	30	1024	4	0	81	2	2100	6	2100	3682	57,03%	56,00%	56,51%
Shadows	90	0	0	110	181	0	0	0	566	566	947	59,77%	82,87%	69,45%
														67,06%

Randomly Selected N Sample without Pre-Processing or Post Processing

Table 171 PUS - ML -Randomly Selected N Sample without Pre-Processing or Post Processing

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5866	7	322	2	4	31	220	175	4	5866	6631	88,46%	95,12%	91,67%
Meadows	43	16640	0	1054	0	871	0	41	0	16640	18649	89,23%	97,16%	93,03%
Gravel	33	1	1811	0	0	1	0	253	0	1811	2099	86,28%	70,99%	77,89%
Trees	0	42	0	3011	0	10	0	0	1	3011	3064	98,27%	73,21%	83,91%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,56%	99,78%
Bare Soil	3	421	0	45	0	4553	0	6	1	4553	5029	90,53%	82,99%	86,60%
Bitumen	60	0	5	0	0	1	1261	3	0	1261	1330	94,81%	85,09%	89,69%
Self-Blocking Bricks	160	15	413	0	0	19	1	3074	0	3074	3682	83,49%	86,54%	84,99%
Shadows	2	0	0	1	2	0	0	0	942	942	947	99,47%	99,37%	99,42%
														90,01%

Table 172 PUS - SVM-RBF -Randomly Selected N Sample without Pre-Processing or Post Processing

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5819	16	120	0	4	51	356	264	1	5819	6631	87,75%	97,95%	92,57%
Meadows	0	16581	12	579	0	1473	0	4	0	16581	18649	88,91%	97,07%	92,81%
Gravel	22	5	1870	0	0	6	2	194	0	1870	2099	89,09%	80,26%	84,44%
Trees	0	96	0	2951	1	16	0	0	0	2951	3064	96,31%	83,46%	89,42%
Painted Metal Sheets	0	0	0	0	1344	1	0	0	0	1344	1345	99,93%	99,63%	99,78%
Bare Soil	6	375	0	6	0	4621	0	21	0	4621	5029	91,89%	74,58%	82,33%
Bitumen	64	0	3	0	0	0	1260	3	0	1260	1330	94,74%	77,44%	85,22%
Self-Blocking Bricks	30	8	325	0	0	28	9	3282	0	3282	3682	89,14%	87,10%	88,11%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,89%	99,95%
														90,41%

Table 173 PUS - SVM-LNR -Randomly Selected N Sample without Pre-Processing or Post Processing

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5511	16	104	0	2	25	689	283	1	5511	6631	83,11%	96,48%	89,30%
Meadows	0	16511	10	598	0	1387	0	143	0	16511	18649	88,54%	96,43%	92,32%
Gravel	20	2	1779	0	0	1	0	297	0	1779	2099	84,75%	78,58%	81,55%
Trees	0	107	0	2931	1	25	0	0	0	2931	3064	95,66%	82,54%	88,62%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,70%	99,85%
Bare Soil	0	479	1	22	1	4509	0	17	0	4509	5029	89,66%	75,48%	81,96%
Bitumen	112	0	0	0	0	0	1216	2	0	1216	1330	91,43%	63,70%	75,08%
Self-Blocking Bricks	69	7	370	0	0	27	4	3205	0	3205	3682	87,05%	81,20%	84,02%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,89%	99,95%
														88,73%

Table 174 PUS - K-NN -Randomly Selected N Sample without Pre-Processing or Post Processing

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5522	10	186	0	2	37	665	209	0	5522	6631	83,28%	97,75%	89,93%
Meadows	2	15964	1	432	0	2246	0	4	0	15964	18649	85,60%	95,01%	90,06%
Gravel	23	1	1846	0	0	3	7	219	0	1846	2099	87,95%	73,25%	79,93%
Trees	0	115	0	2939	1	9	0	0	0	2939	3064	95,92%	86,98%	91,23%
Painted Metal Sheets	1	0	1	0	1343	0	0	0	0	1343	1345	99,85%	99,41%	99,63%
Bare Soil	14	708	6	8	5	4259	1	28	0	4259	5029	84,69%	64,76%	73,39%
Bitumen	25	0	6	0	0	0	1294	5	0	1294	1330	97,29%	65,45%	78,26%
Self-Blocking Bricks	62	4	474	0	0	23	10	3109	0	3109	3682	84,44%	86,99%	85,69%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	100,00%	100,00%
														87,02%

Randomly Selected N Sample with Pre-Processing (PCA)

Table 175 PUS – ML - Randomly Selected N Sample with Pre-Processing (PCA)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6055	5	144	14	1	32	212	167	1	6055	6631	91,31%	97,19%	94,16%
Meadows	4	17531	0	555	0	555	0	4	0	17531	18649	94,01%	98,16%	96,04%
Gravel	29	3	1799	1	0	0	1	266	0	1799	2099	85,71%	79,01%	82,22%
Trees	0	58	0	3002	0	4	0	0	0	3002	3064	97,98%	82,95%	89,84%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,63%	99,81%
Bare Soil	2	248	0	40	0	4735	0	4	0	4735	5029	94,15%	88,49%	91,23%
Bitumen	65	0	1	0	0	0	1264	0	0	1264	1330	95,04%	85,52%	90,03%
Self-Blocking Bricks	62	14	333	7	0	25	1	3240	0	3240	3682	88,00%	88,02%	88,01%
Shadows	13	0	0	0	4	0	0	0	930	930	947	98,20%	99,89%	99,04%
														93,28%

Table 176 PUS – SVM-RBF - Randomly Selected N Sample with Pre-Processing (PCA)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5950	23	91	3	0	18	333	213	0	5950	6631	89,73%	98,20%	93,77%
Meadows	0	17372	0	307	0	891	0	79	0	17372	18649	93,15%	97,61%	95,33%
Gravel	14	5	1797	0	0	0	4	279	0	1797	2099	85,61%	82,85%	84,21%
Trees	0	55	0	3005	0	3	0	1	0	3005	3064	98,07%	90,27%	94,01%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	100,00%	100,00%
Bare Soil	3	323	0	13	0	4684	0	6	0	4684	5029	93,14%	83,58%	88,10%
Bitumen	63	0	1	0	0	0	1264	2	0	1264	1330	95,04%	78,41%	85,93%
Self-Blocking Bricks	29	19	280	1	0	8	11	3334	0	3334	3682	90,55%	85,18%	87,78%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	100,00%	100,00%
														92,80%

