A DETAILED ANALYSIS OF HUMAN ACTIVITY RECOGNITION USING SMARTPHONE MOTION SENSORS

(AKILLI TELEFON HAREKET SENSÖRLERİNİ KULLANARAK AYRINTILI İNSAN AKTİVİTESİ ANALİZİ)

by

Berrenur SAYLAM, B.S.

Thesis

Submitted in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE

in

COMPUTER ENGINEERING

in the

GRADUATE SCHOOL OF SCIENCE AND ENGINEERING

of

GALATASARAY UNIVERSITY

June 2017

This is to certify that the thesis entitled

A DETAILED ANALYSIS OF HUMAN ACTIVITY RECOGNITION USING SMARTPHONE MOTION SENSORS

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ACKNOWLEDGEMENTS

Firstly, I would like to express my sincere gratitude to my advisor Assoc. Prof. Özlem Durmaz İncel for the continuous support, her motivation and knowledge during my master study and related research. Her guidance helped me in all the time during my research.

I would like to thank Prof. Cem Ersoy and Assist. R. Burak Arslan for being in my examining committee and for their constructive comments.

I would like to thank also to Muhammad Shoaib who is a PhD student in University of Twente for his collaboration and to Sümeyye Konak for sharing her knowledge on the subject.

Finally, I thank to my parents for their support and trust.

Berrenur SAYLAM
Istanbul, June 2017

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

Motion sensors available on smart phones make it possible to recognize human activities. Accelerometer, gyroscope, magnetometer and their various combinations are used to classify particularly locomotion activities, ranging from walking to biking. In the literature, the focus is on the collection of data and analyzing the impact of different parameters on the recognition performance. Parameter space includes the types of sensors used, data preprocessing methods, features, classification algorithms, position/orientation of the mobile device. In the literature, only a subset of these parameters are analyzed, however, in this thesis, we investigate the parameter space in detail. Particularly, we investigate the impact of feature normalization in the preprocessing step, impact of using different feature-sets, impact of using different sensors individually and in combination, impact of different classifiers and impact of phone position. First, we explore the feature and sensor parameter space in detail and next we apply an ANOVA analysis to investigate the impact of each parameter on the classification results. We believe that such an analysis is important since we can statistically show how much a parameter is affecting the recognition performance. We also apply feature selection and make the analysis considering five different phone positions.

ÖZET

Akıllı telefonlarda bulunan hareket sensörleri, insan faaliyetlerini tanımayı mümkün kılmaktadır. İvmeölçer, jiroskop, manyetometre ve bunların çeşitli kombinasyonları, yürümekten bisiklete binmeye kadar uzanan özellikle harekete bağlı etkinlikleri sınıflandırmak için kullanılır. Literatürdeki çalışmaların çoğunda, veri toplama ve farklı parametrelerin tanıma performansı üzerindeki etkisini analiz etme üzerine odaklanılmaktadır. Parametre alanı kullanılan sensör tiplerini, veri ön işleme yöntemlerini, öznitelikleri, sınıflandırma algoritmalarını, mobil cihazın konumunu / yönelişini içerir. Çalışmaların çoğunda bu parametrelerin bazılarının etkisi incelenmiştir, ancak bu tezde parametre alanını ayrıntılı olarak araştırıyoruz. Özellikle, ön işlem aşamasındaki öznitelik normalizasyonunun, farklı öznitelik kümelerinin kullanılmasının etkisi, farklı sensörleri tek tek ve birlikte kullanmanın etkisi, farklı sınıflandırıcıların etkisi ve telefon konumunun etkisi incelenmektedir. İlk önce, öznitelik ve sensör parametre alanını detaylı olarak inceledik ve her parametrenin sınıflandırma sonuçlarına olan etkisini araştırmak için bir ANOVA analizi uyguladık. Böyle bir analizin önemli olduğuna inanıyoruz, çünkü böylelikle bir parametrenin tanıma performansını ne kadar etkilediğini istatistiksel olarak gösterebiliyoruz. Ayrıca, öznitelik seçimi uyguluyor ve beş farklı telefon pozisyonunu göz önünde bulundurarak analiz yapıyoruz.

1 INTRODUCTION

Human activity recognition using motion sensors available on mobile devices has been investigated in various studies (Incel et al.; 2013; Shoaib et al.; 2015). Often, a study focuses on the collection of data and analyzing the impact of different parameters on the recognition performance. Parameter space comprises the types of sensors used, whether the sensor data are fused or used separately, data preprocessing methods, features, classification algorithms, position/orientation of the mobile device. In most of the studies, the impact of some these parameters is analyzed. For example, in (Shoaib et al.; 2014), the focus is on analyzing the impact of sensor fusion. While in (Plötz et al.; 2011), impact of different features on the recognition performance is considered.

In this thesis, our aim is to look at the parameter space in detail. Particularly, we investigate the impact of feature normalization in the preprocessing step, impact of using different feature-sets, impact of feature selection, impact of using different sensors individually and in combination, impact of different classifiers and impact of phone position. While in (Shoaib et al.; 2014), the authors analyze the impact of sensor fusion using different sets of features, in this thesis, we expand the feature-set and include 15 different features, extracted from X, Y, Z-axis readings of each sensor as well as the magnitude value computed from these 3-axes. In total, 60 features are extracted from each sensor. We also look at the impact of feature normalization and feature selection different than (Shoaib et al.; 2014).

After exploring the feature and sensor parameter space in detail and gathering results, we apply an ANOVA analysis to investigate the impact of each parameter on the results. To the best of our knowledge, our study is the first to investigate the impact of each parameter, different than the features, using an ANOVA analysis among the studies that focus on human activity recognition using motion sensors available on mobile devices (phones, smart watches). We believe that such an analysis is important since we can statistically show how much a parameter is affecting the recognition performance. Although previous studies also analyze the impact of each parameter on the recognition scores, they only show which parameter setting performs better/worse than another. For example, in (Shoaib et al.; 2014), they show which sensor or sensor combination performs better, but they do not show how much the sensor type affects the recognition result. To summarize, in this thesis we explore the parameter space and analyze the impact of each parameter on the recognition result.

For our analysis, we utilize a dataset (Shoaib et al.; 2014), which includes ten participants performing seven activities. The dataset includes readings from four sensors: accelerometer, gyroscope, magnetometer, linear acceleration. Participants carried five phones at different positions. In our analysis, we make both, position specific analysis, as well as position independent analysis, when all data from different positions are combined. We start with extracting different sets of features and also examine the impact of feature normalization. Features include the used sets of features in similar studies presented in a survey in (Plötz et al.; 2011). Since features have a different range of values, we investigate whether feature normalization can be a better approach and show that when features are normalized, recognition results increase by 1-6%. Then, we apply three different feature selection algorithms. Results show that standard deviation (STD) is the most selected feature by all, except the right pocket position. Other mostly selected features are median, range, RMS, variance, energy, mean, max, and min. When we analyze the performance with using different feature-sets, we observe that four feature-sets (FS1: mean, standard deviation, FS2: mean, standard deviation, range, min, max, FS6: median, ZCR, RMS, FS7: variance, ZCR, RMS) outperform others, while FS5, which includes entropy, spectral energy, and FFT coefficients, does not perform well, but other ones are better.

In the next phase of our analysis, we look at the performance of recognition with different types of sensors. We observe that, when sensors are used individually, accelerometer performs the best. When they are combined, accelerometer, gyroscope and magnetometer combination achieves the highest recognition performance. We observe that when the phone is carried in a belt position the lowest results are achieved, while in the pocket positions the highest performances are achieved. When we look at the activity specific results, it is observed that stairs activity has the lowest performance while walking achieves the best. If we compare the performance of classifiers, random forest and SVM perform better than decision tree and Gaussian naive Bayes. Average performance with the position-specific analysis is observed to be between 70% and 90% depending on the position and feature-set when a single sensor is used. When sensors are combined, up to 97% performance is achieved. However, for position independent analysis, the maximum recognition performance is 88%.

In the final phase of our analysis, we investigate how much each parameter is affecting the recognition result using ANOVA analysis rather than only making observations about the results. Since the parameter space is large, including 11 sensor combinations, 7 feature-sets, 4 classifiers, and 5 positions, it is difficult to interpret the results. Hence, ANOVA analysis makes it easy to discover the impact of each parameter. ANOVA results show that all parameters are significant on the F-measure results and the ranking is as follows: i) sensor, ii) position, iii) classifier, iv) feature.

Overall, our main contribution with this thesis is the exploration of the whole parameter space and we gather results with all possible combinations of these parameters and show the most important parameters on the recognition performance. These results can guide new studies that focus on human activity recognition with mobile devices. The main highlights of the thesis are as follows:

- We make a detailed analysis with features: we investigate the use of a large number of features (in total 300 features), feature normalization, feature selection and investigation with different feature-set.
- Besides a large set of features, we explore a parameter space, including 11 sensor combinations, 7 feature-sets, 4 classifiers, and 5 positions.
- We present an ANOVA analysis showing the impact of different parameters on the recognition success: sensors, classifiers, positions, and features.
- Our results show that, while all parameters are significantly important, sensors affect the performance much more than the other parameters.

The rest of the thesis is organized as follows: In Section 2, we explain the previous studies on using motion sensors for human activity recognition and how this study differs from those. In Section 3, we explain the methodology followed in the analysis. In Section 4, we analyze the impact of each parameter on the recognition performance together with the ANOVA analysis. Section 4.6, we summarize our findings and discuss how these can be improved. Finally, in Section 5, we conclude the thesis.

2 LITERATURE REVIEW

Sensors have become important to facilitate our daily lives. For example, they can be used for monitoring older people and patients. In case of falls (for old people and Epilepsy patients), we need to inform caregivers for emergency intervention by recognizing the activity with the sensors. Sensors are important also to monitor our daily activities to remind us increasing our daily steps, the amount of drinking water or reducing cigarette amount per day. However, carrying lots of sensor separately is compelling and generally, people forgot to use them. As, nowadays mobile phones have advanced a lot in terms of computational capabilities and almost all people use them, use of mobile phones or mobile devices, such as smart watches, smart glasses which contain sensors, the research on this topic advanced. Many sensors are integrated on our phones, like accelerometer, gyroscope, microphone, GPS, camera, ambient light sensor, as shown in Figure 2.1. Sensors can be used for health-care, social networks, transportation, and many other application areas.

To recognize activities, we can write applications which use sensors of mobile phones and distribute them through AppStore's. As we can pick various types of large data from these sensors, even if mobile phones have advanced computationally, these inference steps may spend high energy and/or memory. In such cases, we can realize our inference step through a mobile cloud.

Nowadays, there are many applications on mobile phones about transportation, social networking, environment monitoring, health and well-being. Such as;

- Transportation
  Traffic is a global and environmental problem and prevents human productivity. Mobile phone applications find traffic information and estimate total travel time, then we can select a shorter path.

Figure 2.1: Sensors on mobile phone

- Social networking

  People use social networks to share their locations. By an application which understand user's situation, it's possible to generate his/her state information in social network areas like Twitter or Facebook automatically.

- Environmental Monitoring

  For the environment, measuring and reporting the pollution of a city is important for calculating the carbon emission. Sensors (even on a mobile phone) are enabling personalized environment impact reports.

- Health and well-being

  We can use mobile phone sensors to generate self-health report surveys or for consultation or for encouraging people to do more exercises (Lane et al.; 2010).

We can call these technologies as cognitive assistants for our daily lives. For example, Google designed a glass which consists of sensors like accelerometer, gravity, orientation, magnetic field. This glass facilitates person's image capture, sensing and processing for communication capabilities of the user. The reason to develop such a tool was embed the sensors which can detect and interpret actions of people to help for the purpose of producing a wearable computer. The idea of wearable computers for a cognitive assistant hold on a decade ago, but there was a lack of speed and accuracy for sensor based activity on mobile phones (Ha et al.; 2014).

Once, we collect and use sensor data to facilitate our lives, we can interrogate statistical models about human behavior. This time it is important to answer these questions: how to validate experiments, how we can select a good study group and how we can protect user's privacy.

For scaling in the literature, there are three main parts of sensing: personal, group and community. Also, we can separate according to user's participation in the sensing activity: participatory sensing and opportunistic sensing.

Personal sensing scale is a situation that the applications are designed for just one person. Generally, they focus on data collection and analysis. For example user's health diary (fitness); it generates data but not share with others, except health care applications, they share the information with doctor or health consultant. In group sensing scale if a person wants he/she can share via social network or connected groups. Community sensing scale is useful when once a large number of people who participate. For example tracking the spread of disease across a city or finding migration patterns of birds.

A common difficulty of these sensing scales is to what extent the user is actively involved in the sensing system. So there is participatory and opportunistic sensing. In participatory sensing, sensors collect the data by the orientation of the user. So, quality of data depends on participant enthusiasm to reliably collect sensing data. In opportunistic sensing, sensors collect data independent of the user. But in some cases such as context problem, we need feedback from the user. Maybe it can be solved using more sensors such as light and accelerometer.

Thus, for all sensing scales and paradigms, there is a positive and a negative side. There is no consensus in the architecture of mobile phone sensing in literature. Some of them support the cloud side some of them support hardware side for saving information that is collected. In this distinction, we must keep in mind some criteria such as privacy, providing user real-time feedback, reduction communication cost between phone and cloud. According to these sides of raw data, machine learning algorithms can be adapted (different on phone, in a cloud, phone, and cloud) (Lane et al.; 2010).

Activity Recognition

Activity recognition (AR) can be used in many different domains. One can find a detailed list in (Lockhart et al.; 2012). In Table 2.1 there is a list of activities studied in the literature.

Table 2.1: Studied activities in the literature (Incel et al.; 2013)

Class	Activity Types
Locomotion	Walking, running, sitting, standing, still, lying
Mode of transportation	Biking, travelling with a vehicle, riding a bus, driving
Exercise	Outdoor bicycling, soccer playing, biking on a fitness bike
Health related activities	Falls, rehabilitation activities, following routines
Daily activities	Shopping, using computer, sleeping, going to work, going back home, working, lunch, dinner, breakfast, in a conversation, attending a meeting, using an ATM
Usage of the phone	Text messaging, making a call, browsing the web, composing an email, using an app

To perform an activity recognition, we need to follow some steps: determining a target set of activities, collecting sensor readings, assigning sensor readings to the appropriate activities. For the third step, generally statistical machine learning methods are used. There are two kind of learning process; supervised and unsupervised. We can see typical AR steps in Figure 2.2.

As for AR, we collect information continuously, if classifiers run on the mobile phone, it produces battery problems. Sometimes this is impossible due to computational incompetence on the phone so that we need to process information somewhere else. Another problem is the phone context problem. If the phone is carried inappropriate position (a position that we did not specify) then we cannot collect data in good health. These are some challenges in the activity recognition process.

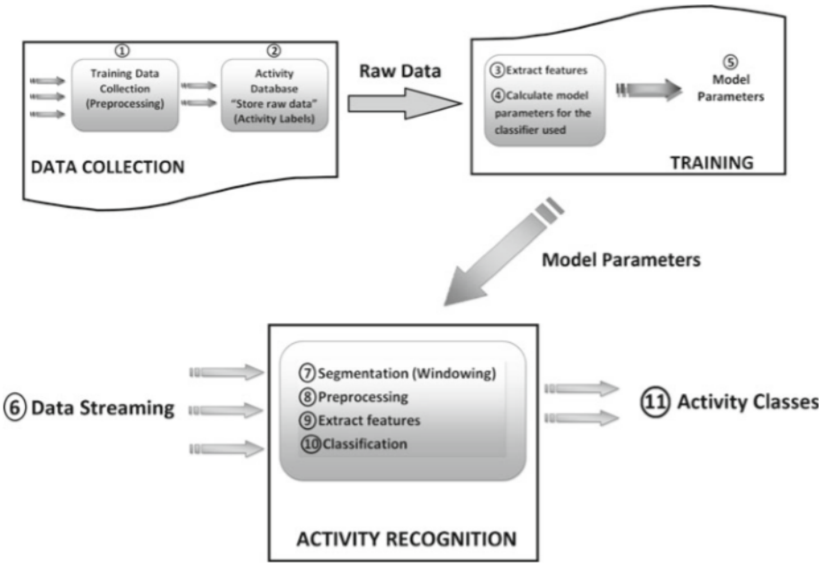

Figure 2.2: Activity recognition steps (Incel et al.; 2013)

There are two dominating types according to their objectives; location and motion associated. Before the integration of sensors on mobile phones, there was generally research on location based activity recognition. In motion based recognition mostly used sensors are inertial, radio and *others*. Inertial sensors are accelerometers (we can use it for finding the orientation of the phone, e.g. ilog, imodel and iclassify are some of three accelerometer sensors of iPhone) gyroscope and magnetometers. Radio sensors provide location information using WiFi and GSM signals. And by *others*, we mean to use these sensors together.

Recognition of Performance

The recognition performance of a human activity recognition process depends on various factors such as sensors, body positions, feature-sets, classifiers and the set of activities being recognized. The impact of these individual aspects has been extensively studied in the last few years (Shoaib et al.; 2014; Incel et al.; 2013). However, this work has been done mainly in a limited context, i.e. on individual level and not in comparison with each other.

For example, in some cases, only one accelerometer is used (Shoaib et al.; 2015, 2014, 2013). In other cases, different sensors such as gyroscope and magnetometer are combined with an accelerometer, but their individual contributions are not evaluated in detail (Altun and Barshan; 2010; Anguita et al.; 2012; Sun et al.; 2010; Susi et al.; 2013). In (Anjum and Ilyas; 2013), the authors show no improvements in the overall recognition performance of various activities due to the addition of gyroscope with accelerometer. They used Naive Bayes, Decision Tree, and K-nearest neighbor for classification whereas multiple body positions was used in this study. In (Wu et al.; 2012), a combination of the accelerometer and gyroscope was also used and found the gyroscope to be useful. However, they used only KNN classifier involving only pocket position. In (Martín et al.; 2013), the authors used a combination of multiple sensors (accelerometer, magnetometer, gyroscope, linear acceleration, gravity) and reported improved results. However, the paper did not discuss the role of the individual sensors. Therefore, it is not clear which sensors contributed (and how much) to the improvement in the activity recognition. The authors in (Yong et al.; 2013) evaluate the gyroscope, the accelerometer, and magnetometer using a single classifier. They have only one participant data for only arm position. Though there are individual studies on different aspects of a human activity recognition process, there is a need of a comprehensive study which covers all these aspects in similar experimental setup. For this, we initially investigated the role of smartphone sensors in detail using these studies as a starting point and published these results in (Shoaib et al.; 2014). This work enabled us to make more confident claims about our reported results.

