İSTANBUL TECHNICAL UNIVERSITY ★ INFORMATICS INSTITUTE

AUTOMATIC DETERMINATION OF PLANT TYPE AND PHENOLOGICAL STAGE WITH DEEP LEARNING METHODS

M.Sc. Thesis

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Computer Sciences Department

Computer Sciences Programme

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ BİLİŞİM ENSTİTÜSÜ

TARLA GÖRÜNTÜLERİNDEN BİTKİ TÜRÜ VE FENOLOJİK EVRESİNİN DERİN ÖĞRENME YÖNTEMLERİ İLE OTOMATİK SAPTANMASI

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Aigerim Kairoldayeva, a M.Sc. student of ITU Informatics Institute student ID 704161001, successfully defended the thesis/dissertation entitled "AUTOMATIC DETERMINATION OF PLANT TYPE AND PHENOLOGICAL STAGE WITH DEEP LEARNING METHODS", which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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FOREWORD

This thesis is written as a completion to the M.Sc. program, at Istanbul Technical University. The subject of this thesis, Automatıc Determınatıon Of Plant Type And Phenologıcal Stage Wıth Deep Learnıng Methods, falls in the field of deep learning in agricultural technology. Accomplishing the work presented in this thesis was challenging but full of learning. Firstly, I would like to express my sincere gratitude to my advisor Ulug Bayazit for his patience, motivation and extensive knowledge. He has always been so supportive and helping to solve all difficulties I have.

Also, I would like to thank my family and relatives for their love and support. They always encouraged me to pursue my dreams, and keep the flag flying.

September 2019 Aigerim KAIROLDAYEVA

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ABBREVIATIONS

ANN : Artificial Neural Network
CNN : Convolutional Neural Network
HOG : Histogram of Orientd Gradients
kNN : k-Nearest Neighbor
LDA : Linear Discriminant Analysis
PCA : Principal Component Analysis
ReLU : Rectifiied Linear Activation
SIFT : Scale-Invariant Feature Transfrom
SVM : Support Vector Machines

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AUTOMATIC DETERMINATION OF PLANT TYPE AND PHENOLOGICAL STAGE WITH DEEP LEARNING METHODS

SUMMARY

One of the important parts of agricultural technology and monitoring of agricultural crops is the automation of precise phenotyping of plants. Ecological conditions have a enormous influence on plant growth. Consequently, a precise phenology supervising ensures a lot of data that can be used to improve crop quality and speed up crop production. The process of automatic identification of plant types can be a valuable help for the application of crop monitoring punctually to enhance the production procedures in the food and pharmaceutical industries. The development of machine learning technologies offers an unlike approaches compared to regular agricultural applications. In this work, there was used the method of deep learning for the recognition and classification of phenology phases of agricultural plants. Different from traditional feature extraction approaches, a pre-trained convolutional neural network (CNN) models are used to automatically extract features of images. CNN's structure and depth are important matters to be considered as they reflect the performance of recognition. In this thesis, there were compared different approaches and were made an analysis of them to find out which features are mostly usable in the classification of plant types and phenological stages using deep learning. Custom data augmentation functions are implemented to improve performance of the classifier. The performance of all approaches has been evaluated on a data set compiled as part of the government-supported TARBIL project, for which more than 1200 agro-establishments are located all over Turkey. The outcomes of experiments on the TARBIL data set affirm that the proposed methods are fairly efficient.

TARLA GÖRÜNTÜLERİNDEN BİTKİ TÜRÜ VE FENOLOJİK EVRESİNİN DERİN ÖĞRENME YÖNTEMLERİ İLE OTOMATİK SAPTANMASI

ÖZET

Tarım teknolojisinin ve tarımsal ürünlerin izlenmesinde önemli bölümlerinden biri bitkilerin kesin fenotiplemesinin otomasyonudur. Ekolojik koşullar bitki büyümesinde büyük bir etkiye sahiptir. Sonuç olarak, hassas bir fenoloji denetimi, mahsul kalitesini artırmak ve mahsul üretimini hızlandırmak için kullanılabilecek birçok veri sağlar. Bitki türlerinin otomatik olarak tanımlanması süreci, gıda ve ilaç endüstrisindeki üretim prosedürlerini geliştirmek için dakik izlemenin zamanında uygulanması için değerli bir yardımcı olabilir.

Tarbil, hükümet tarafından desteklenen Tarımsal İzleme ve Bilgi Sistemi projesidir. Tüm Türkiyede 2019'a kadar bir sürü çeşitlilikteki sensörle birlikte 1200'den fazla tarım istasyonu bulunmaktadır. Bitki görüntüleri toplanıp her 30 dakikada bir sunucuya gönderiliyor. Bitkilerin yetiştirilmesi sırasında birçok çevresel değişiklik meydana gelir. Bu nedenle TARBİL ağı tarafından toplanan görüntülerin sınıflandırılması oldukça zor sayılır.

Tezin amacı arpa, buğday, ayçiçek, mısır, pamuk ve nohut olmak üzere 6 tür bitkinin sınıflandırılmasıdır. Bitkinin sadece türünü bulmak değil, aynı zamanda o bitkinin hangi fenoloji aşamasında olduğunu tanımlamaktır. Günümüzde, bunların güçlü bir manuel insan müdahalesi olmadan yapılması mümkün değildir. Ayrıca bitki tanıma ve sınıflandırma, gözlemsel yeterlilik ve insani çaba gerektirir. Bu sorunu çözmek, süreci otomatik hale getirmeye ve iş gücü ile zaman kazanmaya yardımcı olacaktır.

Bitkilerin fenolojisi hakkında yapılan literatür araştırması, bir çok yöntemin fenolojinin izlenmesi için bir önlem geliştirmek üzere renk bazlı özellikler hakkında olduğunu göstermektedir. Bitki sınıflandırması ile ilgili birçok çalışma yapıldı ancak yine de zor bir görev olmaya devam etmektedir. Bazıları, bitkilerin tanımlanması ve sınıflandırılması için bitki yapraklarının kullanılmasını önermektedir. Büyük Konvolüsyonel Sinir Ağlarının (KSA), normal doku, renk, şekil vb. özelliklerine dayanan nesne tanıma ya da algılama için kullanılan ortak tekniklerden daha iyi performans gösterme potansiyeli olduğu tespit edilmiş. Tip tanımlama problemleri sınıflandırıcı tarafından takip edilen bir özellik çıkarıcı içerir. Tarımsal görevlerin çözümünde bilgisayarlı görme yöntemleri de kullanılmıştır.

Bu çalışmanın temel hedefi, güncel yaklaşımları karşılaştırarak en uygun olanı bulmaktır. Özel görüntü veri üretecinin işlevlerinin uygulanması, seçilen yaklaşımların performansını artıracağı varsayılmaktadır.

Derin öğrenmeyi kullanırken iyi performans elde etmek için büyük miktarda veri gerekir. Bir sınıflandırıcı oluşturmak için yeterli veri olmadığında, veri kümesini genişletmek için veri büyütme işlemi kullanılır. Eğitim görüntülerinin toplanmasının yüksek maliyetlerinden kaçınmak için görüntü büyütme işlemi geliştirilmiştir. Görüntü büyütme, eğitim seti görüntülerinin benzer görüntülerin yeni bir varyantını oluşturacak şekilde değiştirildiği süreçtir. Aynı zamanda, çok çeşitli aydınlatma ve renklendirme durumları sunarak sağlam sınıflandırıcıya yardımcı olur. Varsayılan olarak ayarlamalar rastgele uygulanır. Bu nedenle her görüntü her seferinde