Table 177 PUS – SVM-LNR - Randomly Selected N Sample with Pre-Processing (PCA)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5506	23	102	0	1	24	686	285	4	5506	6631	83,03%	95,79%	88,96%
Meadows	0	16410	4	387	0	1434	0	414	0	16410	18649	87,99%	96,45%	92,03%
Gravel	23	2	1782	0	0	0	2	290	0	1782	2099	84,90%	77,18%	80,85%
Trees	0	126	0	2911	0	23	0	4	0	2911	3064	95,01%	87,79%	91,25%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,93%	99,96%
Bare Soil	2	442	0	18	0	4490	1	76	0	4490	5029	89,28%	75,00%	81,52%
Bitumen	120	0	0	0	0	0	1206	4	0	1206	1330	90,68%	63,31%	74,56%
Self-Blocking Bricks	97	11	421	0	0	16	10	3127	0	3127	3682	84,93%	74,45%	79,35%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,58%	99,79%
														88,19%

Table 178 PUS – K-NN - Randomly Selected N Sample with Pre-Processing (PCA)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5503	9	238	0	1	35	655	189	1	5503	6631	82,99%	98,08%	89,90%
Meadows	1	15947	3	395	0	2291	0	12	0	15947	18649	85,51%	94,97%	89,99%
Gravel	17	0	1867	0	0	4	5	206	0	1867	2099	88,95%	71,95%	79,55%
Trees	0	125	0	2919	2	18	0	0	0	2919	3064	95,27%	87,87%	91,42%
Painted Metal Sheets	1	0	1	0	1343	0	0	0	0	1343	1345	99,85%	99,63%	99,74%
Bare Soil	6	708	2	8	2	4275	1	27	0	4275	5029	85,01%	64,37%	73,26%
Bitumen	20	0	6	0	0	0	1303	1	0	1303	1330	97,97%	65,77%	78,71%
Self-Blocking Bricks	63	3	478	0	0	18	17	3103	0	3103	3682	84,27%	87,70%	85,96%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,89%	99,95%
														86,98%

Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

Table 179 PUS - ML - Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6425	2	82	3	0	10	16	92	1	6425	6631	96,89%	99,00%	97,93%
Meadows	6	17931	0	468	0	237	0	7	0	17931	18649	96,15%	99,57%	97,83%
Gravel	5	0	1964	1	0	0	0	129	0	1964	2099	93,57%	90,59%	92,06%
Trees	0	2	0	3061	0	1	0	0	0	3061	3064	99,90%	86,32%	92,62%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,85%	99,93%
Bare Soil	0	64	0	9	0	4956	0	0	0	4956	5029	98,55%	95,16%	96,83%
Bitumen	19	0	0	0	0	0	1311	0	0	1311	1330	98,57%	98,79%	98,68%
Self-Blocking Bricks	33	9	122	4	0	4	0	3510	0	3510	3682	95,33%	93,90%	94,61%
Shadows	2	0	0	0	2	0	0	0	943	943	947	99,58%	99,89%	99,74%
														96,89%

Table 180 PUS - SVM-RBF - Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6197	3	21	0	0	30	141	239	0	6197	6631	93,45%	99,45%	96,36%
Meadows	0	17488	0	335	0	825	0	1	0	17488	18649	93,77%	99,19%	96,41%
Gravel	7	0	1976	0	0	3	0	113	0	1976	2099	94,14%	92,51%	93,32%
Trees	1	54	0	2969	0	40	0	0	0	2969	3064	96,90%	89,86%	93,25%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,85%	99,93%
Bare Soil	0	82	0	0	0	4938	0	9	0	4938	5029	98,19%	84,41%	90,78%
Bitumen	18	0	0	0	0	1	1311	0	0	1311	1330	98,57%	90,29%	94,25%
Self-Blocking Bricks	8	3	139	0	1	13	0	3518	0	3518	3682	95,55%	90,67%	93,04%
Shadows	0	0	0	0	1	0	0	0	946	946	947	99,89%	100,00%	99,95%
														95,12%

Table 181 PUS - SVM-LNR - Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6051	6	72	0	0	14	243	245	0	6051	6631	91,25%	99,13%	95,03%
Meadows	0	17184	0	471	0	955	0	39	0	17184	18649	92,14%	98,19%	95,07%
Gravel	0	0	1895	0	0	0	0	204	0	1895	2099	90,28%	87,37%	88,80%
Trees	0	58	0	2979	0	23	0	3	1	2979	3064	97,23%	86,35%	91,46%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	100,00%	100,00%
Bare Soil	0	248	0	0	0	4778	0	3	0	4778	5029	95,01%	82,54%	88,33%
Bitumen	31	0	0	0	0	0	1299	0	0	1299	1330	97,67%	84,24%	90,46%
Self-Blocking Bricks	22	5	202	0	0	19	0	3433	1	3433	3682	93,24%	87,42%	90,24%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,79%	99,89%
														93,30%

Table 182 PUS - K-NN - Randomly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6072	2	40	0	3	14	329	171	0	6072	6631	91,57%	99,61%	95,42%
Meadows	0	17521	0	117	0	1009	0	1	1	17521	18649	93,95%	98,73%	96,28%
Gravel	0	0	2035	0	0	1	2	61	0	2035	2099	96,95%	91,79%	94,30%
Trees	2	34	0	3001	3	24	0	0	0	3001	3064	97,94%	96,25%	97,09%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,56%	99,78%
Bare Soil	0	187	0	0	0	4833	0	9	0	4833	5029	96,10%	82,08%	88,54%
Bitumen	8	0	0	0	0	0	1322	0	0	1322	1330	99,40%	79,83%	88,55%
Self-Blocking Bricks	14	2	142	0	0	7	3	3513	1	3513	3682	95,41%	93,56%	94,47%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,79%	99,89%
														94,89%

Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

Table 183 PUS - ML - Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6574	0	0	0	0	5	0	51	1	6574	6631	99,14%	99,53%	99,34%
Meadows	0	18415	1	231	0	2	0	0	0	18415	18649	98,75%	99,70%	99,22%
Gravel	0	0	2096	3	0	0	0	0	0	2096	2099	99,86%	99,90%	99,88%
Trees	0	39	1	3004	0	15	0	3	2	3004	3064	98,04%	92,63%	95,26%
Painted Metal Sheets	1	0	0	0	1329	15	0	0	0	1329	1345	98,81%	99,92%	99,36%
Bare Soil	0	12	0	0	0	5017	0	0	0	5017	5029	99,76%	99,27%	99,51%
Bitumen	0	0	0	0	0	0	1330	0	0	1330	1330	100,00%	100,00%	100,00%
Self-Blocking Bricks	26	5	0	5	0	0	0	3646	0	3646	3682	99,02%	98,54%	98,78%
Shadows	4	0	0	0	1	0	0	0	942	942	947	99,47%	99,68%	99,58%
														99,01%