However, they did not evaluate the impact of each aspect on the recognition performance compared to other aspects. The authors (Shoaib et al.; 2014) looked at the individual impact of various aspects of human activity recognition process with respect to recognition performance and did not look at the impact of how each of these aspects contributes to the overall recognition performance.

In this thesis, we address these issues and improve upon the existing work with a more detailed analysis. We also use ANOVA analysis to investigate the effect of these individual aspects an AR process on the overall recognition performance. We use a more extensive feature-set which were analyzed in different studies in the literature (Plötz et al.; 2011).

3 TOOLS AND METHODOLOGY

In this section, we first explain the tools used in this thesis and the methodology.

3.1 Tools

We used Python language for the implementation. We used mainly sklearn and numpy libraries. Sklearn is an open source library which provides machine learning tools for data mining and data analysis. To develop our codes, we used PyCharm IDE to facilitate the development process.

Scikit library

Scikits are packages developed under Scientific Python (SciPy) (Oliphant; 2007). For example, scikit-optimize package is an optimization toolbox and scikit-fuzzy package is a fuzzy logic toolkit for SciPy. In our thesis, we used scikit-learn (Pedregosa et al.; 2011) package which contains modules for machine learning and data mining. It provides supervised and unsupervised algorithms.

Minitab

Minitab is a statistical software package (Inc; 2010). The main aim of the tool was for the teaching statistics. Therefore, there are many explanations both in the package and on the web about how to choose right method and how to do in minitab. It has several features like basic statistics, graphics, regressions, analysis of variances, multi-variates. We used this package during the analysis of the impact of each and all parameters. Specifically, we used ANOVA under Analysis of Variance and ordinal logistic regression under Regression features.

3.2 Methodology

3.2.1 Dataset

The dataset under examination in this thesis is collected in (Shoaib et al.; 2014) to understand seven physical activities, which are walking, standing, jogging, sitting, biking, walking upstairs and walking downstairs performed by ten participants during $3 - 4$ minutes. The utilized sensors were accelerometer, gyroscope, magnetometer and linear acceleration sensors. Linear acceleration is derived from accelerometer by removing the gravity component.

Data were collected from five different positions which are left pocket, right pocket, belt, upper arm and wrist. In our daily life, we use these positions changing according to our activities. For example, we use upper arm position specifically when we do jogging or similar activities, and as another example, nowadays we start to use smart-watches, so that wrist position has become important. This is why these positions are added to activity recognition process besides the classical positions to carry a smartphone (pocket, belt etc.). To collect data, five smartphones (Samsung Galaxy S2) were placed in these positions and sampled at the same time. The orientation of the smartphones was portrait except for the belt position for which it was landscape. Data sampling rate was 50 samples per second. This value was also used in previous studies (Shoaib et al.; 2013; Wu et al.; 2012) and sufficient to capture human activities. On smartphones, the authors used an activity logger application that they developed in (Shoaib et al.; 2013). More details about the dataset can be found in (Shoaib et al.; 2014).

3.2.2 Preprocessing

Activity data is segmented into windows before extracting features. We use a sliding window approach with a 50% overlap for feature extraction, where the window size is 2 seconds (Wu et al.; 2012; Preece et al.; 2009), and 50% overlap has been reported to produce meaningful results (Wu et al.; 2012; Preece et al.; 2009; Bao and Intille; 2004).

3.2.2.1 Sensors

In the literature, there are already many studies on activity recognition using different sensors, like accelerometer, gyroscope. However, to the best of our knowledge, these works do not give a *global* idea about the parameters of activity recognition. For example, it is difficult to say globally, using such a position, such a feature-set and such a sensor/sensors, we can understand such an activity with a reasonable accuracy as all existent works focus on analysis of some parameters. This also stems from the use of different datasets including different activities. This means that we cannot see the global effect of different parameters of activity recognition using motion sensors on mobile devices, we only see small pieces of the global perspective depending on research focus. For example, in (Wu et al.; 2012), they use just gyroscope and accelerometer in combination and found an improvement on the activity recognition performance (see sec 2). In this work, we aim to present a global view, exploring the whole parameter space and trying all the combinations of these parameters.

One of the most important parameters is the set of sensors used. In our dataset, all the motion sensors available on the smartphones were utilized: accelerometer, gyroscope, magnetometer and linear acceleration sensor. These have been already used in the literature in combination with each other or alone, but not all at the same time with same dataset (Wu et al.; 2012; Ustev et al.; 2013; Altun and Barshan; 2010). To generalize, we also examine all the combinations of these sensors, like accelerometer-gyroscope, gyroscope-magnetometer, accelerometer-gyroscope-magnetometer, except the combinations in which accelerometer and linear acceleration are found at the same time. The main reason to remove them is the production of linear acceleration from acceleration sensor.

Each motion sensor comprises three dimensions which are x-axis, y-axis and z-axis. In our work, to prevent the orientation changes, we added a fourth dimension, called the magnitude. The effect of orientation changes into activity recognition performance was motivated in (Sun et al.; 2010). Magnitude values are calculated according to Eq. 3.1:

$$magnitude = \sqrt{x^2 + y^2 + z^2} \tag{3.1}$$

At the end, the sensor readings are represented in four dimensions: x-axis, y-axis, z-axis and the magnitude dimensions. While extracting our feature-sets from raw data, we also calculated pitch and roll values from the accelerometer and linear acceleration sensors. The use of pitch and roll values was proposed in (Coskun et al.; 2015). However, we see that their contribution to the recognition performance is low, and one can choose not to add them to decrease computational power need for especially in online activity recognition. The definitions of pitch and roll [1] are following:

- **Pitch**: This is the angle between a plane parallel to the device's screen and a plane parallel to the ground. If you hold the device parallel to the ground with the bottom edge closest to you and tilt the top edge of the device toward the ground, the pitch angle becomes positive. Tilting in the opposite direction (moving the top edge of the device away from the ground) causes the pitch angle to become negative. The range of values is -180 degrees to 180 degrees.
- **Roll**: This is the angle between a plane perpendicular to the device's screen and a plane perpendicular to the ground. If you hold the device parallel to the ground with the bottom edge closest to you and tilt the left edge of the device toward the ground, the roll angle becomes positive. Tilting in the opposite direction (moving the right edge of the device toward the ground) causes the roll angle to become negative. The range of values is -90 degrees to 90 degrees.

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[1] https://developer.android.com/guide/topics/sensors/sensors_position.html

3.2.2.2 Feature-Sets

We selected seven feature-sets as shown in Table 3.1. These individual features are selected because they are suitable for running on mobile phones and wearables such as a smartwatch (Figo et al.; 2010). Most of these features have been used in one of such combinations in the previous studies (Figo et al.; 2010). However, all of them are not used in one single study. For this purpose, we formed these seven feature-sets which cover all these different variations in one study. Moreover, we want to be more confident about our observations by conducting our evaluation with a diverse set of features.

Table 3.1: Feature-sets

Feature-set	Features in the Feature-set
FS1	Mean, standard deviation
FS2	Mean, standard deviation, range, min, max
FS3	Mean, median, standard deviation, range, min, max
FS4	Mean, standard deviation, RMS, integration, correlation, absolute difference
FS5	Entropy, spectral energy, sum of first five FFT coefficients
FS6	Median, ZCR, RMS
FS7	Variance, ZCR, RMS

FS1, FS6 and FS7 correspond to FS1, FS2 and FS3 in (Shoaib et al.; 2014), respectively and FS5 is extracted from FS4. The definitions of these features which are not commonly known and how they are used in the literature are described as follows:

- **Standard deviation**: In the literature (Si et al.; 2005; Kawahara et al.; 2007), it is used to recognize movements. It examines the variability of data, so that, gives us an indication about stability of the data.
- **Range**: The difference between the maximum and the minimum of data samples called as the range of these samples. It is useful to separate confusingly activities such that running and walking (Farringdon et al.; 1999).
- **Integration**: This feature is commonly used for accelerometer sensor to understand speed and distance by measuring the signal under the data curve (Nambu; 2007).

With double integration, distance covered by a gesture is computed (Guerreiro et al.; 2008). In (Wiggins; 2008), the authors computed velocity value, and thus they identified gestures.

- **Correlation**: It is calculated by using Equation 3.2 also known as Pearson's product-moment coefficient (Lee Rodgers and Nicewander; 1988). Correlation is useful to separate activities which have translations in a single dimension (Ravi et al.; 2005; Figo et al.; 2010)

$$\rho_{x,y} = \frac{cov(x,y)}{\sigma_x \sigma_y} \tag{3.2}$$

- **Absolute difference**: Sum of the differences between each sample of the magnitude and the average of the window divided by the number of data points.
- **RMS**: Root mean square. It is mainly used to recognize gestures (Figo et al.; 2010).
- **ZCR**: The number of points where a signal crosses through a specific value corresponding to half of the signal range (Figo et al.; 2010). This specific point is the mean of a window segment (Shoaib et al.; 2014) for our work. Thus, the number of zero crossing is the number of times this signal crosses that specific point (Figo et al.; 2010). It is also useful to distinguish activities like running and walking (Farringdon et al.; 1999).
- **Spectral Energy**: It is the squared sum of spectral coefficient of signal over the length of the sample window (Figo et al.; 2010). It is useful to recognize activities using just one single sensor (Nham et al.; 2008).
- **Sum of FFT coefficients**: Here, we use the first five FFT coefficients because they composed of main frequency component (Figo et al.; 2010).
- **Entropy**: It is computed using the normalized information entropy of the discrete FFT coefficient magnitudes excluding the DC component (Ho; 2004). In literature, this feature is used to distinguish activities which have similar energy level. It is more useful together with spectral energy, mean and correlation (Figo et al.; 2010). For example, in (Bao and Intille; 2004), they used entropy to distinguish cycling and jogging.

3.2.2.3 Classifiers and Validation

We use four commonly-utilized classifiers in this work. In (Shoaib et al.; 2014), they used the Weka platform for classification, however in this work we use Scikit-Learn platform based on Python language. These four classifiers, namely naive Bayes, SVM, decision tree and random forest have been extensively used in the literature and have been shown to produce good classification performance (Incel et al.; 2013; Shoaib et al.; 2015). Also, we had to remove KNN classifier from the list of classifiers because of the computational cost in Python. The descriptions of the selected classifiers are as follows:

- **Gaussian Naive Bayes**: Naive Bayes classifier is a classification technique based on Bayes theorem with independence assumptions of predictors (formula 3.3). It means it assumes that the presence (or absence) of a feature is independent from the presence (or absence) of another one.

  $$p(c|f_1, f_2, ..., f_n) = \frac{p(f_1, f_2, ..., f_n|c)p(c)}{p(f_1, f_2, ..., f_n)} \tag{3.3}$$

  Even if this assumption is not realistic, naive bayes classifier works quite well especially in supervised learning. In (Caruana and Niculescu-Mizil; 2006), the authors show that Naive Bayes classification is outperformed according to other methods. The numerator of formula 3.3 can be written as $p(c, f_1, ..., f_n)$ which is $p(c)p(f_1|c)p(f_2|c, f_1)...p(f_n|c, f_1, f_2, ..., f_{n-1})$ using the definition of conditional probability. By definition of naive bayes as each feature is conditionally independent, we can say that $p(f_i|c, f_j) = p(f_i|c)$. So, the numerator becomes equal to $p(c)\prod_1^n p(f_i|c)$ (Rish; 2001).

- **Support Vector Machine**: SVM is supervised learning model and can be used in classification and regression problems. In the training step of model, SVM learns a linear model. Each data value takes part in n-dimensional space (n indicates the number of features). The algorithm searches a hyperplane which differentiates two class. To construct an optimal hyperplane, SVM uses an iterative training algorithm which minimizes the error function.

- **Decision Tree**: It is a supervised learning algorithm organized by test questions and conditions. After construction of decision tree, classification is straightforward. Starting from the root, the test condition is applied until reaching to the leaf node.
- **Random Forest**: This algorithm trains on multiple decision trees drove on slightly different subsets of data. These trees are distinguished by subsets of data on which they are trained. These subsets are chosen randomly from initial data.

To select a validation metric, we compare different techniques used in literature, such that leave one out, random sampling, cross-validation with 5, 10 and 20 folds using first participant's dataset corresponds to accelerometer sensor and belt position. For each validation metric, we select 4 classification methods such that random forest (RF), support vector machine (SVM), gaussian naive bayes (GNB) and decision tree (DT).

- **K-fold cross-validation**: Data is divided into k folds, one of them used for testing and the others for training. This action is repeated k times at each time by changing test set. For each fold, the training algorithm has to be run for a new subset. The average error from k trials is computed for validations' results. At the end, all subsets are used both for training and testing.
- **Random sampling**: This method performs with k data subsets. Each subset is selected randomly from data.
- **Leave one out**: It is a kind of k-fold cross-validation method with k equals to the sample size.

In Table 3.2, the maximum result values colored in red. We observe that leave one out is the best validation metric among the investigated ones which increase F-measure result for almost all classification methods. But we did not choose to use it because it needs to $6 - 7$ min to calculate while other ones need 15 secs. As between other metrics, there is no huge difference, we decide to use 10 fold-stratified cross-validation. In 10 fold cross-validation, data is divided into 10 sets. 9 of them use to train and 1 for testing. It is repeated ten times, at each time with a different set for testing. Thus, all sets are used both for training and testing. We used **stratified** version of cross-validation which means that each set of data have similar length. We use four classifiers explained as above.

Table 3.2: Validation method selection

Validation Metrics	*Classifications*	*F Measure*	*Precision*	*Recall*
Leave one out	RF	0.948	0.949	0.948
	SVM	0.955	0.957	0.955
	GNB	0.868	0.880	0.867
	DT	0.930	0.930	0.931
Cross Validation (5 folds)	RF	0.948	0.949	0.948
	SVM	0.955	0.957	0.955
	GNB	0.863	0.876	0.861
	DT	0.922	0.922	0.923
Cross Validation (10 folds)	RF	0.940	0.941	0.940
	SVM	0.951	0.954	0.951
	GNB	0.865	0.876	0.863
	DT	0.924	0.924	0.924
Cross Validation (20 folds)	RF	0.943	0.943	0.943
	SVM	0.955	0.957	0.955
	GNB	0.868	0.880	0.866
	DT	0.927	0.927	0.927
Random Sampling (Repeat train/test = 10)	RF	0.940	0.942	0.940
	SVM	0.950	0.953	0.950
	GNB	0.858	0.870	0.856
	DT	0.914	0.915	0.915

4 PERFORMANCE ANALYSIS

In this section, we present the results of our classification analysis. As mentioned, we have different parameters: 7 feature-sets, 4 classifiers, 11 sensor combinations and 5 positions. We analyze the performance of all the combinations of parameters. First, in Section 4.1, we start with analyzing the impact of feature normalization. Then, in Section 4.2, we apply three different feature selection methods on the extracted 300 features. In Section 4.3, we present the results of per-position analysis. In this analysis, each position data is processed individually, while in Section 4.4 the data from all phone positions are combined and analyzed together. Finally in Section 4.5, we apply an ANOVA analysis to see the impact of different parameters.

All results given in this work are collected on a Samsung S5 ultra-book with $i5-3317U$ CPU, 1.70 GHz processor, 4 GB RAM and 64 bit operating system. For implementation, we used Python 2.7 with Scikit-learn library version 0.18.1 (Pedregosa et al.; 2011) and for statistical analysis, we used Minitab 17 (Inc; 2010).

In the literature, generally, accuracy is used to interpret the model success. Accuracy is the ratio of the number of correct predictions over the total predictions. If a classifier predicts half of the examples, then we say that the accuracy of that classifier is 50%. For instance, if the true positive rate is 50, the false positive rate is 35, the false negative rate is 15, the true negative rate is 100 percent, then the accuracy is 75%. On the other hand, if the true positive rate is 0, the false positive rate is 0, the false negative rate is 10 and the true negative rate is 150, then the accuracy is 93.75%. When we change the confusion matrix to a completely useless one, we have an increase in accuracy. From that, it is clear that accuracy is not reliable. This is called an *accuracy paradox* in the literature (Valverde-Albacete and Peláez-Moreno; 2014). In a two class problem,

- True positive corresponds correctly predicted event values
- False positive corresponds incorrectly predicted event values
- True negative corresponds correctly predicted no-event values
- False negative corresponds incorrectly predicted no-event values

The recall is the proportion of positive cases in the correctly identified terms and the precision is the proportion of predicted positive cases that were correct. That means precision answers to how many selected items are relevant and recall answers to how many relevant items are selected. Therefore, to measure the performance of the model, F1-score is meaningful, which is the harmonic mean of precision and recall. Thus, in this work, we evaluate our results using F1-score, also called as F-measure.

4.1 Impact of Normalization

After the extraction 300 features, when we look at the feature values, we observed that there was no consensus among their ranges and also fluctuations in F-values prevent us to make general conclusions. In (Shoaib et al.; 2014), they did not normalize the features, and they indicated an analysis of the normalization step as a future work. For this reason, we compare the results with feature normalization and without normalization. We normalize the features by setting all the values between the $0 - 1$ range.

In Figure 4.1, we see F-measure values for corresponding feature-sets and sensors without and with normalization. Clearly, we obtain 1-6% performance enhancement with normalization. In all feature-sets, the combination of accelerometer and gyroscope sensors exhibit the highest results. But the most important effect of normalization is the reduction of the computation time, about 50%. We reached this result by using all positions data-set (we combined all positions information in one file) for each sensor and one by one feature-sets (FS1, FS2,..., FS7). For example, with normalization, we calculate the classification result for magnetometer and FS1 confusion matrix for all classifiers (GNB, SVM, DT, RF) nearly in 2 hours and without normalization, this time is near 4 hours. When we look in detail, we see that SVM takes the longest duration (about 1 and a half for the normalized version). Because of this degradation of computation time, we think that it should be used during preprocessing of data.