değiştirilmiyor. Görüntüleri önceden işlemlemenin birçok yolu vardır: yakınlaştırma, çevirme, döndürme vb.
Örnek veri standardizasyonu, özellik standardizasyonu, rasgele döndürme, kayma, vb. gibi fonksiyonları içeren görüntü veri hazırlama ve büyütme için konfigürasyonu tanımlamak amacıyla kullanılan, Keras tarafından sağlanan hazır bir ImageDataGenerator sınıfıdır.
Keras'ta ImageDataGenerator sınıfı tarafından sağlanan standart veri büyütme tekniklerinin yanı sıra, artırılmış görüntüler üretmek için özel fonksiyonlar oluşturulmuştur. Keras'taki artırmaya yönelik özel ön işleme işlevini uygulamak için özel işlevler tanımlanıyor ve bir argüman olarak ImageDataGenerator'e geçiriliyor.
Onlardan biri yakınlaştırmadır. Yakınlaştırmada orijinal görüntü ile aynı boyuta sahip olmak için görüntünün bir alt bölümü alınıyor. Bu nedenle mevcut bir görüntünün bir kısmını yakınlaştırmak suretiyle yeni bir görüntü oluşturuluyor ve yeni görüntünün boyutu orijinal olanın boyutuyla aynı oluyor.
Histogram eşitlemede, düşük kontrastlı görüntüler alınır ve gölgede hassas farklar yaratmak ve daha yüksek kontrastlı görüntüler oluşturmak için görüntünün göreceli yüksek ve alçakları arasında kısıtlamalar artırılır. Piksel yoğunluklarının dağılımı daha geniş bir değer aralığına uyacak şekilde alınır ve verilir. Böylece görüntünün en aydınlık ve en karanlık kısımları arasındaki kontrast seviyesi artar. Resim kontrastını iyileştirmek için 3 adet resim büyütme tekniği vardır: histogram eşitleme, kontrast germe ve adaptif eşitleme.
Kontrast germede bir görüntüdeki piksel yoğunluklarının dağılımı analiz edilir ve 2. ve 98. yüzdelik değerlere düşen tüm yoğunluklara sahip olacak şekilde görüntü yeniden boyutlandırılır.
Genel olarak istasyon kameraları sabitlendiği ve tüm sekansı aynı zoom faktörü ile yakaladığı için, her kareye diğerlerinden bağımsız olarak rastgele seçilen bir zoom faktörü uygulamak gerçekçi değildir. O yüzden kontrast germe ve histogram dengeleme veri artırma işlevleri çerçevelere birbirlerinden bağımsız olarak, yakınlaştırma işlevi ise tüm diziyi aynı oranda etkileyecek şekilde uygulandı.
Ağı sıfırdan eğitmek için iki sınırlama var. Her şeyden önce ağın birçok parametreyle doldurulması gerekir; uygun parametreler elde etmek için büyük bir veri kümesine sahip olması gerekir. Sonra bu devasa veri setini işlemek ve çoklu yineleme gerektiren ve bilgi işlem kaynaklarını zorlayan eğitim için devasa bilgi işlem gücü gerekir.
Transfer öğreniminin arkasındaki sezgi, eğer yeterince geniş ve genel bir veri kümesi üzerinde eğitilmiş bir model ise, bu modelin görsel dünyanın genel bir modeli olarak etkili bir şekilde hizmet edeceğidir.
Denenen modeller Mobilenet sürüm 1, Mobilenet sürüm 2 ve VGG-16'dır.
Mobilenet'i mimarisinde hafif olduğu için kullandık. Mobilenette derinlemesine ayrılabilir konvolüsyonlar kullanılıyor. Bu temelde üçünü birleştirmek ve düzleştirmek yerine her renk kanalında tek bir konvolüsyon gerçekleştiriliyor.
VGG-16 modeli tamamen bağlı katmanları içeren üst katman olmadan yüklendi. Baz ağın eğitilebilir parametrelerini ayarladıktan sonra sınıflandırıcı evrişimli bazın üstüne eklendi. Bitkilerin fazlarının sınıflandırılmasındaki diğer yöntemlerle karşılaştırıldığında, bu model oldukça daha iyi sonuçlar verdi.
Denenen bitkiler buğday, arpa, mısır, pamuk, nohut ve ayçiçeğidir. Bitkilerin görüntülerini etkileyen birçok hava değişikliği tarım bitkilerinin büyüdüğü tüm dönemde gerçekleşir. Sonuç olarak çeşitli aydınlatma koşullarından istenmeyen etkileri ortadan kaldırmak mümkün değildir.. TARBİL ağı tarafından toplanan görüntüler sınıflandırma için oldukça zorlayıcıdır. Dahası, farklı sınıflardan bitkiler,

büyüme aşamalarında farklı yerler, yönleri çok yavaş bir şekilde değiştiriliyor ve takip eden iki fazdaki orta görüntüleri ayırt etmek zordur.
TARBIL veri setinden 6 bitki sınıfı kullanılarak KSA'ların ince ayar ve özellik çıkarımı yapıldı. Her görüntü büyük parçalara bölündü ve her yama için özellik çıkarımı yapıldı.
KSA kurulumu ve veri seti ile, model, özellikle bitkilerin erken fenolojik aşamalarının sınıflandırılması için nispeten kusurlu bir performans sergiledi. Herhangi bir bitkinin fenolojisinin başlangıcında, görüntünün tamamında çok fazla toprak vardır. Toprağın özellikleri, hangi bitkilerin yetiştirildiğine bağlı olarak değişmez. Aynı zamanda sınıflandırıcı, olgun fenolojik aşamalarında her bitkinin çok özel özelliklere sahip olması nedeniyle, bitkilerin olgun fazları için nispeten daha üstün bir başarı elde etti.
Özel resim veri üreteci fonksiyonlarının eklenmesi, veri setinin ve sağlam sınıflandırıcının büyütülmesine yardım etti. İlk olarak, görüntü veri üreteci kullanmadan sonuçlar elde edildi, doğruluk% 79.69 ve kayıp 0.4685 idi.
Özel histogram eşitlemesi eklendiğinde, görüntü veri üretecine karşılık olarak streching işlevleri, sonuçları % 87.5 ve 0.3798'e yükseltti.
Fenoloji aşamalarının tanımlanması durumunda, görüntü veri büyütmesi kullanılmadan elde edilen sonuçlar, kayıp 0.5927 ve doğrulama kaybı 0.6814'tir. Kontrast gerilmesi eklemek, bu sonuçları 0.5119 ve 0.6409'a yükseltti.
Bu çalışmada, 6 tür bitki ve bitkilerin farklı fenolojik aşamalarının sınıflandırılması için evrişimli bir sinir ağları temelli yaklaşımlar kullanılmıştır. Veri seti TARBİL projesinden alınmıştır. Gözlem sonuçları, KSA tabanlı önceden eğitilmiş ağların üzerinde çalıştığımız 6 tür bitki üzerinde önemli derecede etkili olduğunu gösteriyor. Diğer yöntemlerle karşılaştırıldığında, deneysel sonuçlar MobiletNet v2'nin ince ayar sınıflandırma doğruluğunun, bitki türlerini sınıflandırmadaki diğer yöntemleri geride bıraktığını, ancak VGG-16 modelinin ince ayarının her tesisin fenoloji aşamasının sınıflandırılmasında diğer mimarilerden uzak durduğunu göstermektedir. Dahili ve özel veri büyütme işlevlerinin kullanılması, sınıflandırıcının performansını arttırdı.

1. INTRODUCTION

Progress in technology, including sensors, machines, devices and information technology affected modern farms and agricultural operations act far differently from those some time ago. Nowadays, advanced technologies like robots, aerial images, temperature and moisture sensors, GPS, etc. are used routinely in agriculture. These sophisticated devices and robotic systems allow businesses to be more efficient, safer, more environmentally friendly and more profitable [1]. Technology has played an important role in developing the agricultural industry. Automating precise plant phenotyping is one of the important parts of crop inspection and agricultural technologies.

Phenology is the study of the timing of the biological events in plants such as flowering, leafing, hibernation, reproduction, migration, etc. The timing of such biological events in relation to changes in season and climate are the most interesting part of phenology studying scientists. Accurate monitoring of plant phenotyping can ensure providing enormous information that would be used to increase accelerating crop production and yield quality. Accurate detection of phenology stage alteration of plants subsequently refines the scheduling for the pest control, harvest, farm monitoring, etc [2].

