CONTINUOUS AUTHENTICATION WITH BEHAVIORAL BIOMETRICS ON MOBILE DEVICES

(MOBİL CİHAZLARDA DAVRANIŞSAL BİYOMETRİ KULLANARAK SÜREKLİ KİMLİK DOĞRULAMASI)

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ABSTRACT

With the rapid development of technology, smartphones and tablets have become essential objects for our daily lives. Besides their actual purpose of use, people have begun to use these devices as their personal assistants. They are used to make monetary transfers, to arrange their meetings and to make personal messaging by users. Additionally, smartphones and tablets provide large internal storage which enables users to store their private information, such as personal photos, contact details, call histories, etc. On the other hand, because of their small sizes, these devices could easily get lost, stolen. Therefore, providing the security and privacy of smartphone users against unauthorized access is a very important and crucial area of research. Current solutions use active authentication methods, such as PINs and patterns, or use physical biometric authentication, such as fingerprint or iris scan. An alternative solution is the use of behavioral biometrics which track and identify user's interaction patterns with the device. There are various studies on this topic in the literature. However, the authors generally focus on using touchscreen-based or sensor-based features for building an authentication model. In this thesis, we investigated the impact of using both touchscreen-based and sensor-based features in an authentication model. We combined these feature-sets and applied various classification and attribute selection algorithms to the combined feature-set for detecting which features are distinctive in revealing the behavioral character of users for building an authentication model and we achieved average 4.56 % EER by using the data collected from 20 users in 10 sessions.

ÖZET

Teknolojide yaşanan hızlı gelişmelerle birlikte, akıllı telefonlar ve tabletler günlük yaşantımız için vazgeçilmez objeler haline gelmiştir. İnsanlar, bu cihazları gerçek kullanım amaçlarının dışına çıkarak, kişisel yardımcıları olarak da kullanmaya başlamışlardır. İnsanlar bu cihazları kullanarak parasal işlemlerini yapmakta, buluşmalarını ayarlamakta ve kişisel yazışmalarını gerçekleştirmektedirler. Bunun yanında, akıllı telefonlar ve tabletler, kullanıcılara kişisel fotoğraflarını, adres defteri detaylarını, arama geçmişlerini vb. kişisel bilgilerini saklayabilecekleri geniş bir depolama alanı sağlamaktadırlar. Bu cihazlar küçük boyutları sebebiyle, kolaylıkla kaybedilebilirler veya çalınabilirler. Bu nedenle, akıllı telefon kullanıcılarının güvenliğinin ve gizliliğinin sağlanması oldukça önemli ve elzem bir çalışma konusudur. Günümüzde güncel çözümler, pin ve örüntü gibi aktif kimlik doğrulama yöntemlerini kullanmakta veya fiziksel biyometrik kimlik doğrulama yöntemlerini örneğin parmak izi veya retina taramasını kullanmaktadır. Bunlara alternatif bir çözüm ise, kullanıcının cihaz ile olan etkileşim örüntülerini takip ve tespit eden davranışsal biyometridir. Literatürde bu soruna ilişkin çeşitli makaleler bulunmaktadır. Fakat yazarlar genellikle kimlik doğrulama modellerini oluştururlarken dokunma ekranından alınan özelliklere veya sensorlerden alınan özelliklere dayalı bir model inşa etmektedir. Biz bu tezde, dokunma ekranından alınan özellikler ve sensorlerden alınan özelliklerin kimlik doğrulama modeli inşa ederken yarattığı etkiyi araştırdık. Bu iki veri kümesini birleştirdik ve bir kimlik doğrulama modeli oluşturulurken kullanıcıların davranışsal karakterlerini belirlemede hangi özellik kümesinin daha ayırdedici olduğunu açığa çıkartmak amacıyla bu birleştirilmiş özellikler kümesine çeşitli sınıflandırma ve öznitelik seçilim algoritmaları uyguladık ve 20 kullanıcıdan 10 oturum boyunca toplanan dataları kullanarak ortalama % 4.56 EER'a (Eşit Hata Oranı) ulaştık.

1. INTRODUCTION

Smartphones and tablets are important and commonly used gadgets in our daily lives: users can browse the Internet; listen to, watch and record video streams, photographs, navigate using GPS and handle banking transfers. Also, these devices provide large internal storage that enable users to store huge amount of valuable information, such as personal photos, contact details, call histories, private messages and applications. The private information which is stored in the device makes privacy and security of these devices crucial.

Many people rely on smartphones for many common, personal and work-related tasks. Usually users tend to store their passwords and private information on smartphones. These devices are prone to get lost, stolen, or can be accessed easily by non-owners because of their small sizes. Once an intruder has physical access to a device, he/she can cause monetary or non-monetary damage to the original owner of the device by impersonating the owner. Therefore, protecting the security and privacy of smartphone users against unauthorized access is a very important and crucial area of research.

Different solutions are proposed to ensure the security and privacy of personal information on the smartphones. However, the current security mechanisms have some shortcomings, such as they are weak against shoulder surfing, smudge and other attacks and infeasibility. Most widely used authentication techniques for mobile devices, such as PINs and patterns, are vulnerable against these attacks. Hence, once an intruder captures the PIN or the pattern, these authentication methods fail to detect and identify the intruder.

Main Research Question:

Is it possible to implement a continuous authentication procedure on mobile devices to decide whether users are authenticated or unauthenticated by analyzing the data gathered from device sensors in addition to touch screen related data?

In order to find an answer to our main research question, we begin with a literature review. Different strategies proposed to build a method for providing continuous authentication on smartphones are examined. We found that authors generally focused on either touchscreen based features or sensor based features. However, there was no adequate research which combines these two feature sets and try to build a more inclusive model on the same dataset.

Hence, we proposed an inclusive model which was created by using both touchscreen based and sensor based features and we applied different classification algorithms on the combined feature set. We utilized a dataset (Sitova et al., 2016) which was includes both touch screen data as well as sensor data from motion sensors, namely accelerometer, gyroscope and magnetometer. Most of the used features were proposed in the literature (Frank et al., 2013; Lu & Liu, 2015; Sitova et al., 2016), additionally we proposed the use of additional features extracted from the data coming from the motion sensors. We also applied different feature selection and feature transformation algorithms on our feature set with the intention of identifying which features are distinctive to reveal the behavioral character of users for building a method for continuous authentication on smartphones.

In this thesis, our contributions can be listed as follows:

- We combined sensor based features and touchscreen based features and built an authentication model with this large scale feature-set.
- We applied various attribute selection algorithms for the purpose of deciding which feature-set or features are more distinctive.
- We proposed new features that were not utilized in the literature which can be used for classification.

- We show that our sensor related features could be used for creating a continuous authentication model.

The rest of the thesis is organized as follows: In Chapter 2, we provide a review of the related studies focusing on behavioral biometrics. In Chapter 3, we explain the followed methodology while in Chapter 4, we present the results of our experiments. In the last chapter which is Chapter 5, conclusion and future works are discussed.

2. LITERATURE REVIEW

In this chapter, the general definition of authentication and different approaches to providing authentication on smartphones are investigated. Moreover, an introduction to the use of biometrics is given and the main classes of biometrics are explained. In addition, previous related studies are presented and their experiment results are discussed in comparison to our work.

2.1 Overview of Authentication of Smartphone Users Using Behavioral Biometric

2.1.1 Authentication

Authentication is the process of validating the true user of a system. There are three main approaches to provide authentication. First and the most commonly used one on mobile devices is knowledge based authentication. This technique is based on using a unique and private information which is expected to be known only by the user. This type of authentication mechanism could be a password, an id number or a secret security question. The second one is object based authentication. The object based authentication is based on possession of a distinguishing physical object. A security token, an id card or another trusted object can be used. The third one is biometrics. Biometrics are based on an individual's characterized physical or behavioral attributes. Common examples are fingerprints, keystroke dynamic models of the owner of the device.

Authentication can be active or passive. Active authentication requires dealing with a device and inputting one or more pieces of valid information or answer some questions. Using active authentication for each application, the process becomes frustrating and tedious for users. Personal Index Number (PIN) and a secret pattern which are used on current smartphones as the entry-point authentication are the examples of active authentication. Continuous authentication, also known as implicit, passive or progressive authentication, aims to offer another way to prevent unauthorized accesses of smartphones (Frank et al., 2013). This method works continuously and passively in the background to make a decision.

2.1.2 Biometrics

A biometric characterizes unique physical or behavioral features of an individual. A biometric schema aims to detect and correctly identify the user (Burr et al., 2004). Biometrics are mainly grouped in two categories: behavioral and physical biometrics. Physical biometrics are based on physical attributes of person such as retina or iris scan and fingerprint etc. Behavioral biometrics are based on person's behavior and analysis of person's handwriting, timing key stroke and usage style etc.

2.1.3 Approaches to Authentication

By using implicit or continuous authentication, security and privacy of smartphone users can be provided. These approaches make it possible to analyze interactions of users with the device and build a model which decides to authenticate the current user or not. Our study mainly focuses on keystroke based authentication and touch screen based authentication.

Keystroke Based Authentication

Keystroke based authentication mainly focuses on analysis of typing motions of users. Typing motion can be divided into two categories; static and dynamic typing. In static typing, users are asked to type a predefined text for further motion analyses. However, in dynamic typing, users do not have any restrictions about the text.

There are many studies and papers on this subject in the literature (Alzubaidi & Kallita, 2016). In the related literature, several features are extracted from keystroke motion analysis such as pressure, finger size, x-y coordinates, timestamps, velocity direction, etc. After feature selection and data collection period, various classification algorithms can be applied to the collected data for the purpose of creating a model which decides whether the current user is an authenticated or an unauthenticated user.

Touch Screen Based Authentication

Touch screens are used as input medium on a great majority of smartphones. A touch screen is an electronic visual display for inputs and outputs. By applying classification algorithms to the data collected from touch- screen interactions of users such as micro movements, pressure, finger movements, etc., it is possible to recognize authorized users. There exist various researches that focus on touch screen based authentication in the literature. In these researches, password patterns (De Luca et al., 2012), tapping behavior (Zeng et al., 2014), touch gestures (Zhao et al., 2013) etc. are examined for the purpose of creating a model to decide whether user is authorized or not.

In (Ramadan et al., 2017), users were asked to apply some specific touch gestures on screen without any restriction or guideline. They did not dictate any touch gesture to users for the purpose of obtaining more realistic raw data. 10 users are selected and every user performed around 10 touch sessions. With the collected raw data, two feature models (low-level feature model and high-level abstract feature model) are built and classification algorithms are applied for the purpose of deciding which one gives the best results. In low-level features model, 14%-16% misclassification error on training samples and 25%-30% misclassification error on test samples are obtained. However, in high-level abstracted features model 0% misclassification error of training set and 16%-20% misclassification of training samples are obtained.

In SafeGuard (Lu & Liu, 2015) authors try to achieve continuous authentication by investigating users' interaction with the touchscreen. They collect data from touchscreen inputs, such as sliding dynamics and pressure intensity. The used dataset contains over 10000 slides, collected from 60 volunteers. Their results show that the proposed method can verify a user with 0.03% false acceptance rate (FAR) and 0.05% false rejection rate (FRR) within 0.3 seconds with 15-20 slides of a user.

In HMOG (Sitova et al., 2016) (Hand Movement, Orientation and Grasp), accelerometer, gyroscope and magnetometer readings and tap based features, such as x-y coordinates, finger covered area, pressure, etc., are collected from 100 smartphone users with 24 sessions. Besides the touchscreen related data, authors propose a new set of features, which are derived from micro-movements, obtained from accelerometer, gyroscope and magnetometer sensors data generated while users interact with the touchscreen. Feature selection, feature transformation with principal component analysis (PCA) and outlier removal are performed on these feature sets. They achieved EER of 15.1% using HMOG features combined with tap features.

In Touchalytics (Frank et al., 2013), authors investigate whether a classifier can continuously authenticate users on the basis of their interaction with the touchscreen of their smartphones. The proposed method is based on basic navigation movements such as up-down and left-right scrolling. They suggest a set of thirty touch features extracted from raw data collected from touchscreen. The proposed method achieves 0-4% EER.

In (Shen et al., 2016), authors try to achieve authentication when an intruder physically accessed the device and possessed the passcodes to unlock the device. In their research, they collected data from 49 volunteers (29 males and 19 females) from various ages while participants performing an authentication (i.e., smartphone unlocking) task. They collected the touch-input actions and the motion sensor data (accelerometer and gyroscope). They applied their feature set SVM, neural network and nearest neighbor classifiers for building an authentication model. They achieved best authentication error rates, FAR of 5.01% and a FRR of 6.85% by the one-class SVM classifier.

In (Shen et al., 2018), authors investigate the reliability and applicability of using motion-sensor behavior for active and continuous smartphone authentication. They used accelerometer, gyroscope, orientation, and magnetometer readings while users were performing touch-tapping and single-touch-sliding actions in three different scenarios which were based on device position and users' activity (Hand-hold, Table-hold and Hand-hold-walk). Data collected from 102 participants (40 females and 62 males) from various ages. authors create 192 features from the collected row data set by applying Kalman filter and wavelet-based denoising method. They selected 38 top-performing features and applied Hidden Markov Model (HMM), support vector machine (SVM) and neural network classifiers to this feature set. The best results were achieved in the hand-hold scenario with HMM classifier with 3.98% FAR, 5.03% FRR and 4.71%, EER.

In (Buriro et al., 2016), authors propose a new multi-model biometric authentication model which is based on the features which are collected while the user slide-unlocks the smartphone to answer a call. The features were populated by slide/swipe, arm movements of user answering a call (accelerometer, gyroscope, orientation sensors) and voice recognition. The complete system consists of four parts: slide movement recognition, pickup movement recognition, voice recognition and fusion. 26 participants (16 male and 10 female) were recruited in various ages. Each participant performs at least 20 swipe, 20 pick-ups and 10 voice sample. They applied to the feature set one-class Bayes-Net, one-class random forest and one-class sequential minimal optimization (SMO) classifiers. They achieved best results with the naive Bayes network classifier with a FAR of 11.01% and a FRR of 4.12%.

In this thesis, we extract the same set of features obtained from the last three mentioned studies, namely HMOG (Sitova et al., 2016), Touchalytics (Frank et al., 2013) and SafeGuard (Lu & Liu, 2015). In HMOG predominantly sensor related features are used for achieving continuous authentication. In SafeGuard and Touchalytics, touchscreen related features are used for building a continuous authentication model. However, a large scale feature set which contains sensor related and touchscreen related features is not used for building a continuous authentication method. Our main contribution is combining the existing feature sets and examining which one of the features impact the continuous authentication model on a same dataset. A question may arise why we particularly utilize the features used in these three studies. These three studies utilize different feature sets and the combination of these feature sets cover the most commonly used features in the literature. Additionally, we explore the use of other features extracted from motion sensor readings, that were not utilized in previous studies, such as kurtosis, coefficient sum, entropy, integration, spectral energy, ZCR (Zero Crossing Rate), skewness, signal magnitude area and signal vector magnitude values of X, Y, Z readings of the sensors.

3. METHODOLOGY

In this thesis, our aim is to explore the impact of using different feature sets used in behavioral biometrics for continuous authentication on smartphones. For this purpose, we investigated the most popular and most effective features used in the literature. In particular, we combined HMOG (Sitova et al., 2016), Touchalytics (Frank et al., 2013) and SafeGuard (Lu & Liu, 2015) features since these studies show that their features are effective in identifying users and that include the most common features used in the literature.

Moreover, we also proposed new features which were not utilized in the previous studies. Our proposed features are based on sensor related data. For each of the sensors (accelerometer, gyroscope and magnetometer); kurtosis, coefficient sum, entropy, integration, spectral energy, ZCR (Zero Crossing Rate), skewness, signal magnitude area and signal vector magnitude values are calculated for X, Y, Z axises and magnitude value. These features are commonly used in activity recognition on smartphones (Incel et al., 2013; Shoaib et al., 2015) and we are interested whether they can also help to identify users for authentication while performing activities, such as walking and sitting.

We applied attribute selection and classification algorithms to the combined feature set and our proposed feature set. Our method consists of three phases: data preparation and attribute selection and classification. In the following, we explain the details of these phases. Our methodology simply presented in Figure 3.1.

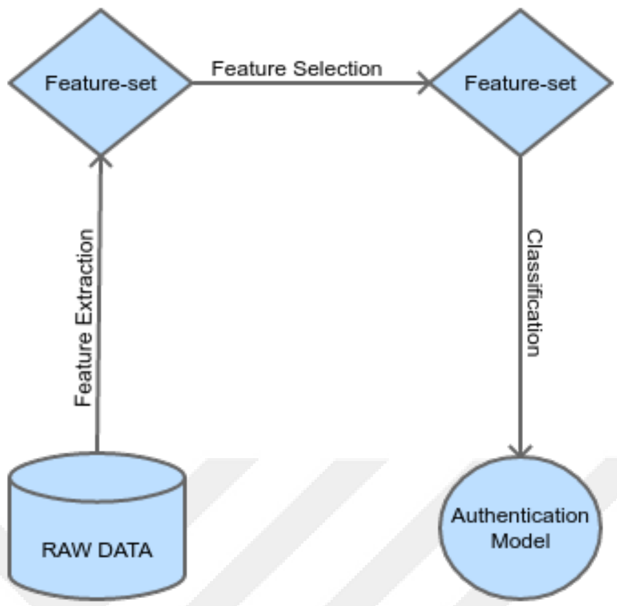

Figure 3.1: Flow chart of our method

3.1 Data Preparation

We use the dataset presented in the HMOG paper (Sitova et al., 2016). This raw data set can be accessed online[1] and it contains data from 100 smartphone users collected within 24 different sessions. Because of our low computational power and the aim to apply more attribute selection and classification algorithms we utilize the data of randomly selected 20 users with their 10 sessions.