Table 184 PUS - SVM-RBF - Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6545	0	0	0	0	29	0	56	1	6545	6631	98,70%	99,60%	99,15%
Meadows	0	18457	0	189	0	3	0	0	0	18457	18649	98,97%	99,50%	99,24%
Gravel	0	0	2096	3	0	0	0	0	0	2096	2099	99,86%	100,00%	99,93%
Trees	0	74	0	2938	0	48	0	3	1	2938	3064	95,89%	93,84%	94,85%
Painted Metal Sheets	1	0	0	0	1329	15	0	0	0	1329	1345	98,81%	99,92%	99,36%
Bare Soil	0	12	0	0	0	5017	0	0	0	5017	5029	99,76%	98,10%	98,93%
Bitumen	0	0	0	0	0	0	1330	0	0	1330	1330	100,00%	100,00%	100,00%
Self-Blocking Bricks	25	6	0	1	0	2	0	3646	2	3646	3682	99,02%	98,41%	98,71%
Shadows	0	0	0	0	1	0	0	0	946	946	947	99,89%	99,58%	99,74%
														98,90%

Table 185 PUS - SVM-LNR - Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6565	0	1	0	0	0	9	55	1	6565	6631	99,00%	99,58%	99,29%
Meadows	0	17942	0	0	0	706	0	1	0	17942	18649	96,21%	99,37%	97,77%
Gravel	0	2	2096	0	0	1	0	0	0	2096	2099	99,86%	98,64%	99,24%
Trees	0	104	0	2908	0	45	0	6	1	2908	3064	94,91%	99,97%	97,37%
Painted Metal Sheets	0	0	0	0	1329	0	1	15	0	1329	1345	98,81%	99,92%	99,36%
Bare Soil	0	2	0	0	0	5027	0	0	0	5027	5029	99,96%	86,99%	93,02%
Bitumen	0	0	0	0	0	0	1330	0	0	1330	1330	100,00%	99,25%	99,63%
Self-Blocking Bricks	28	5	28	1	0	0	0	3620	0	3620	3682	98,32%	97,92%	98,12%
Shadows	0	0	0	0	1	0	0	0	946	946	947	99,89%	99,79%	99,84%
														97,63%

Table 186 PUS - K-NN - Randomly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6564	0	4	0	0	0	6	56	1	6564	6631	98,99%	99,56%	99,27%
Meadows	0	18646	0	0	0	3	0	0	0	18646	18649	99,98%	99,46%	99,72%
Gravel	0	0	2096	0	0	3	0	0	0	2096	2099	99,86%	99,76%	99,81%
Trees	0	89	0	2935	2	34	0	3	1	2935	3064	95,79%	99,97%	97,83%
Painted Metal Sheets	1	0	0	0	1329	15	0	0	0	1329	1345	98,81%	99,77%	99,29%
Bare Soil	0	12	0	0	0	5017	0	0	0	5017	5029	99,76%	98,78%	99,27%
Bitumen	0	0	0	0	0	0	1330	0	0	1330	1330	100,00%	99,55%	99,77%
Self-Blocking Bricks	28	0	1	1	0	7	0	3642	3	3642	3682	98,91%	98,41%	98,66%
Shadows	0	0	0	0	1	0	0	0	946	946	947	99,89%	99,47%	99,68%
														99,37%

Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

Table 187 PUS - ML - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6411	4	59	3	0	17	14	123	0	6411	6631	96,68%	98,66%	97,66%
Meadows	0	18191	0	263	0	195	0	0	0	18191	18649	97,54%	99,77%	98,64%
Gravel	5	0	1919	3	0	0	0	172	0	1919	2099	91,42%	90,82%	91,12%
Trees	0	3	0	3051	0	10	0	0	0	3051	3064	99,58%	91,76%	95,51%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,70%	99,85%
Bare Soil	0	27	0	3	0	4999	0	0	0	4999	5029	99,40%	95,62%	97,47%
Bitumen	41	0	0	0	0	1	1288	0	0	1288	1330	96,84%	98,92%	97,87%
Self-Blocking Bricks	35	8	135	2	0	6	0	3496	0	3496	3682	94,95%	92,22%	93,56%
Shadows	6	0	0	0	4	0	0	0	937	937	947	98,94%	100,00%	99,47%
														97,34%

Table 188 PUS - SVM-RBF - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6376	3	30	2	0	3	27	190	0	6376	6631	96,15%	99,52%	97,81%
Meadows	0	17988	0	98	0	560	0	3	0	17988	18649	96,46%	99,55%	97,98%
Gravel	1	4	1907	0	0	0	0	187	0	1907	2099	90,85%	93,39%	92,10%
Trees	2	16	0	3043	0	3	0	0	0	3043	3064	99,31%	96,79%	98,03%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	100,00%	100,00%
Bare Soil	0	50	0	0	0	4979	0	0	0	4979	5029	99,01%	89,78%	94,17%
Bitumen	20	0	0	0	0	0	1310	0	0	1310	1330	98,50%	97,98%	98,24%
Self-Blocking Bricks	8	9	105	1	0	1	0	3558	0	3558	3682	96,63%	90,35%	93,39%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	100,00%	100,00%
														96,91%

Table 189 PUS - SVM-LNR - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6058	11	117	0	0	5	227	213	0	6058	6631	91,36%	99,26%	95,15%
Meadows	0	17501	1	242	0	699	0	206	0	17501	18649	93,84%	98,88%	96,29%
Gravel	0	2	1869	0	0	0	2	226	0	1869	2099	89,04%	86,73%	87,87%
Trees	0	47	0	2992	0	12	0	12	1	2992	3064	97,65%	92,40%	94,95%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	100,00%	100,00%
Bare Soil	0	136	0	4	0	4878	0	11	0	4878	5029	97,00%	87,15%	91,81%
Bitumen	14	0	0	0	0	0	1315	1	0	1315	1330	98,87%	85,17%	91,51%
Self-Blocking Bricks	31	3	168	0	0	3	0	3477	0	3477	3682	94,43%	83,86%	88,83%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,89%	99,95%
														94,40%