Commonly, manual techniques are used to identify phenology stage of the plants in the agricultural area. Nevertheless, it used to have low efficiency and doubtful accuracy. In order to make a real-time plant phenotyping system with high precision, it has to be fully automated. There are a lot of bounds in the most of the automated system. There are a lot of countries in the world trying to construct governmental observation systems for the agriculture, as enclosing that the phenology data leads to a much insighs of the correlation betwixt surroundings' circumstances, performance, and vegetation health [3]. These network systems have agro-stations tooled with a lot of sensors and they are used to collect agricultural data. But, processing of the phenological information extraction using these systems, still, require a heavy manual human interference [4].

In order to boost yield estimation and crop growth evaluation models there should be developed and automated phenology identification of agricultural fields.

Recently, image analysis methods began to appear as an attempt to automate the process of monitoring plants [5]. Presence of these superiority measurements combined with present-day image processing algorithms dependably increased the applications possibilities in the agriculture. The progress of machine learning techniques offers a dissimilar approaches compared to the conventional ways for agricultural applications.

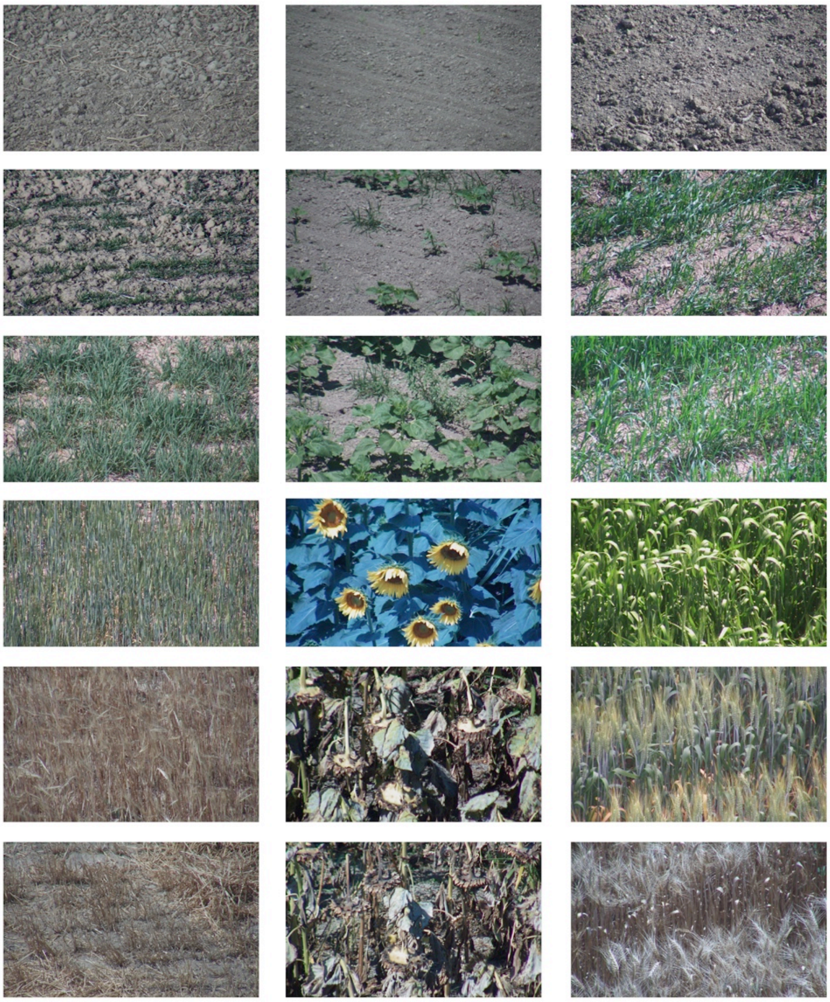
Agricultural Monitoring and Information (TARBİL) System Project is the largest direct and indirect employment provider for Turkey since last years .

Images downloaded directly to the ITU-UHUZAM Satellite Earth Station are processed and transferred to the data collection center. In addition, smart measurement stations have been started to be used to extract plant characteristics from camera images and send data via the Turksat satellite.

There are more than 1200 agro-stations provided with all kinds of sensors placed over entire Turkey to 2019. Images are being assembled to the server and network infrastructure with fast fiber. Accumulated images contain intimate frames of some areas of interest of an agriculture. Plant images are taken and collected to the server each 30 minutes [6]. Plant types that were experimented are barley, sunflower, wheat, corn, chickpea, cotton. Many environmental changes take place during the cultivate time of plants. Images gathered by TARBIL network are reasonably hard for classification. Moreover, while the growing stages, plants from each class look differently, it is challenging to distinguish the images that are in the center of the 2 consecutive phases as the appearances change very gradually.

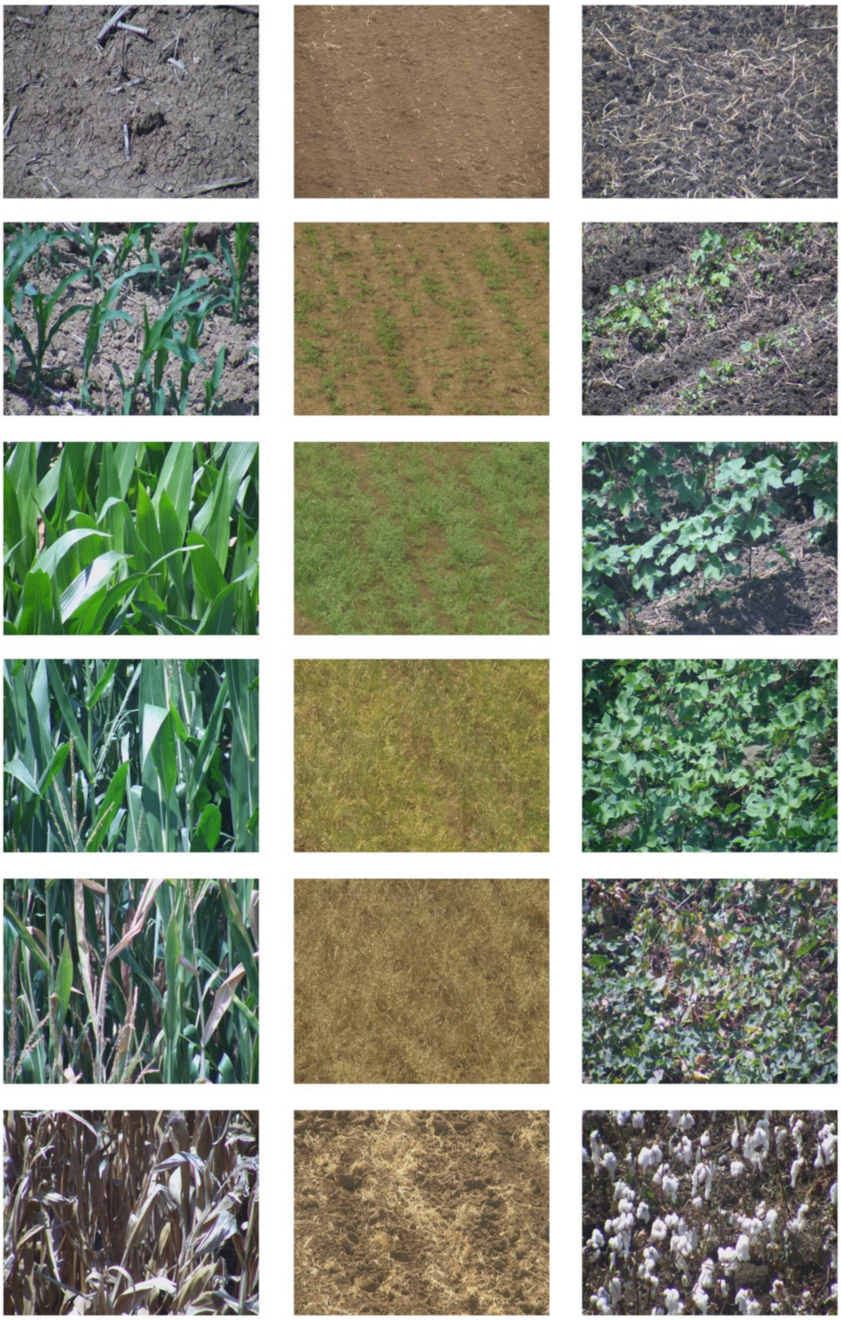
1.1 Purpose of the Thesis

Purpose of the thesis is the classification of 6 types of plants, which are barley, wheat, sunflower, corn, cotton, and chickpea, not only to find the type of the plant but also to identify in which phenology stage is that plant. Samples of this plants in different phases are shown in Figure 1.1 and Figure 1.2. Nowadays, these are not possible to do without a strong manual human intervention. Moreover, plant recognition and classification of their stages require observational proficiency and human effort. Solving this problem will help to automate this process and save labor power and time.