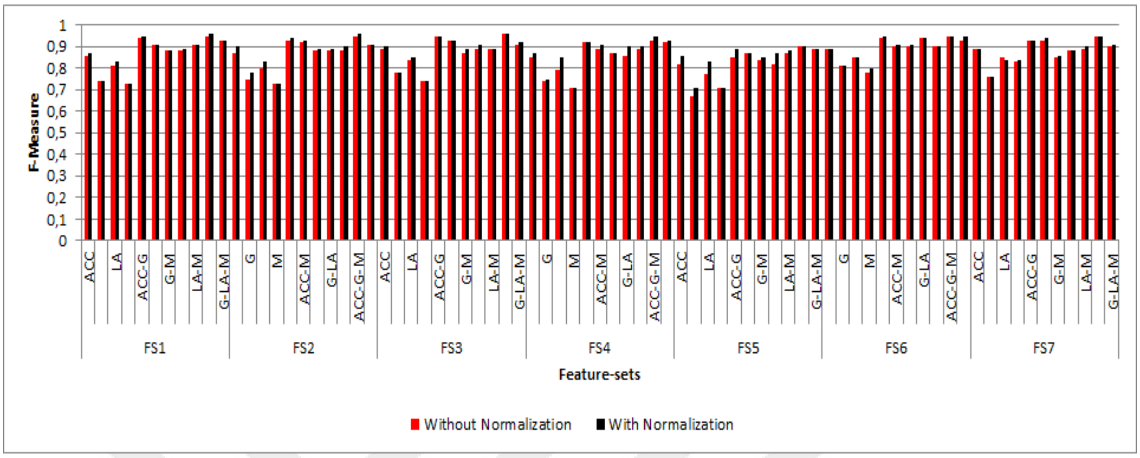


Figure 4.1: Effect of feature normalization

4.2 Impact of Feature Selection

As mentioned, we selected seven feature-sets as shown in Table 3.1. Most of these features have been used in one of such combinations in the previous studies (Figo et al.; 2010). However, all of them are not used in one single study. For this purpose, we formed these seven feature-sets which cover all these different variations in one study. However, it is clear that, to analyze a dataset with machine learning techniques, we need to select features from data to separate irrelevant features to avoid negative impact on the model performance. Computation time reduction during the training phase and avoidance from overfitting are among the advantages of feature selection. Here, we use three main feature selection techniques available under skilearn toolkit, *feature_selection* module.

- **Recursive Feature Elimination**: It removes recursively features depending on the weights until reaching a specific number of features.
- **Univariate Feature Selection with Chi^2**: Using statistical tests, we can also select features. In Python's scikit library, *SelectKBest* class provides us possibility to implement it. We used for our analysis, chi-squared test.

- **Feature Selection with Random Forest Feature Importance**: Random Forest provides two methods for feature selection: mean decrease impurity and mean decrease accuracy. In mean decrease impurity method, the idea is to split data into two parts using impurity optimal condition. Features are ranked according to weighted impurity in the tree for each feature. As if the dataset contains correlated features, the result of feature selection based on impurity is biased, we decided to use the mean decrease accuracy method which is based on permutation of features and towards these results, it measures the impact of each one on the model's accuracy.

To analyze our dataset, we combined accelerometer-gyroscope-linear acceleration-magnetometer sensors, then we calculated first 50 features among 300 for each feature selection technique (Tables 4.1, 4.3, 5.13, 5.14, 5.15, 5.16). In these tables, they are enumerated from 1 to 50 but for Recursive Feature Elimination methods, given selected features all have the same priority. But, the other two methods give an order for the selected ones.

4.2.1 Per-position

First, we applied the feature selection methods to each position data. For each position (belt, left pocket, right pocket, upper arm and wrist), we computed the first 50 features using three feature selection methods that we explained in Section 4.2. We highlight the common selected features in red.

In this section, as an example we show the results of only the belt position in Table 4.1. The results of other positions can be found in the Appendix, in Tables 5.13, 5.14, 5.15, 5.16.

As mentioned, we have computed 300 features: from x, y, z axes of each sensor and their magnitude values. From the accelerometer and linear acceleration sensors, we also compute features from pitch and roll values. In the tables, feature names in each row are given in the following format: *sensor-feature-component*. The component names are as follows, x:x-axis, y:y-axis, z:z-axis, mag:magnitude, pitch and roll. When we analyze

Table 4.1: Feature selection for Belt position

(a) Recursive Feature Elimination

Selected Features			
1	ACC-mean-y	26	G-energy-z
2	ACC-std-y	27	G-range-m
3	ACC-std-m	28	G-min-z
4	ACC-median-y	29	G-max-y
5	ACC-median-z	30	G-absDif-z
6	ACC-median-m	31	G-absDif-m
7	ACC-variance-y	32	LA-std-y
8	ACC-variance-m	33	LA-std-z
9	ACC-RMS-z	34	LA-std-m
10	ACC-energy-z	35	LA-median-z
11	ACC-energy-m	36	LA-variance-x
12	ACC-min-z	37	LA-variance-m
13	ACC-max-y	38	LA-RMS-y
14	ACC-max-m	39	LA-energy-y
15	ACC-correl	40	LA-range-z
16	ACC-absDif-z	41	LA-min-y
17	ACC-entropy-x	42	LA-min-z
18	ACC-entropy-y	43	LA-absDif-m
19	ACC-entropy-z	44	M-energy-x
20	G-mean-y	45	M-coefSum-x
21	G-std-y	46	M-range-y
22	G-median-y	47	M-min-x
23	G-RMS-y	48	M-max-y
24	G-RMS-z	49	M-entropy-y
25	G-energy-y	50	M-entropy-y

(b) Univariate Feature selection with Chi^2

Selected Features			
1	ACC-std-x	26	G-energy-m
2	ACC-std-y	27	G-energy-z
3	ACC-std-z	28	G-range-x
4	ACC-std-y	29	G-integ-m
5	ACC-std-m	30	G-absDif-m
6	ACC-variance-x	31	LA-mean-m
7	ACC-variance-y	32	LA-std-x
8	ACC-variance-m	33	LA-std-y
9	ACC-variance-z	34	LA-std-z
10	ACC-RMS-m	35	LA-std-m
11	ACC-range-x	36	LA-median-m
12	ACC-range-y	37	LA-variance-x
13	ACC-range-z	38	LA-variance-z
14	ACC-range-m	39	LA-variance-m
15	ACC-range-pitch	40	LA-RMS-x
16	ACC-range-roll	41	LA-RMS-y
17	ACC-min-m	42	LA-RMS-z
18	ACC-min-pitch	43	LA-RMS-m
19	ACC-max-m	44	LA-energy-x
20	ACC-entropy-x	45	LA-energy-y
21	G-mean-m	46	LA-energy-z
22	G-std-x	47	LA-energy-m
23	G-std-z	48	LA-coefSum-m
24	G-RMS-z	49	LA-range-x
25	G-RMS-m	50	LA-range-y

(c) Selection with Random Forest

Selected Features			
1	M-RMS-y	26	ACC-variance-x
2	ACC-median-m	27	ACC-max-x
3	M-max-x	28	M-max-m
4	M-range-y	29	ACC-max-z
5	M-std-y	30	ACC-max-roll
6	ACC-median-x	31	ACC-max-m
7	M-range-m	32	ACC-energy-m
8	ACC-energy-z	33	G-std-x
9	G-min-z	34	G-variance-z
10	M-variance-y	35	ACC-mean-y
11	LA-variance-m	36	ACC-min-y
12	M-range-z	37	ACC-median-roll
13	ACC-integ-roll	38	ACC-integ-y
14	ACC-absDif-roll	39	ACC-std-x
15	ACC-absDif-z	40	ACC-RMS-z
16	ACC-correl	41	LA-min-y
17	ACC-integ-x	42	G-median-m
18	LA-max-m	43	LA-min-z
19	LA-max-x	44	G-mean-y
20	ACC-mean-roll	45	M-median-y
21	LA-range-x	46	G-median-roll
22	M-min-x	47	ACC-entropy-x
23	ACC-RMS-pitch	48	LA-std-m
24	LA-energy-x	49	ACC-integ-z
25	LA-range-z	50	LA-min-m

the results in Table 4.1, only four features are common among the three methods: max value of acceleration magnitude, entropy of x-axis of accelerometer, variance and standard deviation of linear acceleration magnitude. Similar results hold for other positions as well.

Table 4.2: Mostly selected features, per position and all positions

	BELT		**LEFT POCKET**		**RIGHT POCKET**		**ARM**		**WRIST**		**ALL POSITIONS**		**ALL CASES**	
1	STD	21	STD	19	Mean	19	STD	19	STD	20	STD	21	STD	121
2	Range	17	Energy	19	Median	19	Max	17	Range	18	Median	19	Range	97
3	Energy	15	Range	16	STD	16	RMS	15	RMS	16	Range	16	Energy	97
4	variance	15	RMS	15	Range	15	Energy	15	Max	14	Energy	16	RMS	83
5	Min	13	Median	14	Min	14	Range	14	variance	14	variance	14	variance	83
6	Max	13	Min	14	Max	14	variance	14	Energy	13	ABS	13	Median	82
7	RMS	13	variance	13	Integration	13	Median	13	Median	12	RMS	12	Min	69
8	Median	12	Integration	8	Correlation	8	Min	11	Min	10	Min	10	Max	65
9	Mean	7	ABS	8	ABS	8	Mean	8	Mean	9	Mean	9	Mean	53
10	ABS	7	Mean	6	RMS	6	ABS	7	ABS	8	Max	8	ABS	51
11	entropy	7	Max	6	ZCR	6	Integration	6	Integration	4	entropy	5	Integration	33
12	Integration	5	coefSum	5	Energy	5	Correlation	5	Correlation	3	Integration	2	entropy	19
13	Correlation	2	entropy	3	coefSum	3	coefSum	2	coefSum	2	Correlation	2	Correlation	17
14	coefSum	2	Correlation	2	entropy	2	ZCR	0	entropy	2	coefSum	2	coefSum	15
15	ZCR	0	ZCR	0	variance	0	entropy	0	ZCR	0	ZCR	0	ZCR	0

In Table 4.2, we present the selection of 15 features per position by all three methods. Next to each feature what is shown is the number of times this feature is selected by the three methods. All-cases column shows the number of times a feature selected in five positions and when all data from different positions are combined. Standard deviation (STD) is the mostly selected feature by all, however, it ranks as the third for the right pocket position. Other most selected features are median, range, RMS, variance, energy, mean, max, min. As we will discuss the impact of feature-set in Sections 4.2.1, and in Section 4.2.2, FS3, FS2, FS7 and FS6 which include these mostly selected features score as the highest sets in recognizing this set of activities.

Table 4.3: Feature selection for all positions

(a) Recursive Feature Elimination

Selected Features			
1	ACC-std-x	26	G-std-m
2	ACC-std-y	27	G-median-x
3	ACC-std-z	28	G-median-z
4	ACC-std-m	29	G-median-m
5	ACC-median-y	30	G-variance-m
6	ACC-median-z	31	G-energy-y
7	ACC-median-m	32	G-range-y
8	ACC-variance-x	33	G-absDif-m
9	ACC-variance-y	34	LA-std-y
10	ACC-variance-m	35	LA-median-m
11	ACC-RMS-z	36	LA-variance-x
12	ACC-energy-x	37	LA-energy-z
13	ACC-energy-y	38	LA-range-z
14	ACC-energy-z	39	LA-min-y
15	ACC-min-z	40	LA-min-z
16	ACC-min-m	41	LA-absDif-m
17	ACC-max-y	42	M-mean-x
18	ACC-max-m	43	M-median-x
19	ACC-entropy-x	44	M-range-y
20	ACC-entropy-y	45	M-range-z
21	ACC-entropy-z	46	M-range-m
22	ACC-entropy-pitch	47	M-min-x
23	G-mean-y	48	M-absDif-x
24	G-mean-m	49	M-absDif-y
25	G-std-y	50	M-absDif-z

(b) Univariate Feature selection with Chi^2

Selected Features			
1	ACC-std-x	26	G-energy-y
2	ACC-std-y	27	G-energy-m
3	ACC-std-m	28	G-coefSum-m
4	ACC-std-roll	29	G-range-y
5	ACC-variance-x	30	G-max-m
6	ACC-variance-y	31	G-integ-m
7	ACC-variance-m	32	G-absDif-m
8	ACC-RMS-m	33	LA-mean-m
9	ACC-range-x	34	LA-std-x
10	ACC-range-y	35	LA-std-y
11	ACC-range-z	36	LA-std-m
12	ACC-range-m	37	LA-median-m
13	ACC-range-pitch	38	LA-variance-x
14	ACC-range-roll	39	LA-variance-y
15	ACC-min-y	40	LA-RMS-x
16	ACC-min-roll	41	LA-RMS-m
17	ACC-max-m	42	LA-energy-x
18	G-mean-m	43	LA-energy-m
19	G-std-x	44	LA-coefSum-m
20	G-std-y	45	LA-range-x
21	G-median-m	46	LA-range-y
22	G-RMS-x	47	LA-range-m
23	G-RMS-y	48	LA-max-m
24	G-RMS-m	49	LA-integ-m
25	G-energy-x	50	LA-absDif-m

(c) Selection with Random Forest

Selected Features			
1	M-std-m	26	M-max-x
2	ACC-max-y	27	LA-mean-x
3	ACC-energy-roll	28	ACC-std-z
4	G-absDif-y	29	ACC-variance-pitch
5	ACC-median-m	30	LA-absDif-x
6	ACC-variance-x	31	LA-energy-x
7	ACC-RMS-m	32	G-energy-z
8	ACC-entropy-y	33	G-median-m
9	ACC-mean-z	34	ACC-range-m
10	ACC-median-y	35	ACC-median-pitch
11	ACC-absDif-z	36	G-correl
12	LA-median-m	37	G-median-y
13	ACC-min-y	38	ACC-std-y
14	ACC-energy-x	39	ACC-min-z
15	M-RMS-y	40	ACC-median-x
16	ACC-std-pitch	41	LA-median-y
17	G-mean-y	42	ACC-mean-pitch
18	ACC-RMS-x	43	ACC-correl
19	ACC-absDif-pitch	44	LA-variance-m
20	ACC-RMS-pitch	45	ACC-median-z
21	ACC-std-x	46	LA-max-x
22	ACC-absDif-roll	47	G-min-z
23	G-energy-x	48	ACC-variance-m
24	LA-max-m	49	ACC-energy-m
25	ACC-RMS-y	50	G-absDif-x

4.2.2 All-positions

We also calculated features for our combined sensor dataset when we combined positions (position independent). The results can be found in Table 4.3 (common selected features are colored in red).

At the end of the feature selection analysis, we found relevant features for our dataset. But, as there are already many features used in literature, we mainly conducted our work based on these feature-sets. Again, the ranking of mostly selected features is presented in Table 4.2. We present the recognition results with the selected features in Section 4.4.3 and compare the performance with the organized feature-sets.

4.3 Per-Position Analysis

In this section, we discuss the classification performance for each position individually: belt, left-pocket, right-pocket, upper arm and wrist. We examine the impact of feature-sets in Section 4.3.1 and sensor/sensors 4.3.2 on the recognition performance (mean value of all activities in terms of F-measure).

4.3.1 Impact of Feature-Set

In order to understand the performance of feature-sets according to different positions, we evaluated them using four classifiers and all sensor combinations. However, in this section, we present only the results with the accelerometer sensor for ease of presentation and to focus on the effect of feature-set. However, we present the results with other sensor combinations in the Appendix (Figures 5.1, 5.2, 5.3, 5.4, 5.5, 5.6, 5.7, 5.8, 5.9, 5.10). For activity independent results per-positions can be found in Tables 5.1, 5.2, 5.3, 5.4 for RF, GNB, SVM, DT classifiers respectively.

In Figures 4.2a, 4.2b, 4.2c, 4.2d, we see corresponding results with GNB, SVM, RF, DT classifiers respectively.

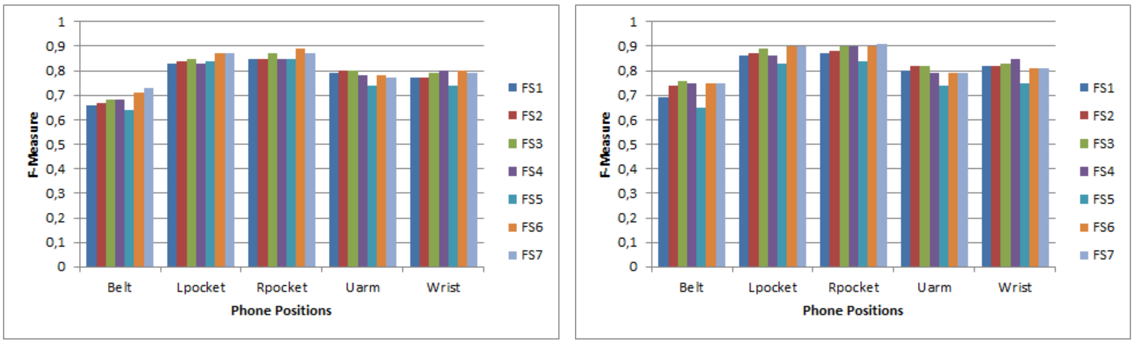
If we analyze the results one by one per classifier, in Figure 4.2a, the best feature-sets are FS6,FS7 for the belt and pocket positions, while in upper arm and wrist positions they exhibit very similar performance with the FS3 and FS4. All feature-sets perform better in pocket positions compared to other positions, between 80% and 90%. Pocket position can capture the leg movements and for this set of activities, it has been the most commonly used position in the literature.

Arm and wrist positions follow the pocket position with 80% F-measure results. The order is as FS$2, 3, 1, 4, 6, 7, 5$ for the upper arm position, while it is as FS$4, 6, 7, 3, 1, 2, 5$ for the wrist position, in terms recognition performance. The lowest F-measure results are observed in the belt position, close to 70%. Compared to the other positions, the phone is more stationary. When we compare the performance of the feature-sets, FS6 and FS7 are the best performing sets, achieving a score of 71% and 73%, respectively. We present example confusion matrices for the belt position in Table 4.4 and the right pocket position in Table 4.5, with the FS7 feature-set using GNB, to have a detailed look. In both of the positions, walking downstairs activity is confused with walking and walking upstairs activities. However, in the belt position, the walking activity is also confused with downstairs and upstairs activities, while in this is not true for the pocket position and the confusion rate of the walking activity is less. As expected, standing and sitting activities are confused with each other in the belt position, while this is not the case for the pocket position.