Our main goal is to create a continuous authentication method by combining sensor and touchscreen based data. For this purpose, we merged three different feature sets. First one was HMOG grasp resistance features which offer a quite rich content for accelerometer, gyroscope and magnetometer related data. Second one was the combination of Touchalytics (Frank et al., 2013) and SafeGuard (Lu & Liu, 2015) data features which offer various useful features based on touchscreen related data. Third one was our proposed feature set which is again based on sensor related data. All of the features were created by using the sub-dataset from HMOG public dataset.

[1] http://www.cs.wm.edu/~qyang/hmog.html

3.2 Features

Firstly, an application was created by using Python libraries for the purpose of extracting grasp resistance features by implementing the algorithm which was presented in HMOG paper (Sitova et al., 2016). The created data represents our sensor-related feature set.

Secondly, an application was created for extracting Touchalytics (Frank et al., 2013) and SafeGuard (Lu & Liu, 2015) feature combination set by using Python libraries. The extracted data set represents our touchscreen-based feature set.

Thirdly, an application was created for extracting kurtosis, coefficient-sum, entropy, integration, spectral energy, ZCR, skewness, signal magnitude area and signal vector features by using Python libraries. For the calculation of skewness and kurtosis tsfresh library[2] of pypi is used. The created data was also sensor-related feature set as the HMOG features.

As mentioned, Touchalytics/SafeGuard and HMOG features were selected because one of them mainly focused on sensor collected data and the other one achieved results which were based on touchscreen collected data.

Combination of these three feature sets consists of 99 attributes. These features and the related paper are shown in Table 3.1, and our proposed features are also shown in Table 3.2. Afterwards, feature selection and classification algorithms are applied to this combined feature set as explained in the following section.

REFERENCE PAPER	ATTRIBUTE	Raw Data
HMOG	Mean of X during taps	Accelerometer Readings

[2] https://pypi.org/project/tsfresh/

HMOG	Mean of Y during taps	Accelerometer Readings
HMOG	Mean of Z during taps	Accelerometer Readings
HMOG	Mean of M during taps	Accelerometer Readings
HMOG	Standard deviation of X during taps	Accelerometer Readings
HMOG	Standard deviation of Y during taps	Accelerometer Readings
HMOG	Standard deviation of Z during taps	Accelerometer Readings
HMOG	Standard deviation of M during taps	Accelerometer Readings
HMOG	Difference in X Readings before and after a tap event	Accelerometer Readings
HMOG	Difference in Y Readings before and after a tap event	Accelerometer Readings
HMOG	Difference in Z Readings before and after a tap event	Accelerometer Readings
HMOG	Difference in M Readings before and after a tap event	Accelerometer Readings
HMOG	Net change in X Readings caused by a tap	Accelerometer Readings
HMOG	Net change in Y Readings caused by a tap	Accelerometer Readings
HMOG	Net change in Z Readings caused by a tap	Accelerometer Readings
HMOG	Net change in M Readings caused by a tap	Accelerometer Readings
HMOG	Maximum change in X readings caused by a tap	Accelerometer Readings
HMOG	Maximum change in Y readings caused by a tap	Accelerometer Readings
HMOG	Maximum change in Z readings caused by a tap	Accelerometer Readings
HMOG	Maximum change in M readings caused by a tap	Accelerometer Readings
HMOG	Mean of X during taps	Gyroscope Readings

HMOG	Mean of Y during taps	Gyroscope Readings
HMOG	Mean of Z during taps	Gyroscope Readings
HMOG	Mean of M during taps	Gyroscope Readings
HMOG	Standard deviation of X during taps	Gyroscope Readings
HMOG	Standard deviation of Y during taps	Gyroscope Readings
HMOG	Standard deviation of Z during taps	Gyroscope Readings
HMOG	Standard deviation of M during taps	Gyroscope Readings
HMOG	Difference in X Readings before and after a tap event	Gyroscope Readings
HMOG	Difference in Y Readings before and after a tap event	Gyroscope Readings
HMOG	Difference in Z Readings before and after a tap event	Gyroscope Readings
HMOG	Difference in M Readings before and after a tap event	Gyroscope Readings
HMOG	Net change in X Readings caused by a tap	Gyroscope Readings
HMOG	Net change in Y Readings caused by a tap	Gyroscope Readings
HMOG	Net change in Z Readings caused by a tap	Gyroscope Readings
HMOG	Net change in M Readings caused by a tap	Gyroscope Readings
HMOG	Maximum change in X readings caused by a tap	Gyroscope Readings
HMOG	Maximum change in Y readings caused by a tap	Gyroscope Readings
HMOG	Maximum change in Z readings caused by a tap	Gyroscope Readings
HMOG	Maximum change in M readings caused by a tap	Gyroscope Readings

HMOG	Mean of X during taps	Magnetometer Readings
HMOG	Mean of Y during taps	Magnetometer Readings
HMOG	Mean of Z during taps	Magnetometer Readings
HMOG	Mean of M during taps	Magnetometer Readings
HMOG	Standard deviation of X during taps	Magnetometer Readings
HMOG	Standard deviation of Y during taps	Magnetometer Readings
HMOG	Standard deviation of Z during taps	Magnetometer Readings
HMOG	Standard deviation of M during taps	Magnetometer Readings
HMOG	Difference in X Readings before and after a tap event	Magnetometer Readings
HMOG	Difference in Y Readings before and after a tap event	Magnetometer Readings
HMOG	Difference in Z Readings before and after a tap event	Magnetometer Readings
HMOG	Difference in M Readings before and after a tap event	Magnetometer Readings
HMOG	Net change in X Readings caused by a tap	Magnetometer Readings
HMOG	Net change in Y Readings caused by a tap	Magnetometer Readings
HMOG	Net change in Z Readings caused by a tap	Magnetometer Readings
HMOG	Net change in M Readings caused by a tap	Magnetometer Readings
HMOG	Maximum change in X readings caused by a tap	Magnetometer Readings
HMOG	Maximum change in Y readings caused by a tap	Magnetometer Readings
HMOG	Maximum change in Z readings caused by a tap	Magnetometer Readings

HMOG	Maximum change in M readings caused by a tap	Magnetometer Readings
Touchalytics	20%-perc. pairwise velocity	Scroll Event
Touchalytics	50%-perc. pairwise velocity	Scroll Event
Touchalytics	80%-perc. pairwise velocity	Scroll Event
Touchalytics	20%-perc. pairwise acceleration	Scroll Event
Touchalytics	50%-perc. pairwise acceleration	Scroll Event
Touchalytics	80%-perc. pairwise acceleration	Scroll Event
Touchalytics	Median velocity at last 3 pts	Scroll Event
Touchalytics	Largest deviation from end-to-end line	Scroll Event
Touchalytics	start x	Scroll Event
Touchalytics	start y	Scroll Event
Touchalytics	stop x	Scroll Event
Touchalytics	stop y	Scroll Event
Touchalytics	direct end-to-end distance	Scroll Event
Touchalytics	median velocity at last 3 pts	Scroll Event
Touchalytics	ratio end-to-end dist and length of trajectory	Scroll Event
Touchalytics	average velocity	Scroll Event
Touchalytics	median acceleration at first 5 points	Scroll Event
SafeGuard	Mean of distance	Scroll Event
SafeGuard	Standard deviation of distance	Scroll Event

SafeGuard	Mean of direction	Scroll Event
SafeGuard	Standard deviation of direction	Scroll Event
SafeGuard	Mean of angle	Scroll Event
SafeGuard	Standard deviation of angle	Scroll Event

Table 3.1: Selected Features Table

	ATTRIBUTE	**Raw Data**
Proposed Features	kurtosis of X	Accelerometer Readings
Proposed Features	kurtosis of Y	Accelerometer Readings
Proposed Features	kurtosis of Z	Accelerometer Readings
Proposed Features	kurtosis of M	Accelerometer Readings
Proposed Features	skewness of X	Accelerometer Readings
Proposed Features	skewness of Y	Accelerometer Readings
Proposed Features	skewness of Z	Accelerometer Readings
Proposed Features	skewness of M	Accelerometer Readings
Proposed Features	signal magnitude area	Accelerometer Readings
Proposed Features	signal vector magnitude	Accelerometer Readings
Proposed Features	coefficient sum of X	Accelerometer Readings
Proposed Features	entropy of X	Accelerometer Readings

Proposed Features	integration of X	Accelerometer Readings
Proposed Features	spectral energy of X	Accelerometer Readings
Proposed Features	zcr of X	Accelerometer Readings
Proposed Features	coefficient sum of Y	Accelerometer Readings
Proposed Features	entropy of Y	Accelerometer Readings
Proposed Features	integration of Y	Accelerometer Readings
Proposed Features	spectral energy of Y	Accelerometer Readings
Proposed Features	zcr of Y	Accelerometer Readings
Proposed Features	coefficient sum of Z	Accelerometer Readings
Proposed Features	entropy of Z	Accelerometer Readings
Proposed Features	integration of Z	Accelerometer Readings
Proposed Features	spectral energy of Z	Accelerometer Readings
Proposed Features	zcr of Z	Accelerometer Readings
Proposed Features	coefficient sum of M	Accelerometer Readings
Proposed Features	entropy of M	Accelerometer Readings
Proposed Features	integration of M	Accelerometer Readings
Proposed Features	spectral energy of M	Accelerometer Readings
Proposed Features	zcr of M	Accelerometer Readings
Proposed Features	kurtosis of X	Gyroscope Readings

Proposed Features	kurtosis of Y	Gyroscope Readings
Proposed Features	kurtosis of Z	Gyroscope Readings
Proposed Features	kurtosis of M	Gyroscope Readings
Proposed Features	skewness of X	Gyroscope Readings
Proposed Features	skewness of Y	Gyroscope Readings
Proposed Features	skewness of Z	Gyroscope Readings
Proposed Features	skewness of M	Gyroscope Readings
Proposed Features	signal magnitude area	Gyroscope Readings
Proposed Features	signal vector magnitude	Gyroscope Readings
Proposed Features	coefficient sum of X	Gyroscope Readings
Proposed Features	entropy of X	Gyroscope Readings
Proposed Features	integration of X	Gyroscope Readings
Proposed Features	spectral energy of X	Gyroscope Readings
Proposed Features	zcr of X	Gyroscope Readings
Proposed Features	coefficient sum of Y	Gyroscope Readings
Proposed Features	entropy of Y	Gyroscope Readings
Proposed Features	integration of Y	Gyroscope Readings
Proposed Features	spectral energy of Y	Gyroscope Readings
Proposed Features	zcr of Y	Gyroscope Readings
Proposed Features	coefficient sum of Z	Gyroscope Readings

Proposed Features	entropy of Z	Gyroscope Readings
Proposed Features	integration of Z	Gyroscope Readings
Proposed Features	spectral energy of Z	Gyroscope Readings
Proposed Features	zcr of Z	Gyroscope Readings
Proposed Features	coefficient sum of M	Gyroscope Readings
Proposed Features	entropy of M	Gyroscope Readings
Proposed Features	integration of M	Gyroscope Readings
Proposed Features	spectral energy of M	Gyroscope Readings
Proposed Features	zcr of M	Gyroscope Readings
Proposed Features	kurtosis of X	Magnetometer Readings
Proposed Features	kurtosis of Y	Magnetometer Readings
Proposed Features	kurtosis of Z	Magnetometer Readings
Proposed Features	kurtosis of M	Magnetometer Readings
Proposed Features	skewness of X	Magnetometer Readings
Proposed Features	skewness of Y	Magnetometer Readings
Proposed Features	skewness of Z	Magnetometer Readings
Proposed Features	skewness of M	Magnetometer Readings
Proposed Features	signal magnitude area	Magnetometer Readings
Proposed Features	signal vector magnitude	Magnetometer Readings

Proposed Features	coefficient sum of X	Magnetometer Readings
Proposed Features	entropy of X	Magnetometer Readings
Proposed Features	integration of X	Magnetometer Readings
Proposed Features	spectral energy of X	Magnetometer Readings
Proposed Features	zcr of X	Magnetometer Readings
Proposed Features	coefficient sum of Y	Magnetometer Readings
Proposed Features	entropy of Y	Magnetometer Readings
Proposed Features	integration of Y	Magnetometer Readings
Proposed Features	spectral energy of Y	Magnetometer Readings
Proposed Features	zcr of Y	Magnetometer Readings
Proposed Features	coefficient sum of Z	Magnetometer Readings
Proposed Features	entropy of Z	Magnetometer Readings
Proposed Features	integration of Z	Magnetometer Readings
Proposed Features	spectral energy of Z	Magnetometer Readings
Proposed Features	zcr of Z	Magnetometer Readings
Proposed Features	coefficient sum of M	Magnetometer Readings
Proposed Features	entropy of M	Magnetometer Readings
Proposed Features	integration of M	Magnetometer Readings
Proposed Features	spectral energy of M	Magnetometer Readings

Proposed Features	zcr of M	Magnetometer Readings

Table 3.2: Proposed Features

3.3 Feature Selection and Classification

After creating the feature set from touch events and sensor data, attribute selection and classification is the last step of the applied methodology. Classification is the process of building a model of classes from a set of records that contain class labels. Because the number of attributes in feature set is high, attribute selection is also applied to the feature set. User id column of feature set is modified as binary decision model because the main purpose is to differentiate authenticated user and intruder. Therefore, twenty different feature sets (or files in other words) are created for each selected user and also one feature set is created which contains all of the user id information for all users.

An application is implemented by using JAVA with WEKA library[3] for the purpose of classification and attribute selection phases. As the performance metric we used EER (equal error rate) in line with the similar studies in the literature. Weka does not provide EER values, however and EER library which is available online is used[4].

As the attribute selection algorithms; CFS Subset Evaluation and Consistency Subset Evaluation algorithms are selected. We apply feature selection algorithms to see which features are more efficient in terms of authenticating users since we have a large feature set. Moreover, using a large feature set may not be feasible when applying continuous authentication on smartphones due to resource limitations, such as battery consumption, and real-time authentication.

As the classification algorithms Random Forest, J48 and Naive Bayes algorithms are selected, which were also commonly used in the related studies (Frank et al., 2013; Lu

[3] https://mvnrepository.com/artifact/nz.ac.waikato.cms.weka/weka-stable/3.8.0

[4] https://github.com/marmundo/eer

& Liu, 2015; Sitova et al., 2016). For each feature set, selected classification algorithms are applied with CFS subset evaluation, consistency subset evaluation algorithms or without any attribute selection algorithm.

3.4 Definition of Used Classifiers

Decision Tree (J48) Algorithm is to find out the way the attributes-vector behaves for a number of instances. Also on the bases of the training instances the classes for the newly generated instances are being found. J48 algorithm generates the rules for the prediction of the target variable. With the help of J48 algorithm, the critical distribution of the data is easily understandable.

Random Forest Classifier is an ensemble algorithm. Ensembled algorithms are those which combine more than one algorithm of the same or different kind for classifying objects. Random forest classifier creates a set of decision trees from randomly selected subset of training set. It then aggregates the votes from different decision trees to decide the final class of the test object (Ho, 1995).

Naive Bayes is a simple technique for constructing classifiers: models that assign class labels to problem instances, represented as vectors of feature values, where the class labels are drawn from some finite set. Naive Bayes classifiers assume that the value of a particular feature is independent of the value of any other feature, given the class variable (Mozina et al., 2004).

For details please refer to the Table 5.5 that is presented in Appendix.

3.5 Definition of Used Attribute Selection Algorithms

Correlation-based Feature Subset (CFS) Subset Evaluation: Evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them. Subsets of features that are highly correlated with the class while having low inter-correlation are preferred[5].

ConsistencySubSetEval: Evaluates the worth of a subset of attributes by the level of consistency in the class values when the training instances are projected onto the subset of attributes. Consistency of any subset can never be lower than that of the full set of

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[5] http://weka.sourceforge.net/doc.dev/weka/attributeSelection/CfsSubsetEval.html

attributes, hence the usual practice is to use this subset evaluator in conjunction with a Random or Exhaustive search which looks for the smallest subset with consistency equal to that of the full set of attributes[6].

[6] http://weka.sourceforge.net/doc.stable/weka/attributeSelection/ConsistencySubsetEval.html

4. AUTHENTICATION PERFORMANCE

In this chapter, firstly we compare the results obtained separately with the features proposed in HMOG (Sitova et al., 2016), Touchalytics (Frank et al., 2013) and SafeGuard (Lu & Liu, 2015) papers. Then, we present the results when all the feature sets are combined together. Then, we apply feature selection algorithms and present the results with the selected set of features. Finally, we provide a comparison and a discussion on the obtained results.

4.1 Comparison of the Performance of HMOG, SafeGuard and Touchalytics Features

In HMOG, authors investigated their dataset with respect to different activities performed by the users, such as walking, sitting, while collecting the data. They achieved the best results while users were walking. On the walking-dataset, they achieved 7.16% EER with only HMOG, Tap and Keystroke Dynamics features; 8.53% EER with HMOG and tap features and 10.79% EER with tap and keystroke dynamic features. Additionally, the best performance with only HMOG features was 13.62% EER. The authors used SVM classifier and performed score-level fusion with HMOG, tap and keystroke dynamics; keystroke dynamics with tap and HMOG and tap.

In Touchalytics, authors used only touch-screen based scroll data while creating their authentication model. They used two different classifiers, k-nearest-neighbors (k-NN) and a support-vector machine with an rbf-kernel (SVM). They achieved the best results with SVM between 0% and 4% EER range.