a b c

Figure 1.1 : Samples of plants in different phenology stages (a) Barley, (b) Sunflower, (c) Wheat.



a b c

Figure 1.2 : Samples of plants in different phenology stages (a) Corn, (b) Chickpea, (c) Cotton.

1.2 Literature Review

Literature research made about phenology of the plants shows that most methods are about color-based features to develop a measure for monitoring of the phenology [7]. Color distribution in an image is used in color analysis, but there are a lot of conditions to contravene the temporal consistency of the color feature.

Statistical and structural relationships between pixels, like a contrast, smoothness, randomness, linearity, etc., are described in the textural features. Some patterns based on the co-occurrence matrixes and local binary patterns have been provided using statistical approaches [8],[9].

There were made a lot of studies about plant classification, but still, it remains to be a challenging task. Some of them suggest using plant leaves for identification and classification of the plants [10]-[12]. Features as color and shape of the leaf images are used by Caglayan et al. to classify plants [11]. Visual features were extracted by applying Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) by Gaber et al. [12]. k-Nearest Neighbor (kNN) and Artificial Neural Networks (ANN) classifiers were applied to the Flavia image dataset's leaf images by Satti et al. [13].

There were identified the prospective of the huge Convolutional Neural Networks to perform better than common techniques for object recognition or detection that are based on ordinary texture, color, and shape features, etc. [14]-[17]. Mostly the CNN models that were used in these wide-ranging plant type identification problems contain a feature extractor succeed by a classifier. Computer vision methods also were used in solving agricultural tasks. For example, there is a Landscape classification of aerial images using machine learning methods in agricultural computing [18],[19]. Last years, deep learning methods have been developed a lot. Deep learning approaches perform better than usual methods in solving complex tasks like object recognition and image classification. Before deep learning methods become widely used in the computer vision field, handcrafted feature based approaches were popular in applying for image recognition. But this required high computational power and time, because of complexity of the preprocession, feature extraction and classification. The best known handcrafted feature approaches are Histogram of Oriented Gradients (HOG) [20] and Scale-Invariant Feature Transform

(SIFT) [21] and they are generally integrated with classifiers like Support Vector Machines (SVM). Deep learning, in its turn, has an facility of extracting its own features to identify complicated relations and patterns between the data [22].

Convolutional Neural Networks is a well-liked method to extract features in image recognition problems and used in a series of areas, like agriculture, robotics, etc. There are many applications on agricultural data which advantage deep learning methods to solve issues like a plant recognition. Pawara et al. have proven that CNN-based methods fulfill better than local feature descriptors while recognizing ten types of plants [22]. Deep learning approaches are used widely on plant recognition tasks, which can be seen in reports of many publications. In some researches deep learning is applied to extract features and then that features are given as an input to well-known classifiers[23], in others, pre-trained CNN architectures are directly employed [24]-[26]. Moreover, the idea of CNN was applied to recognise plant diseases and performed well results on different floras [27]-[29]. Two approaches were compared to differentiate 26 types of diseases included in 14 crops using the Plant Village Dataset in [29].

1.3 Hypothesis

In this thesis, there will be investigated different approaches to classify 6 kinds of plants and to find in which phenology stage it is. There will be proposed new model to do classification, and made pre-processing of input images to improve classification accuracy. Main goal of this study is to compare up to date approaches to find most suitable one. It is supposed that implementation of custom image data generator functions will enhance performance of chosen approaches.

2. METHODS AND DATA

2.1 Artificial Intelligence

In the last years, there was tremendous growth in bridging the gap between the facilities of machines and human beings. Artificial intelligence is a field which is intended to make machines able to see the world as humans do, make able to do all tasks that man do easily such as image and video recognition, image analysis and classification, natural language processing, recommendation systems, etc. The progression in Computer Vision with Deep Learning has been built and enhanced by time, essentially over a Convolutional Neural Network.

2.2 Convolutional Neural Networks

Convolutional Neural Network (CNN) is a deep Learning algorithm which takes an image as an input, assigns learnable weights and biases to different objects in the image to distinguish them from each other. There is no need for much pre-processing of data comparing to other classification algorithms. While in primal approaches filters are controlled manually, CNN's have the ability to learn these characteristics by itself if there were made enough training.

2.2.1 Architecture of CNN

The architecture of CNN is same to the neurons connectivity pattern in the human brain. Discrete neurons respond to stimuli only in a limited region of the visual area known as the receptive field. A collection of such fields overlap to cover the full visual area.

Application of relevant filters is used in CNN to grap the dimensional and temporal dependencies in the image. Reduction of the involved number of parameters and reusing of weights causes the architecture to perform a better fitting to the dataset of images. So, the network is trained to get the sophistication of the image better. The model is shown in Figure 2.1.

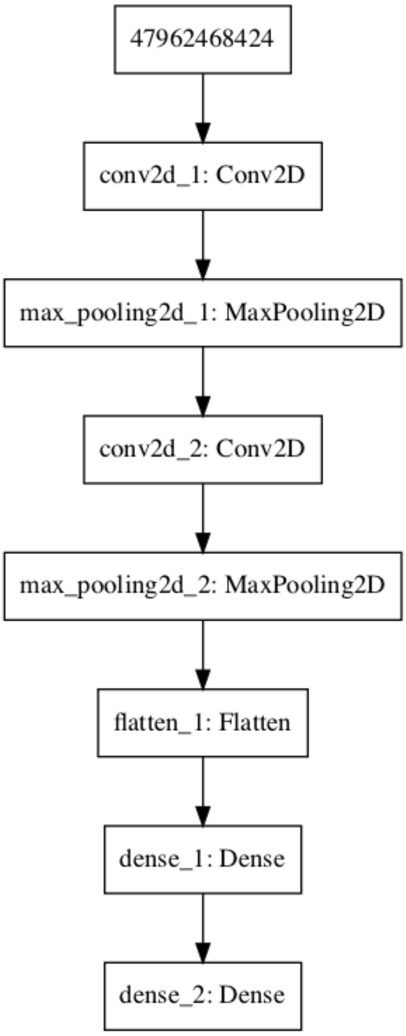


Figure 2.1 : Convolutional Neural Networks Architecture.

2.2.2 Layers of CNN

Images are reduced into a form in the CNN, which is much easier to process in the absence of critical features for getting a good prediction. Traditionally, low-level features like color, orientation of gradients, etc. are captured in the first layers of CNN. Following levels are responsible for high-level features which provide a wholesome understanding of images in the dataset.

The role of the pooling layer is to reduce convolved feature's dimensional size. This is required to reduce computational power which is needed to data processing. Moreover, it is valuable to extract rotational and positional invariant features to preserve the process of efficient model training.

The flattened output is assured to a feed-forward neural network and backpropagation applied to every iteration of training. The model is able to distinguish between ruling and some low-level features in images after a series of epochs.

Dense layers are used to perform classification on the features extracted by the convolutional layers and downsampled by the pooling layers. In a dense layer, every node in the layer is connected to every node in the previous layer.