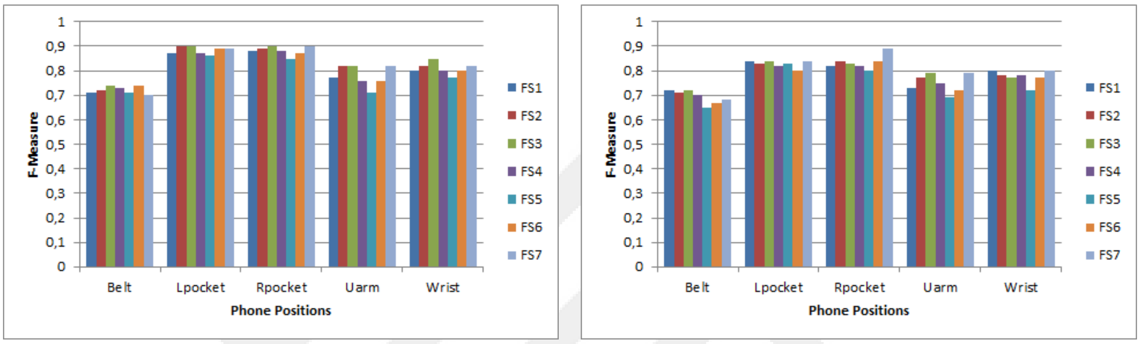
Table 4.4: Confusion matrix for the Belt position with Accelerometer, FS7 and GNB

	walk	stand	jog	sit	bike	upstairs	downstairs
walk	**618**	0	2	0	6	750	424
stand	0	**1557**	3	174	64	2	0
jog	3	0	**1733**	0	0	5	59
sit	0	179	2	**1593**	24	0	2
bike	8	154	2	0	**1564**	45	27
upstairs	313	0	2	0	4	**1416**	65
downstairs	575	0	88	0	11	310	**815**

When we look at the performance of SVM, Figure 4.2b, we observe that results are better than the performance of the GNB classifier. FS6 and FS7 again perform well but are



(a) GNB classifier (b) SVM classifier



(c) RF classifier (d) DT classifier

Figure 4.2: Impact of using different feature-sets with four classifiers

Table 4.5: Confusion matrix for the Right Pocket position with Accelerometer, FS7 and GNB

	walk	stand	jog	sit	bike	upstairs	downstairs
walk	**1470**	0	0	0	0	73	257
stand	0	**1772**	1	0	25	2	0
jog	8	0	**1763**	0	0	7	22
sit	0	0	0	**1750**	50	0	0
bike	0	0	0	0	**1794**	1	5
upstairs	15	0	4	0	4	**1474**	303
downstairs	166	0	55	0	0	605	**973**

not always the best (except left pocket). FS3 and FS4 are better performing in wrist and upper arm positions. At upper arm, feature-sets are ordered as FS$2, 3, 1, 4, 6, 7, 5$ and at wrist, feature-sets ordered as FS$4, 3, 1, 2, 6, 7, 5$. In belt and left pocket positions, the performance of FS3 and FS4 is similar to that of FS6 and FS7. The only difference between FS6 and FS7 is that one includes median while the other has variance. FS6 and FS7 include only 3 features, while FS3 and FS4 have 6 and 7 features, respectively. FS1 and FS2 also exhibit similar F-measure values, differing up to 5% lower rate, and these two sets also include very simple features to compute. FS5, on the other hand, exhibits lower performance in all positions. FS5 includes mostly the frequency domain features: entropy, spectral energy, sum of first five FFT coefficients. These features require more computation compared to the other simple time-domain features, hence it is not required to use them for this set of activities, particularly in a real time recognition application running on phones.

In Figure 4.2c, we see the performance results with the Random Forest classifier. The results are similar to SVM and better than GNB. However, SVM achieves higher F-measure for the Belt position. In the random forest case, FS3 is the best performing set in all positions. However, the difference is only between 0% and 3% compared to FS2 and FS7 for all positions.

Finally, in Figure 4.2d, when we look at the results of the Decision Tree classifier, performance is lower than random forest and SVM. There is no feature-set that outperforms the others in all positions. For example, FS7 performs the best in right pocket position, while FS3 is the best in upper arm. However, a similar trend is visible: FS5 has worse performance than the other feature-sets, except the pocket positions. FS5 exhibits worse performance also in pocket positions with SVM.

The ranking of the feature-sets is presented in Table 4.6 for a comparison. Each cell of the table shows the ranking of a specific feature-set with a specific classifier in a specific position in terms of F-measure performance. The last row shows the final ranking of the feature-sets when all cases (all positions and classifiers) are considered. The final ranking is as follows: 1) FS3, 2) FS8, 3) FS2, 4) FS7, 5) FS4, 6) FS1, 7) FS5. Similarly, FS5 which includes the frequency domain features does not perform well in most of the cases. Although FS1 performed as the best feature-set with decision tree in three positions, in other cases it did not score well with the other classifiers. Similar observations hold for FS4 and FS6. FS3 is always among the best four feature-sets in all cases, while it is always the best scoring set with the random forest classifier in all positions. FS7 and FS2 follow that. FS3 includes mean, median, standard deviation, range, min, max.

Table 4.6: Ranking of each feature-set (from 1 to 7) in a specific position with a specific classifier

	Position	FS1	FS2	FS3	FS4	FS5	FS6	FS7
GNB	Belt	6	5	3	3	7	2	1
	Left Pocket	6	4	3	6	4	1	1
	Right Pocket	4	4	2	4	4	1	2
	Upper Arm	3	1	1	4	7	4	6
	Wrist	5	5	3	1	7	1	3
SVM	Belt	6	5	1	2	7	2	2
	Left Pocket	5	4	3	5	7	1	1
	Right Pocket	6	5	2	2	7	2	1
	Upper Arm	3	1	1	4	7	4	4
	Wrist	3	3	2	1	7	5	5
DT	Belt	1	3	1	4	7	6	5
	Left Pocket	1	4	1	6	4	7	1
	Right Pocket	5	2	4	5	7	2	1
	Upper Arm	5	3	1	4	7	6	1
	Wrist	1	3	5	3	7	5	1
RF	Belt	5	4	1	3	5	1	7
	Left Pocket	5	1	1	5	7	3	3
	Right Pocket	4	3	1	4	7	6	1
	Upper Arm	4	1	1	5	7	5	1
	Wrist	4	2	1	4	7	4	2
	Sum of Ranks	78	61	37	71	122	64	47
	Final Ranking	**6**	**3**	**1**	**5**	**7**	**4**	**2**

The only difference between FS3 and FS2 is the addition of the median value as a feature, but this increases the classification performance. FS7 includes variance, ZCR, RMS as the features which are totally different from FS1 and it includes variance while FS6 includes the median beside the other two features.

As a final evaluation, we combined the features in FS3 and FS7 to show if we can achieve a better performance (Table 4.7). For SVM, when we combine FS3 and FS7, we obtain lower or equal performance than we obtain just using FS3 or FS7. On the other hand, when we use Random Forest classifier, we can achieve higher or equal performance than we obtain just using FS3 and FS7.

Table 4.7: FS3 and FS7 combination results comparison

		Belt	LPocket	RPocket	UArm	Wrist
SVM	FS3	0.76	0.89	0.90	0.82	0.83
	FS7	0.75	0.90	0.91	0.79	0.81
	FS3+FS7	0.76	0.78	0.83	0.79	0.77
RF	FS3	0.74	0.90	0.90	0.82	0.85
	FS7	0.70	0.89	0.90	0.82	0.82
	FS3+FS7	0.78	0.90	0.89	0.84	0.84

In Table 4.8, we present the ranking of features per position. Here, the performance of all classifiers is considered. FS3 is always among the first two best scoring sets (Right pocket ranking is 3, however since it is the same as FS7, they are ranked as the 3rd). FS7 again follows that. FS5 is the lowest scoring sets in almost all positions.

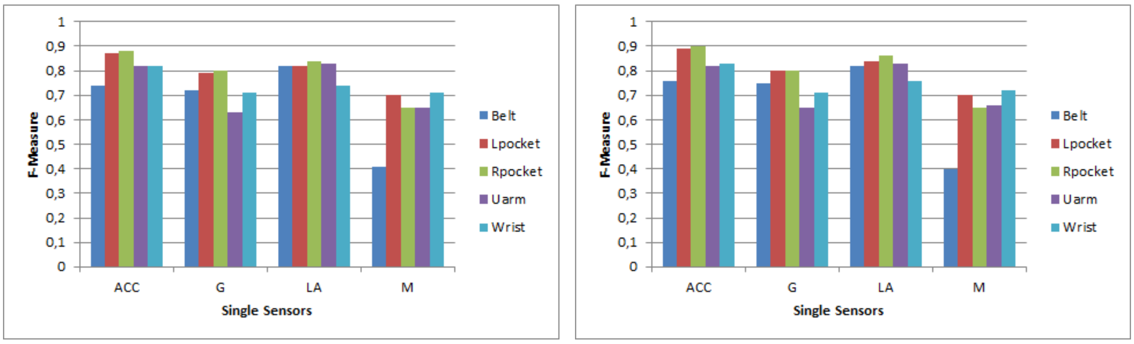
To conclude, we can recommend using FS3 and FS7 for recognizing this set of applications with random forest classifier or with SVM. However, these results are only valid for the accelerometer. In Section 4.3.2, we also discuss this with other sensors and sensor combinations.

Table 4.8: Ranking of feature-sets per position

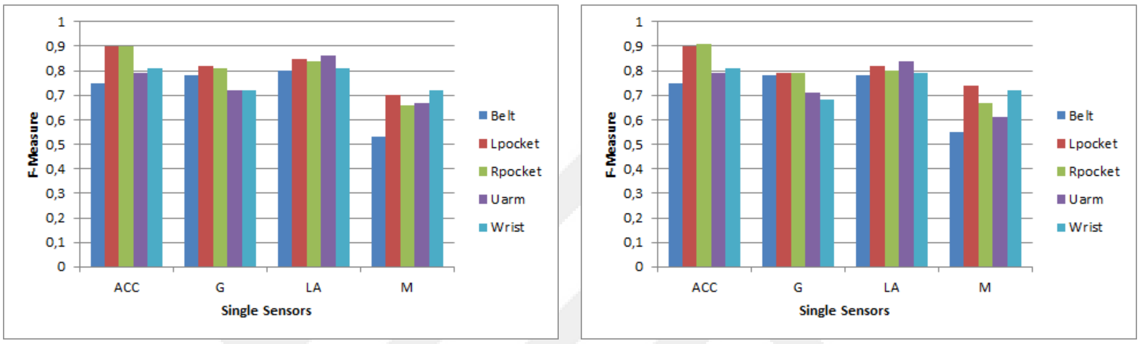
	FS1	FS2	FS3	FS4	FS5	FS6	FS7
Belt	6	5	1	3	7	2	4
Left Pocket	6	4	2	5	7	3	1
Right Pocket	5	5	3	1	7	6	3
Upper Arm	6	5	1	3	7	2	4
Wrist	6	4	2	5	7	3	1

4.3.2 Impact of Sensor Type and Sensor Fusion

In order to understand the effect of sensors and their combinations according to different positions, we evaluate them by using different combinations. In this section, we only present the results of the SVM classifier, which was shown to perform well in Section 4.3.1, and the FS2, FS3, FS6 and FS7 feature-sets which performed the best with SVM. All the other results with other combinations are presented in Appendix in Tables 5.1, 5.2, 5.3, 5.4.



(a) FS2 (b) FS3

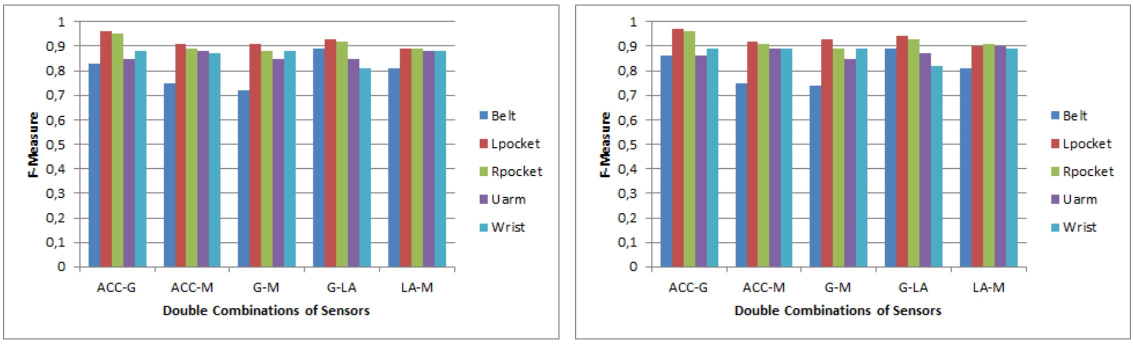


(c) FS6 (d) FS7

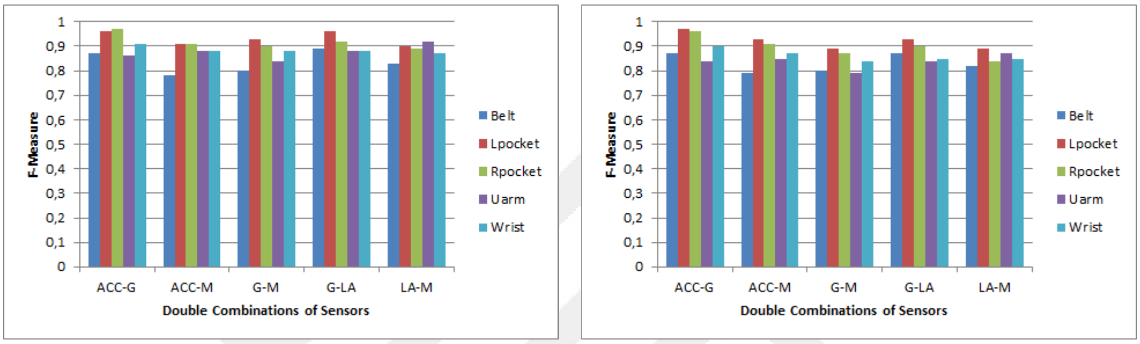
Figure 4.3: Impact of using different sensor combinations with the SVM classifier with single sensors

The F-measure results are presented in Figure 4.3 for single sensors, in Figure 4.4 for double combinations of sensors and in Figure 4.5 for triple combinations of sensors. Additionally, in Table 4.9, we present the ranking of sensors for different positions and four feature-sets. Each row shows the ranking of sensors according to their performance when a specific feature-set is used in a specific position.

If we compare the performance when a single sensor is used (Figure 4.3), the performance differs per position. In the pocket positions, accelerometer is the best performing sensor. However, in belt position, linear acceleration performs much better. For example, with FS3, accelerometer performs with 76% score, while linear acceleration sensors exhibit 82% F-measure. In upper arm position, linear acceleration performs slightly better for the four feature-sets. In wrist position, either they perform the same or accelerometer slightly performs better. Gyroscope follows their performance in all positions, ranging between 63% to 82% F-measure. However, magnetometer performs much worse, particularly in



(a) FS2 (b) FS3



(c) FS6 (d) FS7

Figure 4.4: Impact of using different sensor combinations with the SVM classifier with double sensor combinations

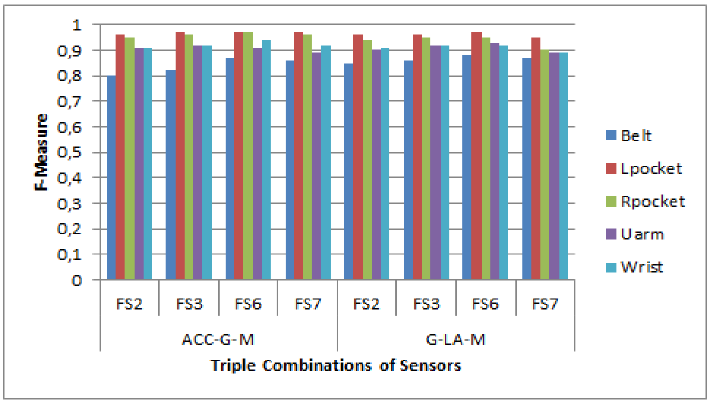


Figure 4.5: Impact of using different sensor combinations with the SVM classifier with triple sensor combinations

the belt position.

When we consider the double combinations of the sensors (Figure 4.4), the scores increase compared to the use of a single sensor. For pocket positions, accelerometer-gyroscope

Table 4.9: Ranking of sensors with SVM, per position

Feature-Set	Position	ACC	G	LA	M	ACC-G	ACC-M	G-M	G-LA	LA-M	ACC-G-M	G-LA-M
FS3	Belt	7	8	4	11	2	8	10	1	6	4	2
	Lpocket	8	10	9	11	1	6	5	4	7	1	3
	Rpocket	7	10	9	11	1	5	8	4	5	1	3
	Uarm	9	11	8	10	6	4	7	5	3	1	1
	Wrist	7	11	9	10	3	3	3	8	3	1	1
FS2	Belt	8	9	4	11	3	7	9	1	5	6	2
	Lpocket	8	10	9	11	1	5	5	4	7	1	1
	Rpocket	7	10	9	11	1	5	7	4	5	1	3
	Uarm	9	11	8	10	5	3	5	5	3	1	2
	Wrist	7	10	9	10	3	6	3	8	3	1	1
FS6	Belt	10	8	6	11	3	8	6	1	5	3	2
	Lpocket	7	10	9	11	3	6	5	3	7	1	1
	Rpocket	6	10	9	11	1	5	6	4	8	1	3
	Uarm	9	10	6	11	6	4	8	4	2	3	1
	Wrist	8	10	8	10	3	4	4	4	7	1	2
FS7	Belt	10	8	8	11	1	7	6	1	5	4	1
	Lpocket	6	10	9	11	1	4	7	4	7	1	3
	Rpocket	3	10	9	11	1	3	7	5	8	1	5
	Uarm	8	10	5	11	5	4	8	5	3	1	1
	Wrist	8	11	9	10	2	4	7	5	5	1	3
	Sum of Ranks	152	197	156	214	52	101	126	80	104	35	41
	Final Ranking	8	10	9	11	3	5	7	4	6	1	2

combination performs the best. In belt positions, however, linear acceleration gyroscope combination is the best performing couple. This combination even performs better than the triple combination of sensors in the belt position. In upper arm position, linear acceleration and magnetometer combination is the best performing couple, achieving 92% F-measure with FS6. In wrist position, accelerometer-gyroscope, accelerometer-magnetometer and linear acceleration-magnitude combinations perform similarly.

Looking at the triple combinations (Figure 4.5), in pocket positions, performance increases up to 97% F-measure. The performance is the highest in all positions, except the belt position. For this position, the double combination of sensors performs better. In upper arm position, performance increases up to 93%, in the belt the maximum is 89%, and in wrist 94%. Belt position has different characteristics than the other positions. The phone is more stationary, while in other positions it moves with the activities. Moreover, as shown before, it is difficult to differentiate walking upstairs, downstairs and walking activities in the belt position.