In SafeGuard, authors selected 14 features based on users' on-screen operations. They applied five machine learning methods to the feature-set: decision tree, naive Bayes, k-nearest neighbor, logistic regression and support vector machine. They achieved the best results with SVM with almost 0% EER.

In this thesis, we use random forest, j48 and naive Bayes classification algorithms with consistency subset evaluation and correlation-based feature selection as attribute selection algorithms and without applying any attribute selection algorithm.

4.2 Performance Using All Features

Our main purpose is to differentiate an authenticated user and an unauthenticated user. Therefore, we modified our dataset in order to have a two-class classification problem by making the investigated user id 1 and other users' ids as 0. In addition, we also used the feature-set which contains all users' ids and approached the problem as a multi-class classification. Our results with the selected classifiers are given in Figure 4.1 without any attribute selection. Average EER values for all users with random forest, naive Bayes and J48 classifiers are 4.56%, 20.75% and 16.42% respectively. The best results are achieved with the random forest classifier. The worst results are achieved with the naive Bayes classifier. This showed that tree-like structures were more successful for this feature set (In all figures user 99 represents the file which contains all user ids.). For more detail please refer to the Figure 5.1, Figure 5.2, Figure 5.3 and Figure 5.4 that are presented in Appendix.

Classifier	RF	NB	J48
EER (%)	4.56	20.75	16.42

Table 4.1: Average classifier results for all features

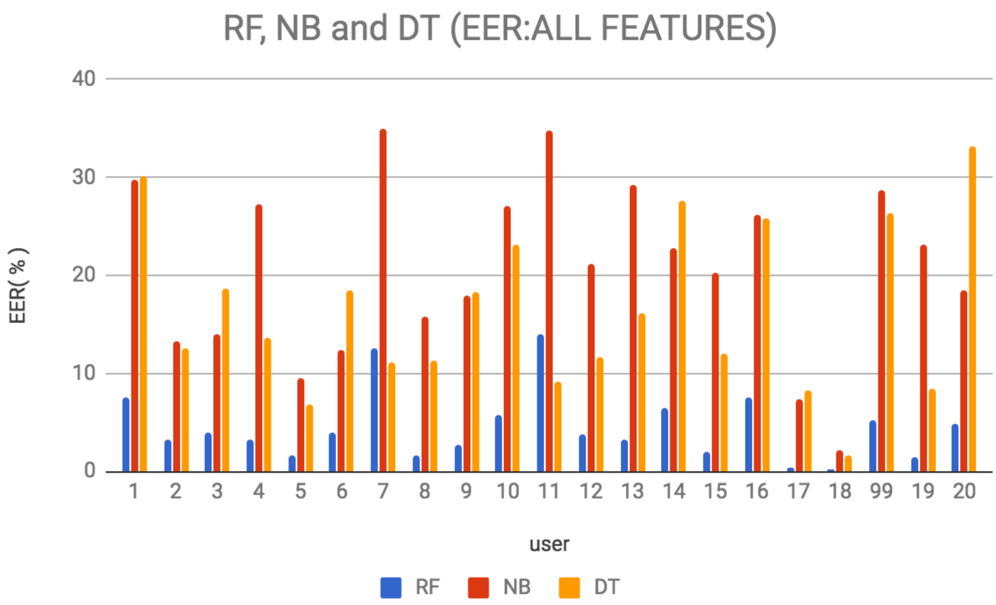


Figure 4.1: Applied classifier results using all features

4.3 Impact of Feature Selection Per User

Results with cfs subset evaluation attribute selection algorithm and the selected classifiers are represented in Figure 4.2. Average EER values for all datasets which represent users with random forest, naive Bayes and J48 classifiers were 4.85%, 15.62% and 14.90% respectively. When we applied cfs attribute selection algorithm 17.17 attributes are selected on average per user. The best results are again obtained with the random forest classifier. The worst results are obtained with the naive Bayes classifier. Applying cfs algorithm to the data set significantly reduces the EER values of the naive Bayes and J48 classifiers and give better results than applying these classifiers without any attribute selection algorithm. For more detail please refer to the Figure 5.5, Figure 5.6, Figure 5.7 and Figure 5.8 that are presented in Appendix.

Classifier	RF	NB	J48
EER (%)	4.85	15.62	14.90

Table 4.2: Average classifier results with CfsSubSetEvaluation

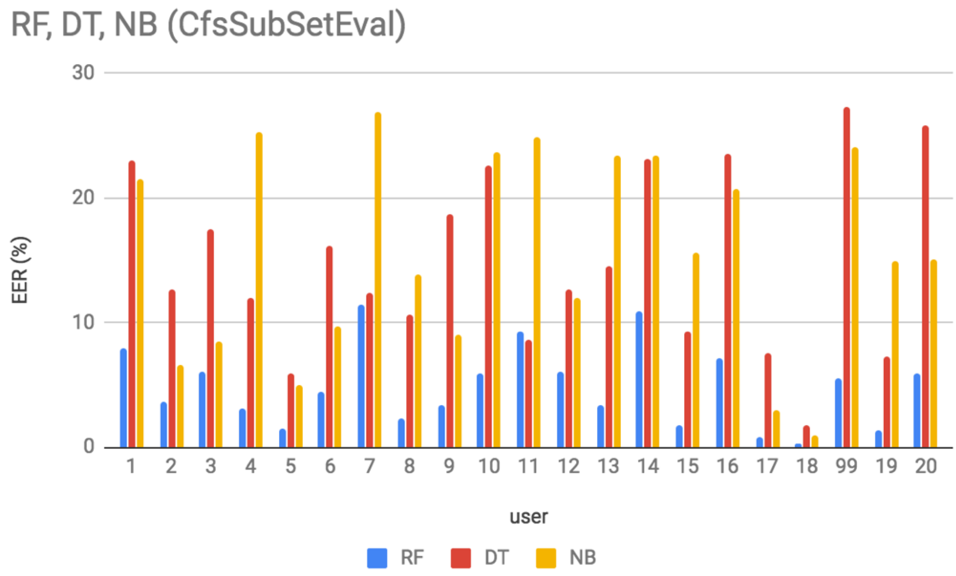


Figure 4.2: Applied classifier results with CfsSubSetEvaluation

Results with consistency subset evaluation attribute selection algorithm and the selected classifiers are presented in Figure 4.3. Average EER values for all users with random forest, naive Bayes and J48 classifiers are 5.60%, 17.18% and 14.25% respectively. When we applied consistency subset attribute selection algorithm 10.55 attributes are selected on average per user. The best results are obtained with the random forest classifiers. The worst results are obtained with naive Bayes classifier. Applying the consistency subset evaluation algorithm slightly reduces the EER values of J48 classifiers with respect to EER values in comparison with the cfs subset evaluation algorithm. For more detail please refer to the Figure 5.9, Figure 5.10, Figure 5.11 and Figure 5.12 that are presented in Appendix.

Classifier	RF	NB	J48
EER (%)	5.60	17.18	14.25

Table 4.3: Average classifier results with ConsistencySubSetEval

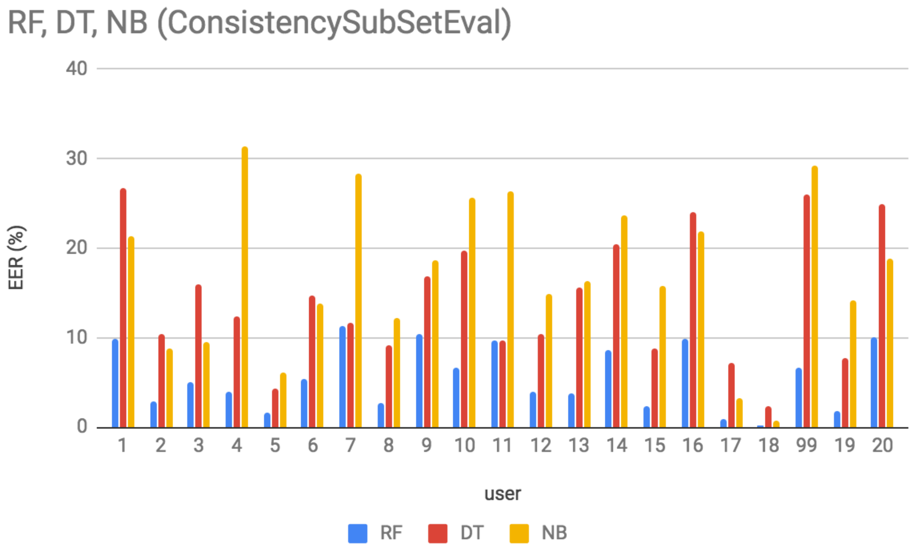


Figure 4.3: Applied classifier results with ConsistencySubSetEval

We achieved the best results with the random forest classifier, EERs with and without applying selected attribute selection algorithms as summarized in Figure 4.4. When we examined the results that are shown in Figure 4.4, we see that for two users applying Random Forest classifier without any attribute selection algorithm gave worse results than the others. When we investigated the feature-set, we could not see any dramatic difference between the number of raw data of these users and others.

Therefore, we concluded that, behavioral characteristic of these users were different and not suitable for our model. Additionally, the results showed that Cfs attribute selection algorithm generally gave better results when it was used with Random Forest algorithm than ConsistencySubsetEval algorithm because of the nature of the feature-set. All of the used classifier and attribute selection results with different statistical (kappa statistics, correctly classified instances etc.) analyses are given in Appendix chapter. (Table 5.1)

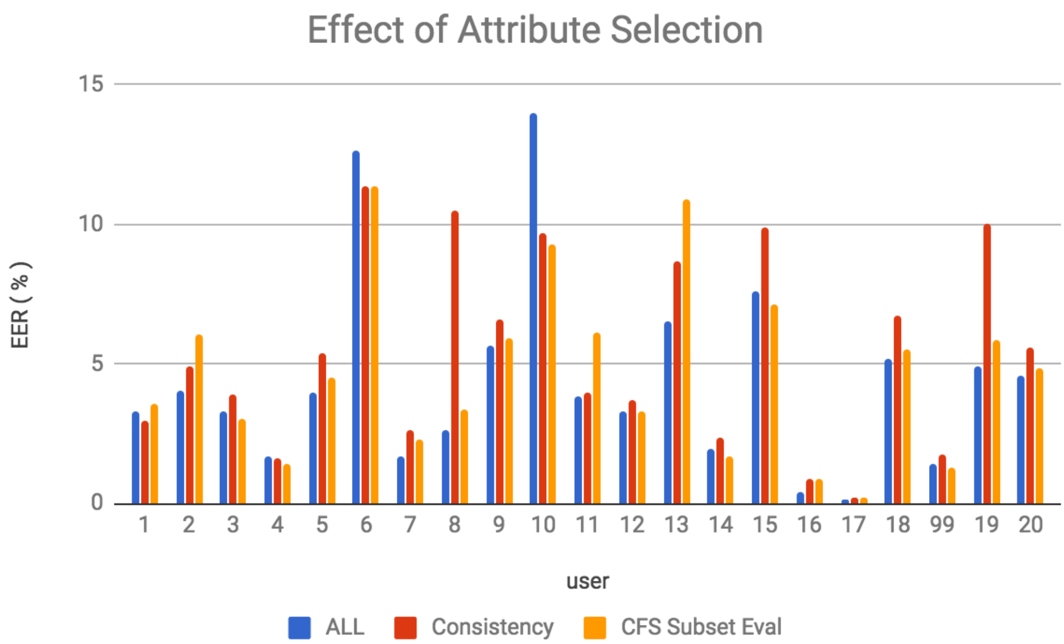


Figure 4.4: Random forest results for all cases

In the previous analysis, the best results are achieved with the random forest classifier without any attribute selection algorithm, with average 4.56 % EER. Thus, we applied random forest classification algorithm to the HMOG, Touchalytics, SafeGuard and our proposed feature-sets separately for comparison. The results showed that the best results are obtained with selected HMOG feature set with average 4.51% EER. The average EER of Touchalytics, SafeGuard and our proposed feature-set were 17.34%, 33.90% and 14.05% respectively. Our proposed features gave promising results with random forest algorithm. All results are given in Figure 4.5.

The results in Figure 4.5 have shown that the HMOG feature set achieved clearly the best results for authentication of all users with respect to EER range. The SafeGuard feature set gave the worst results for each users because we used only small portion of their features while creating our sub feature-set.

Touchalytics feature-set and SafeGuard-feature set results were worse than the results of original papers. The reason of this for SafeGuard results were we only selected a small subset of used features in the original paper. We achieved worse results than the original paper for Touchalytics because of the selected HMOG row dataset contains fewer row data than original dataset and the model was not suitable for selected HMOG dataset.

	HMOG	Touchalytics	SafeGuard	Proposed
EER (%)	4.51	17.34	33.90	14.05

Table 4.4: Average Random Forest results of all feature-sets individually

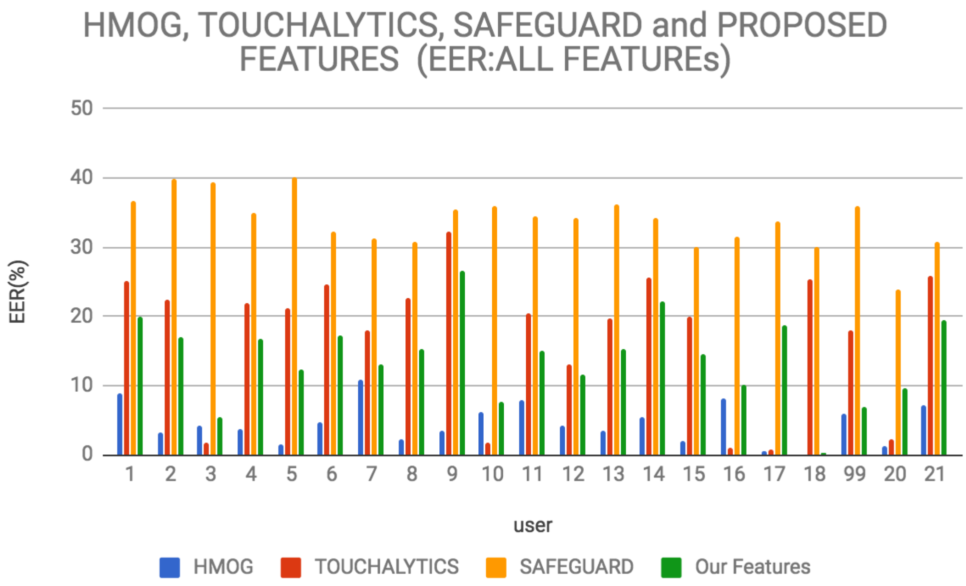


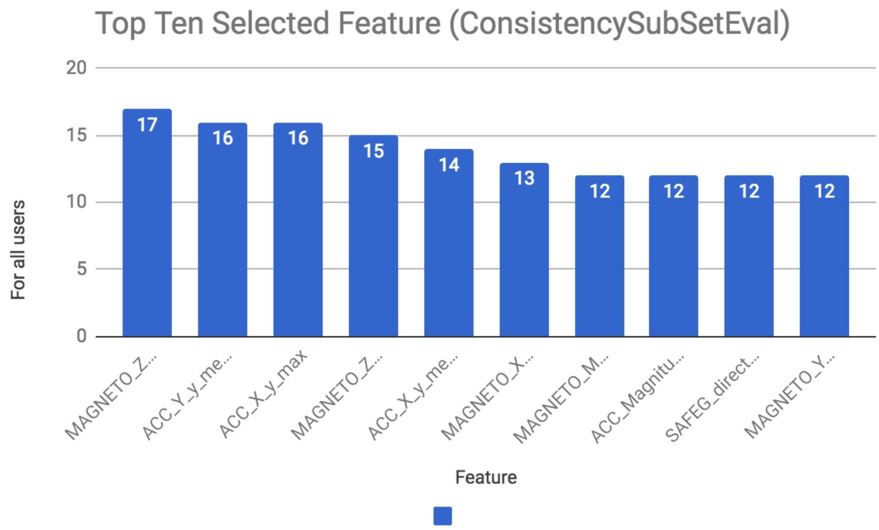
Figure 4.5: Random forest to all feature-sets individually

4.4 Results After Feature Selection

In Section 4.2, feature selection algorithms were applied per person and selected features were used in the classification phase per user. However, it may not be feasible to apply feature selection algorithms on a user basis.

4.4.1 Top Selected Features

In the previous section, we applied feature selection algorithms per user. In this section, we make use of the commonly selected features considering all users. We are interested in investigating whether there can be a common feature set in successfully identifying users. For the purpose of deciding which features are important for classification we identify the top ten selected features for applied attribute selection algorithm and overall selected attribute. These results are presented in Figure 4.6. For more detail please refer to the Table 5.2 and Table 5.3 that are presented in Appendix.