2.2.3 Dataset

Out of the 9,000 images are provided in the dataset, 6,000 are given for training and 3,000 are given for testing. By default, the shape of every image in the dataset is 2288x1712. Next, dataset inputs are reshaped to 224x224.

Table 2.1: Dataset division for training and testing sets.

Plant	Training Set	Testing Set	Number of Classes
Barley	2041	1560	9
Sunflower	561	239	7
Wheat	1571	657	9
Corn	990	429	8
Chickpea	68	32	7
Cotton	749	254	8

2.2.4 Model Parameters

The model type that was used is Sequential. It allows building a model layer by layer. Our first 2 layers are Conv2D layers followed by MaxPooling layers. These are convolution layers that deal with our input images, which are seen as 2-dimensional matrices. The activation function that was used for the first 2 convolutional layers is Rectified Linear Activation (ReLU). This activation function has been shown good results in neural networks. Then pooled featured map is flattened into a one-dimensional array. Dense is the layer type that was used in the output layer. Dense is a standard layer type that is used on many occasions for neural networks. The activation is ReLU and Sigmoid. Sigmoid makes the output to be in the range between 0 and 1 so the output can be interpreted as probabilities. The model then makes its prediction based on which option has the highest probability.

Compiling the model takes three parameters: optimizer, loss, and metrics. The optimizer controls the learning rate. There was used ‘adam’ as an optimizer. The learning rate is adjusted throughout training in the Adam optimizer. The learning rate defines how fast the optimal weights for the model are calculated. More accurate weights can be taken by a smaller learning rate, but the time it takes to compute the weights is longer. ‘Categorical_crossentropy’ was used for the loss function. This is the most spread choice for classification. A lower score determines that the model is performing better. And as metrics, there was used an accuracy.

2.3 Data Augmentation

Huge amount of data is required to get good performance while using deep learning. When there are not enough data to build a classifier, data augmentation is used to expand dataset. Image augmentation has been developed to avoid the high costs of gathering training images. Image augmentation is the process where training set images are altered to create new variant of the similar images. At the same time it helps to robust classifier by providing a large variaty of lighting and colouring environment. By default, the adjustments are applied randomly, so not every image is modified every time. There are a lot of ways to pre-process images, like zooming, flipping, rotating etc.

There is a ready ImageDataGenerator class which is provided by Keras that is used to define the configuration for image data preparation and augmentation, which contains functions like sample-wise standardization, feature-wise standardization, random rotation, shifts, shear and flips, etc.

One of the traditional ways to generate more data for the classifier is a zooming. It takes subsection of the image to have same dimension of the original image. So that, new image is created by zooming in a portion of an existing image, the size of the new image is identical to the size of the original one.

Rotation is also one of the methods to generate new data. Image dimension is not preserved after this operation. But if the image is a square, image size is preserved when rotating is done at right angles.

Apart from the standard techniques of data augmentation provided by the ImageDataGenerator class in Keras, there were created custom functions to generate augmented images. To implement custom preprocessing function for augmentation in Keras, there were defined custom functions and passed to ImageDataGenerator as an argument.

In histogram equalization, there low contrast images are taken and the constrast is increased between the image's relative highs and lows to make delicate differences in shade and create a higher contrast images. Distribution of pixel intensities are taken and stretched to fit a wider range of values thus contrast level between the lightest and darkest portions of an image are increased. There are 3 image normalization techniques for improving image constrast, which are histogram equalization, contrast stretching and adaptive equalization.

In histogram equalization, distribution of pixel densities are calculated and plotted on a histogram in order to increase contrast of images. The histogram is then examined to detect ranges of pixel brightnesses that are not being utilized to be stretched to cover all ranges, after it is back projected onto the image to enlarge the general constrast of the image.

In contrast stretching, distribution of pixel densities in an image is analyzed and image is rescaled to have all intensities that fall in the 2nd and 98th percentiles.

In adaptive equalization, there several different histograms are computed to different parts of the image.

Our dataset contains images which are taken in different weather conditions and in different view. There are 2 zooming options for every data. Total number of dataset is about 9000 images, this is quite small to build a classifier, that is why data augmentation was used expand dataset and improve classifier's performance.

Contrast stretching and histogram equalisation data normalization functions were applied to frames independently of each other.

2.4 Mobilenet Version 1

Transfer learning uses the model that has been already trained on another problem. Then it is re-trained on a corresponding problem. Nowadays, no one processes deep learning from scratch, because it takes some days, but using transfer learning can descrease that time.

There was used the model that was trained on the ImageNet Large Visual Recognition Challenge dataset. ImageNet models are used to distinguish a huge number of classes. Training is done only in the last layer of the network, that is why it does not take much time. ImageNet does not contain any of these plants' types images from our dataset. Despite that, the pattern of information that makes it possible for ImageNet to distinguish among 1,000 classes is also useful for differentiating other objects. That information is used as input to the final classification layer that distinguishes our plants' classes and phases. The architecture of the model is shown in Figure 2.2.

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
$5\times$ Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Figure 2.2 : Mobilenet Version 1 Architecture.

MobileNet is a small efficient CNN. Calculations are performed at each location in the image that is why it is called convolutional. Image resolution that used as an input is 224. The relative size of the model as a fraction of the largest MobileNet is 0.5. The first retraining command iterates only 500 times. The first phase analyzes entire images on disk and the bottleneck values are calculated for each of them.

A lot of layers stacked on top of each other in ImageNet models. Pre-training is done at these layers and they have very useful at finding and summing up information that helps to classify plant images.

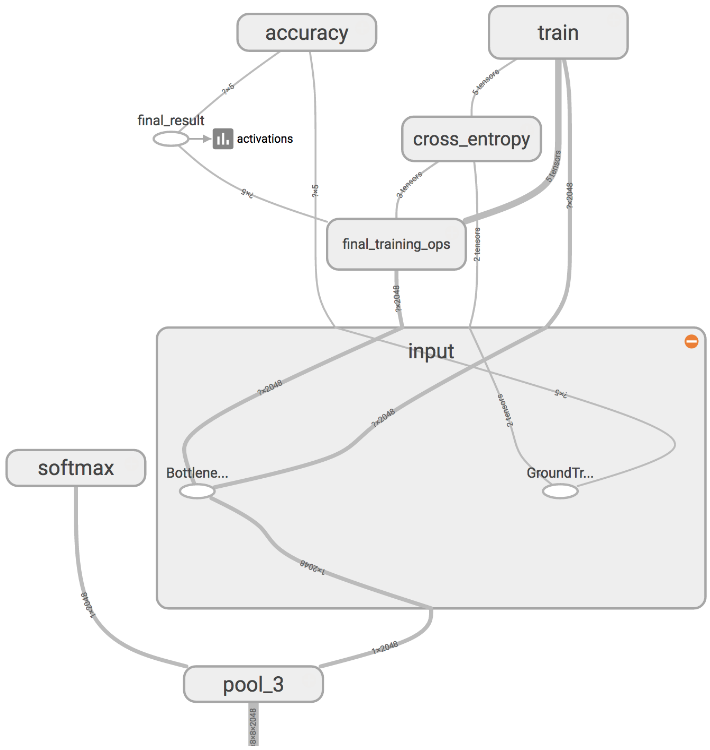


Figure 2.3 : Softmax layer architecture.

"Softmax" label in the node is the output layer of the original model in the above Figure 2.3. Other labels were added by the retraining script.

The layer just before the last output layer which does the classification is called a bottleneck. It does not mean that the layer is decelerating the network, it means close to the output, the representation is much more compact comparing to the main body of the network.

While the training, each image is reused numerous times. Calculating the layers behind the bottleneck for every image takes a long time. Output is not reflected from these lower layers of the network that are why can be cached and reused. Accordingly, the script runs only in the permanent part of the network. When all the bottleneck files are generated by the script, there began the actual training of the last layer.

The script runs 4000 training steps. In each step, there are chosen random 10 images from the training step, found their bottlenecks from the cache and predictions are done in the final layer. Then, those predictions are compared with the real labels, and the results of this comparison are used to update the final layer weights using a backpropagation process.