4.4 Analysis with All Positions

Having investigated the performance by positions, in this section, we explore the position-independent recognition performance results, from the point of view of the feature-sets and sensor/sensor combinations. In Section 4.2.1, the models were built and validated per position data, while in this section we combine all the data from five positions and build the models. If position information is known, the recognition performance may increase for some positions, such as pocket, however, in general, average performance does not differ too much, as shown in the literature (Coskun et al.; 2015). Moreover, it may not be possible to have the position information, hence a general classifier can be more practical in a real-time recognition application. In Section 4.4.1, we examine the effect of feature-sets, and in Section 4.4.2, we examine the effect of sensor/sensors on the recognition performance.

4.4.1 Impact of Feature-Set

In this section, we present the results with the accelerometer sensor, with all the feature-sets and with the four classifiers and we investigate the effect of feature-sets. The results for other sensors can be found in the Appendix (Figures 5.11, 5.12). For activity independent results all-positions can be found in Table 5.5.

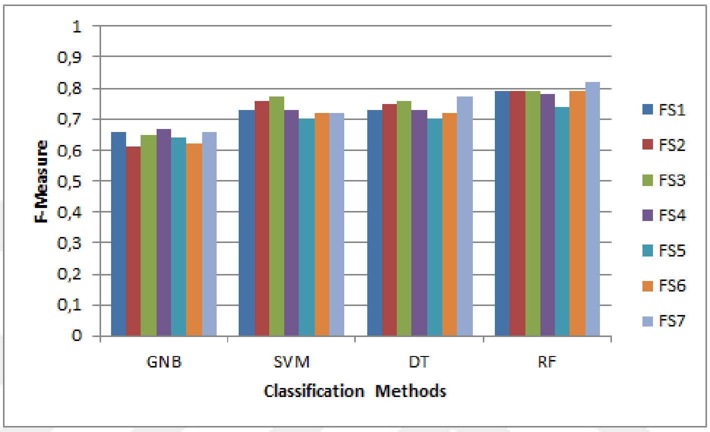


Figure 4.6: Impact of feature-sets

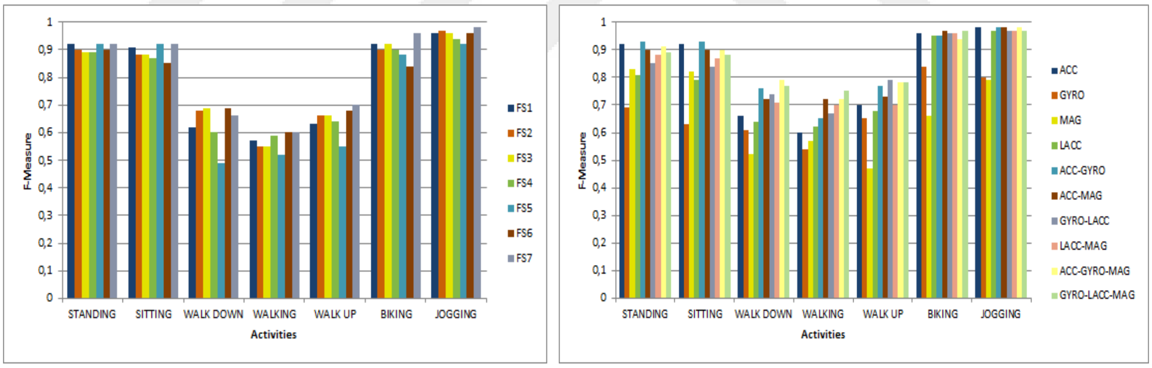
In Figure 4.6, random forest classifier performs the best for each feature-set. It achieves the maximum measure with FS7:82%. SVM achieves 77% F-measure with FS3 and decision tree achieves 76% with FS4. Except GNB, the other classifiers' performance is higher than 70% with all the feature-sets. In Table 4.10, we show the feature ranking with all the classifiers. When random forest is used, FS1, FS2, FS3 and FS6 achieve the same rates, while FS7 achieves 3% higher measure. With SVM, the ranking is as FS3 (77%), FS2 (76%), FS1 and FS4 with 73%, so on. Different from these, FS4 achieves the highest measure with the decision tree classifier, 76%.

When we compare our findings with the results of Section 4.3.1, FS3 is again the best performing feature-set among all the classifiers and FS5 is the worst ones. Here, the ranking is as: FS3, FS1, FS4, FS2 and FS7, FS6, FS5, considering the performance of all the classifiers, while it was FS3, FS7, FS2, FS6, FS4, FS1, FS5, FS6, per position results as shown in Table 4.6. These results are only for the accelerometer sensor, however, we present the rankings considering the other sensor and/or sensor combinations in Section 4.4.2.

Table 4.10: Feature ranking with all positions, per classifier, using Accelerometer

	FS1	FS2	FS3	FS4	FS5	FS6	FS7
GNB	2	7	4	1	5	6	2
SVM	3	2	1	3	7	5	5
DT	3	3	2	1	3	7	6
RF	2	2	2	6	7	2	1
Sum of Ranks	10	14	9	11	22	21	14
Final Ranking	2	5	1	3	7	6	5

To show the results per activity, we present the results of random forest using the accelerometer in Figure 4.7a. For other sensor combinations and classifiers, results are presented in Appendix, in Tables 5.6, 5.7, 5.8, 5.9, 5.10, 5.11, 5.12. As we discussed earlier, mostly confused activities are the walking upstairs, downstairs and the walking activity and their scores are lower. However, standing and sitting activities are classified with more than 90% F-measure and jogging and biking activities are classified with more than 95%.



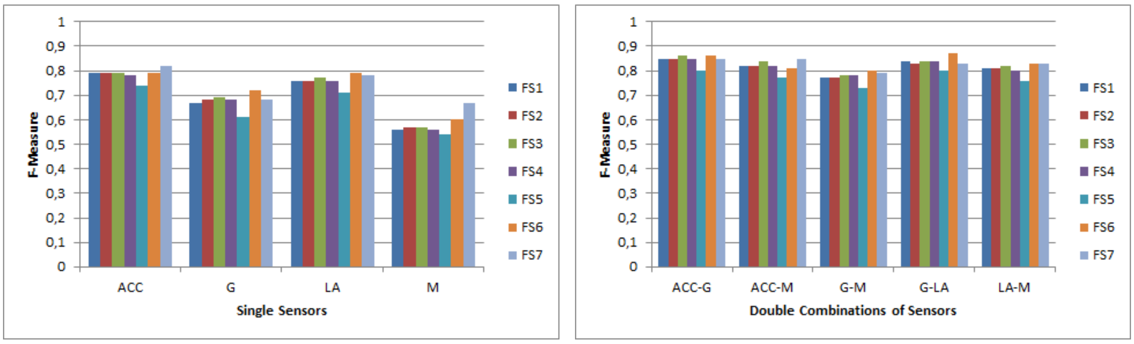
(a) Impact of feature-sets with random forest and accelerometer on all activities

(b) Impact of sensors with random forest classifier with FS7

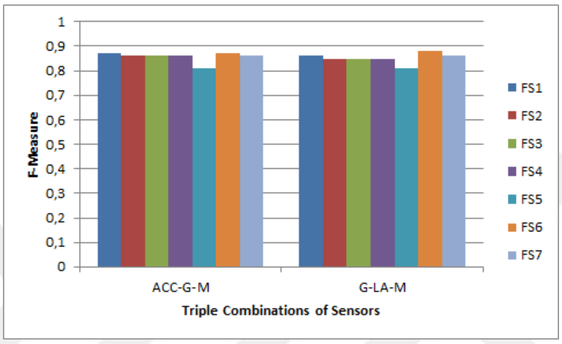
Figure 4.7: Impact of parameters on activities

4.4.2 Impact of Sensor and Fusion

To investigate the effect of sensors and their combinations, we present the results with the best performed classifier that is found in Section 4.4.1 which is random forest. However, performance with all the classifiers can be found in the Appendix in Table 5.5.



(a) Results with single sensors (b) Results with double sensor combinations



(c) Results with triple sensor combinations

Figure 4.8: Impact of sensors and their fusion

Results are presented in Figure 4.8 for all feature-sets. If we compare the performance when a single sensor is used, then it is clear that accelerometer alone performs the best with all feature-sets. FS3 achieves 77% F-measure while FS2 is 76%, and FS6 and FS7 present 72% performance. This is followed by the linear acceleration sensor. The maximum F-measure is achieved with FS6: 69%. Gyroscope alone performs close to linear acceleration, 64% with FS6. On the other hand, magnetometer achieves the lowest measure: maximum 58% with FS7 and 44% with FS2 and FS3.

When we consider the double combinations of the sensors, accelerometer-gyroscope combination achieves the best performance with all the feature-sets. Moreover, FS1 with this combination achieves the best performance with all the combinations. This is followed by linear acceleration and gyroscope combination. Compared to single use of sensors, in double combinations, performance increases. For example, accelerometer alone achieves 77% F-measure, while the accelerometer-gyroscope combination achieves 85%. When we look at the triple combinations of sensors, they perform slightly better than the double combinations. However, the difference is only 1-2%. The highest performance is 88%. The combination of acceleration, gyroscope and magnetometer sensors perform very similarly to the combination of linear acceleration, gyroscope and magnetometer sensors.

Table 4.11: Ranking of sensors and sensor combinations with Random Forest

	ACC	GYRO	MAG	LACC	ACC-GYRO	ACC-MAG	GYRO-MAG	GYRO-LACC	LACC-MAG	ACC-GYRO-MAG	GYRO-LACC-MAG
FS1	7	10	11	9	3	5	8	4	6	1	2
FS2	7	10	11	9	2	5	8	4	6	1	2
FS3	7	10	11	9	1	4	8	4	6	1	3
FS4	7	10	11	9	2	5	7	4	6	1	2
FS5	7	10	11	9	3	5	8	3	6	1	1
FS6	8	10	11	8	4	6	7	2	5	2	1
FS7	7	10	11	9	3	3	8	5	5	1	1
Sum of Ranks	50	70	77	62	18	33	54	26	40	8	12
Final Ranking	8	10	11	9	3	5	7	4	6	1	2

Table 4.12: Feature ranking with different sensors using Random Forest

	FS1	FS2	FS3	FS4	FS5	FS6	FS7
ACC	2	2	2	6	7	2	1
GYRO	6	3	2	3	7	1	3
MAG	5	3	3	5	7	2	1
LACC	4	4	3	4	7	1	2
ACC-GYRO	3	3	1	3	7	1	3
ACC-MAG	3	3	2	3	7	6	1
GYRO-MAG	5	5	3	3	7	1	2
GYRO-LACC	2	5	2	2	7	1	5
LACC-MAG	4	4	3	6	7	1	1
ACC-GYRO-MAG	1	3	3	3	7	1	3
GYRO-LACC-MAG	2	4	4	4	7	1	2
Sum of Ranks	37	39	28	42	77	18	24
Final Ranking	4	5	3	6	7	1	2

In Table 4.11, we present the sensor rankings. Each row shows the ranking of sensors according to their performance when a specific feature-set is used. This was also shown in Figure 4.8. Accelerometer, gyroscope, magnetometer combinations perform the best with all feature-sets. This is followed by linear acceleration, gyroscope, magnetometer combinations. The combination of accelerometer and gyroscope follows that, which is then followed by the linear acceleration and gyroscope. It is clear that accelerometer and linear acceleration sensors are the dominating sensors. However, as shown in the literature, linear acceleration sensor consumes more power than the accelerometer. Gyroscope and magnetometer support the performance. However, the effect of gyroscope is definitely higher. If battery/power consumption is a concern, then a single sensor should be used and this should be the accelerometer. However, supporting sensors, such as gyroscope, can be turned on/off when needed.

Additionally, we present the feature rankings in Table 4.12. Each row shows the ranking of features according to their performance when a specific sensor/sensors are used. When we consider all sensors and sensor combinations, similar to our findings in Section 4.3.1, FS7 and FS3 are among the best performing feature-sets. However, FS6 ranks the best. It was ranked as the 6th only in the accelerometer-magnetometer combination. It ranked 4th in Section 4.3.1. Again, FS5 is the worst performing feature-set.

To show the impact of sensors on classifying individual activities, we present the results of random forest using FS7 in Figure 4.7b. For other feature-sets and classifiers, results are presented in Appendix, in Tables 5.6, 5.7, 5.8, 5.9, 5.10, 5.11, 5.12. When sensors are combined, F-measure of walking activities also increases up to 80%, other activities are classified with more than 90% F-measure.

4.4.3 Classification with Selected Features

In this section, using selected features from three feature selection methods described in Section 4.2, data from all positions is analyzed with cross-validation using Random Forest classifier. In Table 4.13, we see the F-measure results corresponding to each activity and each feature selection method. At the last row of the table, we give F-measure results independently from activities (mean value for all activities as presented before in the Figures). Features selected by recursive feature elimination and feature importance methods perform better than feature propositions of the chi-squared method. Compared to the results presented in Figure 4.8, 88% F-measure was also achieved with FS6 with the combination of accelerometer, gyroscope and magnetometer combination as well as the gyroscope, linear acceleration and magnitude combination. We also evaluated common selected features which were colored in red in Table 4.3. We found that with just these common ones, we can understand very well biking and jogging activities.

Table 4.13: Selected 50 features from 3 methods cross-validation results with RF classifier

	Recursive Feature Elimination	***Chi-squared***	***Feature Importance***	***Common***
walking	0.74	0.63	0.74	0.48
standing	0.91	0.91	0.90	0.77
jogging	0.98	0.98	0.98	0.97
sitting	0.90	0.91	0.89	0.76
biking	0.96	0.96	0.95	0.93
upstairs	0.82	0.71	0.81	0.59
downstairs	0.84	0.72	0.81	0.63
activity independent	0.88	0.83	0.87	0.73

4.5 Analysis of Impact of Each and All Parameters

Up to this section, we investigate the performance of parameters by comparing one to another. Even if we can have an idea about the effects of each parameter, we cannot see the global picture because of the dependency of too many parameters. In this section, using statistical analysis, we examine the effects of each parameter (sensors, positions, feature-sets, classifiers) on the performance and we give exact impact values. To the best of our knowledge, this is the first work which analyzes such an impact. After collecting all F-measure results according to all possible cases, we constructed a new data file which contains all of the parameter combinations and F-measures achieved with that combination. For impact analysis, we use Minitab statistical software (Inc; 2010).

Firstly, we converted F-measure values into categorical types for regression analysis. For that, we suppose that F-values between $0 - 50\%$ is considered as bad if $50 - 60\%$ it is considered low, if $60 - 70\%$ then medium, if $70 - 80\%$ then good, if $80 - 90\%$ then very good, finally if $90 - 100\%$ then it is considered as excellent. To examine the effect of sensors, features, positions, classifiers on the target (F-measure), as the target value is categorical and ordinary, we used ordinal logistic regression. We choose 0.05 for significance level (α) for all analysis done in this section. It is said that a parameter is statistically significant if the corresponding p-value is lower than 0.05. We see that only position and feature is significant (see Table 4.14).

Table 4.14: Ordinal logistic regression

Predictor	**p-value**
sensors	0.952
positions	0.000
features	0.000
classifiers	0.147

Moreover, we repeated this analysis by not converting target values into categorical types. Now, since the target value is continuous, we use ANOVA analysis. As a result of this analysis, we see that all parameters are significant for the target value. When we look in detail (Table 4.15), we see that, the ranking is as follows: sensor > position > classifier > feature. According to these results, we can say that when we convert target values into categorical type, we lose detail, thus we observed that sensor and classifier are not significant, which is not true as we see in Table 4.15.

We also investigate the parameter combinations and the exact effect ratio on the target. For this purpose, we use adjusted R squared and predicted R squared statistical terms. Adjusted squared R term defines the variance percentage on the target value, which is explained by the input variables. In other terms, it defines variance percentage in response which can be explained by the model. On the other hand, predicted R squared explains how well a model predicts new observations. As the predicted R value is calculated with new observations, this one is more reliable to understand the model.

Table 4.15: Activity independent Anova analysis

Parameters	**R-sq(adj)**	**R-sq(pred)**
sensor-position-feature-classifier	98.67%	98.28%
sensor-position-classifier	90.27%	88.64%
sensor-position-feature	81.81%	79.73%
sensor-position	79.61%	75.84%
sensor-classifier	63.80%	62.71%
sensor-feature-classifier	62.46%	58.05%
sensor-feature	57.23%	54.95%
sensor	54.78%	54.42%
position-classifier	23.58%	22.53%
position-feature-classifier	21.65%	20.75%
position-feature	17.87%	16.91%
position	15.90%	15.57%
feature-classifier	10.12%	8.40%
classifier	7.85%	7.55%
feature	2.94%	2.44%

For our analysis with activity independent ANOVA analysis, the order given by the adjusted R squared and predicted R squared terms are the same which means the given impact order by two terms are coherent.

Table 4.15 should be interpreted as follows: by knowing just the feature, the model could predict 2.94% of the target value and by knowing the sensor-position-feature-classifier at the same time, the model could correctly predict the 98.67% of the target.

So far, we explained the general impact of parameters. We also want to know the effect of **each** sensor, **each** classifier, **each** feature-set, and **each** position on the F-measure results. For this purpose, we analyzed the impact of sensors (in Table 4.16), feature-sets (in Table 4.17), classifiers (in Table 4.18) and positions (in Table 4.19) by constructing new files deducted from files which are used for activity independent analysis.

As we see from the Tables (4.16, 4.18), there are not all sensors/sensor combinations (we have 11), all feature-sets (we have 7). If p-value of one parameter is less than 0.05, it means that parameter is not statistically significant. So that we did not add non-significant values in our tables. From Table 4.16, we understand that the performance of activity recognition is mostly influenced by the changes of magnetometer and gyroscope.

Table 4.16: Sensor-focused look

Sensors	R-sq(adj)	R-sq(pred)
M	30.30%	30.14%
G	12.22%	12.11%
ACC-G-M	5.46%	5.31%
G-LA-M	4.99%	4.88%
ACC-G	3.22%	3.09%
LA-M	1.46%	1.35%
LA-G	1.10%	0.97%
ACC-M	0.79%	0.65%
LA	0.32%	0.20%

As we see during the graphical interpretation of results, FS5 is the worst feature-set. Table 4.17 confirms this result. We see that the performance of FS5 affects 2.75% of the final performance. Other features are not significant in terms of affectation of the result.