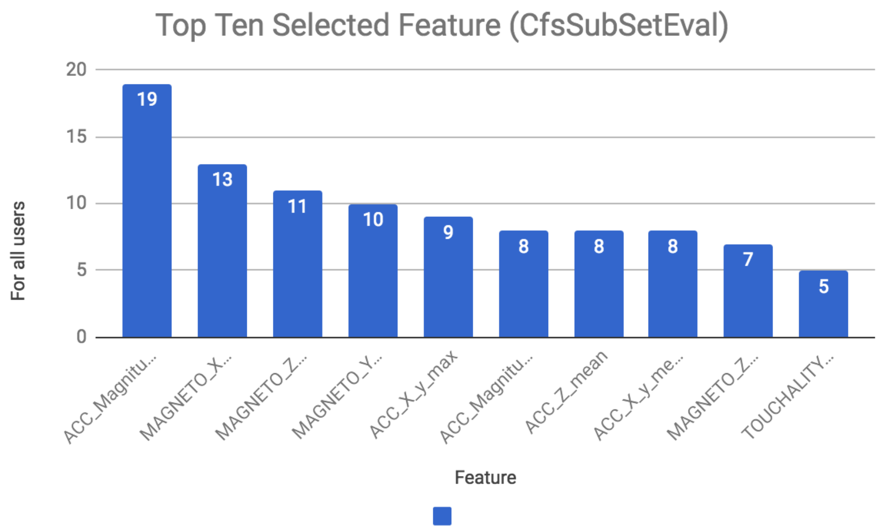


Figure 4.6: Top ten selected features

With these top selected features, we built two models: Model-1 and Model-2. In Model-1, top ten selected features with CfsSubSetEvaluation attribute selection algorithm are used while building the model. In Model-2, top ten selected features with ConsistencySubSetEval attribute selection algorithm were used while building model. The results are shown in Figure 4.7 and Figure 4.8 respectively.

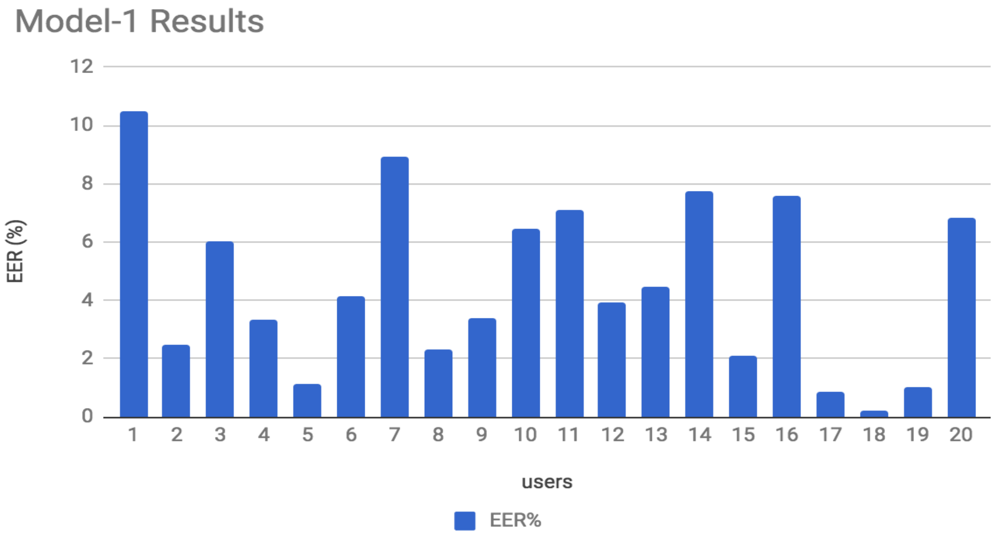


Figure 4.7: Results with top ten selected features by CFS with RF

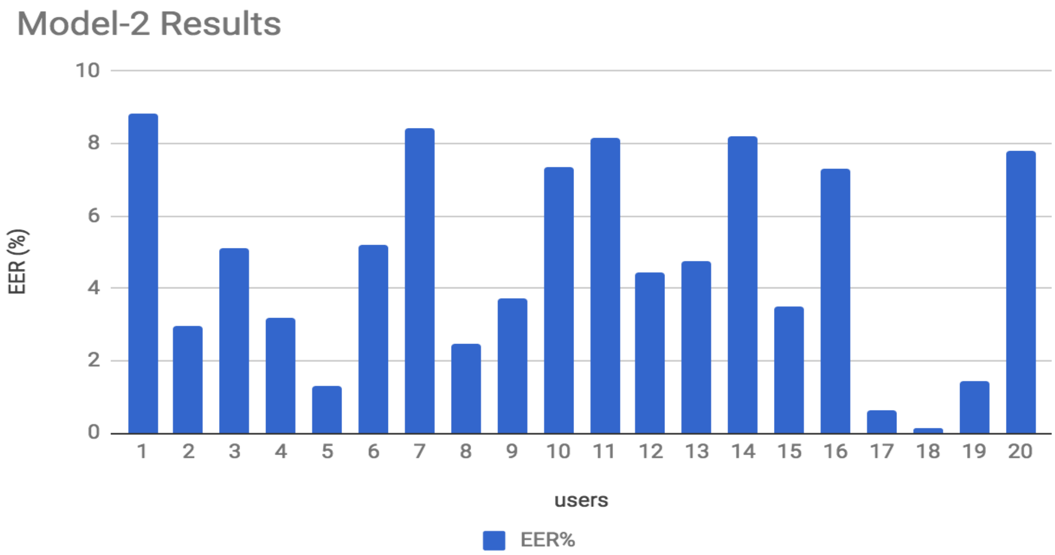


Figure 4.8: Results with top ten selected features by ConsistencySubSetEval with RF

When we applied Model-1 and Model-2 to the same data set which consists of data from twenty different users, similar performances were obtained from both models, 4.53% average EER was achieved by Model-1 and 4.75% EER was achieved with Model-2. There was a correlation between the results that were shown in Figure 4.7 and Figure 4.8. For all twenty users, there was no contradiction, the results were similar for each of the users. Model-1 gave slightly better results for every user compared with results of Model-2.

Achieved EER results were lower than 10% except for four users'. When the feature set of these four users were investigated, no distinguishing attribute was found. Therefore, we concluded that behavioral characteristic of these users were not suitable for our model.

Results showed that we achieved better EER than in HMOG results, by combining their selected feature-set with selected Touchalytics and SafeGuard features. However, we got worse results than full feature-set of Touchalytics and SafeGuard. This may be due to the fact that they have used their own datasets and these datasets were not as challenging as the HMOG dataset which includes different activities and gestures. Therefore, we will be going to add more features from these feature set to our combined feature-set.

4.4.2 Results of Proposed Features

Results of combined feature set shows that the best results were achieved with random forest classifier without any attribute selection algorithm. Therefore, we applied random forest classifier without any attribute selection algorithm to our proposed feature set. The results showed that the proposed feature set gave promising results (14.05% EER) for building an authentication model.

In Addition, we combined HMOG feature set and our proposed feature set and we applied random forest classifier with consistency subset and cfs attribute selection algorithms. The results were achieved with consistency subset and cfs attribute selection algorithms 8.66% EER and 9.03% EER respectively. (Details can be found in Table 5.4 that is presented in Appendix.)

When the top 15 selected attributes were examined results showed that the proposed features were not selected by consistency subset attribute selection algorithm. However, three of the proposed features were selected by cfs attribute selection algorithm. Some of the proposed features could be used to improve the accuracy of EER. However, we could not achieve the EER (4.51%) achieved with the HMOG features used alone. In terms of number of features, HMOG includes 60 features, however here we use 10-15 features, hence this can be acceptable. Compared to the use of SafeGuard and Touchalytics features, these features are all sensor based. In the future, we will explore the use of sensor based feature in detail.

The proposed feature set achieved better EER results than selected Touchalytics and SafeGuard feature sets. Thus, we concluded that sensor related features achieved better results than touch screen related features.

4.5 Discussion

In this thesis, we applied two different attribute selection algorithms and three different classification algorithms to the combined feature set for the purpose of creating a continuous authentication model. Firstly, we applied the selected classification algorithms (random forest, j48 and naive bayes) to the combined feature sets with selected attribute selection algorithms (consistency subset evaluation and cfs) and without any attribute selection algorithm. The results showed that, the best EER (4.56%) is obtained when we applied random forest classifier without any attribute selection algorithms.

Since the best results are obtained with random forest classifier, we applied random forest to the selected HMOG, Touchalytics, SafeGuard and our proposed feature sets separately. HMOG feature set gave the best EER result (4.51%). Moreover, our proposed feature set gave promising EER result (14.05%) which is better than the results of selected Touchalytics and SafeGuard feature sets.

Then, we created two feature sets with top ten selected features from consistency subset evaluation and cfs algorithms results and we applied random forest classifier which gave the best EER results among the selected classifiers to the combined feature sets. The best EER result (4.53%) is obtained with top ten features which are selected cfs subset evaluation attribute selection algorithm.

Moreover, when we combined our proposed feature set with HMOG features and applied the attribute selection algorithms to this combined feature set, we see that our proposed features are selected by cfs attribute selection algorithm in top 15 selected features.

We achieved acceptable EER's by applying random forest classifier without applying any attribute selection algorithms to the combined feature set. However, the best results are achieved by applying random forest classifier to the selected HMOG feature set not the combined feature set.

Our proposed feature set is derived from sensor based data. By applying random forest classifier to the proposed feature set, we achieved better EER than touch screen based feature sets (Touchalytics and SafeGuard). Besides that, we achieved the best EER's by applying random forest classifier to selected HMOG feature set.

The results showed that the best results are always achieved with the sensor based features. Additionally, sensor based features are commonly selected with the attribute selection algorithms. Therefore, we can conclude that sensor based features are more appropriate than touch screen based features for building a continuous authentication model on the utilized dataset.

5. CONCLUSION

In this thesis, we compared the effect of sensor based and touchscreen based features for building a continuous authentication method. Therefore, we combined three feature-sets which were proposed for continuous authentication on smartphones in the literature. We selected a sub-feature-set from HMOG, Touchalytics and SafeGuard papers. Then, we applied various classification and attribute selection algorithm to the combined feature-set for the purpose of deciding which attribute set has more effect to build a classification model.

In addition, we also proposed a new feature set based on sensor-related data and applied these features random forest classifier which gave the best results for the combined feature set.

Our results show that sensor based features were more useful than touch based features while building a continuous authentication model. When we used only sensor-based features we achieved approximately 4.51% EER. However, when we applied same classification and attribute selection algorithms to combined feature-set we achieved 4.56% EER.

Our Touchalytics and SafeGuard selected feature-set results gave worse results than the original papers when we applied random forest classifier to the feature-set. In Touchalytics and SafeGuard, authors achieved almost 0% EER. However, by applying random forest classifier to our selected feature set for Touchalytics and SafeGuard we achieved 17.34% EER and 33.90% EER respectively.

The results of applied classifiers without any attribute selection algorithms generally show better performance. However, applying attribute selection to the feature set decreases the number of features and correspondingly decreases the computational cost. Additionally, creating a general authentication model will be more effective than using a user-based authentication model because user-based authentication model needs some time to process the pre-collected user data.

This thesis mainly focused on the importance of sensor related and touchscreen related features. We combined the touch screen and sensor based features and applied various attribute selection and classification algorithms. Therefore, we think that this thesis forms a basis for researches which are willing to study the topic.

In this thesis, we applied three classification and two attribute selection algorithms to the combined feature-set. We are planning to apply much more classification and attribute selection algorithms to the combined feature-set for the purpose of making more comprehensive comparison between touchscreen based and sensor based feature-sets.

We used HMOG raw data-set for building our continuous authentication model on smartphones. For the future experiments, our main goal is to collect data from smartphone users and create our own raw data-set. Moreover, HMOG data set contains 100 users' raw data, we have used only 20 of them. We want to increase the sample size for our future work. Therefore, we have started to develop an Android application which is an imitation of a mobile banking application. We will try to authenticate the user while the user is making monetary transfers.