2.5 Mobiletnet Version 2

The preserved network that was trained before on an enormous dataset, usually on a large-scale image classification problem is called a pre-trained model. The pre-trained model can be used by itself or transfer learning using the pre-trained CNN.

The idea of transfer learning is if the model is trained on a big and general dataset, it efficiently serves the common model of the perceptible world. These learned feature maps can be leveraged without training a huge model on a huge dataset by using trained models as a base for the specific to task model.

Transfer learning using the pre-trained model can be used in 2 ways. First one is Feature Extraction - using representations of learned by the earlier network to get relevant features from a new dataset. The new classifier is added on top of the pre-trained model to be trained from scratch, so as feature maps learned before reused for new samples. There are only used feature extraction part of the pre-trained convolutional base. But, the classification part of the pre-trained model is specific to the plants' classes.

The second one is Fine-Tuning - unfreezing of some of the frozen model's top layers that are needed for extracting features, and training added classifier layers with the last layers of the frozen model. This helps to fine-tune the upper order feature representations in addition to the final classifier.

Table 2.2: Mobilenet version 2 Fine Tuning.

Layer (type)	Output Shape	Param #
mobilenetv2_1.00_160 (Model)	(None, 5, 5, 1280)	2257984
global_average_pooling2d_1	(None, 1280)	0
dense_1 (Dense)	(None, 6)	7686

There was used MobileNet Version 2 model developed by Google, which is pre-trained on the ImageNet dataset, to create the base model. ImageGenerator has been used to re-scale the images.

First of all, one of the intermediate layers is taken from MobileNet Version 2 model to extract features. The classifier is added on top of it and top-level classifier is trained.

Only some layers on top of the MobileNet Version 2 base model are trained in the feature extraction. While training, the weights of the pre-trained network are not changed. In order to get better results, the weights of the top layers of the pre-trained model side by side to the top-level classifier should be fine-tuned. The weights are tuned from generic feature maps to features related to plants dataset in the training process.

In the CNN, higher layers are more specialized, that is why the top layers of the pre-trained model are fine-tuned, rather than whole layers of it. Initial few layers in the CNN are used to learn basic and generic features, which are almost general to most of the images. Following layers are responsible for more concrete to the dataset features, that the model was trained on. The aim of the fine-tuning is the customization of the specialized features to classify on a new dataset.

2.6 VGG-16

In order to train network from zero, there appeared to be two constraints. First of all, the network has to be filled with a lot of parameters, to get a favorable set of parameters there is a request to have a huge dataset. Then, to process this enormous dataset, huge computing power is required for training, which needs multiple iterations and takes a toll on the computing resources. VGG16 model, which is shown in the following Figure 2.4, is used for fine-tuning Figure 2.5.

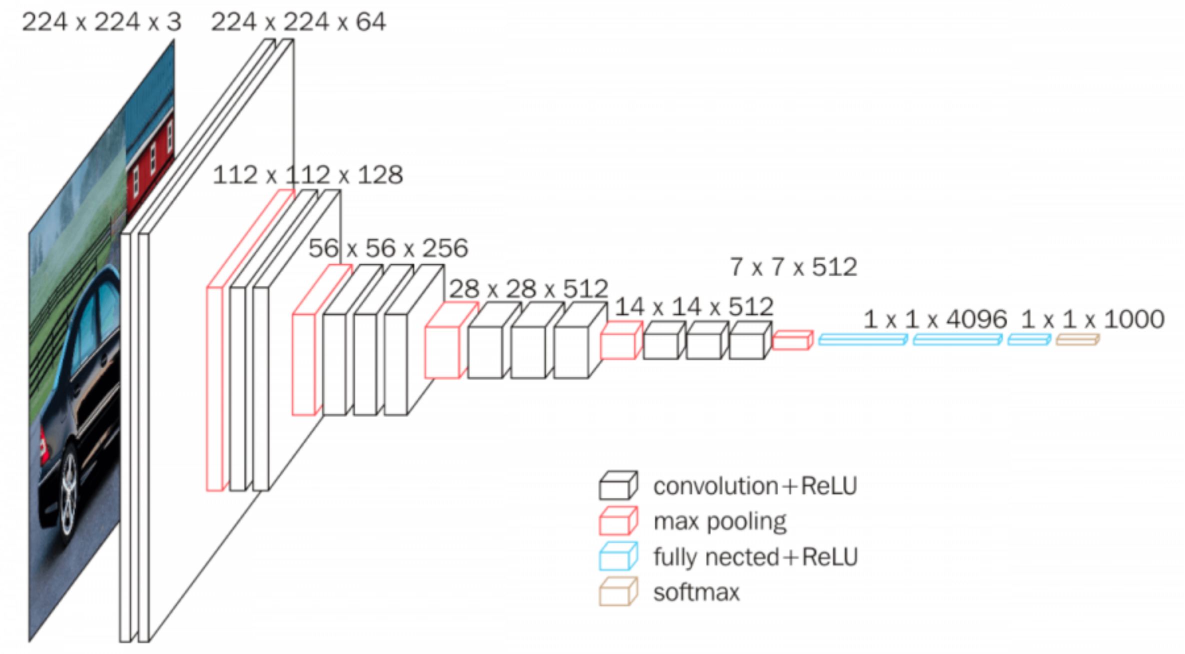


Figure 2.4 : VGG-16 Architecture.

In the beginning, the VGG model was loaded without the top layer, which contains fully connected layers. After setting trainable parameters of the base network, the classifier was added on top of the convolutional base.

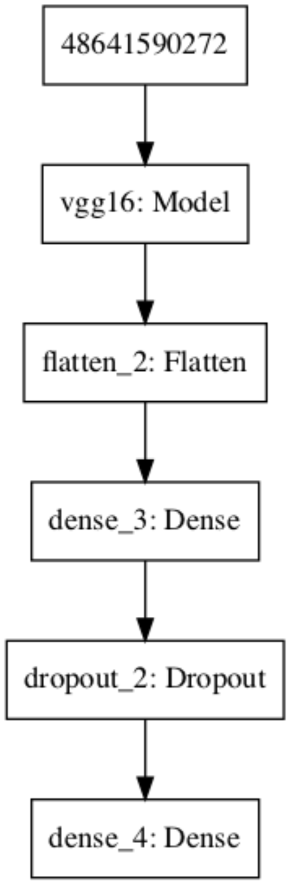


Figure 2.5 : VGG-16 Fine-Tuning.

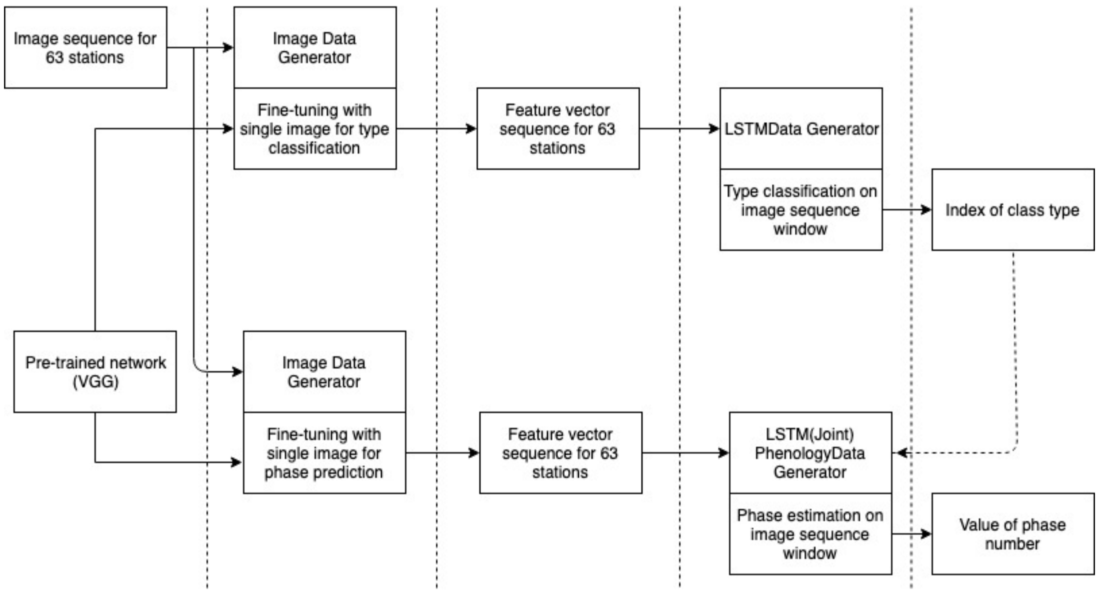


Figure 2.6 : Block diagram.