Table 4.17: Feature-focused look

Features	R-sq(adj)	R-sq(pred)
FS5	2.75%	2.56%
FS6	0.79%	0.60%

The changes in DT and RF classifiers affect the final performance much more than GNB and SVM (Table 4.18).

Table 4.18: Classifier-focused look

Classifiers	R-sq(adj)	R-sq(pred)
DT	4.03%	3.86%
RF	3.06%	2.90%
SVM	2.02%	1.81%
GNB	1.34%	1.14%

Finally, we analyzed the effect of changes in the AR performance from the point of view of positions (Table 4.19). Belt, left pocket and right pocket affect, but other positions are not statistically significant.

For example, in Section 4, in all Figures we see that the worst feature-set is FS5. As it has poor performance, it affects much more the overall performance recognition according to other features, but in the negative sense, using the ANOVA analysis.

Table 4.19: Position-focused look

Position	R-sq(adj)	R-sq(pred)
belt	12.35%	12.16%
left pocket	4.83%	4.67%
right pocket	2.70%	2.52%

In addition, when we interpret the parameter focused tables, we must consider the results that we present in Table 4.15. For a detailed look on sensor, feature-set, position, and classifier, we expanded our main result file that we constructed to analyze impacts by activity independently. Each time, according to focus, we expand the corresponding parameter. For example, if we want to look in detail sensor parameters, then we expand sensor column by specifying 11 sensor combinations. So, by focused analysis, we actually look in detail to the results that we found in Tables 4.15 which means that the impact found in focused look on parameters must be lower or equal to the impact that found in Tables 4.15. For example, the maximum effect on Table 4.16 cannot be higher than (magnetometer has the maximum impact which is 30.30%) the general sensor effect that we presented in Table 4.15 which is 54.78%.

4.6 Discussion

In this section, we summarize our findings and discuss possible improvements.

- FS3, FS7, FS6, FS2 perform the best while FS5 is the worst: When we consider the performance with different feature-sets, it is observed that FS3, FS7, FS6, FS2 perform the best. FS3 includes mean, median, standard deviation, range, min, max. The only difference between FS3 and FS2 is the addition of the median value as a feature but this definitely increases the classification performance. FS7 includes variance, ZCR, RMS as the features which are totally different than FS1 and it includes variance while FS6 includes the median beside the other two features. FS5 (entropy, spectral energy, sum of first five FFT coefficients) is the worst performing sets.

- Most selected features: Results show that standard deviation (STD) is the most selected feature by all, except the right pocket position. Other mostly selected features are median, range, RMS, variance, energy, mean, max, and min. When we analyze the performance with using different feature-sets, we observe that four feature-sets (FS1: mean, standard deviation, FS2: mean, standard deviation, range, min, max, FS6: median, ZCR, RMS, FS7: variance, ZCR, RMS) outperform others. Although energy is among the selected features, FS5, which includes this feature does not perform well. Probably, it is due to the other features included in this set. When we analyze the performance with most selected features, performance is the same or even lower with using the organized feature-sets.

- Accelerometer is the dominating sensor: When we discuss the impact of sensors on the recognition performance, it is clear that accelerometer is the best performing sensor. In some cases, linear acceleration also performs well. However, gyroscope and magnetometer do not perform as good as them, when used alone.

- Tradeoff with using more sensors and battery consumption: As we discussed fusing information from different sensors increases the recognition performance. On the other hand, this also increases the computational burden. Since more sensors will be sampled, this will be a burden on the battery consumption. Hence, more sensors should be used when necessary. It would be interesting to explore a dynamic sampling of sensors when needed.

- Different phone positions: When we consider different phone positions, highest scores are achieved in the pocket positions, close to 90% F-measure. Arm and wrist positions follow the pocket position with 80% F-measure results. The lowest results are observed in the belt position, close to 70%. Compared to the other positions, the phone is more stationary and its orientation was different. In this position, it was difficult to differentiate walking activity from walking downstairs and upstairs activities, while in this is not true for the pocket position and the confusion rate of the walking activity is less. Additionally, standing and sitting activities are confused with each other in the belt position, while this is not the case for the pocket positions. However, we believe that it is necessary to test the performance with different positions since people carry phones in very different positions.

- Recognition Performance of Individual Activities: Mostly confused activities are the walking upstairs, downstairs and the walking activity and their scores are lower. However, standing and sitting activities are classified with more than 90% F-measure and jogging and biking activities are classified with more than 95%. These three confused activities have very similar patterns and it may be necessary to use other sensors such as pressure to differentiate the elevation.
- ANOVA results reveal that sensors have the highest impact on the performance which is followed by position, classifier, and feature-set. Hence, these two parameters can be explored with different values when studying human activity recognition with mobile devices.

5 CONCLUSION

In this thesis, we explored the parameter space of human activity recognition using motion sensors available on smart phones. We use a dataset collected from ten participants, from five different positions, with four different sensors, including seven different motion activities. In the preprocessing step, we investigate the impact of feature normalization in the preprocessing step. We show that feature normalization has an effect of up to 6% increase in the F-measure scores. Then, we focus on the feature selection step and apply three different feature selection methods to the extracted 300 features. We show that most selected feature-sets include standard deviation, median, range, RMS, variance, energy, mean, max, min.

Then we analyze the performance of activity recognition according to the five different positions of the phone. First, we investigate the impact of feature-set and then focus on the use of different sensors or sensor combinations. We show that, while accelerometer alone performs well when it is combined with gyroscope, performance increases, while the addition of magnetometer does not very much increase the F-measure values. Moreover, linear acceleration has a similar performance to the accelerometer, alone and with the combination of other sensors. Looking at the performance of various feature-sets, we show that feature-set FS3, which includes mean, median, standard deviation, range, min, max, gives the best performance and it is followed by FS7, which includes variance, zero-crossing rate, root mean square.

Since position information may not be always available, or phones can be carried in different positions, we investigate the performance with no position information, which means that data from all positions are combined and analyzed. Similar to the per-position analysis, accelerometer is found to be the dominating sensor. When we investigate the performance of feature-sets, FS3 is again the best performing feature-set among all the classifiers and FS5 (entropy, spectral energy, sum of first five FFT coefficients) is the worst one.

In the final part of the thesis, we make an ANOVA analysis, to investigate the impact of different parameters on the recognition scores. The results show that sensors have the higher impact into the performance, which is followed by position, classifier, and feature-set. When we combine parameters then the recognition performance increase. The best performance is achieved by combinations of sensor, position, feature and classifier.

As a future work, we plan to extend our analysis to other datasets, particularly those including multiple positions and sensor information. We intend to apply the findings in this study, to real-time activity recognition and for energy-efficient recognition, the dynamic selection of parameters will be further investigated. We will also extend the activity dataset to include more complex activities and also the device set to include smart watches.

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APPENDIX

Table 5.1: Per-position results - RF

POSITION	*FEATURE-SET*	*ACC*	*GYRO*	*MAG*	*LACC*	*ACC-GYRO*	*ACC-MAG*	*GYRO-MAG*	*GYRO-LACC*	*LACC-MAG*	*ACC-GYRO-MAG*	*GYRO-LACC-MAG*
BELT	**FS**1	0.71	0.74	0.58	0.82	0.78	0.75	0.76	0.84	0.83	0.81	0.87
	FS2	0.72	0.72	0.57	0.80	0.82	0.74	0.74	0.85	0.82	0.81	0.84
	FS3	0.74	0.75	0.58	0.80	0.82	0.75	0.77	0.86	0.84	0.80	0.86
	FS4	0.73	0.75	0.55	0.80	0.83	0.77	0.75	0.85	0.85	0.83	0.87
	FS5	0.71	0.68	0.55	0.78	0.75	0.74	0.72	0.82	0.83	0.78	0.84
	FS6	0.74	0.77	0.56	0.78	0.84	0.78	0.84	0.87	0.85	0.85	0.87
	FS7	0.70	0.76	0.68	0.79	0.80	0.77	0.82	0.86	0.83	0.85	0.88
LPOCKET	**FS**1	0.87	0.74	0.73	0.83	0.95	0.91	0.88	0.89	0.91	0.96	0.93
	FS2	0.90	0.78	0.73	0.83	0.94	0.93	0.89	0.89	0.90	0.96	0.91
	FS3	0.90	0.78	0.74	0.85	0.95	0.93	0.89	0.91	0.89	0.96	0.92
	FS4	0.87	0.75	0.71	0.85	0.92	0.91	0.87	0.90	0.90	0.95	0.93
	FS5	0.86	0.71	0.71	0.83	0.89	0.87	0.85	0.87	0.88	0.90	0.89
	FS6	0.89	0.81	0.80	0.85	0.95	0.89	0.89	0.94	0.90	0.95	0.95
	FS7	0.89	0.76	0.84	0.84	0.93	0.94	0.86	0.88	0.90	0.95	0.91
RPOCKET	**FS**1	0.88	0.78	0.67	0.86	0.94	0.89	0.87	0.93	0.89	0.93	0.93
	FS2	0.89	0.77	0.69	0.86	0.94	0.90	0.86	0.91	0.89	0.92	0.90
	FS3	0.90	0.77	0.67	0.87	0.94	0.92	0.88	0.91	0.90	0.95	0.90
	FS4	0.88	0.78	0.67	0.88	0.95	0.90	0.84	0.91	0.89	0.95	0.91
	FS5	0.85	0.75	0.61	0.81	0.90	0.86	0.82	0.89	0.85	0.90	0.89
	FS6	0.87	0.81	0.73	0.85	0.94	0.90	0.90	0.93	0.87	0.95	0.92
	FS7	0.90	0.78	0.79	0.83	0.94	0.91	0.86	0.89	0.88	0.94	0.92
UARM	**FS**1	0.77	0.70	0.72	0.85	0.85	0.88	0.85	0.89	0.90	0.91	0.91
	FS2	0.82	0.69	0.73	0.85	0.85	0.89	0.86	0.88	0.91	0.92	0.91
	FS3	0.82	0.69	0.73	0.86	0.86	0.88	0.86	0.88	0.91	0.91	0.92
	FS4	0.76	0.71	0.70	0.85	0.86	0.87	0.84	0.88	0.90	0.90	0.92
	FS5	0.71	0.64	0.68	0.79	0.78	0.81	0.80	0.84	0.85	0.84	0.87
	FS6	0.76	0.73	0.67	0.88	0.86	0.84	0.86	0.91	0.92	0.90	0.93
	FS7	0.82	0.69	0.70	0.88	0.85	0.88	0.78	0.89	0.90	0.89	0.91
WRIST	**FS**1	0.80	0.73	0.78	0.77	0.88	0.88	0.89	0.85	0.87	0.93	0.91
	FS2	0.82	0.75	0.78	0.78	0.88	0.88	0.89	0.86	0.87	0.92	0.91
	FS3	0.85	0.75	0.78	0.78	0.89	0.89	0.89	0.85	0.89	0.93	0.91
	FS4	0.80	0.75	0.77	0.77	0.87	0.87	0.90	0.85	0.86	0.92	0.91
	FS5	0.77	0.68	0.75	0.71	0.85	0.85	0.84	0.79	0.81	0.89	0.86
	FS6	0.80	0.77	0.72	0.81	0.89	0.87	0.88	0.88	0.87	0.93	0.93
	FS7	0.82	0.74	0.81	0.82	0.87	0.90	0.86	0.85	0.86	0.91	0.89

Table 5.2: Per-position results - GNB

POSITION	FEATURE-SET	ACC	GYRO	MAG	LACC	ACC-GYRO	ACC-MAG	GYRO-MAG	GYRO-LACC	LACC-MAG	ACC-GYRO-MAG	GYRO-LACC-MAG
BELT	**FS1**	0.66	0.62	0.50	0.79	0.73	0.69	0.72	0.82	0.79	0.72	0.82
	FS2	0.67	0.63	0.50	0.76	0.71	0.70	0.73	0.78	0.77	0.72	0.78
	FS3	0.68	0.64	0.49	0.78	0.74	0.70	0.74	0.80	0.78	0.74	0.80
	FS4	0.68	0.64	0.45	0.79	0.76	0.70	0.73	0.82	0.79	0.73	0.82
	FS5	0.64	0.59	0.47	0.75	0.70	0.66	0.68	0.80	0.75	0.68	0.79
	FS6	0.71	0.70	0.51	0.78	0.79	0.71	0.81	0.85	0.78	0.77	0.84
	FS7	0.73	0.65	0.54	0.62	0.80	0.77	0.79	0.67	0.78	0.80	0.80
LPOCKET	**FS1**	0.83	0.67	0.64	0.83	0.90	0.88	0.86	0.89	0.88	0.93	0.91
	FS2	0.84	0.70	0.62	0.80	0.88	0.89	0.85	0.87	0.87	0.91	0.90
	FS3	0.85	0.73	0.62	0.83	0.92	0.89	0.87	0.90	0.88	0.93	0.92
	FS4	0.83	0.67	0.61	0.82	0.91	0.85	0.84	0.89	0.85	0.92	0.92
	FS5	0.84	0.62	0.61	0.78	0.89	0.87	0.80	0.84	0.84	0.90	0.88
	FS6	0.87	0.78	0.72	0.85	0.94	0.89	0.91	0.92	0.89	0.95	0.94
	FS7	0.87	0.68	0.75	0.81	0.91	0.90	0.84	0.86	0.88	0.93	0.90
RPOCKET	**FS1**	0.85	0.69	0.60	0.81	0.92	0.88	0.82	0.82	0.89	0.93	0.90
	FS2	0.85	0.68	0.61	0.78	0.90	0.87	0.83	0.81	0.88	0.91	0.88
	FS3	0.87	0.71	0.61	0.80	0.92	0.88	0.85	0.83	0.89	0.93	0.90
	FS4	0.85	0.69	0.62	0.83	0.94	0.88	0.85	0.83	0.88	0.94	0.91
	FS5	0.85	0.64	0.58	0.71	0.90	0.86	0.79	0.76	0.82	0.91	0.87
	FS6	0.89	0.78	0.72	0.79	0.94	0.92	0.90	0.81	0.89	0.95	0.92
	FS7	0.87	0.71	0.73	0.68	0.91	0.89	0.82	0.74	0.85	0.93	0.79
UARM	**FS1**	0.79	0.62	0.59	0.84	0.85	0.84	0.80	0.82	0.88	0.89	0.89
	FS2	0.80	0.62	0.60	0.81	0.78	0.84	0.81	0.76	0.86	0.87	0.88
	FS3	0.80	0.63	0.58	0.84	0.84	0.84	0.81	0.79	0.87	0.88	0.90
	FS4	0.78	0.64	0.53	0.84	0.85	0.80	0.81	0.85	0.87	0.87	0.90
	FS5	0.74	0.58	0.60	0.77	0.79	0.76	0.74	0.79	0.81	0.81	0.85
	FS6	0.78	0.67	0.65	0.89	0.86	0.84	0.83	0.86	0.92	0.89	0.93
	FS7	0.77	0.62	0.63	0.74	0.76	0.86	0.76	0.76	0.86	0.83	0.80
WRIST	**FS1**	0.77	0.63	0.71	0.62	0.87	0.84	0.85	0.70	0.80	0.88	0.86
	FS2	0.77	0.61	0.71	0.57	0.85	0.83	0.83	0.67	0.78	0.86	0.84
	FS3	0.79	0.62	0.71	0.60	0.87	0.83	0.85	0.69	0.80	0.88	0.86
	FS4	0.80	0.63	0.71	0.62	0.88	0.84	0.86	0.70	0.81	0.89	0.86
	FS5	0.74	0.62	0.72	0.59	0.85	0.81	0.81	0.69	0.79	0.86	0.83
	FS6	0.80	0.69	0.74	0.75	0.88	0.86	0.86	0.79	0.85	0.89	0.87
	FS7	0.79	0.64	0.72	0.71	0.85	0.84	0.81	0.74	0.81	0.87	0.83

Table 5.3: Per-position results - SVM

POSITION	*FEATURE-SET*	*ACC*	*GYRO*	*MAG*	*LACC*	*ACC-GYRO*	*ACC-MAG*	*GYRO-MAG*	*GYRO-LACC*	*LACC-MAG*	*ACC-GYRO-MAG*	*GYRO-LACC-MAG*
BELT	**FS1**	0.69	0.69	0.38	0.81	0.80	0.73	0.69	0.88	0.81	0.78	0.85
	FS2	0.74	0.72	0.41	0.82	0.83	0.75	0.72	0.89	0.81	0.80	0.85
	FS3	0.76	0.75	0.40	0.82	0.86	0.75	0.74	0.89	0.81	0.82	0.86
	FS4	0.75	0.73	0.43	0.82	0.86	0.79	0.77	0.90	0.82	0.86	0.87
	FS5	0.65	0.69	0.49	0.77	0.71	0.68	0.70	0.83	0.79	0.73	0.82
	FS6	0.75	0.78	0.53	0.80	0.87	0.78	0.80	0.89	0.83	0.87	0.88
	FS7	0.75	0.78	0.55	0.78	0.87	0.79	0.80	0.87	0.82	0.86	0.87
LPOCKET	**FS1**	0.86	0.75	0.70	0.84	0.96	0.92	0.91	0.95	0.90	0.97	0.96
	FS2	0.87	0.79	0.70	0.82	0.96	0.91	0.91	0.93	0.89	0.96	0.96
	FS3	0.89	0.80	0.70	0.84	0.97	0.92	0.93	0.94	0.90	0.97	0.96
	FS4	0.86	0.75	0.68	0.83	0.97	0.91	0.91	0.95	0.90	0.98	0.96
	FS5	0.83	0.72	0.66	0.79	0.92	0.87	0.87	0.87	0.86	0.93	0.92
	FS6	0.90	0.82	0.70	0.85	0.96	0.91	0.93	0.96	0.90	0.97	0.97
	FS7	0.90	0.79	0.74	0.82	0.97	0.93	0.89	0.93	0.89	0.97	0.95
RPOCKET	**FS1**	0.87	0.78	0.64	0.86	0.96	0.90	0.88	0.94	0.90	0.97	0.95
	FS2	0.88	0.80	0.65	0.84	0.95	0.89	0.88	0.92	0.89	0.95	0.94
	FS3	0.90	0.80	0.65	0.86	0.96	0.91	0.89	0.93	0.91	0.96	0.95
	FS4	0.90	0.76	0.63	0.87	0.97	0.90	0.87	0.94	0.90	0.97	0.94
	FS5	0.84	0.72	0.59	0.78	0.92	0.85	0.81	0.88	0.82	0.92	0.90
	FS6	0.90	0.81	0.66	0.84	0.97	0.91	0.90	0.92	0.89	0.97	0.95
	FS7	0.91	0.79	0.67	0.80	0.96	0.91	0.87	0.90	0.84	0.96	0.90
UARM	**FS1**	0.80	0.65	0.65	0.82	0.86	0.88	0.86	0.86	0.88	0.92	0.91
	FS2	0.82	0.63	0.65	0.83	0.85	0.88	0.85	0.85	0.88	0.91	0.90
	FS3	0.82	0.65	0.66	0.83	0.86	0.89	0.85	0.87	0.90	0.92	0.92
	FS4	0.79	0.69	0.61	0.82	0.87	0.85	0.86	0.88	0.88	0.91	0.92
	FS5	0.74	0.64	0.65	0.75	0.80	0.79	0.80	0.80	0.81	0.85	0.85
	FS6	0.79	0.72	0.67	0.86	0.86	0.88	0.84	0.88	0.92	0.91	0.93
	FS7	0.79	0.71	0.61	0.84	0.84	0.85	0.79	0.84	0.87	0.89	0.89
WRIST	**FS1**	0.82	0.70	0.68	0.72	0.89	0.84	0.88	0.81	0.87	0.92	0.92
	FS2	0.82	0.71	0.71	0.74	0.88	0.87	0.88	0.81	0.88	0.91	0.91
	FS3	0.83	0.71	0.72	0.76	0.89	0.89	0.89	0.82	0.89	0.92	0.92
	FS4	0.85	0.74	0.71	0.76	0.89	0.89	0.90	0.86	0.88	0.93	0.92
	FS5	0.75	0.67	0.75	0.67	0.86	0.83	0.86	0.80	0.83	0.89	0.88
	FS6	0.81	0.72	0.72	0.81	0.91	0.88	0.88	0.88	0.87	0.94	0.92
	FS7	0.81	0.68	0.72	0.79	0.90	0.87	0.84	0.85	0.85	0.92	0.89