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APPENDIX

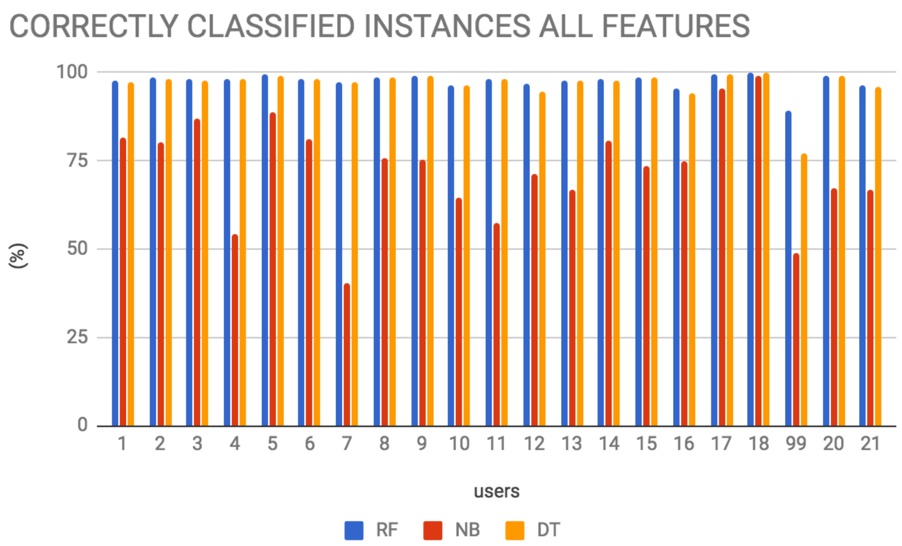

Figure 5.1: Correctly classified instances for all features

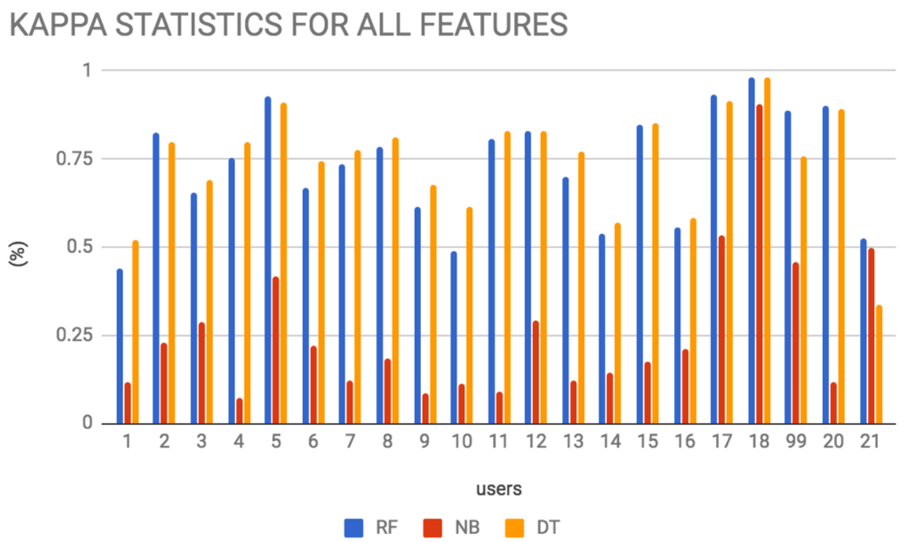

Figure 5.2: Kappa statistics for all features

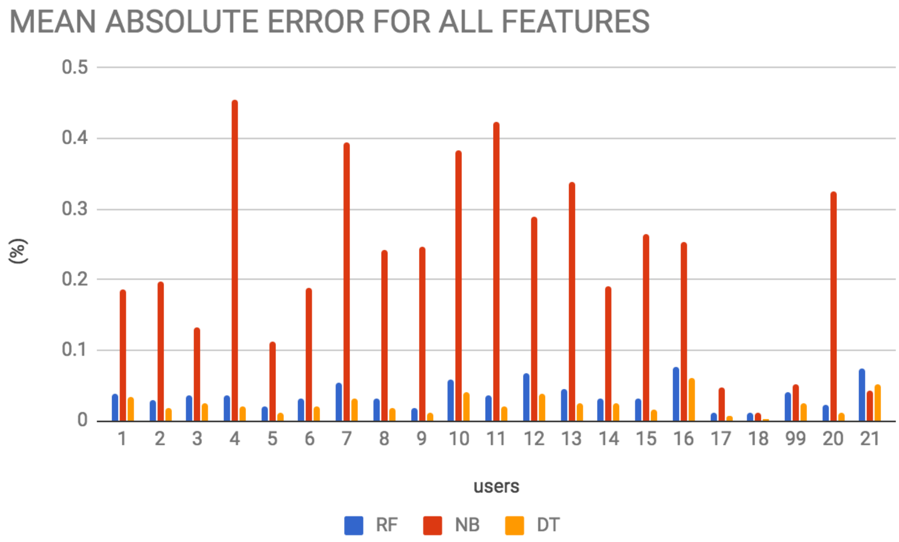

Figure 5.3: Mean absolute error for all features

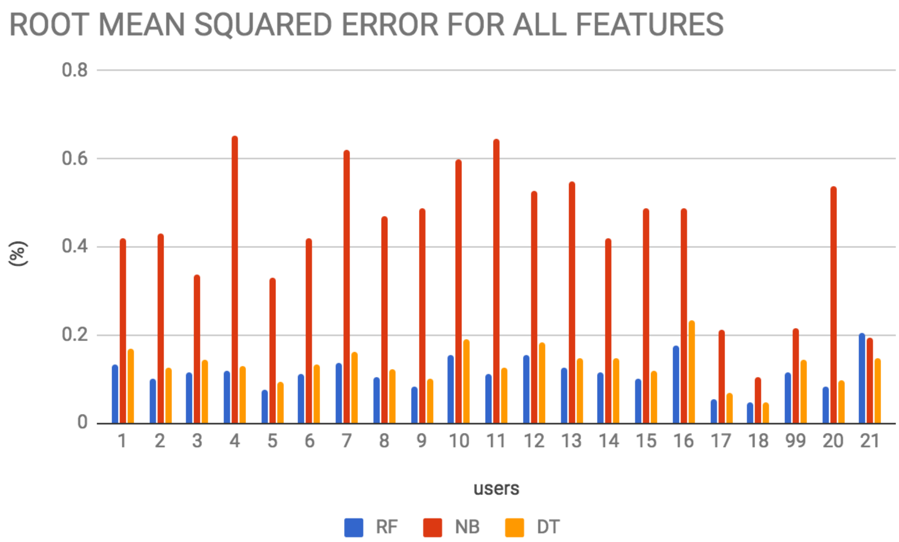

Figure 5.4: Root mean squared error for all features

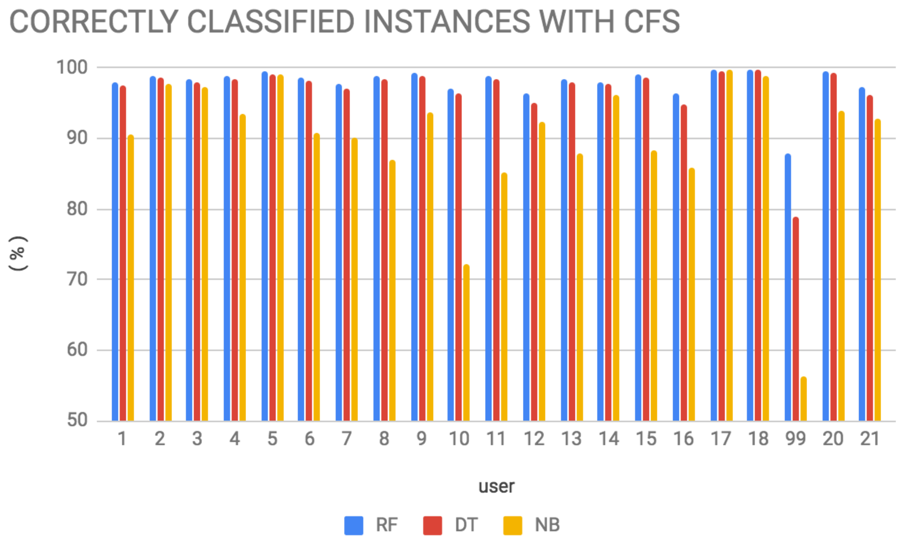

Figure 5.5: Correctly classified instances with CFS

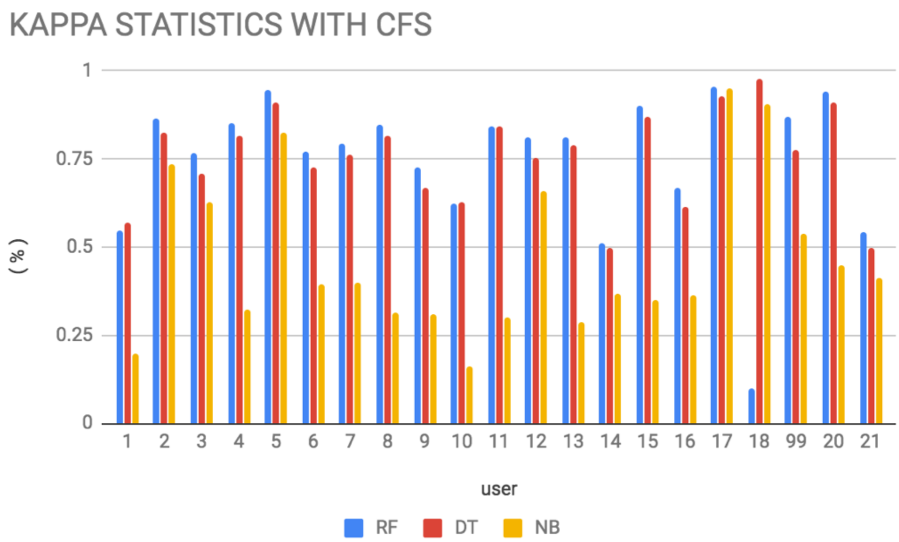

Figure 5.6: Kappa statistics with CFS

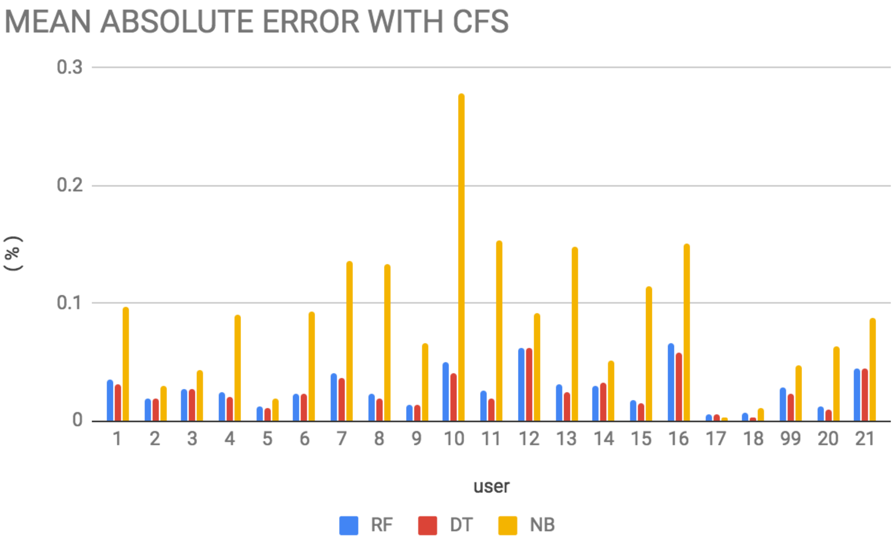

Figure 5.7: Mean absolute error with CFS

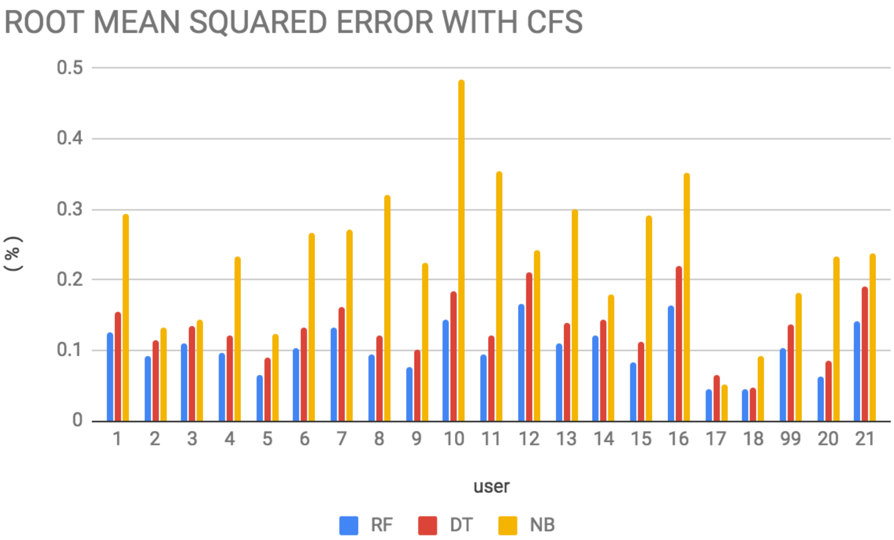

Figure 5.8: Root mean squared error with CFS

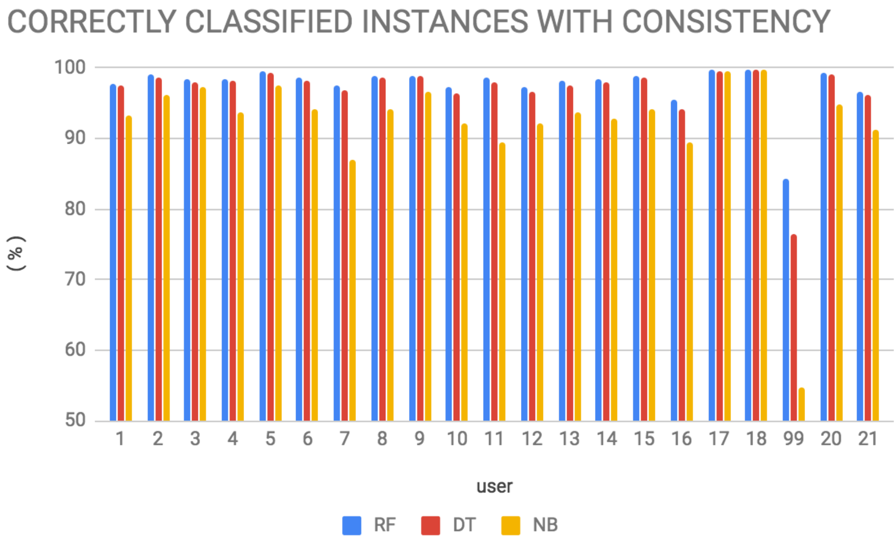

Figure 5.9: Correctly classified instances with Consistency

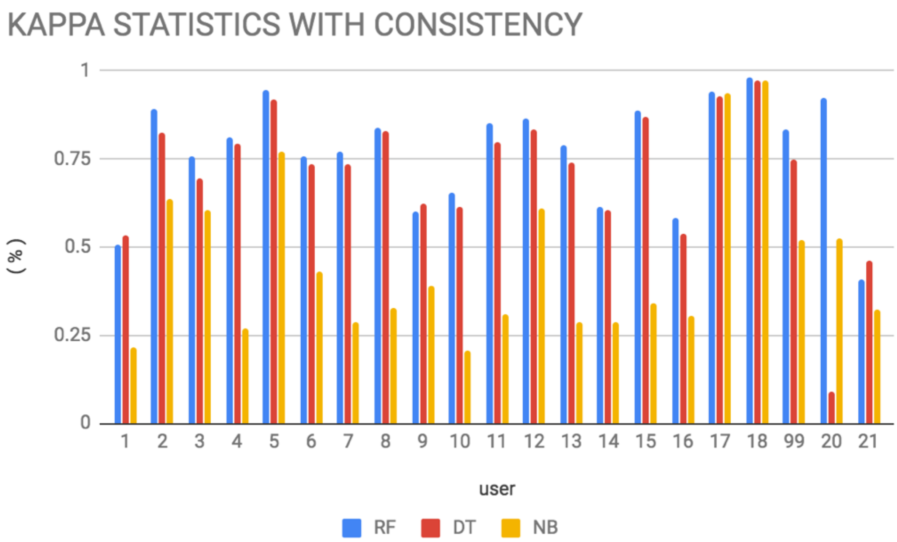

Figure 5.10: Kappa statistics with Consistency

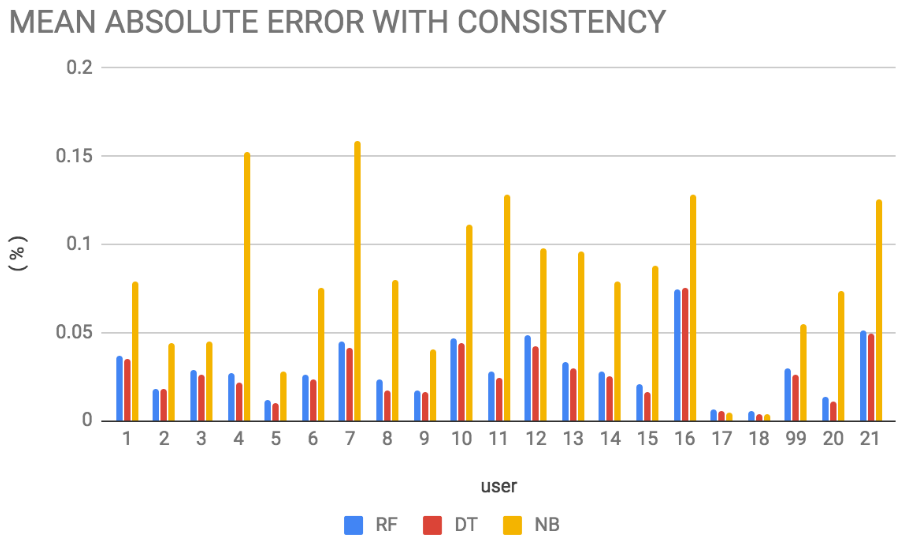

Figure 5.11: Mean absolute error with Consistency

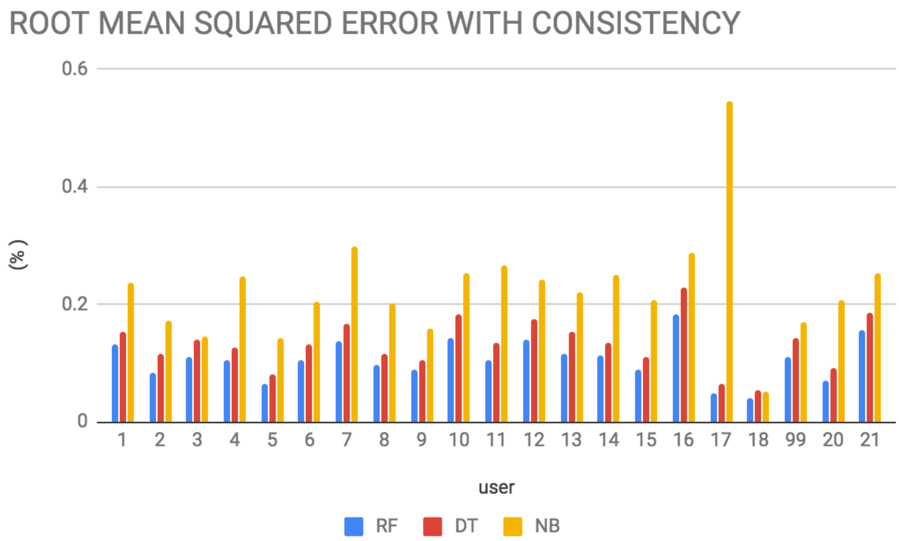

Figure 5.12: Root mean squared error with Consistency

USER_ID	Classifier	Attribute Sel. Alg.	Selected Attributes	EER(%)	Correctly Classified Instances(%)	Kappa Statistics	Mean absolute error	Root mean squared error
398248	Random Forest	None	All	7.551752053	97.6151	0.4382	0.039	0.1313
398248	J48	None	All	30.18480493	97.0653	0.5223	0.033	0.1674
398248	Naive Bayes	None	All	29.77412731	81.512	0.1164	0.1854	0.4211
398248	Random Forest	Cfs	ACC_Magnitude_mean ACC_Z_max ACC_Y_y_mean ACC_X_y_mean ACC_X_y_std ACC_X_y_max ACC_before_nowXmaxdiff ACC_before_nowZmaxdiff GYRO_Y_y_mean GYRO_Y_y_std GYRO_Y_y_max GYRO_before_nowYdiff GYRO_before_nowMdiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_std MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_std MAGNETO_X_y_mean MAGNETO_X_y_std MAGNETO_before_nowMmaxdiff TOUCHALITYCS_directionOfEndtoEnfLine TOUCHALITYCS_duration SAFEG_direction_mean	8.008213552	97.9391	0.5465	0.0348	0.1248
398248	J48	Cfs	ACC_Magnitude_mean ACC_Z_max ACC_Y_y_mean ACC_X_y_mean ACC_X_y_std ACC_X_y_max ACC_before_nowXmaxdiff ACC_before_nowZmaxdiff GYRO_Y_y_mean GYRO_Y_y_std GYRO_Y_y_max GYRO_before_nowYdiff GYRO_before_nowMdiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_std MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_std MAGNETO_X_y_mean MAGNETO_X_y_std MAGNETO_before_nowMmaxdiff TOUCHALITYCS_directionOfEndtoEnfLine TOUCHALITYCS_duration SAFEG_direction_mean	22.99794661	97.4227	0.5715	0.0312	0.155
398248	Naive Bayes	Cfs	ACC_Magnitude_mean ACC_Z_max ACC_Y_y_mean ACC_X_y_mean ACC_X_y_std ACC_X_y_max ACC_before_nowXmaxdiff ACC_before_nowZmaxdiff GYRO_Y_y_mean GYRO_Y_y_std GYRO_Y_y_max	21.56057495	90.543	0.1954	0.0963	0.2939

			GYRO_before_nowYdiff GYRO_before_nowMdiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_std MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_std MAGNETO_X_y_mean MAGNETO_X_y_std MAGNETO_before_nowMmaxdiff TOUCHALITYCS_directionOfEndto EnfLine TOUCHALITYCS_duration SAFEG_direction_mean					
398248	Random Forest	Consistency	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_max ACC_Mdiff ACC_before_nowYdiff ACC_before_nowMdiff GYRO_Z_max GYRO_Ydiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_std MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_StartY	9.856262834	97.7732	0.506	0.0366	0.1312
398248	J48	Consistency	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_max ACC_Mdiff ACC_before_nowYdiff ACC_before_nowMdiff GYRO_Z_max GYRO_Ydiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_std MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_StartY	26.76436961	97.5258	0.5323	0.0354	0.1528
398248	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_max ACC_Mdiff ACC_before_nowYdiff ACC_before_nowMdiff GYRO_Z_max GYRO_Ydiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_std MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_StartY	21.35523614	93.2921	0.2141	0.0788	0.2369
405035	Random Forest	None	All	3.276131045	98.7148	0.8246	0.0292	0.1
405035	J48	None	All	12.63650546	98.3643	0.7995	0.0181	0.1248
405035	Naive Bayes	None	All	13.26053042	80.323	0.2307	0.1972	0.4308
405035	Random Forest	Cfs	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max GYRO_Mdiff GYRO_before_nowYmaxdiff MAGNETO_Z_mean TOUCHALITYCS_A_pair20 SAFEG_angle_std	3.588143526	98.9553	0.8669	0.0195	0.0918
405035	J48	Cfs	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max	12.63844937	98.6048	0.8268	0.0189	0.1142