Table 190 PUS - K-NN - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6088	1	59	0	0	21	303	159	0	6088	6631	91,81%	99,67%	95,58%
Meadows	1	17596	0	107	0	943	0	2	0	17596	18649	94,35%	98,87%	96,56%
Gravel	0	0	2052	0	0	2	0	45	0	2052	2099	97,76%	93,49%	95,58%
Trees	0	38	0	3005	0	21	0	0	0	3005	3064	98,07%	96,47%	97,26%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	100,00%	100,00%
Bare Soil	0	162	0	3	0	4862	0	2	0	4862	5029	96,68%	82,94%	89,28%
Bitumen	2	0	0	0	0	0	1328	0	0	1328	1330	99,85%	81,32%	89,64%
Self-Blocking Bricks	17	0	84	0	0	13	2	3566	0	3566	3682	96,85%	94,49%	95,65%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	100,00%	100,00%
														95,35%

Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

Table 191 PUS - ML - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	**Meadows**	**Gravel**	**Trees**	**Painted Metal Sheets**	**Bare Soil**	**Bitumen**	**Self-Blocking Bricks**	**Shadows**	**Correctly Classified**	**Ground Truth**	**Recall**	**Precision**	**F-Measure**
Asphalt	6574	0	0	0	0	5	0	51	1	6574	6631	99,14%	99,43%	99,28%
Meadows	0	18457	0	189	0	3	0	0	0	18457	18649	98,97%	99,67%	99,32%
Gravel	0	0	2096	3	0	0	0	0	0	2096	2099	99,86%	100,00%	99,93%
Trees	0	44	0	2993	0	24	0	3	0	2993	3064	97,68%	93,88%	95,75%
Painted Metal Sheets	1	0	0	0	1329	15	0	0	0	1329	1345	98,81%	99,92%	99,36%
Bare Soil	0	12	0	0	0	5017	0	0	0	5017	5029	99,76%	99,07%	99,42%
Bitumen	0	0	0	0	0	0	1330	0	0	1330	1330	100,00%	100,00%	100,00%
Self-Blocking Bricks	33	5	0	3	0	0	0	3641	0	3641	3682	98,89%	98,54%	98,71%
Shadows	4	0	0	0	1	0	0	0	942	942	947	99,47%	99,89%	99,68%
														99,07%

Table 192 PUS - SVM-RBF - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6544	19	23	1	0	8	0	36	0	6544	6631	98,69%	98,41%	98,55%
Meadows	0	18629	0	16	0	4	0	0	0	18629	18649	99,89%	99,43%	99,66%
Gravel	1	0	2026	0	0	0	0	72	0	2026	2099	96,52%	98,88%	97,69%
Trees	101	78	0	2798	0	67	0	5	15	2798	3064	91,32%	99,22%	95,11%
Painted Metal Sheets	1	0	0	0	1324	12	3	4	1	1324	1345	98,44%	99,85%	99,14%
Bare Soil	0	0	0	0	0	5029	0	0	0	5029	5029	100,00%	98,22%	99,10%
Bitumen	1	2	0	0	0	0	1327	0	0	1327	1330	99,77%	99,77%	99,77%
Self-Blocking Bricks	2	7	0	4	0	0	0	3669	0	3669	3682	99,65%	96,91%	98,26%
Shadows	0	0	0	1	2	0	0	0	944	944	947	99,68%	98,33%	99,00%
														98,86%

Table 193 PUS - SVM-LNR - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6396	19	23	1	0	25	20	147	0	6396	6631	96,46%	98,43%	97,43%
Meadows	0	18642	0	3	0	4	0	0	0	18642	18649	99,96%	99,25%	99,61%
Gravel	1	0	1996	0	0	0	0	102	0	1996	2099	95,09%	98,86%	96,94%
Trees	100	112	0	2724	0	56	0	16	56	2724	3064	88,90%	99,67%	93,98%
Painted Metal Sheets	1	0	0	0	1324	11	3	5	1	1324	1345	98,44%	99,85%	99,14%
Bare Soil	0	0	0	0	0	5029	0	0	0	5029	5029	100,00%	98,13%	99,05%
Bitumen	0	2	0	0	0	0	1327	0	1	1327	1330	99,77%	98,15%	98,96%
Self-Blocking Bricks	0	7	0	4	0	0	2	3669	0	3669	3682	99,65%	93,15%	96,29%
Shadows	0	0	0	1	2	0	0	0	944	944	947	99,68%	94,21%	96,87%
														98,31%

Table 194 PUS - K-NN - Randomly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6461	19	36	1	0	6	0	108	0	6461	6631	97,44%	98,42%	97,92%
Meadows	0	18620	0	13	0	16	0	0	0	18620	18649	99,84%	99,36%	99,60%
Gravel	1	0	2098	0	0	0	0	0	0	2098	2099	99,95%	98,31%	99,13%
Trees	99	101	0	2789	0	52	0	6	17	2789	3064	91,02%	99,36%	95,01%
Painted Metal Sheets	4	0	0	0	1323	17	0	0	1	1323	1345	98,36%	99,85%	99,10%
Bare Soil	0	0	0	0	0	5029	0	0	0	5029	5029	100,00%	97,97%	98,98%
Bitumen	0	0	0	0	0	2	1327	0	1	1327	1330	99,77%	100,00%	99,89%
Self-Blocking Bricks	0	0	0	4	0	11	0	3667	0	3667	3682	99,59%	96,98%	98,27%
Shadows	0	0	0	0	2	0	0	0	945	945	947	99,79%	98,03%	98,90%
														98,79%

Uniformly Selected N Sample without Pre-Processing or Post Processing

Table 195 PUS - ML - Uniformly Selected N Sample without Pre-Processing or Post Processing

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5827	5	331	0	3	38	229	194	4	5827	6631	87,88%	95,87%	91,70%
Meadows	34	16757	1	935	0	860	0	62	0	16757	18649	89,85%	97,25%	93,41%
Gravel	39	2	1819	0	0	1	0	238	0	1819	2099	86,66%	69,43%	77,09%
Trees	0	41	0	3010	0	12	0	0	1	3010	3064	98,24%	76,01%	85,71%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,63%	99,81%
Bare Soil	2	414	0	15	0	4592	0	6	0	4592	5029	91,31%	83,17%	87,05%
Bitumen	47	0	6	0	0	0	1274	3	0	1274	1330	95,79%	84,71%	89,91%
Self-Blocking Bricks	126	11	463	0	0	18	1	3063	0	3063	3682	83,19%	85,89%	84,52%
Shadows	3	0	0	0	2	0	0	0	942	942	947	99,47%	99,47%	99,47%
														90,31%

Table 196 PUS - SVM-RBF - Uniformly Selected N Sample without Pre-Processing or Post Processing