Table 5.4: Per-position results - DT

POSITION	*FEATURE-SET*	*ACC*	*GYRO*	*MAG*	*LACC*	*ACC-GYRO*	*ACC-MAG*	*GYRO-MAG*	*GYRO-LACC*	*LACC-MAG*	*ACC-GYRO-MAG*	*GYRO-LACC-MAG*
BELT	**FS1**	0.72	0.69	0.46	0.75	0.75	0.74	0.70	0.80	0.74	0.78	0.80
	FS2	0.71	0.71	0.51	0.76	0.75	0.68	0.67	0.78	0.77	0.72	0.77
	FS3	0.72	0.69	0.50	0.77	0.77	0.71	0.68	0.77	0.73	0.74	0.74
	FS4	0.70	0.68	0.51	0.77	0.77	0.69	0.67	0.80	0.78	0.86	0.78
	FS5	0.65	0.62	0.51	0.72	0.69	0.64	0.67	0.75	0.77	0.69	0.78
	FS6	0.67	0.72	0.48	0.75	0.77	0.69	0.71	0.80	0.74	0.73	0.77
	FS7	0.68	0.71	0.58	0.73	0.74	0.72	0.75	0.81	0.77	0.75	0.82
LPOCKET	**FS1**	0.84	0.69	0.68	0.78	0.89	0.87	0.82	0.80	0.84	0.88	0.85
	FS2	0.83	0.69	0.70	0.78	0.90	0.85	0.80	0.80	0.82	0.90	0.82
	FS3	0.84	0.70	0.70	0.79	0.93	0.87	0.79	0.81	0.82	0.93	0.85
	FS4	0.82	0.67	0.68	0.80	0.89	0.85	0.81	0.81	0.83	0.90	0.85
	FS5	0.83	0.64	0.63	0.76	0.82	0.82	0.75	0.80	0.82	0.83	0.82
	FS6	0.80	0.77	0.70	0.81	0.90	0.83	0.82	0.87	0.81	0.88	0.88
	FS7	0.84	0.79	0.72	0.80	0.86	0.87	0.79	0.83	0.85	0.89	0.82
RPOCKET	**FS1**	0.82	0.70	0.61	0.80	0.89	0.83	0.79	0.86	0.82	0.88	0.83
	FS2	0.84	0.71	0.61	0.81	0.88	0.86	0.78	0.80	0.81	0.88	0.82
	FS3	0.83	0.72	0.62	0.82	0.88	0.85	0.80	0.82	0.81	0.88	0.83
	FS4	0.82	0.71	0.61	0.80	0.88	0.84	0.78	0.84	0.82	0.89	0.83
	FS5	0.80	0.69	0.56	0.75	0.84	0.80	0.74	0.78	0.77	0.83	0.78
	FS6	0.84	0.73	0.64	0.82	0.89	0.84	0.80	0.87	0.82	0.91	0.85
	FS7	0.89	0.71	0.67	0.79	0.90	0.86	0.82	0.83	0.83	0.90	0.84
UARM	**FS1**	0.73	0.66	0.63	0.79	0.82	0.82	0.77	0.82	0.85	0.83	0.87
	FS2	0.77	0.62	0.65	0.79	0.80	0.82	0.79	0.82	0.83	0.84	0.85
	FS3	0.79	0.66	0.65	0.80	0.79	0.83	0.79	0.81	0.82	0.83	0.86
	FS4	0.75	0.67	0.59	0.81	0.82	0.82	0.79	0.84	0.84	0.85	0.87
	FS5	0.69	0.59	0.60	0.73	0.75	0.75	0.72	0.78	0.76	0.78	0.79
	FS6	0.72	0.67	0.60	0.85	0.80	0.79	0.80	0.86	0.87	0.84	0.89
	FS7	0.79	0.65	0.58	0.84	0.80	0.83	0.69	0.84	0.86	0.85	0.85
WRIST	**FS1**	0.80	0.67	0.69	0.70	0.85	0.85	0.80	0.79	0.80	0.87	0.85
	FS2	0.78	0.67	0.71	0.72	0.85	0.81	0.78	0.79	0.82	0.86	0.86
	FS3	0.77	0.69	0.72	0.71	0.82	0.81	0.79	0.77	0.81	0.86	0.87
	FS4	0.78	0.68	0.68	0.71	0.81	0.79	0.83	0.77	0.82	0.85	0.85
	FS5	0.72	0.64	0.69	0.66	0.79	0.78	0.76	0.73	0.73	0.84	0.77
	FS6	0.77	0.71	0.65	0.76	0.86	0.83	0.82	0.82	0.80	0.89	0.87
	FS7	0.80	0.67	0.74	0.78	0.83	0.85	0.80	0.79	0.83	0.85	0.83

Table 5.5: All Positions activity independent results

CLASSIFIER	***FEATURE-SET***	***ACC***	***GYRO***	***MAG***	***LACC***	***ACC-GYRO***	***ACC-MAG***	***GYRO-MAG***	***GYRO-LACC***	***LACC-MAG***	***ACC-GYRO-MAG***	***GYRO-LACC-MAG***
GNB	**FS1**	0.66	0.51	0.44	0.50	0.71	0.69	0.65	0.57	0.65	0.74	0.69
	FS2	0.61	0.51	0.45	0.46	0.67	0.67	0.65	0.53	0.63	0.70	0.65
	FS3	0.65	0.52	0.45	0.49	0.72	0.68	0.67	0.56	0.64	0.73	0.68
	FS4	0.67	0.51	0.40	0.54	0.72	0.70	0.67	0.57	0.68	0.75	0.71
	FS5	0.64	0.49	0.45	0.52	0.68	0.63	0.60	0.56	0.63	0.67	0.66
	FS6	0.62	0.53	0.55	0.60	0.70	0.69	0.68	0.62	0.70	0.72	0.72
	FS7	0.66	0.46	0.50	0.53	0.62	0.71	0.64	0.53	0.69	0.70	0.67
SVM	**FS1**	0.73	0.58	0.42	0.64	0.82	0.76	0.69	0.68	0.72	0.83	0.78
	FS2	0.76	0.61	0.44	0.65	0.82	0.78	0.72	0.73	0.72	0.83	0.80
	FS3	0.77	0.63	0.44	0.66	0.83	0.79	0.73	0.74	0.75	0.84	0.81
	FS4	0.73	0.59	0.46	0.67	0.83	0.76	0.71	0.74	0.72	0.84	0.80
	FS5	0.70	0.56	0.47	0.59	0.74	0.71	0.65	0.64	0.69	0.76	0.73
	FS6	0.72	0.64	0.57	0.69	0.84	0.78	0.73	0.76	0.77	0.85	0.83
	FS7	0.72	0.61	0.58	0.67	0.82	0.77	0.71	0.73	0.74	0.83	0.80
DT	**FS1**	0.73	0.59	0.51	0.69	0.80	0.73	0.69	0.77	0.74	0.79	0.79
	FS2	0.75	0.59	0.51	0.70	0.80	0.74	0.69	0.76	0.73	0.78	0.77
	FS3	0.76	0.61	0.51	0.71	0.81	0.75	0.69	0.77	0.74	0.79	0.77
	FS4	0.73	0.61	0.51	0.70	0.77	0.73	0.70	0.77	0.73	0.78	0.76
	FS5	0.70	0.55	0.49	0.65	0.74	0.70	0.65	0.72	0.68	0.72	0.74
	FS6	0.72	0.64	0.51	0.73	0.80	0.71	0.71	0.79	0.75	0.79	0.79
	FS7	0.77	0.62	0.60	0.72	0.78	0.77	0.71	0.76	0.75	0.78	0.77
RF	**FS1**	0.79	0.67	0.56	0.76	0.85	0.82	0.77	0.84	0.81	0.87	0.86
	FS2	0.79	0.68	0.57	0.76	0.85	0.82	0.77	0.83	0.81	0.86	0.85
	FS3	0.79	0.69	0.57	0.77	0.86	0.84	0.78	0.84	0.82	0.86	0.85
	FS4	0.78	0.68	0.56	0.76	0.85	0.82	0.78	0.84	0.80	0.86	0.85
	FS5	0.74	0.61	0.54	0.71	0.80	0.77	0.73	0.80	0.76	0.81	0.81
	FS6	0.79	0.72	0.60	0.79	0.86	0.81	0.80	0.87	0.83	0.87	0.88
	FS7	0.82	0.68	0.67	0.78	0.85	0.85	0.79	0.83	0.83	0.86	0.86

Table 5.6: All Positions walking results

CLASSIFIER	*FEATURE-SET*	*ACC*	*GYRO*	*MAG*	*LACC*	*ACC-GYRO*	*ACC-MAG*	*GYRO-MAG*	*GYRO-LACC*	*LACC-MAG*	*ACC-GYRO-MAG*	*GYRO-LACC-MAG*
GNB	**FS1**	0.39	0.48	0.34	0.37	0.59	0.56	0.51	0.51	0.49	0.62	0.55
	FS2	0.21	0.47	0.34	0.22	0.50	0.50	0.49	0.47	0.42	0.54	0.48
	FS3	0.40	0.48	0.30	0.37	0.59	0.53	0.49	0.51	0.45	0.58	0.51
	FS4	0.52	0.48	0.15	0.41	0.59	0.54	0.48	0.52	0.44	0.60	0.54
	FS5	0.46	0.37	0.02	0.37	0.47	0.21	0.19	0.44	0.19	0.32	0.31
	FS6	0.45	0.38	0.23	0.45	0.45	0.48	0.36	0.47	0.47	0.45	0.47
	FS7	0.39	0.37	0.45	0.21	0.39	0.51	0.50	0.32	0.55	0.48	0.49
SVM	**FS1**	0.57	0.51	0.30	0.51	0.66	0.64	0.54	0.60	0.55	0.68	0.62
	FS2	0.58	0.54	0.35	0.55	0.65	0.65	0.58	0.62	0.61	0.67	0.65
	FS3	0.60	0.57	0.35	0.57	0.66	0.66	0.58	0.67	0.61	0.68	0.68
	FS4	0.55	0.52	0.36	0.54	0.67	0.60	0.52	0.67	0.51	0.67	0.63
	FS5	0.53	0.38	0.28	0.39	0.50	0.52	0.41	0.40	0.39	0.52	0.44
	FS6	0.53	0.47	0.44	0.55	0.66	0.59	0.50	0.65	0.61	0.67	0.67
	FS7	0.54	0.46	0.44	0.46	0.63	0.63	0.49	0.55	0.56	0.64	0.60
DT	**FS1**	0.49	0.39	0.35	0.56	0.62	0.59	0.50	0.62	0.59	0.67	0.63
	FS2	0.51	0.63	0.37	0.55	0.59	0.56	0.51	0.60	0.56	0.63	0.59
	FS3	0.53	0.43	0.36	0.56	0.64	0.60	0.50	0.60	0.59	0.65	0.59
	FS4	0.53	0.45	0.34	0.56	0.56	0.60	0.54	0.57	0.59	0.61	0.58
	FS5	0.46	0.37	0.32	0.43	0.49	0.49	0.46	0.51	0.46	0.50	0.52
	FS6	0.54	0.49	0.44	0.54	0.60	0.57	0.56	0.61	0.59	0.59	0.58
	FS7	0.56	0.46	0.47	0.52	0.54	0.64	0.57	0.55	0.58	0.59	0.61
RF	**FS1**	0.57	0.53	0.41	0.65	0.68	0.68	0.66	0.72	0.70	0.76	0.75
	FS2	0.55	0.71	0.43	0.64	0.67	0.70	0.64	0.69	0.70	0.74	0.72
	FS3	0.55	0.57	0.42	0.66	0.67	0.72	0.66	0.71	0.71	0.72	0.74
	FS4	0.59	0.57	0.41	0.65	0.70	0.68	0.66	0.72	0.71	0.71	0.74
	FS5	0.52	0.45	0.40	0.55	0.58	0.61	0.60	0.60	0.59	0.65	0.64
	FS6	0.60	0.60	0.53	0.62	0.68	0.71	0.68	0.76	0.71	0.73	0.76
	FS7	0.60	0.54	0.57	0.62	0.65	0.72	0.67	0.67	0.70	0.72	0.75

Table 5.7: All Positions standing results

CLASSIFIER	*FEATURE-SET*	*ACC*	*GYRO*	*MAG*	*LACC*	*ACC-GYRO*	*ACC-MAG*	*GYRO-MAG*	*GYRO-LACC*	*LACC-MAG*	*ACC-GYRO-MAG*	*GYRO-LACC-MAG*
GNB	**FS1**	0.80	0.14	0.73	0.13	0.73	0.80	0.76	0.17	0.81	0.80	0.72
	FS2	0.80	0.13	0.75	0.21	0.76	0.82	0.79	0.16	0.82	0.82	0.75
	FS3	0.80	0.14	0.75	0.17	0.79	0.82	0.79	0.17	0.83	0.82	0.77
	FS4	0.82	0.15	0.77	0.33	0.79	0.85	0.82	0.18	0.85	0.84	0.80
	FS5	0.84	0.22	0.85	0.47	0.80	0.87	0.83	0.31	0.86	0.83	0.83
	FS6	0.78	0.29	0.83	0.42	0.79	0.85	0.83	0.37	0.84	0.82	0.81
	FS7	0.74	0.10	0.70	0.30	0.51	0.85	0.80	0.20	0.81	0.80	0.75
SVM	**FS1**	0.81	0.52	0.73	0.52	0.87	0.85	0.80	0.48	0.86	0.88	0.83
	FS2	0.82	0.59	0.74	0.57	0.85	0.85	0.81	0.62	0.86	0.87	0.86
	FS3	0.81	0.58	0.73	0.56	0.86	0.85	0.80	0.60	0.87	0.88	0.85
	FS4	0.85	0.49	0.71	0.66	0.88	0.91	0.83	0.63	0.86	0.93	0.87
	FS5	0.88	0.61	0.84	0.59	0.91	0.93	0.86	0.62	0.89	0.94	0.89
	FS6	0.83	0.61	0.79	0.61	0.90	0.89	0.85	0.62	0.87	0.92	0.88
	FS7	0.85	0.61	0.82	0.69	0.88	0.89	0.86	0.68	0.87	0.92	0.87
DT	**FS1**	0.86	0.63	0.79	0.75	0.89	0.84	0.82	0.75	0.85	0.86	0.85
	FS2	0.88	0.63	0.78	0.74	0.90	0.85	0.81	0.76	0.84	0.82	0.83
	FS3	0.91	0.64	0.79	0.75	0.89	0.86	0.80	0.80	0.82	0.86	0.82
	FS4	0.87	0.63	0.82	0.75	0.88	0.84	0.80	0.80	0.82	0.87	0.81
	FS5	0.87	0.61	0.82	0.73	0.89	0.86	0.82	0.78	0.85	0.86	0.85
	FS6	0.84	0.62	0.70	0.75	0.88	0.80	0.82	0.80	0.85	0.87	0.84
	FS7	0.90	0.63	0.81	0.76	0.90	0.87	0.83	0.80	0.83	0.86	0.82
RF	**FS1**	0.92	0.70	0.81	0.79	0.90	0.91	0.82	0.83	0.86	0.90	0.86
	FS2	0.90	0.71	0.82	0.79	0.91	0.89	0.82	0.83	0.85	0.88	0.87
	FS3	0.89	0.71	0.82	0.80	0.90	0.90	0.84	0.84	0.87	0.90	0.86
	FS4	0.89	0.69	0.81	0.79	0.90	0.92	0.84	0.84	0.85	0.91	0.86
	FS5	0.92	0.69	0.83	0.77	0.92	0.92	0.85	0.85	0.86	0.89	0.86
	FS6	0.90	0.69	0.81	0.82	0.91	0.89	0.84	0.86	0.86	0.91	0.88
	FS7	0.92	0.69	0.83	0.81	0.93	0.90	0.85	0.85	0.88	0.91	0.89