			GYRO_Mdiff GYRO_before_nowYmaxdiff MAGNETO_Z_mean TOUCHALITYCS_A_pair20 SAFEG_angle_std					
405035	Naive Bayes	Cfs	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max GYRO_Mdiff GYRO_before_nowYmaxdiff MAGNETO_Z_mean TOUCHALITYCS_A_pair20 SAFEG_angle_std	6.55226209	97.6701	0.735	0.03	0.1316
405035	Random Forest	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_Y_y_mean ACC_X_y_mean GYRO_Z_max GYRO_Y_y_mean MAGNETO_Z_mean MAGNETO_Y_y_mean TOUCHALITYCS_distance TOUCHALITYCS_duration SAFEG_direction_mean	2.964118565	99.1546	0.8937	0.0177	0.0844
405035	J48	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_Y_y_mean ACC_X_y_mean GYRO_Z_max GYRO_Y_y_mean MAGNETO_Z_mean MAGNETO_Y_y_mean TOUCHALITYCS_distance TOUCHALITYCS_duration SAFEG_direction_mean	10.4524181	98.5911	0.8253	0.0178	0.1152
405035	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_Y_y_mean ACC_X_y_mean GYRO_Z_max GYRO_Y_y_mean MAGNETO_Z_mean MAGNETO_Y_y_mean TOUCHALITYCS_distance TOUCHALITYCS_duration SAFEG_direction_mean	8.736349454	96.2062	0.6349	0.0442	0.1714
219303	Random Forest	None	All	4.029304029	98.0756	0.6545	0.0362	0.1163
219303	J48	None	All	18.65382458	97.7938	0.6888	0.0241	0.1452
219303	Naive Bayes	None	All	13.91941392	87.0103	0.2886	0.1326	0.3366
219303	Random Forest	Cfs	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max GYRO_Magnitude_mean MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_distance SAFEG_direction_mean	6.043956044	98.507	0.7685	0.0272	0.1098
219303	J48	Cfs	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max GYRO_Magnitude_mean MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_distance	17.45998967	97.945	0.7081	0.0266	0.1355

			SAFEG_direction_mean					
219303	Naive Bayes	Cfs	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max GYRO_Magnitude_mean MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_distance SAFEG_direction_mean	8.424908425	97.2371	0.628	0.0425	0.1444
219303	Random Forest	Consistency	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max ACC_Xdiff ACC_Ydiff ACC_before_nowXdiff MAGNETO_Magnitude_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_pairwiseDisplacement	4.945054945	98.4674	0.7597	0.0288	0.1105
219303	J48	Consistency	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max ACC_Xdiff ACC_Ydiff ACC_before_nowXdiff MAGNETO_Magnitude_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_pairwiseDisplacement	15.93406593	97.9038	0.6928	0.0265	0.1394
219303	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max ACC_Xdiff ACC_Ydiff ACC_before_nowXdiff MAGNETO_Magnitude_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_pairwiseDisplacement	9.523809524	97.3608	0.6047	0.0449	0.1454
579284	Random Forest	None	All	3.328509407	98.1718	0.7531	0.0365	0.1171
579284	J48	None	All	13.70823989	98.2131	0.7969	0.0195	0.1308
579284	Naive Bayes	None	All	27.20694645	54.378	0.0702	0.4542	0.6532
579284	Random Forest	Cfs	ACC_Magnitude_mean ACC_Z_mean ACC_Z_std ACC_Y_y_mean ACC_Y_y_std ACC_Y_y_max ACC_X_y_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_Zdiff TOUCHALITYCS_StartX TOUCHALITYCS_StartY TOUCHALITYCS_distance	3.039073806	98.7904	0.8498	0.0237	0.0972

			SAFEG_direction_mean					
579284	J48	Cfs	ACC_Magnitude_mean ACC_Z_mean ACC_Z_std ACC_Y_y_mean ACC_Y_y_std ACC_Y_y_max ACC_X_y_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_Zdiff TOUCHALITYCS_StartX TOUCHALITYCS_StartY TOUCHALITYCS_distance SAFEG_direction_mean	12.01157742	98.3986	0.8171	0.0199	0.1208
579284	Naive Bayes	Cfs	ACC_Magnitude_mean ACC_Z_mean ACC_Z_std ACC_Y_y_mean ACC_Y_y_std ACC_Y_y_max ACC_X_y_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_Zdiff TOUCHALITYCS_StartX TOUCHALITYCS_StartY TOUCHALITYCS_distance SAFEG_direction_mean	25.32561505	93.4502	0.3239	0.0899	0.233
579284	Random Forest	Consistency	ACC_Magnitude_mean ACC_Magnitude_std ACC_Magnitude ACC_X_y_max ACC_Xdiff ACC_before_nowMmaxdiff GYRO_Zdiff MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_duration	3.907380608	98.5223	0.8099	0.0271	0.1056
579284	J48	Consistency	ACC_Magnitude_mean ACC_Magnitude_std ACC_Magnitude ACC_X_y_max ACC_Xdiff ACC_before_nowMmaxdiff GYRO_Zdiff MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_duration	12.44573082	98.2337	0.7939	0.022	0.1278
579284	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Magnitude_std ACC_Magnitude ACC_X_y_max ACC_Xdiff ACC_before_nowMmaxdiff GYRO_Zdiff MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_duration	31.40376266	93.6426	0.2707	0.1527	0.2477
352716	Random Forest	None	All	1.699346405	99.3333	0.9288	0.0212	0.0765
352716	J48	None	All	6.797385621	99.1065	0.9087	0.0106	0.0924

352716	Naive Bayes	None	All	9.54248366	88.7973	0.4158	0.1112	0.3284
352716	Random Forest	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Z_max ACC_Y_y_mean ACC_Y_y_std ACC_X_y_max GYRO_Z_std MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max TOUCHALITYCS_StartX TOUCHALITYCS_Y SAFEG_angle_mean	1.437908497	99.4777	0.946	0.0122	0.0658
352716	J48	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Z_max ACC_Y_y_mean ACC_Y_y_std ACC_X_y_max GYRO_Z_std MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max TOUCHALITYCS_StartX TOUCHALITYCS_Y SAFEG_angle_mean	5.882352941	99.1271	0.9107	0.011	0.0906
352716	Naive Bayes	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Z_max ACC_Y_y_mean ACC_Y_y_std ACC_X_y_max GYRO_Z_std MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max TOUCHALITYCS_StartX TOUCHALITYCS_Y SAFEG_angle_mean	4.967320261	99.1237	0.8242	0.0191	0.123
352716	Random Forest	Consistency	ACC_Magnitude_mean ACC_Magnitude_std ACC_Z_max ACC_X_y_max GYRO_Zdiff MAGNETO_Magnitude_max MAGNETO_Z_max MAGNETO_X_y_mean	1.631900099	99.4708	0.946	0.012	0.0646
352716	J48	Consistency	ACC_Magnitude_mean ACC_Magnitude_std ACC_Z_max ACC_X_y_max GYRO_Zdiff MAGNETO_Magnitude_max MAGNETO_Z_max MAGNETO_X_y_mean	4.31372549	99.2921	0.9206	0.0095	0.0821
352716	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Magnitude_std ACC_Z_max ACC_X_y_max	6.14379085	97.4433	0.7713	0.0275	0.1433

			GYRO_Zdiff MAGNETO_Magnitude_max MAGNETO_Z_max MAGNETO_X_y_mean					
539502	Random Forest	None	All	3.956834532	98.1306	0.6676	0.0325	0.1124
539502	J48	None	All	18.3879878	98.1993	0.7454	0.0201	0.1316
539502	Naive Bayes	None	All	12.41007194	81.0859	0.222	0.1888	0.4206
539502	Random Forest	Cfs	ACC_Y_y_mean ACC_X_y_max GYRO_Y_y_mean GYRO_before_nowYmaxdiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_A_pair50 TOUCHALITYCS_StartY SAFEG_direction_mean SAFEG_direction_std	4.496402878	98.5911	0.7719	0.0236	0.1027
539502	J48	Cfs	ACC_Y_y_mean ACC_X_y_max GYRO_Y_y_mean GYRO_before_nowYmaxdiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_A_pair50 TOUCHALITYCS_StartY SAFEG_direction_mean SAFEG_direction_std	16.18705036	98.1168	0.7283	0.0229	0.1326
539502	Naive Bayes	Cfs	ACC_Y_y_mean ACC_X_y_max GYRO_Y_y_mean GYRO_before_nowYmaxdiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_A_pair50 TOUCHALITYCS_StartY SAFEG_direction_mean SAFEG_direction_std	9.712230216	90.8454	0.393	0.0935	0.2669
539502	Random Forest	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_Z_max ACC_X_y_mean GYRO_X_y_mean GYRO_Xdiff GYRO_Ydiff GYRO_before_nowYdiff MAGNETO_Magnitude_max MAGNETO_Y_y_mean MAGNETO_X_y_max TOUCHALITYCS_duration	5.395683453	98.5292	0.7586	0.0257	0.1057
539502	J48	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_Z_max ACC_X_y_mean GYRO_X_y_mean GYRO_Xdiff GYRO_Ydiff GYRO_before_nowYdiff MAGNETO_Magnitude_max	14.74820144	98.1649	0.7365	0.0231	0.1307

			MAGNETO_Y_y_mean MAGNETO_X_y_max TOUCHALITYCS_duration					
539502	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_Z_max ACC_X_y_mean GYRO_X_y_mean GYRO_Xdiff GYRO_Ydiff GYRO_before_nowYdiff MAGNETO_Magnitude_max MAGNETO_Y_y_mean MAGNETO_X_y_max TOUCHALITYCS_duration	13.84892086	94.1581	0.4326	0.0758	0.2055
540641	Random Forest	None	All	12.61682243	97.299	0.7349	0.0533	0.1371
540641	J48	None	All	11.13707165	97.2577	0.7746	0.031	0.161
540641	Naive Bayes	None	All	35.04672897	40.4811	0.1225	0.395	0.6194
540641	Random Forest	Cfs	ACC_X_y_mean ACC_X_y_max GYRO_Y_y_mean MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_max TOUCHALITYCS_StartY TOUCHALITYCS_V_median3 TOUCHALITYCS_X TOUCHALITYCS_distance	11.37071651	97.7182	0.7929	0.0406	0.1318
540641	J48	Cfs	ACC_X_y_mean ACC_X_y_max GYRO_Y_y_mean MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_max TOUCHALITYCS_StartY TOUCHALITYCS_V_median3 TOUCHALITYCS_X TOUCHALITYCS_distance	12.38317757	97.1409	0.7611	0.0367	0.1615
540641	Naive Bayes	Cfs	ACC_X_y_mean ACC_X_y_max GYRO_Y_y_mean MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_max TOUCHALITYCS_StartY TOUCHALITYCS_V_median3 TOUCHALITYCS_X TOUCHALITYCS_distance	26.9470405	90.055	0.3981	0.1353	0.2707
540641	Random Forest	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_X_y_max ACC_Ydiff GYRO_before_nowZdiff MAGNETO_Z_max MAGNETO_X_y_mean MAGNETO_Xdiff TOUCHALITYCS_A_first5 TOUCHALITYCS_duration	11.37071651	97.5533	0.7722	0.0446	0.1374
540641	J48	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_X_y_max ACC_Ydiff GYRO_before_nowZdiff MAGNETO_Z_max MAGNETO_X_y_mean MAGNETO_Xdiff TOUCHALITYCS_A_first5 TOUCHALITYCS_duration	11.61461291	96.866	0.7339	0.0409	0.1679

540641	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_X_y_max ACC_Ydiff GYRO_before_nowZdiff MAGNETO_Z_max MAGNETO_X_y_mean MAGNETO_Xdiff TOUCHALITYCS_A_first5 TOUCHALITYCS_duration	28.27102804	87.0309	0.2893	0.1589	0.2981
526319	Random Forest	None	All	1.692307692	98.4674	0.7861	0.0308	0.1026
526319	J48	None	All	11.38461538	98.4192	0.8115	0.0171	0.1218
526319	Naive Bayes	None	All	15.84615385	75.9519	0.1844	0.2428	0.4708
526319	Random Forest	Cfs	ACC_Y_y_mean ACC_X_y_mean ACC_Mdiff GYRO_Y_y_max GYRO_X_y_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_X_y_max MAGNETO_before_nowZmaxdiff TOUCHALITYCS_A_pair20 TOUCHALITYCS_A_pair50 TOUCHALITYCS_A_pair80 TOUCHALITYCS_directionOfEndtoEnfLine TOUCHALITYCS_duration SAFEG_angle_std	2.307692308	98.8385	0.8477	0.0224	0.0939
526319	J48	Cfs	ACC_Y_y_mean ACC_X_y_mean ACC_Mdiff GYRO_Y_y_max GYRO_X_y_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_X_y_max MAGNETO_before_nowZmaxdiff TOUCHALITYCS_A_pair20 TOUCHALITYCS_A_pair50 TOUCHALITYCS_A_pair80 TOUCHALITYCS_directionOfEndtoEnfLine TOUCHALITYCS_duration SAFEG_angle_std	10.61723548	98.4536	0.8163	0.0184	0.1202
526319	Naive Bayes	Cfs	ACC_Y_y_mean ACC_X_y_mean ACC_Mdiff GYRO_Y_y_max GYRO_X_y_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_X_y_max MAGNETO_before_nowZmaxdiff TOUCHALITYCS_A_pair20 TOUCHALITYCS_A_pair50 TOUCHALITYCS_A_pair80 TOUCHALITYCS_directionOfEndtoEnfLine TOUCHALITYCS_duration	13.84615385	87.0034	0.3162	0.1329	0.3204

			SAFEG_angle_std					
526319	Random Forest	Consistency	ACC_Magnitude_mean ACC_Z_mean GYRO_Y_y_mean MAGNETO_Z_mean MAGNETO_Y_y_max MAGNETO_X_y_max TOUCHALITYCS_A_first5 TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_directionOfEndtoEnfLine	2.615384615	98.756	0.8364	0.0232	0.0961
526319	J48	Consistency	ACC_Magnitude_mean ACC_Z_mean GYRO_Y_y_mean MAGNETO_Z_mean MAGNETO_Y_y_max MAGNETO_X_y_max TOUCHALITYCS_A_first5 TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_directionOfEndtoEnfLine	9.230769231	98.5636	0.8278	0.0172	0.1148
526319	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Z_mean GYRO_Y_y_mean MAGNETO_Z_mean MAGNETO_Y_y_max MAGNETO_X_y_max TOUCHALITYCS_A_first5 TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_directionOfEndtoEnfLine	12.20353297	94.0687	0.3273	0.0795	0.2011
395129	Random Forest	None	All	2.621722846	98.9897	0.6158	0.018	0.0845
395129	J48	None	All	18.35205993	98.9278	0.6788	0.0119	0.1013
395129	Naive Bayes	None	All	17.97752809	75.3952	0.086	0.246	0.4885
395129	Random Forest	Cfs	ACC_Magnitude_mean ACC_Z_mean ACC_Z_std ACC_Y_y_mean ACC_X_y_mean ACC_X_y_std ACC_X_y_max GYRO_Magnitude_std GYRO_before_nowYmaxdiff MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_A_first5 TOUCHALITYCS_V_median3 TOUCHALITYCS_directionOfEndtoEnfLine TOUCHALITYCS_duration SAFEG_direction_mean	3.370786517	99.2096	0.7244	0.014	0.0768
395129	J48	Cfs	ACC_Magnitude_mean ACC_Z_mean ACC_Z_std ACC_Y_y_mean ACC_X_y_mean ACC_X_y_std ACC_X_y_max GYRO_Magnitude_std GYRO_before_nowYmaxdiff MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max	18.70645089	98.9072	0.6667	0.0132	0.101

			MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_A_first5 TOUCHALITYCS_V_median3 TOUCHALITYCS_directionOfEndtoEnfLine TOUCHALITYCS_duration SAFEG_direction_mean					
395129	Naive Bayes	Cfs	ACC_Magnitude_mean ACC_Z_mean ACC_Z_std ACC_Y_y_mean ACC_X_y_mean ACC_X_y_std ACC_X_y_max GYRO_Magnitude_std GYRO_before_nowYmaxdiff MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_A_first5 TOUCHALITYCS_V_median3 TOUCHALITYCS_directionOfEndtoEnfLine TOUCHALITYCS_duration SAFEG_direction_mean	8.988764045	93.6426	0.3088	0.0665	0.225
395129	Random Forest	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_X_y_std ACC_X_y_max ACC_Xdiff ACC_before_nowYmaxdiff GYRO_Ydiff MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_directionOfEndtoEnfLine SAFEG_direction_mean	10.48689139	98.9485	0.6001	0.0175	0.0878
395129	J48	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_X_y_std ACC_X_y_max ACC_Xdiff ACC_before_nowYmaxdiff GYRO_Ydiff MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_directionOfEndtoEnfLine SAFEG_direction_mean	16.85393258	98.8316	0.6231	0.016	0.1048
395129	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_X_y_std ACC_X_y_max ACC_Xdiff ACC_before_nowYmaxdiff GYRO_Ydiff MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_directionOfEndtoEnfLine SAFEG_direction_mean	18.72659176	96.6529	0.3903	0.0405	0.1577