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5824	15	102	0	2	49	390	249	0	5824	6631	87,83%	97,69%	92,50%
Meadows	1	16610	4	601	0	1430	0	3	0	16610	18649	89,07%	97,57%	93,13%
Gravel	23	6	1882	0	0	5	5	178	0	1882	2099	89,66%	81,51%	85,39%
Trees	0	82	0	2969	1	11	0	0	1	2969	3064	96,90%	82,82%	89,31%
Painted Metal Sheets	0	0	0	0	1344	1	0	0	0	1344	1345	99,93%	99,63%	99,78%
Bare Soil	10	301	0	15	2	4683	0	18	0	4683	5029	93,12%	75,43%	83,35%
Bitumen	66	0	3	0	0	0	1258	3	0	1258	1330	94,59%	75,65%	84,06%
Self-Blocking Bricks	38	9	318	0	0	29	10	3278	0	3278	3682	89,03%	87,91%	88,46%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,89%	99,95%
														90,69%

Table 197 PUS - SVM-LNR - Uniformly Selected N Sample without Pre-Processing or Post Processing

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5508	17	94	0	2	22	711	276	1	5508	6631	83,06%	96,26%	89,18%
Meadows	0	16574	8	511	0	1454	0	102	0	16574	18649	88,87%	96,28%	92,43%
Gravel	15	2	1804	0	0	0	3	275	0	1804	2099	85,95%	77,93%	81,74%
Trees	0	128	0	2905	0	31	0	0	0	2905	3064	94,81%	84,45%	89,33%
Painted Metal Sheets	0	1	0	0	1342	0	0	2	0	1342	1345	99,78%	99,85%	99,81%
Bare Soil	0	485	1	24	0	4490	0	29	0	4490	5029	89,28%	74,58%	81,27%
Bitumen	123	0	0	0	0	0	1205	2	0	1205	1330	90,60%	62,60%	74,04%
Self-Blocking Bricks	76	7	408	0	0	23	6	3162	0	3162	3682	85,88%	82,17%	83,98%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,89%	99,95%
														88,69%

Table 198 PUS - K-NN - Uniformly Selected N Sample without Pre-Processing or Post Processing

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5500	13	221	0	1	37	641	218	0	5500	6631	82,94%	97,52%	89,64%
Meadows	5	15850	0	379	0	2402	0	13	0	15850	18649	84,99%	94,92%	89,68%
Gravel	26	1	1856	0	0	1	6	209	0	1856	2099	88,42%	72,22%	79,50%
Trees	0	106	0	2950	1	7	0	0	0	2950	3064	96,28%	88,35%	92,14%
Painted Metal Sheets	0	0	1	0	1343	1	0	0	0	1343	1345	99,85%	99,33%	99,59%
Bare Soil	9	726	2	10	7	4238	1	36	0	4238	5029	84,27%	63,21%	72,23%
Bitumen	25	0	6	0	0	1	1293	5	0	1293	1330	97,22%	66,24%	78,79%
Self-Blocking Bricks	75	3	484	0	0	18	11	3091	0	3091	3682	83,95%	86,53%	85,22%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	100,00%	100,00%
														86,66%

Uniformly Selected N Sample with Pre-Processing (PCA)

Table 199 PUS – ML - Uniformly Selected N Sample with Pre-Processing (PCA)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6019	4	178	1	5	34	215	174	1	6019	6631	90,77%	97,10%	93,83%
Meadows	5	17540	0	644	0	452	0	8	0	17540	18649	94,05%	98,14%	96,05%
Gravel	30	3	1793	1	0	0	0	272	0	1793	2099	85,42%	77,45%	81,24%
Trees	0	35	0	3019	0	10	0	0	0	3019	3064	98,53%	81,62%	89,28%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,26%	99,63%
Bare Soil	0	278	0	34	0	4713	0	4	0	4713	5029	93,72%	90,13%	91,89%
Bitumen	71	0	2	0	0	0	1256	1	0	1256	1330	94,44%	85,27%	89,62%
Self-Blocking Bricks	62	12	342	0	0	20	2	3244	0	3244	3682	88,10%	87,60%	87,85%
Shadows	12	0	0	0	5	0	0	0	930	930	947	98,20%	99,89%	99,04%
														93,18%

Table 200 PUS – SVM-RBF - Uniformly Selected N Sample with Pre-Processing (PCA)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5982	18	106	3	0	9	328	185	0	5982	6631	90,21%	98,23%	94,05%
Meadows	0	17247	0	375	0	1004	0	23	0	17247	18649	92,48%	98,16%	95,23%
Gravel	11	8	1810	0	0	0	4	266	0	1810	2099	86,23%	81,38%	83,74%
Trees	0	41	0	3017	0	6	0	0	0	3017	3064	98,47%	88,60%	93,28%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	100,00%	100,00%
Bare Soil	3	240	0	10	0	4767	0	9	0	4767	5029	94,79%	82,23%	88,07%
Bitumen	52	0	3	0	0	0	1273	2	0	1273	1330	95,71%	78,68%	86,36%
Self-Blocking Bricks	42	17	305	0	0	11	13	3294	0	3294	3682	89,46%	87,17%	88,30%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	100,00%	100,00%
														92,77%

Table 201 PUS – SVM-LNR - Uniformly Selected N Sample with Pre-Processing (PCA)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5532	24	131	2	0	34	696	209	3	5532	6631	83,43%	95,69%	89,14%
Meadows	0	16485	2	491	0	1400	0	271	0	16485	18649	88,40%	96,25%	92,16%
Gravel	16	4	1790	0	0	0	1	288	0	1790	2099	85,28%	76,66%	80,74%
Trees	0	101	0	2931	0	26	0	6	0	2931	3064	95,66%	85,33%	90,20%
Painted Metal Sheets	0	0	0	1	1344	0	0	0	0	1344	1345	99,93%	100,00%	99,96%
Bare Soil	1	503	0	10	0	4476	0	39	0	4476	5029	89,00%	75,19%	81,52%
Bitumen	114	0	0	0	0	0	1215	1	0	1215	1330	91,35%	63,28%	74,77%
Self-Blocking Bricks	118	10	412	0	0	17	8	3117	0	3117	3682	84,66%	79,29%	81,89%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,68%	99,84%
														88,45%