2.7 LSTM

Finetuning on image sequence data is very problematic in terms of memory requirements and overfitting problems that may lead to limited training. Even at low resolutions (224x224) accepted by pre-educated networks such as VGG, the introduction of several images at once to a distributed or LSTM network caused out-of-memory errors. It has therefore been found that fine tuning can only be applied in the form of classification with a single image. There has been developed two-stages for classification of plant type and phenology stage of plants as shown in Figure 2.6.

3. RESULTS AND RECOMMENDATIONS

3.1 Results

The plants that were experimented are wheat, barley, corn, cotton, chickpea, and sunflower. Many weather changes, that affect the images of plants, occur within the entire period of cultivation of agricultural plants. Consequently, it is impossible to clear off undesirable effects from various lighting conditions. Images gathered by TARBIL network are pretty demanding for classification. Moreover, plants from different classes look differently during the growing stages, aspects modified very slowly, and it is difficult to differenciate middle images that are in the between of 2 following phases.

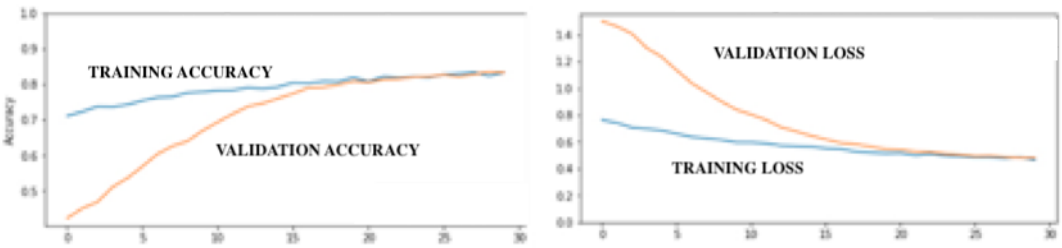


Figure 3.1 : Training and Validation Accuracy&Loss of Feature Extraction Mobilenet V2.

There was performed fine-tuning and feature extraction of CNNs using 6 plant classes from TARBIL dataset and every image is splitted into big pieces and extraction of features are done for every patch. Images originally have 2288 x 1712 pixels size, but it is resized to 224 x 224 patches in order to increase the number of the training and the testing data.

Trials were done in Python programming language, Mac OS High Sierra 64-bit operating system computer with Intel Core i7, 8.00 GB RAM, AMD Radeon HD 6750M 1024 MB, Intel HD Graphics 3000 512 MB.

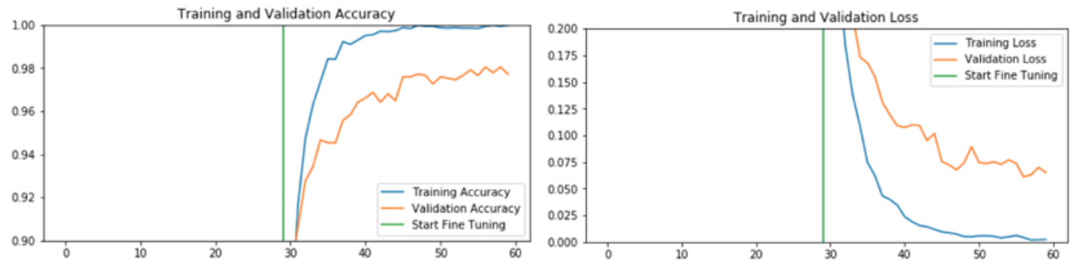


Figure 3.2 : Training and validation Accuracy&Loss of Fine-Tuning of Mobilenet V2.

In Table 3.1, the classification results of CNN based approaches are shown. Training and validation accuracy, as well as training and validation loss for feature extraction and fine-tuning of Mobilenet V2 are shown in Figure 3.1 and Figure 3.2 correspondingly.

The validation accuracy for classification of 6 types of plants using pre-trained convolutional neural networks ranges from 80.3% to 97.72%.

Table 3.1: Accuracy of different models for plant types.

Model	Accuracy, %
CNN	82.19
MobileNet - Feature Extraction	80.3
MobileNet V2 - Feature Extraction	83.27
MobileNet V2 - Fine Tuning	97.72
VGG16 - Fine Tuning	93.98

With the actual CNN installation and dataset, the model performed relatively imperfect, as it is shown in Table 3.2, particularly for classification of the early phenological stages of the plants. At the beginning of the phenology of any plant, there are a lot of soil in the entire image. The characteristics of the soil are not changed in demand which plants are grown. In the same time, classifier accomplished comparatively superior for mature phases of plants, since in the mature phenological stages each plant has very exclusive feature properties.

Table 3.2: Accuracy of CNN model for the phenology stages of plants.

Phenology stages	Accuracy, %
Phases of Barley	69.62
Phases of Sunflower	76.03
Phases of Wheat	59.93
Phases of Corn	74.82
Phases of Cotton	70.5

Table 3.3: Accuracy of VGG-16 model for phenology stages of plants.

Phenolofy stages	Accuracy, %
Phases of Barley	82.62
Phases of Sunflower	80.14
Phases of Wheat	71.02
Phases of Corn	75.82
Phases of Cotton	78.36

Accuracy results of fine-tuning of VGG-16 model for classification of phenology stages of plants are given in the Table 3.3. Comparing to other methods in classifying of plants' phases, this model showed quite better results.

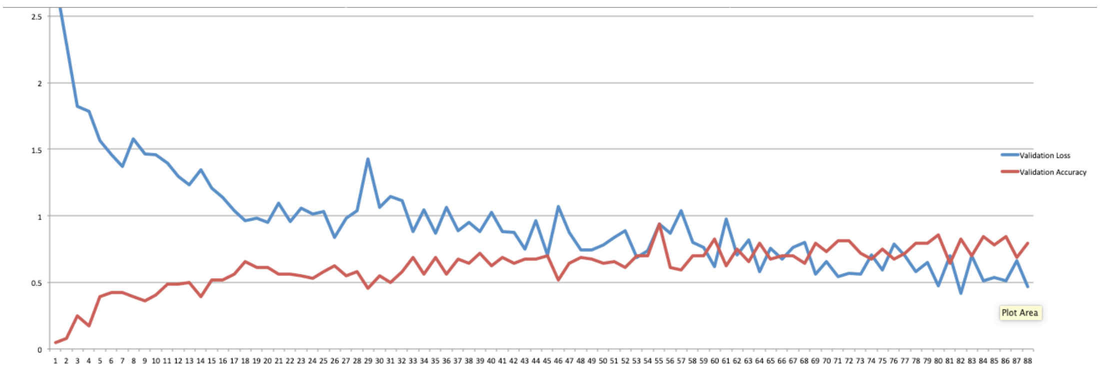


Figure 3.3 : Validation Accuracy&Loss of VGG-16 model without Image data normalization for plant type.

Adding custom image data normalization functions assisted in adjusting dataset and robusting classifier. Firstly, there were obtained results without using image data normalization for classification of plant types as shown in Figure 3.3, accuracy was 79.69% and loss was 0.4685.

Adding custom histogram equalisation, contrast stretching functions for normalisation of image data improved this results to 87.5% and 0.3798 as showing in Figure 3.4. Accuracy was increased from 64.46% to 65.10% when LSTM with windows size 2 was used for classification of plan type as shown in Figure 3.7. Adding contrast stretching showed better results in first and third epochs.