594887	Random Forest	None	All	5.677419355	96.4536	0.4873	0.0575	0.1535
594887	J48	None	All	23.09677419	96.2062	0.6141	0.0414	0.191
594887	Naive Bayes	None	All	27.09677419	64.4708	0.1108	0.3842	0.5983
594887	Random Forest	Cfs	ACC_Z_mean ACC_Z_max ACC_Y_y_mean ACC_Y_y_std ACC_Y_y_max ACC_X_y_mean ACC_X_y_std ACC_X_y_max ACC_Mdiff ACC_before_nowXmaxdiff GYRO_Z_std GYRO_X_y_mean GYRO_Xdiff GYRO_Zdiff GYRO_before_nowXdiff GYRO_before_nowZdiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Y_y_std MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_X_y_max TOUCHALITYCS_A_pair20 TOUCHALITYCS_A_pair80 TOUCHALITYCS_StartX TOUCHALITYCS_V_pair50 TOUCHALITYCS_V_median3 TOUCHALITYCS_Y TOUCHALITYCS_X TOUCHALITYCS_directionOfEndtoEnfLine TOUCHALITYCS_ratio	5.935483871	97.1203	0.6222	0.05	0.1431
594887	J48	Cfs	ACC_Z_mean ACC_Z_max ACC_Y_y_mean ACC_Y_y_std ACC_Y_y_max ACC_X_y_mean ACC_X_y_std ACC_X_y_max ACC_Mdiff ACC_before_nowXmaxdiff GYRO_Z_std GYRO_X_y_mean GYRO_Xdiff GYRO_Zdiff GYRO_before_nowXdiff GYRO_before_nowZdiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Y_y_std MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_X_y_max TOUCHALITYCS_A_pair20 TOUCHALITYCS_A_pair80 TOUCHALITYCS_StartX TOUCHALITYCS_V_pair50 TOUCHALITYCS_V_median3 TOUCHALITYCS_Y TOUCHALITYCS_X TOUCHALITYCS_directionOfEndtoEnfLine TOUCHALITYCS_ratio	22.58064516	96.4399	0.6275	0.0409	0.1842

594887	Naive Bayes	Cfs	ACC_Z_mean ACC_Z_max ACC_Y_y_mean ACC_Y_y_std ACC_Y_y_max ACC_X_y_mean ACC_X_y_std ACC_X_y_max ACC_Mdiff ACC_before_nowXmaxdiff GYRO_Z_std GYRO_X_y_mean GYRO_Xdiff GYRO_Zdiff GYRO_before_nowXdiff GYRO_before_nowZdiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Y_y_std MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_X_y_max TOUCHALITYCS_A_pair20 TOUCHALITYCS_A_pair80 TOUCHALITYCS_StartX TOUCHALITYCS_V_pair50 TOUCHALITYCS_V_median3 TOUCHALITYCS_Y TOUCHALITYCS_X TOUCHALITYCS_directionOfEndtoEnfLine TOUCHALITYCS_ratio	23.61290323	72.2337	0.1615	0.2784	0.4842
594887	Random Forest	Consistency	ACC_Magnitude ACC_Y_y_max ACC_X_y_mean ACC_Mdiff GYRO_Z_mean GYRO_Z_std GYRO_before_nowXdiff MAGNETO_Z_mean MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_directionOfEndtoEnfLine	6.580645161	97.2784	0.6538	0.0463	0.1415
594887	J48	Consistency	ACC_Magnitude ACC_Y_y_max ACC_X_y_mean ACC_Mdiff GYRO_Z_mean GYRO_Z_std GYRO_before_nowXdiff MAGNETO_Z_mean MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_directionOfEndtoEnfLine	19.69105929	96.3711	0.6154	0.0436	0.1826
594887	Naive Bayes	Consistency	ACC_Magnitude ACC_Y_y_max ACC_X_y_mean ACC_Mdiff GYRO_Z_mean GYRO_Z_std GYRO_before_nowXdiff MAGNETO_Z_mean MAGNETO_Y_y_max MAGNETO_X_y_mean TOUCHALITYCS_directionOfEndtoEnfLine	25.67741935	92.0893	0.2045	0.1113	0.2522
100669	Random Forest	None	All	13.99631676	98.3299	0.8062	0.0369	0.1121
100669	J48	None	All	9.208103131	98.3093	0.8295	0.0194	0.1269

100669	Naive Bayes	None	All	34.80662983	57.4914	0.0889	0.4247	0.6445
100669	Random Forest	Cfs	CC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Y_y_mean ACC_X_y_max ACC_Mdiff GYRO_Y_y_max GYRO_X_y_mean GYRO_X_y_std GYRO_Xdiff GYRO_before_nowYmaxdiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_max MAGNETO_Xdiff TOUCHALITYCS_pairwiseDisplacement TOUCHALITYCS_StartX TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_Y TOUCHALITYCS_X TOUCHALITYCS_distance TOUCHALITYCS_directionOfEndtoEnfLine SAFEG_direction_mean SAFEG_angle_std	9.300184162	98.8454	0.8428	0.0261	0.0946
100669	J48	Cfs	CC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Y_y_mean ACC_X_y_max ACC_Mdiff GYRO_Y_y_max GYRO_X_y_mean GYRO_X_y_std GYRO_Xdiff GYRO_before_nowYmaxdiff MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_max MAGNETO_Xdiff TOUCHALITYCS_pairwiseDisplacement TOUCHALITYCS_StartX TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_Y TOUCHALITYCS_X TOUCHALITYCS_distance TOUCHALITYCS_directionOfEndtoEnfLine SAFEG_direction_mean SAFEG_angle_std	8.658045248	98.4811	0.8448	0.0184	0.121
100669	Naive Bayes	Cfs	CC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Y_y_mean ACC_X_y_max ACC_Mdiff GYRO_Y_y_max GYRO_X_y_mean GYRO_X_y_std GYRO_Xdiff GYRO_before_nowYmaxdiff MAGNETO_Magnitude_mean	24.86187845	85.244	0.2988	0.1528	0.3538

			MAGNETO_Magnitude_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_max MAGNETO_Xdiff TOUCHALITYCS_pairwiseDisplacement TOUCHALITYCS_StartX TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_Y TOUCHALITYCS_X TOUCHALITYCS_distance TOUCHALITYCS_directionOfEndtoEnfLine SAFEG_direction_mean SAFEG_angle_std					
100669	Random Forest	Consistency	ACC_Magnitude_mean ACC_Magnitude_std GYRO_Magnitude_std GYRO_Y_y_mean MAGNETO_Magnitude_mean MAGNETO_Z_mean MAGNETO_X_y_max TOUCHALITYCS_pairwiseDisplacement TOUCHALITYCS_StartX TOUCHALITYCS_StartY	9.668508287	98.6667	0.8527	0.0281	0.1051
100669	J48	Consistency	ACC_Magnitude_mean ACC_Magnitude_std GYRO_Magnitude_std GYRO_Y_y_mean MAGNETO_Magnitude_mean MAGNETO_Z_mean MAGNETO_X_y_max TOUCHALITYCS_pairwiseDisplacement TOUCHALITYCS_StartX TOUCHALITYCS_StartY	9.760589319	98.0619	0.7985	0.0242	0.1346
100669	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Magnitude_std GYRO_Magnitude_std GYRO_Y_y_mean MAGNETO_Magnitude_mean MAGNETO_Z_mean MAGNETO_X_y_max TOUCHALITYCS_pairwiseDisplacement TOUCHALITYCS_StartX TOUCHALITYCS_StartY	26.42725599	89.5395	0.3109	0.1281	0.2668
248252	Random Forest	None	All	3.812824957	96.8247	0.8314	0.067	0.1541
248252	J48	None	All	11.6117851	94.5017	0.8307	0.0382	0.183
248252	Naive Bayes	None	All	21.08607741	71.1615	0.2894	0.2889	0.527
248252	Random Forest	Cfs	ACC_Z_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max GYRO_Y_y_mean GYRO_Y_y_std MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Ydiff TOUCHALITYCS_Y TOUCHALITYCS_X TOUCHALITYCS_duration	6.123627961	96.3093	0.813	0.0617	0.1661
248252	J48	Cfs	ACC_Z_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max	12.70672998	94.9897	0.753	0.622	0.2107

			GYRO_Y_y_mean GYRO_Y_y_std MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Ydiff TOUCHALITYCS_Y TOUCHALITYCS_X TOUCHALITYCS_duration					
248252	Naive Bayes	Cfs	ACC_Z_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max GYRO_Y_y_mean GYRO_Y_y_std MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Ydiff TOUCHALITYCS_Y TOUCHALITYCS_X TOUCHALITYCS_duration	12.0161756 2	92.433	0.6613	0.0916	0.2431
248252	Rando m Forest	Consisten cy	ACC_Magnitude_mean ACC_Z_mean ACC_X_y_max ACC_before_nowZdiff ACC_before_nowXmaxdiff GYRO_X_y_max MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_StartY TOUCHALITYCS_Y	3.98613518 2	97.3471	0.8668	0.0486	0.1405
248252	J48	Consisten cy	ACC_Magnitude_mean ACC_Z_mean ACC_X_y_max ACC_before_nowZdiff ACC_before_nowXmaxdiff GYRO_X_y_max MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_StartY TOUCHALITYCS_Y	10.4448482 4	96.5773	0.8336	0.0422	0.1747
248252	Naive Bayes	Consisten cy	ACC_Magnitude_mean ACC_Z_mean ACC_X_y_max ACC_before_nowZdiff ACC_before_nowXmaxdiff GYRO_X_y_max MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_StartY TOUCHALITYCS_Y	14.8469093	92.2405	0.6095	0.0978	0.2416
527796	Rando m Forest	None	All	3.32906530 1	97.5739	0.6974	0.0444	0.1274
527796	J48	None	All	16.1331626 1	97.732	0.7704	0.0255	0.1472
527796	Naive Bayes	None	All	29.1933418 7	66.6254	0.1226	0.3385	0.5486
527796	Rando m Forest	Cfs	ACC_Magnitude_mean ACC_Magnitude_std ACC_Y_y_max ACC_X_y_mean ACC_X_y_max GYRO_Y_y_mean GYRO_X_y_std MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_max MAGNETO_X_y_max	3.32906530 1	98.3162	0.81	0.0307	0.111

			TOUCHALITYCS_StartX TOUCHALITYCS_directionOfEndtoEnfLine SAFEG_direction_mean SAFEG_angle_std					
527796	J48	Cfs	ACC_Magnitude_mean ACC_Magnitude_std ACC_Y_y_max ACC_X_y_mean ACC_X_y_max GYRO_Y_y_mean GYRO_X_y_std MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_max MAGNETO_X_y_max TOUCHALITYCS_StartX TOUCHALITYCS_directionOfEndtoEnfLine SAFEG_direction_mean SAFEG_angle_std	14.4686299 6	97.9244	0.7883	0.0248	0.1396
527796	Naive Bayes	Cfs	ACC_Magnitude_mean ACC_Magnitude_std ACC_Y_y_max ACC_X_y_mean ACC_X_y_max GYRO_Y_y_mean GYRO_X_y_std MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_max MAGNETO_X_y_max TOUCHALITYCS_StartX TOUCHALITYCS_directionOfEndtoEnfLine SAFEG_direction_mean SAFEG_angle_std	23.4314980 8	87.9931	0.287	0.1483	0.3015
527796	Rando m Forest	Consisten cy	ACC_Magnitude_mean ACC_Magnitude_std ACC_Z_mean ACC_Y_y_mean ACC_X_y_mean GYRO_Magnitude_std GYRO_X_y_std MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_max TOUCHALITYCS_A_first5	3.71318822	98.1649	0.7904	0.0333	0.116
527796	J48	Consisten cy	ACC_Magnitude_mean ACC_Magnitude_std ACC_Z_mean ACC_Y_y_mean ACC_X_y_mean GYRO_Magnitude_std GYRO_X_y_std MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_max TOUCHALITYCS_A_first5	15.6805311 5	97.4639	0.7405	0.0293	0.1533
527796	Naive Bayes	Consisten cy	ACC_Magnitude_mean ACC_Magnitude_std ACC_Z_mean ACC_Y_y_mean ACC_X_y_mean GYRO_Magnitude_std GYRO_X_y_std MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_max TOUCHALITYCS_A_first5	16.3892445 6	93.622	0.2879	0.0958	0.2196

501973	Random Forest	None	All	6.52173913	98.2131	0.5366	0.0312	0.1153
501973	J48	None	All	27.63160675	97.7251	0.5688	0.0252	0.1481
501973	Naive Bayes	None	All	22.70531401	80.8797	0.1417	0.1914	0.4205
501973	Random Forest	Cfs	ACC_Magnitude ACC_X_y_mean GYRO_Xdiff MAGNETO_Z_mean TOUCHALITYCS_StartY TOUCHALITYCS_distance	10.86956522	98	0.5102	0.0301	0.1218
501973	J48	Cfs	ACC_Magnitude ACC_X_y_mean GYRO_Xdiff MAGNETO_Z_mean TOUCHALITYCS_StartY TOUCHALITYCS_distance	23.1884058	97.7182	0.4992	0.0328	0.1438
501973	Naive Bayes	Cfs	ACC_Magnitude ACC_X_y_mean GYRO_Xdiff MAGNETO_Z_mean TOUCHALITYCS_StartY TOUCHALITYCS_distance	23.42995169	96.2062	0.3686	0.0518	0.1794
501973	Random Forest	Consistency	ACC_Magnitude ACC_Z_mean ACC_X_y_max ACC_Xdiff ACC_Ydiff ACC_before_nowMmaxdiff GYRO_X_y_max GYRO_Ydiff GYRO_before_nowZdiff MAGNETO_Magnitude_max MAGNETO_Z_max TOUCHALITYCS_V_pair80	8.695652174	98.3986	0.6164	0.028	0.1129
501973	J48	Consistency	ACC_Magnitude ACC_Z_mean ACC_X_y_max ACC_Xdiff ACC_Ydiff ACC_before_nowMmaxdiff GYRO_X_y_max GYRO_Ydiff GYRO_before_nowZdiff MAGNETO_Magnitude_max MAGNETO_Z_max TOUCHALITYCS_V_pair80	20.53140097	98.0481	0.6053	0.0252	0.1356
501973	Naive Bayes	Consistency	ACC_Magnitude ACC_Z_mean ACC_X_y_max ACC_Xdiff ACC_Ydiff ACC_before_nowMmaxdiff GYRO_X_y_max GYRO_Ydiff GYRO_before_nowZdiff MAGNETO_Magnitude_max MAGNETO_Z_max TOUCHALITYCS_V_pair80	23.67149758	92.7904	0.288	0.0788	0.2492
525584	Random Forest	None	All	1.978891821	98.6804	0.8489	0.0314	0.1004
525584	J48	None	All	12.06610672	98.5567	0.8497	0.0157	0.1183
525584	Naive Bayes	None	All	20.18469657	73.4708	0.1736	0.2645	0.4866
525584	Random Forest	Cfs	ACC_Magnitude ACC_Z_mean ACC_Y_y_max ACC_X_y_mean ACC_X_y_max	1.715039578	99.0859	0.9014	0.0179	0.0831

			ACC_before_nowYdiff MAGNETO_Magnitude_mean MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_Xdiff TOUCHALITYCS_A_pair20 TOUCHALITYCS_StartX TOUCHALITYCS_X TOUCHALITYCS_duration SAFEG_distance_mean SAFEG_direction_mean					
525584	J48	Cfs	ACC_Magnitude ACC_Z_mean ACC_Y_y_max ACC_X_y_mean ACC_X_y_max ACC_before_nowYdiff MAGNETO_Magnitude_mean MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_Xdiff TOUCHALITYCS_A_pair20 TOUCHALITYCS_StartX TOUCHALITYCS_X TOUCHALITYCS_duration SAFEG_distance_mean SAFEG_direction_mean	9.234828496	98.7148	0.8676	0.015	0.1113
525584	Naive Bayes	Cfs	ACC_Magnitude ACC_Z_mean ACC_Y_y_max ACC_X_y_mean ACC_X_y_max ACC_before_nowYdiff MAGNETO_Magnitude_mean MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_Xdiff TOUCHALITYCS_A_pair20 TOUCHALITYCS_StartX TOUCHALITYCS_X TOUCHALITYCS_duration SAFEG_distance_mean SAFEG_direction_mean	15.56728232	88.2749	0.3514	0.11428	0.2914
525584	Random Forest	Consistency	ACC_Magnitude_mean ACC_Z_mean ACC_Z_max ACC_Y_y_mean ACC_Ydiff ACC_before_nowZdiff GYRO_before_nowZmaxdiff MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_X	2.374670185	98.9622	0.887	0.0203	0.0889
525584	J48	Consistency	ACC_Magnitude_mean ACC_Z_mean ACC_Z_max ACC_Y_y_mean ACC_Ydiff ACC_before_nowZdiff GYRO_before_nowZmaxdiff MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_X	8.839050132	98.7285	0.8681	0.0158	0.1098

525584	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Z_mean ACC_Z_max ACC_Y_y_mean ACC_Ydiff ACC_before_nowZdiff GYRO_before_nowZmaxdiff MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_X	15.69920844	94.1168	0.342	0.088	0.2074
171538	Random Forest	None	All	7.569257617	95.4296	0.5542	0.0771	0.1777
171538	J48	None	All	25.85895118	94.2749	0.5843	0.061	0.2329
171538	Naive Bayes	None	All	26.13019892	74.6804	0.2127	0.2538	0.4885
171538	Random Forest	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Z_max ACC_Y_y_mean ACC_Y_y_std ACC_X_y_max ACC_Xdiff ACC_Mdiff ACC_before_nowYmaxdiff GYRO_Magnitude_mean GYRO_Z_mean GYRO_Z_std GYRO_Xdiff GYRO_Ydiff GYRO_Zdiff MAGNETO_Magnitude_std MAGNETO_Magnitude_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_X_y_max TOUCHALITYCS_StartX TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_X TOUCHALITYCS_distance TOUCHALITYCS_directionOfEndtoEnfLine SAFEG_direction_mean	7.142857143	96.2887	0.668	0.0663	0.1645
171538	J48	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Z_max ACC_Y_y_mean ACC_Y_y_std ACC_X_y_max ACC_Xdiff ACC_Mdiff ACC_before_nowYmaxdiff GYRO_Magnitude_mean GYRO_Z_mean GYRO_Z_std GYRO_Xdiff GYRO_Ydiff GYRO_Zdiff MAGNETO_Magnitude_std MAGNETO_Magnitude_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_X_y_max TOUCHALITYCS_StartX TOUCHALITYCS_StartY	23.59855335	94.8866	0.6122	0.0579	0.2198