Table 202 PUS – K-NN - Uniformly Selected N Sample with Pre-Processing (PCA)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	5507	13	220	0	1	37	635	218	0	5507	6631	83,05%	97,59%	89,73%
Meadows	5	15850	0	381	0	2399	0	14	0	15850	18649	84,99%	94,94%	89,69%
Gravel	23	1	1859	0	0	2	6	208	0	1859	2099	88,57%	72,19%	79,55%
Trees	0	107	0	2949	1	7	0	0	0	2949	3064	96,25%	88,29%	92,10%
Painted Metal Sheets	0	0	1	0	1343	1	0	0	0	1343	1345	99,85%	99,33%	99,59%
Bare Soil	9	720	2	10	7	4244	1	36	0	4244	5029	84,39%	63,26%	72,31%
Bitumen	25	0	6	0	0	1	1293	5	0	1293	1330	97,22%	66,41%	78,91%
Self-Blocking Bricks	74	3	487	0	0	18	12	3088	0	3088	3682	83,87%	86,52%	85,17%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	100,00%	100,00%
														86,68%

Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

Table 203 PUS - ML - Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6371	5	135	0	0	15	14	91	0	6371	6631	96,08%	99,04%	97,54%
Meadows	1	18011	0	417	0	203	0	17	0	18011	18649	96,58%	99,60%	98,06%
Gravel	4	1	1985	0	0	0	0	109	0	1985	2099	94,57%	89,33%	91,88%
Trees	0	7	0	3043	0	14	0	0	0	3043	3064	99,31%	87,87%	93,24%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,70%	99,85%
Bare Soil	0	54	0	2	0	4973	0	0	0	4973	5029	98,89%	95,43%	97,13%
Bitumen	18	0	0	0	0	0	1312	0	0	1312	1330	98,65%	98,94%	98,80%
Self-Blocking Bricks	37	6	102	1	0	6	0	3530	0	3530	3682	95,87%	94,21%	95,03%
Shadows	2	0	0	0	4	0	0	0	941	941	947	99,37%	100,00%	99,68%
														97,04%

Table 204 PUS - SVM-RBF - Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6269	2	20	0	0	20	98	222	0	6269	6631	94,54%	99,24%	96,83%
Meadows	0	17388	0	404	0	855	0	2	0	17388	18649	93,24%	99,34%	96,19%
Gravel	6	1	1981	0	0	2	0	109	0	1981	2099	94,38%	94,15%	94,27%
Trees	0	40	0	3003	0	21	0	0	0	3003	3064	98,01%	88,14%	92,81%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	100,00%	100,00%
Bare Soil	0	68	0	0	0	4957	0	4	0	4957	5029	98,57%	84,45%	90,96%
Bitumen	25	0	0	0	0	0	1305	0	0	1305	1330	98,12%	93,01%	95,50%
Self-Blocking Bricks	17	5	103	0	0	15	0	3542	0	3542	3682	96,20%	91,31%	93,69%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	100,00%	100,00%
														95,23%

Table 205 PUS - SVM-LNR - Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6132	5	62	0	0	11	191	230	0	6132	6631	92,47%	99,11%	95,68%
Meadows	0	17132	0	434	0	1063	0	20	0	17132	18649	91,87%	98,39%	95,01%
Gravel	1	2	1885	0	0	0	1	210	0	1885	2099	89,80%	88,08%	88,94%
Trees	0	51	0	2984	0	24	0	5	0	2984	3064	97,39%	87,30%	92,07%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	100,00%	100,00%
Bare Soil	0	218	0	0	0	4809	0	2	0	4809	5029	95,63%	81,21%	87,83%
Bitumen	18	0	0	0	0	0	1312	0	0	1312	1330	98,65%	87,23%	92,59%
Self-Blocking Bricks	36	5	193	0	0	15	0	3433	0	3433	3682	93,24%	88,03%	90,56%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	100,00%	100,00%
														93,46%

Table 206 PUS - K-NN - Uniformly Selected N Sample with Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6134	3	64	0	0	16	280	134	0	6134	6631	92,50%	99,69%	95,96%
Meadows	1	17570	0	145	0	931	0	1	1	17570	18649	94,21%	98,70%	96,40%
Gravel	5	0	2049	0	0	0	0	45	0	2049	2099	97,62%	91,84%	94,64%
Trees	0	35	0	3008	4	17	0	0	0	3008	3064	98,17%	95,37%	96,75%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,70%	99,85%
Bare Soil	0	194	0	0	0	4830	0	5	0	4830	5029	96,04%	83,29%	89,21%
Bitumen	1	0	0	0	0	0	1329	0	0	1329	1330	99,92%	82,34%	90,29%
Self-Blocking Bricks	12	0	118	1	0	5	5	3541	0	3541	3682	96,17%	95,03%	95,60%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	99,89%	99,95%
														95,27%

Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

Table 207 PUS - ML - Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6574	0	0	0	0	5	0	51	1	6574	6631	99,14%	99,53%	99,34%
Meadows	0	18406	1	240	0	0	0	2	0	18406	18649	98,70%	99,73%	99,21%
Gravel	0	0	2096	3	0	0	0	0	0	2096	2099	99,86%	99,90%	99,88%
Trees	0	38	1	3007	0	13	0	3	2	3007	3064	98,14%	92,10%	95,02%
Painted Metal Sheets	1	0	0	0	1329	15	0	0	0	1329	1345	98,81%	99,92%	99,36%
Bare Soil	0	2	0	10	0	5017	0	0	0	5017	5029	99,76%	99,35%	99,55%
Bitumen	0	0	0	0	0	0	1330	0	0	1330	1330	100,00%	100,00%	100,00%
Self-Blocking Bricks	26	10	0	5	0	0	0	3641	0	3641	3682	98,89%	98,49%	98,69%
Shadows	4	0	0	0	1	0	0	0	942	942	947	99,47%	99,68%	99,58%
														98,99%

Table 208 PUS - SVM-RBF - Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6570	0	0	0	0	0	0	60	1	6570	6631	99,08%	99,61%	99,34%
Meadows	0	18457	0	189	0	3	0	0	0	18457	18649	98,97%	99,58%	99,27%
Gravel	0	0	2096	3	0	0	0	0	0	2096	2099	99,86%	100,00%	99,93%
Trees	0	70	0	2934	0	56	0	3	1	2934	3064	95,76%	93,83%	94,78%
Painted Metal Sheets	1	0	0	0	1329	15	0	0	0	1329	1345	98,81%	99,92%	99,36%
Bare Soil	0	2	0	0	0	5027	0	0	0	5027	5029	99,96%	98,51%	99,23%
Bitumen	0	0	0	0	0	0	1330	0	0	1330	1330	100,00%	100,00%	100,00%
Self-Blocking Bricks	25	6	0	1	0	2	0	3646	2	3646	3682	99,02%	98,30%	98,66%
Shadows	0	0	0	0	1	0	0	0	946	946	947	99,89%	99,58%	99,74%
														98,97%