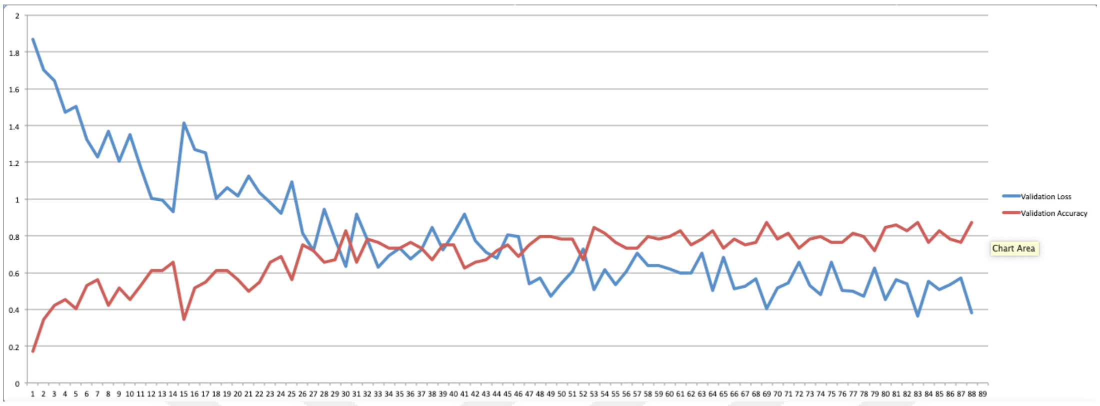


Figure 3.4 : Validation Accuracy&Loss of VGG-16 model with Image data normalization for plant type.

In case of identification of phenology stages, results obtained without using image data normalization with LSTM are shown in Figure 3.5, where loss was 0.5927 and validation loss was 0.6814. Adding contrast stretching improved these results to 0.5119 and 0.6409 as shown in Figure 3.6.

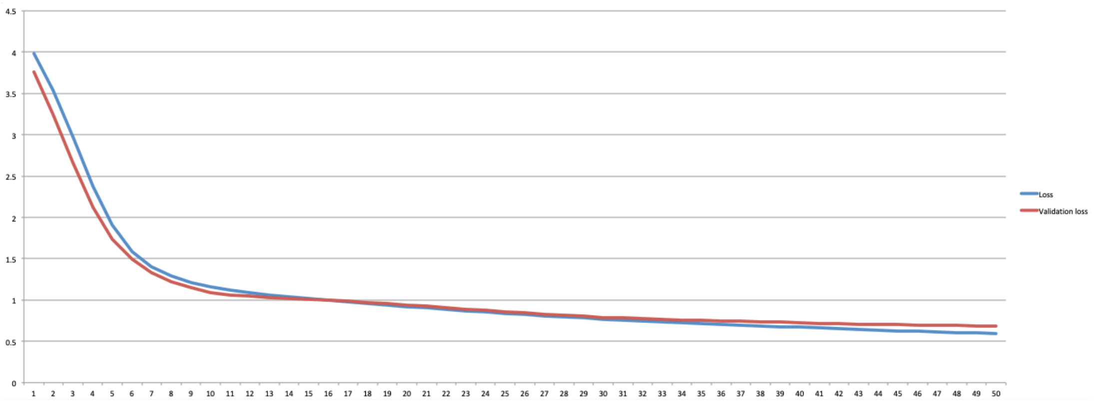


Figure 3.5 : Loss&Validation Loss of LSTM without Image Data Normalization for phenology.

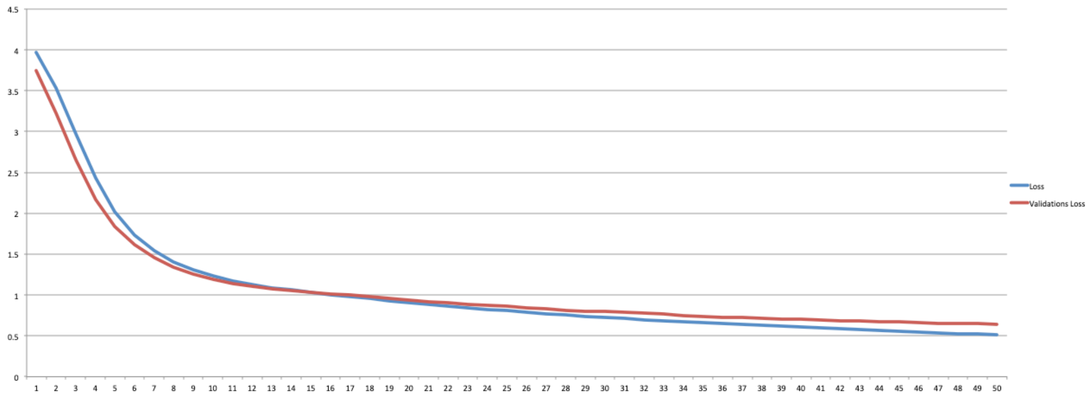


Figure 3.6 : Loss&Validation Loss of LSTM with Image Data Normalization for phenology.

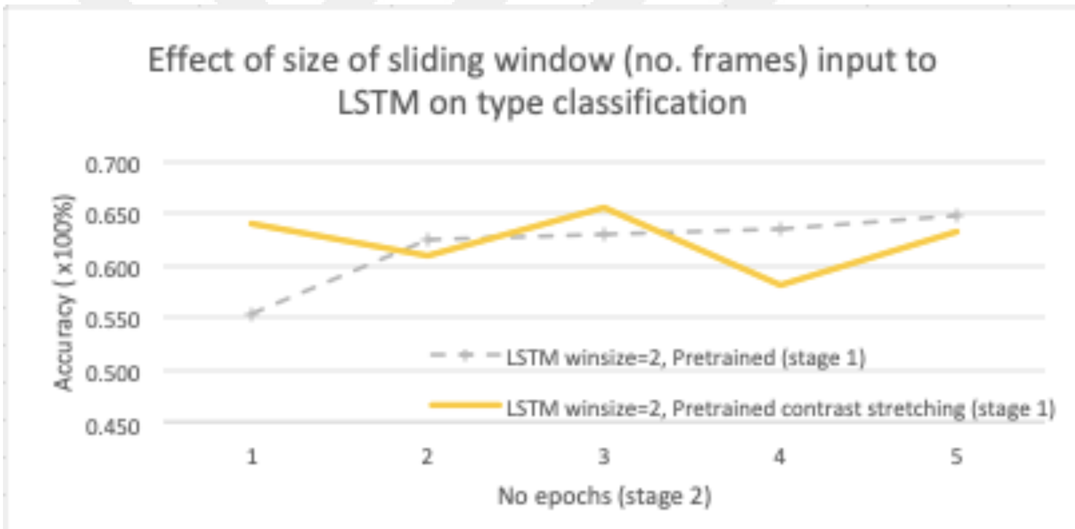


Figure 3.7 : Loss&Validation Loss of LSTM with Image Data Normalization for plant type.

4. CONCLUSION

4.1 Conclusion

In this work, a convolutional neural networks based approaches were employed for the classification of 6 types of plants and different phenological stages of plants. Dataset was taken from TARBIL project. Observational outcomes point that CNN based pre-trained networks perform significantly effective on the 6 types of plants we have worked on. Compared with other methods, experimental results shows that the classification accuracy of fine-tuning MobiletNet v2 outperforms other methods on classifying plants types, but in classification of phenology stage of each plant fine-tuning of VGG16 model stay ahead from other architectures. Using built-in and custom data normalization functions improved performance of the classifier.

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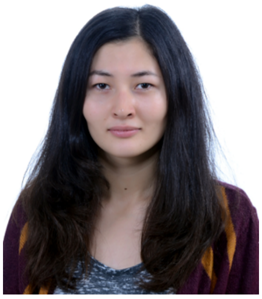
CURRICULUM VITAE



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