			TOUCHALITYCS_V_pair80 TOUCHALITYCS_X TOUCHALITYCS_distance TOUCHALITYCS_directionOfEndtoEnfLine SAFEG_direction_mean					
171538	Naive Bayes	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Z_max ACC_Y_y_mean ACC_Y_y_std ACC_X_y_max ACC_Xdiff ACC_Mdiff ACC_before_nowYmaxdiff GYRO_Magnitude_mean GYRO_Z_mean GYRO_Z_std GYRO_Xdiff GYRO_Ydiff GYRO_Zdiff MAGNETO_Magnitude_std MAGNETO_Magnitude_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_X_y_max TOUCHALITYCS_StartX TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_X TOUCHALITYCS_distance TOUCHALITYCS_directionOfEndtoEnfLine SAFEG_direction_mean	20.70524412	85.7732	0.362	0.1505	0.3513
171538	Random Forest	Consistency	ACC_Magnitude_mean ACC_Z_max ACC_X_y_mean GYRO_Z_mean GYRO_Zdiff MAGNETO_Z_max MAGNETO_X_y_mean MAGNETO_before_nowXmaxdiff TOUCHALITYCS_StartX TOUCHALITYCS_directionOfEndtoEnfLine	9.855334539	95.512	0.5845	1.0741	0.1833
171538	J48	Consistency	ACC_Magnitude_mean ACC_Z_max ACC_X_y_mean GYRO_Z_mean GYRO_Zdiff MAGNETO_Z_max MAGNETO_X_y_mean MAGNETO_before_nowXmaxdiff TOUCHALITYCS_StartX TOUCHALITYCS_directionOfEndtoEnfLine	23.960217	94.11	0.5367	0.075	0.2292
171538	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Z_max ACC_X_y_mean GYRO_Z_mean GYRO_Zdiff MAGNETO_Z_max MAGNETO_X_y_mean MAGNETO_before_nowXmaxdiff TOUCHALITYCS_StartX TOUCHALITYCS_directionOfEndtoEnfLine	21.88065099	89.4639	0.3056	0.1285	0.2887
389015	Random Forest	None	All	0.4319654428	99.6151	0.9337	0.0108	0.0541

389015	J48	None	All	8.207343413	99.4914	0.9162	0.0061	0.07
389015	Naive Bayes	None	All	7.343412527	95.2852	0.535	0.0475	0.2127
389015	Random Forest	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Y_y_mean GYRO_Magnitude_mean MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_Y SAFEG_direction_std SAFEG_angle_mean	0.8639308855	99.732	0.9549	0.0057	0.0454
389015	J48	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Y_y_mean GYRO_Magnitude_mean MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_Y SAFEG_direction_std SAFEG_angle_mean	7.559395248	99.5739	0.9292	0.0052	0.0646
389015	Naive Bayes	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Y_y_mean GYRO_Magnitude_mean MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_Y SAFEG_direction_std SAFEG_angle_mean	3.023758099	99.7045	0.9511	0.0031	0.0522
389015	Random Forest	Consistency	ACC_Magnitude_mean ACC_Z_mean ACC_before_nowYdiff ACC_before_nowMmaxdiff GYRO_Z_max MAGNETO_Z_mean MAGNETO_X_y_mean TOUCHALITYCS_Y	0.8639308855	99.6632	0.943	0.0065	0.0494
389015	J48	Consistency	ACC_Magnitude_mean ACC_Z_mean ACC_before_nowYdiff ACC_before_nowMmaxdiff GYRO_Z_max MAGNETO_Z_mean MAGNETO_X_y_mean TOUCHALITYCS_Y	7.127429806	99.5739	0.9292	0.0058	0.0641
389015	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Z_mean ACC_before_nowYdiff ACC_before_nowMmaxdiff GYRO_Z_max MAGNETO_Z_mean MAGNETO_X_y_mean TOUCHALITYCS_Y	3.239740821	99.6289	0.937	0.0044	0.5464
151985	Random Forest	None	All	0.1184834123	99.8076	0.9822	0.0107	0.048
151985	J48	None	All	1.658767773	99.7801	0.9799	0.0028	0.0463

151985	Naive Bayes	None	All	2.132701422	98.9347	0.9071	0.0109	0.1027
151985	Random Forest	Cfs	ACC_Y_y_mean ACC_before_nowYmaxdiff GYRO_Magnitude_std GYRO_before_nowYdiff MAGNETO_Magnitude_max MAGNETO_Y_y_mean MAGNETO_X_y_mean MAGNETO_X_y_max TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_duration	0.2369668246	99.7938	0.0981	0.0064	0.0439
151985	J48	Cfs	ACC_Y_y_mean ACC_before_nowYmaxdiff GYRO_Magnitude_std GYRO_before_nowYdiff MAGNETO_Magnitude_max MAGNETO_Y_y_mean MAGNETO_X_y_mean MAGNETO_X_y_max TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_duration	1.777251185	99.7732	0.9792	0.0029	0.0463
151985	Naive Bayes	Cfs	ACC_Y_y_mean ACC_before_nowYmaxdiff GYRO_Magnitude_std GYRO_before_nowYdiff MAGNETO_Magnitude_max MAGNETO_Y_y_mean MAGNETO_X_y_mean MAGNETO_X_y_max TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_duration	0.9478672986	98.9003	0.9068	0.011	0.0921
151985	Random Forest	Consistency	ACC_Magnitude_mean ACC_Y_y_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_directionOfEndtoEnfLine	0.2369668246	99.8007	0.9816	0.0051	0.0415
151985	J48	Consistency	ACC_Magnitude_mean ACC_Y_y_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_directionOfEndtoEnfLine	2.369668246	99.6907	0.9716	0.0039	0.0545
151985	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Y_y_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_X_y_mean TOUCHALITYCS_directionOfEndtoEnfLine	0.7109004739	99.6976	0.9726	0.0035	0.05
All	Random Forest	None	All	5.161290323	89.3265	0.8865	0.0399	0.1167
All	J48	None	All	26.4516129	77.1684	0.7575	0.024	0.1437
All	Naive Bayes	None	All	28.64516129	48.7354	0.4594	0.0517	0.2147
All	Random Forest	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Y_y_mean ACC_Y_y_max ACC_X_y_mean ACC_X_y_max GYRO_Z_mean MAGNETO_Magnitude_mean MAGNETO_Magnitude_max	5.548387097	87.89	0.8712	0.0281	0.1024

			MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_X_y_max MAGNETO_before_nowMmaxdiff TOUCHALITYCS_pairwiseDisplacement TOUCHALITYCS_duration SAFEG_direction_mean					
All	J48	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Y_y_mean ACC_Y_y_max ACC_X_y_mean ACC_X_y_max GYRO_Z_mean MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_X_y_max MAGNETO_before_nowMmaxdiff TOUCHALITYCS_pairwiseDisplacement TOUCHALITYCS_duration SAFEG_direction_mean	27.35483871	78.8935	0.7758	0.0227	0.1372
All	Naive Bayes	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Y_y_mean ACC_Y_y_max ACC_X_y_mean ACC_X_y_max GYRO_Z_mean MAGNETO_Magnitude_mean MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_Y_y_max MAGNETO_X_y_mean MAGNETO_X_y_max MAGNETO_before_nowMmaxdiff TOUCHALITYCS_pairwiseDisplacement TOUCHALITYCS_duration SAFEG_direction_mean	24.10536779	56.268	0.5376	0.0468	0.1816
All	Random Forest	Consistency	ACC_Magnitude_mean ACC_Y_y_max ACC_X_y_std ACC_X_y_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_X_y_mean SAFEG_direction_mean	6.709677419	84.3436	0.8335	0.0299	0.1101
All	J48	Consistency	ACC_Magnitude_mean ACC_Y_y_max ACC_X_y_std ACC_X_y_max MAGNETO_Z_max MAGNETO_Y_y_mean MAGNETO_X_y_mean SAFEG_direction_mean	25.93548387	76.5086	0.7504	0.0257	0.1438
All	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Y_y_max ACC_X_y_std ACC_X_y_max MAGNETO_Z_max	29.16129032	54.6942	0.518	0.0544	0.1707

			MAGNETO_Y_y_mean MAGNETO_X_y_mean SAFEG_direction_mean					
368258	Random Forest	None	All	1.44092219	99.1821	0.902	0.022	0.0819
368258	J48	None	All	8.357348703	99.0309	0.8899	0.0117	0.0967
368258	Naive Bayes	None	All	23.19884726	67.4021	0.1161	0.3257	0.5391
368258	Random Forest	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Y_y_max ACC_X_y_max GYRO_X_y_std MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_X_y_mean MAGNETO_X_y_max TOUCHALITYCS_A_pair80 TOUCHALITYCS_pairwiseDisplacement TOUCHALITYCS_V_pair20 SAFEG_distance_mean SAFEG_direction_mean	1.296829971	99.4983	0.9429	0.0118	0.0639
368258	J48	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Y_y_max ACC_X_y_max GYRO_X_y_std MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_X_y_mean MAGNETO_X_y_max TOUCHALITYCS_A_pair80 TOUCHALITYCS_pairwiseDisplacement TOUCHALITYCS_V_pair20 SAFEG_distance_mean SAFEG_direction_mean	7.204610951	99.2234	0.9117	0.0097	0.0853
368258	Naive Bayes	Cfs	ACC_Magnitude_mean ACC_Magnitude ACC_Y_y_max ACC_X_y_max GYRO_X_y_std MAGNETO_Z_mean MAGNETO_Z_max MAGNETO_X_y_mean MAGNETO_X_y_max TOUCHALITYCS_A_pair80 TOUCHALITYCS_pairwiseDisplacement TOUCHALITYCS_V_pair20 SAFEG_distance_mean SAFEG_direction_mean	14.98559078	93.9244	0.4483	0.0627	0.2339
368258	Random Forest	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Y_y_max ACC_X_y_mean ACC_before_nowYmaxdiff MAGNETO_Z_mean MAGNETO_Y_y_mean SAFEG_direction_mean	1.729106628	99.3471	0.9243	0.0138	0.0709
368258	J48	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Y_y_max ACC_X_y_mean ACC_before_nowYmaxdiff MAGNETO_Z_mean MAGNETO_Y_y_mean SAFEG_direction_mean	7.636887608	99.1134	0.09	0.0109	0.0916

368258	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Magnitude ACC_Z_mean ACC_Y_y_max ACC_X_y_mean ACC_before_nowYmaxdiff MAGNETO_Z_mean MAGNETO_Y_y_mean SAFEG_direction_mean	14.12103746	94.8797	0.5256	0.0732	0.2063
588087	Random Forest	None	All	4.92845787	96.5498	0.336	0.0519	0.1478
588087	J48	None	All	33.22734499	96.0825	0.4982	0.0424	0.1924
588087	Naive Bayes	None	All	18.44197138	66.8935	0.1262	0.3333	0.5556
588087	Random Forest	Cfs	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max GYRO_Magnitude_mean GYRO_Z_std GYRO_Xdiff GYRO_before_nowXdiff MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean MAGNETO_X_y_max MAGNETO_before_nowMdiff MAGNETO_before_nowYmaxdiff TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_Y TOUCHALITYCS_distance TOUCHALITYCS_averageVelocity SAFEG_direction_mean	5.882352941	97.1959	0.5412	0.044	0.1407
588087	J48	Cfs	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max GYRO_Magnitude_mean GYRO_Z_std GYRO_Xdiff GYRO_before_nowXdiff MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean MAGNETO_X_y_max MAGNETO_before_nowMdiff MAGNETO_before_nowYmaxdiff TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_Y TOUCHALITYCS_distance TOUCHALITYCS_averageVelocity SAFEG_direction_mean	25.75516693	96.1237	0.4987	0.0442	0.19
588087	Naive Bayes	Cfs	ACC_Magnitude_mean ACC_Y_y_mean ACC_X_y_mean ACC_X_y_max GYRO_Magnitude_mean GYRO_Z_std GYRO_Xdiff GYRO_before_nowXdiff MAGNETO_Magnitude_max MAGNETO_Z_mean MAGNETO_Y_y_mean MAGNETO_X_y_mean MAGNETO_X_y_max MAGNETO_before_nowMdiff MAGNETO_before_nowYmaxdiff	15.10333863	92.8729	0.4138	0.0877	0.2371

			TOUCHALITYCS_StartY TOUCHALITYCS_V_pair80 TOUCHALITYCS_Y TOUCHALITYCS_distance TOUCHALITYCS_averageVelocity SAFEG_direction_mean					
588087	Random Forest	Consistency	ACC_Magnitude_mean ACC_Z_max ACC_Y_y_max ACC_X_y_mean ACC_X_y_std ACC_Zdiff GYRO_Xdiff MAGNETO_Magnitude_mean MAGNETO_X_y_max MAGNETO_Zdiff TOUCHALITYCS_A_pair50 TOUCHALITYCS_StartY TOUCHALITYCS_V_pair50 TOUCHALITYCS_duration	10.01589825	96.7148	0.4064	0.0509	0.155
588087	J48	Consistency	ACC_Magnitude_mean ACC_Z_max ACC_Y_y_max ACC_X_y_mean ACC_X_y_std ACC_Zdiff GYRO_Xdiff MAGNETO_Magnitude_mean MAGNETO_X_y_max MAGNETO_Zdiff TOUCHALITYCS_A_pair50 TOUCHALITYCS_StartY TOUCHALITYCS_V_pair50 TOUCHALITYCS_duration	24.96025437	96.268	0.4609	0.049	0.1847
588087	Naive Bayes	Consistency	ACC_Magnitude_mean ACC_Z_max ACC_Y_y_max ACC_X_y_mean ACC_X_y_std ACC_Zdiff GYRO_Xdiff MAGNETO_Magnitude_mean MAGNETO_X_y_max MAGNETO_Zdiff TOUCHALITYCS_A_pair50 TOUCHALITYCS_StartY TOUCHALITYCS_V_pair50 TOUCHALITYCS_duration	18.75993641	91.1959	0.3215	0.1257	0.2541

Table 5.1: All Results Table

Top Selected Features CFSSubSetEval	**Count**
MAGNETO_Z_mean	17
ACC_Y_y_mean	16
ACC_X_y_max	16
MAGNETO_Z_max	15
ACC_X_y_mean	14
MAGNETO_X_y_mean	13
MAGNETO_Magnitude_max	12
ACC_Magnitude_mean	12
SAFEG_direction_mean	12
MAGNETO_Y_y_max	12

Table 5.2: Top ten selected features with CfsSubSetEvaluation

Top Selected Features ConsistencySubSetEval	**Count**
ACC_Magnitude_mean	19
MAGNETO_X_y_mean	13
MAGNETO_Z_mean	11
MAGNETO_Y_y_mean	10
ACC_X_y_max	9
ACC_Magnitude	8
ACC_Z_mean	8
ACC_X_y_mean	8
MAGNETO_Z_max	7
TOUCHALITYCS_directionOfEndtoEndLine	5

Table 5.3: Top ten selected features with ConsistencySubSetEval

Top 15 Cfs	Count
MAGNETO_Z_mean	17
ACC_Y_mean	15
ACC_X_max	13
MAGNETO_Z_max	13
MAGNETO_X_mean	12
ACC_X_mean	12
MAGNETO_Y_max	11
ACC_SignalVectorMagnitude	11
MAGNETO_Y_mean	11
MAGNETO_Magnitude_max	10
ACC_X_INTEGRATION	10
ACC_Magnitude_mean	9
MAGNETO_Z_COEFF_SUM	9
MAGNETO_X_max	9
ACC_Z_mean	9

Top 15 Consistency	Count
ACC_Magnitude_mean	15
ACC_X_mean	12
MAGNETO_X_mean	10
MAGNETO_Y_max	9
MAGNETO_Z_mean	9
MAGNETO_Y_mean	8
ACC_Magnitude_max	8
ACC_X_max	7
MAGNETO_Z_max	6
MAGNETO_X_max	6
ACC_Z_mean	6
MAGNETO_Magnitude_max	5
ACC_Y_max	5
ACC_Y_mean	5
GYRO_Z_mean	5

Table 5.4: Top 15 selected features with Consistency and CFS

Naive Bayes	
Kernel Estimator	false
Batch Size	10

J48	
Confidence Threshold	0,25
Number of Folds	2

Random Forest	
Percentage of Training Set	100
Number of Iterations	100
Number of Execution Slots	1
Number of Attributes Randomly Investigate	0
Minimum Number of Instances per Leaf	1
Minimum Variance for Split	0.001
Seed for Random Number Operator	1

Table 5.5: Used Classifier Parameters

BIOGRAPHICAL SKETCH

Tonguç Çataklı was born on August 14, 1991 in Rize. After graduating from Ordu Science High School/Math and High School in 2009, he began to study in Computer Engineering department in Boğaziçi University. He graduated from Computer Engineering department in 2015 and after that he enrolled in M.Sc. program in Computer Engineering department in Galatasaray University. During the same time, he worked as a Software Developer in MSU Software & Consultancy for two and a half year and for six months in Kron Telecommunication.

He has one conference paper produced out of bachelor thesis, entitled as "Implementation of Group Key Agreement Protocols on Wireless Sensor Networks" supervised by Prof. Dr. Mehmet Ufuk Çağlayan & Prof. Dr. Cem Ersoy was presented at "Akademik Bilişim 2016" conference.