Table 209 PUS - SVM-LNR - Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6532	13	0	0	0	0	0	85	1	6532	6631	98,51%	99,65%	99,07%
Meadows	0	17942	0	0	0	706	0	1	0	17942	18649	96,21%	99,36%	97,76%
Gravel	0	2	2096	0	0	1	0	0	0	2096	2099	99,86%	99,57%	99,71%
Trees	0	92	0	2924	0	39	0	6	3	2924	3064	95,43%	99,97%	97,65%
Painted Metal Sheets	0	0	0	0	1329	12	0	4	0	1329	1345	98,81%	99,92%	99,36%
Bare Soil	0	2	0	0	0	5027	0	0	0	5027	5029	99,96%	86,90%	92,97%
Bitumen	0	0	0	0	0	0	1330	0	0	1330	1330	100,00%	100,00%	100,00%
Self-Blocking Bricks	23	7	9	1	0	0	0	3640	2	3640	3682	98,86%	97,43%	98,14%
Shadows	0	0	0	0	1	0	0	0	946	946	947	99,89%	99,37%	99,63%
														97,64%

Table 210 PUS - K-NN - Uniformly Selected N Sample with Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6557	0	0	0	0	0	13	60	1	6557	6631	98,88%	99,59%	99,24%
Meadows	0	18646	0	0	0	3	0	0	0	18646	18649	99,98%	99,45%	99,72%
Gravel	0	0	2096	0	0	3	0	0	0	2096	2099	99,86%	100,00%	99,93%
Trees	0	96	0	2916	2	46	0	3	1	2916	3064	95,17%	99,97%	97,51%
Painted Metal Sheets	1	0	0	0	1329	15	0	0	0	1329	1345	98,81%	99,77%	99,29%
Bare Soil	0	2	0	0	0	5027	0	0	0	5027	5029	99,96%	98,65%	99,30%
Bitumen	0	0	0	0	0	0	1330	0	0	1330	1330	100,00%	99,03%	99,51%
Self-Blocking Bricks	26	5	0	1	0	2	0	3646	2	3646	3682	99,02%	98,30%	98,66%
Shadows	0	0	0	0	1	0	0	0	946	946	947	99,89%	99,58%	99,74%
														99,34%

Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

Table 211 PUS - ML - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Asphalt	**Meadows**	**Gravel**	**Trees**	**Painted Metal Sheets**	**Bare Soil**	**Bitumen**	**Self-Blocking Bricks**	**Shadows**	**Correctly Classified**	**Ground Truth**	**Recall**	**Precision**	**F-Measure**
Asphalt	6395	4	92	0	0	14	20	106	0	6395	6631	96,44%	98,93%	97,67%
Meadows	0	18093	0	305	0	251	0	0	0	18093	18649	97,02%	99,62%	98,30%
Gravel	9	2	1995	0	0	0	0	93	0	1995	2099	95,05%	92,23%	93,62%
Trees	0	4	0	3046	0	14	0	0	0	3046	3064	99,41%	90,82%	94,92%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,78%	99,89%
Bare Soil	0	53	0	2	0	4974	0	0	0	4974	5029	98,91%	94,60%	96,70%
Bitumen	22	0	0	0	0	0	1308	0	0	1308	1330	98,35%	98,49%	98,42%
Self-Blocking Bricks	33	6	76	1	0	5	0	3561	0	3561	3682	96,71%	94,71%	95,70%
Shadows	5	0	0	0	3	0	0	0	939	939	947	99,16%	100,00%	99,58%
														97,38%

Table 212 PUS - SVM-RBF - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6369	6	34	5	0	4	45	168	0	6369	6631	96,05%	99,67%	97,83%
Meadows	0	18017	0	82	0	549	0	1	0	18017	18649	96,61%	99,54%	98,05%
Gravel	1	2	1944	0	0	0	0	152	0	1944	2099	92,62%	93,60%	93,10%
Trees	0	21	0	3041	0	1	0	1	0	3041	3064	99,25%	97,19%	98,21%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,93%	99,96%
Bare Soil	0	48	0	0	0	4981	0	0	0	4981	5029	99,05%	89,97%	94,29%
Bitumen	10	0	0	0	0	0	1319	1	0	1319	1330	99,17%	96,70%	97,92%
Self-Blocking Bricks	10	6	99	1	0	1	0	3565	0	3565	3682	96,82%	91,69%	94,19%
Shadows	0	0	0	0	1	0	0	0	946	946	947	99,89%	100,00%	99,95%
														97,08%

Table 213 PUS - SVM-LNR - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6137	6	102	0	0	17	160	209	0	6137	6631	92,55%	99,32%	95,82%
Meadows	0	17522	1	249	0	644	0	233	0	17522	18649	93,96%	98,79%	96,31%
Gravel	1	3	1856	0	0	0	2	237	0	1856	2099	88,42%	86,21%	87,30%
Trees	0	46	0	3004	0	9	0	5	0	3004	3064	98,04%	92,35%	95,11%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	100,00%	100,00%
Bare Soil	0	155	0	0	0	4868	0	6	0	4868	5029	96,80%	87,85%	92,11%
Bitumen	9	0	0	0	0	0	1321	0	0	1321	1330	99,32%	89,08%	93,92%
Self-Blocking Bricks	32	4	194	0	0	3	0	3449	0	3449	3682	93,67%	83,33%	88,20%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	100,00%	100,00%
														94,56%

Table 214 PUS - K-NN - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Filtering with 3x3 window)

	Asphalt	**Meadows**	**Gravel**	**Trees**	**Painted Metal Sheets**	**Bare Soil**	**Bitumen**	**Self-Blocking Bricks**	**Shadows**	**Correctly Classified**	**Ground Truth**	**Recall**	**Precision**	**F-Measure**
Asphalt	6141	2	53	0	0	16	287	132	0	6141	6631	92,61%	99,69%	96,02%
Meadows	1	17554	0	142	0	951	0	1	0	17554	18649	94,13%	98,78%	96,40%
Gravel	5	0	2054	0	0	0	0	40	0	2054	2099	97,86%	92,52%	95,11%
Trees	0	34	0	3009	4	17	0	0	0	3009	3064	98,20%	95,46%	96,81%
Painted Metal Sheets	0	0	0	0	1345	0	0	0	0	1345	1345	100,00%	99,70%	99,85%
Bare Soil	0	180	0	0	0	4845	0	4	0	4845	5029	96,34%	83,03%	89,19%
Bitumen	1	0	0	0	0	0	1329	0	0	1329	1330	99,92%	82,04%	90,10%
Self-Blocking Bricks	12	0	113	1	0	6	4	3546	0	3546	3682	96,31%	95,25%	95,77%
Shadows	0	0	0	0	0	0	0	0	947	947	947	100,00%	100,00%	100,00%
														95,31%

Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

Table 215 PUS - ML - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6574	0	0	0	0	5	0	51	1	6574	6631	99,14%	99,40%	99,27%
Meadows	0	18457	1	189	0	2	0	0	0	18457	18649	98,97%	99,67%	99,32%
Gravel	0	0	2096	3	0	0	0	0	0	2096	2099	99,86%	99,90%	99,88%
Trees	2	42	1	2993	0	23	0	3	0	2993	3064	97,68%	93,88%	95,75%
Painted Metal Sheets	1	0	0	0	1329	15	0	0	0	1329	1345	98,81%	99,92%	99,36%
Bare Soil	0	12	0	0	0	5017	0	0	0	5017	5029	99,76%	99,11%	99,44%
Bitumen	0	0	0	0	0	0	1330	0	0	1330	1330	100,00%	100,00%	100,00%
Self-Blocking Bricks	33	7	0	3	0	0	0	3639	0	3639	3682	98,83%	98,54%	98,68%
Shadows	4	0	0	0	1	0	0	0	942	942	947	99,47%	99,89%	99,68%
														99,07%

Table 216 PUS - SVM-RBF - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6545	19	23	1	0	9	0	34	0	6545	6631	98,70%	97,32%	98,01%
Meadows	0	18645	0	0	0	4	0	0	0	18645	18649	99,98%	99,43%	99,70%
Gravel	75	0	1952	0	0	0	0	72	0	1952	2099	93,00%	98,84%	95,83%
Trees	101	79	0	2791	0	66	0	5	22	2791	3064	91,09%	99,79%	95,24%
Painted Metal Sheets	1	0	0	0	1331	8	0	4	1	1331	1345	98,96%	99,85%	99,40%
Bare Soil	0	0	0	0	0	5029	0	0	0	5029	5029	100,00%	98,30%	99,14%
Bitumen	1	2	0	0	0	0	1327	0	0	1327	1330	99,77%	100,00%	99,89%
Self-Blocking Bricks	2	7	0	4	0	0	0	3669	0	3669	3682	99,65%	96,96%	98,29%
Shadows	0	0	0	1	2	0	0	0	944	944	947	99,68%	97,62%	98,64%
														98,73%

Table 217 PUS - SVM-LNR - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	Meadows	Gravel	Trees	Painted Metal Sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows	Correctly Classified	Ground Truth	Recall	Precision	F-Measure
Asphalt	6517	0	19	0	0	0	9	85	1	6517	6631	98,28%	99,60%	98,94%
Meadows	0	18646	0	0	0	0	0	3	0	18646	18649	99,98%	99,45%	99,72%
Gravel	0	0	2096	3	0	0	0	0	0	2096	2099	99,86%	98,04%	98,94%
Trees	0	91	0	2928	0	39	0	6	0	2928	3064	95,56%	99,86%	97,67%
Painted Metal Sheets	0	0	0	0	1329	0	1	15	0	1329	1345	98,81%	99,92%	99,36%
Bare Soil	0	2	0	0	0	5027	0	0	0	5027	5029	99,96%	99,23%	99,59%
Bitumen	0	0	0	0	0	0	1330	0	0	1330	1330	100,00%	99,11%	99,55%
Self-Blocking Bricks	26	10	23	1	0	0	2	3620	0	3620	3682	98,32%	97,08%	97,69%
Shadows	0	0	0	0	1	0	0	0	946	946	947	99,89%	99,89%	99,89%
														99,21%

Table 218 PUS - K-NN - Uniformly Selected N Sample with Pre-Processing (PCA) and Post-Processing (Majority Voting with Meanshift Segmentation)

	Asphalt	**Meadows**	**Gravel**	**Trees**	**Painted Metal Sheets**	**Bare Soil**	**Bitumen**	**Self-Blocking Bricks**	**Shadows**	**Correctly Classified**	**Ground Truth**	**Recall**	**Precision**	**F-Measure**
Asphalt	6574	0	0	0	0	0	0	56	1	6574	6631	99,14%	99,61%	99,37%
Meadows	0	18645	0	1	0	3	0	0	0	18645	18649	99,98%	99,43%	99,71%
Gravel	0	0	2096	3	0	0	0	0	0	2096	2099	99,86%	100,00%	99,93%
Trees	0	104	0	2933	2	21	0	3	1	2933	3064	95,72%	99,83%	97,73%
Painted Metal Sheets	1	0	0	0	1329	15	0	0	0	1329	1345	98,81%	99,77%	99,29%
Bare Soil	0	2	0	0	0	5027	0	0	0	5027	5029	99,96%	99,03%	99,50%
Bitumen	0	0	0	0	0	0	1330	0	0	1330	1330	100,00%	100,00%	100,00%
Self-Blocking Bricks	25	0	0	1	0	10	0	3644	2	3644	3682	98,97%	98,41%	98,69%
Shadows	0	0	0	0	1	0	0	0	946	946	947	99,89%	99,58%	99,74%
														99,41%

TEZ FOTOKOPİSİ İZİN FORMU

<u>ENSTİTÜ</u>

Fen Bilimleri Enstitüsü ☐

Sosyal Bilimler Enstitüsü ☐

Uygulamalı Matematik Enstitüsü ☐

Enformatik Enstitüsü X

Deniz Bilimleri Enstitüsü ☐

<u>YAZARIN</u>

Soyadı : Özdemir
Adı : Okan Bilge
Bölümü : Bilişim Sistemleri

<u>TEZİN ADI</u> (İngilizce) : An Investigation On Hyperspectral Image Classifiers For Remote Sensing
<u>TEZİN TÜRÜ</u> : Yüksek Lisans X Doktora ☐

1. Tezimin tamamından kaynak gösterilmek şartıyla fotokopi alınabilir. X
2. Tezimin içindekiler sayfası, özet, indeks sayfalarından ve/veya bir bölümünden X
   kaynak gösterilmek şartıyla fotokopi alınabilir.
3. Tezimden bir (1) yıl süreyle fotokopi alınamaz. ☐

<u>TEZİN KÜTÜPHANEYE TESLİM TARİHİ:</u>