Table 5.8: All Positions jogging results

CLASSIFIER	*FEATURE-SET*	*ACC*	*GYRO*	*MAG*	*LACC*	*ACC-GYRO*	*ACC-MAG*	*GYRO-MAG*	*GYRO-LACC*	*LACC-MAG*	*ACC-GYRO-MAG*	*GYRO-LACC-MAG*
GNB	**FS1**	0.96	0.69	0.29	0.94	0.94	0.95	0.73	0.89	0.94	0.94	0.90
	FS2	0.92	0.71	0.26	0.84	0.90	0.92	0.77	0.81	0.87	0.91	0.84
	FS3	0.92	0.72	0.26	0.88	0.90	0.92	0.78	0.83	0.90	0.91	0.86
	FS4	0.96	0.70	0.26	0.95	0.92	0.94	0.74	0.90	0.95	0.93	0.91
	FS5	0.83	0.68	0.31	0.91	0.83	0.80	0.70	0.86	0.91	0.82	0.86
	FS6	0.83	0.73	0.64	0.91	0.85	0.85	0.79	0.87	0.90	0.85	0.88
	FS7	0.95	0.72	0.63	0.91	0.92	0.93	0.77	0.87	0.91	0.92	0.88
SVM	**FS1**	0.97	0.68	0.29	0.96	0.98	0.97	0.76	0.96	0.96	0.98	0.96
	FS2	0.97	0.72	0.25	0.96	0.98	0.97	0.81	0.96	0.95	0.97	0.95
	FS3	0.97	0.74	0.25	0.96	0.98	0.97	0.80	0.96	0.95	0.98	0.95
	FS4	0.97	0.69	0.26	0.96	0.98	0.97	0.77	0.96	0.96	0.98	0.96
	FS5	0.89	0.68	0.25	0.93	0.87	0.89	0.76	0.93	0.93	0.88	0.93
	FS6	0.96	0.75	0.64	0.94	0.94	0.97	0.78	0.94	0.93	0.94	0.93
	FS7	0.97	0.74	0.65	0.95	0.97	0.97	0.78	0.95	0.95	0.97	0.95
DT	**FS1**	0.92	0.64	0.34	0.92	0.93	0.86	0.72	0.94	0.93	0.89	0.93
	FS2	0.92	0.64	0.35	0.93	0.93	0.88	0.72	0.93	0.92	0.89	0.92
	FS3	0.91	0.66	0.35	0.94	0.92	0.89	0.73	0.93	0.93	0.91	0.94
	FS4	0.91	0.69	0.33	0.93	0.93	0.89	0.74	0.94	0.93	0.92	0.93
	FS5	0.89	0.62	0.30	0.93	0.87	0.87	0.71	0.92	0.91	0.87	0.92
	FS6	0.91	0.75	0.54	0.95	0.90	0.91	0.76	0.95	0.94	0.89	0.95
	FS7	0.94	0.73	0.68	0.94	0.93	0.94	0.78	0.93	0.94	0.93	0.94
RF	**FS1**	0.96	0.70	0.39	0.97	0.97	0.97	0.82	0.97	0.97	0.97	0.97
	FS2	0.97	0.73	0.40	0.97	0.97	0.97	0.83	0.97	0.96	0.97	0.97
	FS3	0.96	0.74	0.40	0.97	0.97	0.97	0.84	0.97	0.97	0.97	0.97
	FS4	0.94	0.73	0.39	0.96	0.97	0.96	0.82	0.97	0.96	0.98	0.98
	FS5	0.92	0.70	0.35	0.96	0.93	0.92	0.79	0.96	0.96	0.92	0.96
	FS6	0.96	0.83	0.67	0.97	0.96	0.96	0.88	0.98	0.97	0.95	0.97
	FS7	0.98	0.80	0.79	0.97	0.98	0.98	0.87	0.97	0.97	0.98	0.97

Table 5.9: All Positions sitting results

CLASSIFIER	*FEATURE-SET*	*ACC*	*GYRO*	*MAG*	*LACC*	*ACC-GYRO*	*ACC-MAG*	*GYRO-MAG*	*GYRO-LACC*	*LACC-MAG*	*ACC-GYRO-MAG*	*GYRO-LACC-MAG*
GNB	**FS1**	0.81	0.68	0.69	0.66	0.80	0.82	0.85	0.67	0.84	0.84	0.81
	FS2	0.81	0.67	0.75	0.67	0.80	0.83	0.85	0.66	0.84	0.85	0.81
	FS3	0.81	0.67	0.76	0.66	0.82	0.83	0.85	0.67	0.84	0.85	0.82
	FS4	0.83	0.68	0.53	0.67	0.82	0.86	0.86	0.67	0.86	0.85	0.84
	FS5	0.84	0.68	0.85	0.70	0.82	0.86	0.86	0.69	0.87	0.84	0.85
	FS6	0.75	0.69	0.80	0.68	0.82	0.83	0.86	0.69	0.85	0.84	0.84
	FS7	0.79	0.68	0.49	0.68	0.74	0.87	0.84	0.68	0.79	0.85	0.81
SVM	**FS1**	0.81	0.49	0.73	0.67	0.87	0.85	0.82	0.54	0.87	0.88	0.85
	FS2	0.80	0.51	0.77	0.66	0.85	0.84	0.82	0.66	0.87	0.88	0.88
	FS3	0.80	0.51	0.76	0.65	0.87	0.84	0.82	0.64	0.88	0.88	0.87
	FS4	0.84	0.52	0.73	0.67	0.88	0.91	0.85	0.66	0.86	0.94	0.88
	FS5	0.87	0.64	0.84	0.54	0.90	0.94	0.86	0.64	0.90	0.94	0.90
	FS6	0.76	0.65	0.80	0.64	0.89	0.89	0.86	0.64	0.87	0.92	0.89
	FS7	0.80	0.65	0.83	0.69	0.88	0.87	0.86	0.67	0.85	0.91	0.85
DT	**FS1**	0.86	0.65	0.78	0.74	0.90	0.83	0.82	0.75	0.86	0.87	0.86
	FS2	0.88	0.64	0.76	0.73	0.92	0.87	0.83	0.75	0.84	0.84	0.83
	FS3	0.90	0.65	0.78	0.75	0.89	0.86	0.83	0.80	0.82	0.87	0.82
	FS4	0.86	0.65	0.80	0.75	0.87	0.81	0.81	0.80	0.83	0.85	0.81
	FS5	0.88	0.63	0.79	0.73	0.90	0.85	0.83	0.79	0.84	0.84	0.85
	FS6	0.76	0.62	0.72	0.75	0.89	0.76	0.82	0.79	0.84	0.87	0.86
	FS7	0.90	0.62	0.78	0.76	0.90	0.87	0.83	0.80	0.82	0.87	0.81
RF	**FS1**	0.91	0.66	0.81	0.77	0.90	0.90	0.82	0.82	0.86	0.91	0.85
	FS2	0.88	0.67	0.79	0.77	0.90	0.88	0.82	0.82	0.85	0.88	0.87
	FS3	0.88	0.67	0.80	0.78	0.90	0.90	0.84	0.82	0.87	0.90	0.86
	FS4	0.87	0.64	0.80	0.77	0.89	0.91	0.85	0.83	0.85	0.90	0.85
	FS5	0.92	0.65	0.82	0.75	0.92	0.91	0.85	0.85	0.86	0.90	0.87
	FS6	0.85	0.63	0.78	0.79	0.92	0.84	0.84	0.86	0.85	0.90	0.88
	FS7	0.92	0.63	0.82	0.79	0.93	0.90	0.85	0.84	0.87	0.90	0.88

Table 5.10: All Positions biking results

CLASSIFIER	*FEATURE-SET*	*ACC*	*GYRO*	*MAG*	*LACC*	*ACC-GYRO*	*ACC-MAG*	*GYRO-MAG*	*GYRO-LACC*	*LACC-MAG*	*ACC-GYRO-MAG*	*GYRO-LACC-MAG*
GNB	**FS1**	0.74	0.57	0.39	0.60	0.72	0.76	0.62	0.65	0.65	0.74	0.69
	FS2	0.70	0.63	0.42	0.59	0.69	0.72	0.67	0.65	0.64	0.73	0.68
	FS3	0.73	0.63	0.45	0.59	0.71	0.75	0.67	0.66	0.65	0.75	0.69
	FS4	0.75	0.57	0.43	0.60	0.75	0.77	0.68	0.65	0.69	0.78	0.71
	FS5	0.81	0.61	0.58	0.54	0.77	0.84	0.68	0.65	0.72	0.80	0.72
	FS6	0.72	0.57	0.53	0.82	0.81	0.83	0.69	0.79	0.85	0.84	0.83
	FS7	0.81	0.52	0.54	0.73	0.76	0.82	0.61	0.68	0.80	0.78	0.72
SVM	**FS1**	0.90	0.73	0.38	0.77	0.88	0.90	0.75	0.79	0.75	0.90	0.78
	FS2	0.91	0.75	0.41	0.77	0.89	0.91	0.76	0.80	0.73	0.90	0.79
	FS3	0.90	0.77	0.40	0.78	0.89	0.90	0.77	0.81	0.75	0.90	0.80
	FS4	0.87	0.75	0.52	0.80	0.90	0.87	0.79	0.84	0.79	0.91	0.86
	FS5	0.88	0.71	0.56	0.73	0.90	0.86	0.76	0.76	0.76	0.90	0.80
	FS6	0.79	0.77	0.56	0.92	0.91	0.87	0.77	0.94	0.89	0.91	0.93
	FS7	0.82	0.76	0.57	0.91	0.92	0.90	0.78	0.93	0.91	0.93	0.94
DT	**FS1**	0.85	0.73	0.54	0.78	0.88	0.83	0.75	0.88	0.78	0.87	0.83
	FS2	0.87	0.74	0.53	0.80	0.91	0.86	0.76	0.86	0.80	0.88	0.82
	FS3	0.86	0.75	0.54	0.78	0.88	0.84	0.77	0.84	0.78	0.85	0.84
	FS4	0.78	0.72	0.53	0.78	0.81	0.78	0.76	0.85	0.78	0.84	0.83
	FS5	0.85	0.69	0.50	0.75	0.88	0.84	0.75	0.84	0.76	0.83	0.81
	FS6	0.76	0.77	0.47	0.90	0.86	0.77	0.78	0.91	0.86	0.85	0.89
	FS7	0.90	0.78	0.57	0.91	0.89	0.86	0.80	0.91	0.90	0.89	0.88
RF	**FS1**	0.92	0.81	0.61	0.84	0.94	0.92	0.84	0.92	0.87	0.94	0.93
	FS2	0.90	0.81	0.62	0.86	0.92	0.92	0.85	0.91	0.88	0.92	0.91
	FS3	0.92	0.82	0.63	0.86	0.94	0.93	0.83	0.92	0.87	0.93	0.91
	FS4	0.90	0.81	0.61	0.85	0.94	0.93	0.85	0.92	0.86	0.94	0.92
	FS5	0.88	0.76	0.59	0.81	0.92	0.91	0.83	0.90	0.86	0.93	0.90
	FS6	0.84	0.85	0.56	0.95	0.95	0.87	0.86	0.96	0.95	0.95	0.96
	FS7	0.96	0.84	0.66	0.95	0.95	0.97	0.88	0.96	0.96	0.94	0.97

Table 5.11: All Positions upstairs results

CLASSIFIER	*FEATURE-SET*	*ACC*	*GYRO*	*MAG*	*LACC*	*ACC-GYRO*	*ACC-MAG*	*GYRO-MAG*	*GYRO-LACC*	*LACC-MAG*	*ACC-GYRO-MAG*	*GYRO-LACC-MAG*
GNB	**FS1**	0.46	0.50	0.32	0.31	0.60	0.51	0.55	0.53	0.40	0.62	0.56
	FS2	0.40	0.47	0.33	0.27	0.51	0.45	0.50	0.46	0.37	0.52	0.48
	FS3	0.40	0.51	0.33	0.27	0.59	0.48	0.55	0.52	0.38	0.60	0.54
	FS4	0.42	0.50	0.36	0.33	0.60	0.51	0.55	0.54	0.44	0.63	0.57
	FS5	0.31	0.39	0.35	0.24	0.50	0.41	0.46	0.45	0.45	0.52	0.52
	FS6	0.42	0.53	0.38	0.39	0.57	0.47	0.58	0.55	0.43	0.58	0.57
	FS7	0.50	0.46	0.41	0.41	0.53	0.54	0.52	0.47	0.50	0.56	0.52
SVM	**FS1**	0.52	0.53	0.32	0.50	0.68	0.54	0.54	0.65	0.54	0.69	0.66
	FS2	0.57	0.55	0.32	0.51	0.70	0.59	0.56	0.68	0.53	0.69	0.69
	FS3	0.60	0.60	0.33	0.55	0.70	0.61	0.61	0.70	0.58	0.71	0.72
	FS4	0.52	0.53	0.30	0.54	0.70	0.52	0.55	0.70	0.55	0.69	0.68
	FS5	0.43	0.38	0.28	0.48	0.54	0.43	0.41	0.50	0.50	0.55	0.52
	FS6	0.57	0.63	0.27	0.55	0.74	0.57	0.67	0.70	0.58	0.75	0.72
	FS7	0.55	0.53	0.26	0.49	0.70	0.57	0.59	0.62	0.53	0.69	0.65
DT	**FS1**	0.57	0.54	0.36	0.56	0.67	0.60	0.58	0.71	0.59	0.68	0.69
	FS2	0.59	0.55	0.37	0.58	0.68	0.59	0.57	0.69	0.59	0.67	0.68
	FS3	0.61	0.56	0.37	0.58	0.69	0.62	0.58	0.71	0.59	0.69	0.70
	FS4	0.59	0.55	0.36	0.58	0.67	0.59	0.60	0.71	0.58	0.69	0.69
	FS5	0.50	0.44	0.34	0.49	0.60	0.50	0.48	0.60	0.49	0.60	0.61
	FS6	0.61	0.63	0.36	0.60	0.72	0.58	0.64	0.72	0.58	0.72	0.70
	FS7	0.62	0.57	0.42	0.59	0.68	0.61	0.59	0.68	0.60	0.68	0.65
RF	**FS1**	0.63	0.66	0.44	0.65	0.77	0.68	0.71	0.81	0.69	0.81	0.81
	FS2	0.66	0.65	0.45	0.67	0.77	0.69	0.70	0.79	0.71	0.80	0.80
	FS3	0.66	0.66	0.45	0.68	0.78	0.71	0.71	0.80	0.71	0.79	0.80
	FS4	0.64	0.66	0.43	0.67	0.77	0.67	0.70	0.80	0.68	0.79	0.81
	FS5	0.55	0.51	0.40	0.57	0.68	0.57	0.59	0.70	0.60	0.69	0.72
	FS6	0.68	0.72	0.41	0.69	0.81	0.70	0.76	0.84	0.71	0.82	0.82
	FS7	0.70	0.65	0.47	0.68	0.77	0.73	0.68	0.79	0.70	0.78	0.78

Table 5.12: All Positions downstairs results

CLASSIFIER	*FEATURE-SET*	*ACC*	*GYRO*	*MAG*	*LACC*	*ACC-GYRO*	*ACC-MAG*	*GYRO-MAG*	*GYRO-LACC*	*LACC-MAG*	*ACC-GYRO-MAG*	*GYRO-LACC-MAG*
GNB	**FS1**	0.43	0.52	0.33	0.51	0.59	0.41	0.55	0.57	0.45	0.58	0.58
	FS2	0.42	0.47	0.33	0.45	0.52	0.42	0.49	0.51	0.43	0.50	0.49
	FS3	0.46	0.51	0.32	0.49	0.63	0.44	0.53	0.58	0.47	0.58	0.56
	FS4	0.40	0.52	0.31	0.50	0.59	0.42	0.56	0.56	0.50	0.61	0.59
	FS5	0.42	0.45	0.20	0.41	0.55	0.37	0.46	0.52	0.43	0.53	0.52
	FS6	0.40	0.53	0.44	0.53	0.62	0.50	0.61	0.62	0.57	0.63	0.64
	FS7	0.44	0.38	0.29	0.44	0.50	0.42	0.40	0.47	0.43	0.50	0.50
SVM	**FS1**	0.55	0.63	0.20	0.54	0.80	0.58	0.64	0.75	0.54	0.80	0.76
	FS2	0.65	0.65	0.24	0.50	0.81	0.65	0.69	0.75	0.51	0.81	0.75
	FS3	0.68	0.65	0.23	0.58	0.84	0.69	0.70	0.78	0.58	0.84	0.79
	FS4	0.53	0.61	0.29	0.54	0.80	0.55	0.66	0.74	0.54	0.79	0.75
	FS5	0.40	0.49	0.21	0.48	0.60	0.36	0.51	0.61	0.48	0.60	0.62
	FS6	0.61	0.62	0.49	0.60	0.83	0.66	0.72	0.70	0.65	0.85	0.82
	FS7	0.52	0.54	0.49	0.46	0.74	0.58	0.61	0.71	0.54	0.76	0.73
DT	**FS1**	0.55	0.56	0.40	0.55	0.70	0.57	0.62	0.72	0.60	0.70	0.72
	FS2	0.59	0.58	0.41	0.57	0.70	0.60	0.62	0.71	0.60	0.71	0.70
	FS3	0.59	0.60	0.41	0.60	0.73	0.61	0.63	0.72	0.62	0.72	0.71
	FS4	0.55	0.58	0.40	0.56	0.70	0.58	0.63	0.72	0.61	0.70	0.71
	FS5	0.46	0.47	0.35	0.46	0.59	0.46	0.50	0.63	0.48	0.57	0.61
	FS6	0.60	0.61	0.38	0.60	0.74	0.61	0.62	0.72	0.62	0.72	0.72
	FS7	0.59	0.55	0.45	0.55	0.64	0.61	0.57	0.63	0.60	0.66	0.64
RF	**FS1**	0.62	0.64	0.46	0.62	0.80	0.68	0.72	0.81	0.70	0.82	0.83
	FS2	0.68	0.66	0.47	0.64	0.79	0.72	0.72	0.79	0.69	0.83	0.80
	FS3	0.69	0.67	0.47	0.67	0.82	0.73	0.73	0.82	0.71	0.82	0.83
	FS4	0.60	0.65	0.44	0.64	0.80	0.66	0.74	0.82	0.69	0.79	0.82
	FS5	0.49	0.53	0.38	0.54	0.68	0.53	0.61	0.72	0.57	0.68	0.71
	FS6	0.69	0.69	0.46	0.69	0.82	0.71	0.75	0.83	0.73	0.83	0.84
	FS7	0.66	0.61	0.52	0.64	0.76	0.72	0.69	0.74	0.71	0.79	0.77

Table 5.13: Feature selection for LPocket position

(a) Recursive Feature Elimination

	Selected Features		
1	ACC-std-y	26	G-min-x
2	ACC-std-pitch	27	G-min-z
3	ACC-median-z	28	G-max-z
4	ACC-variance-y	29	G-integ-z
5	ACC-RMS-z	30	G-integ-m
6	ACC-RMS-pitch	31	G-correl
7	ACC-energy-x	32	G-absDif-m
8	ACC-energy-y	33	LA-std-m
9	ACC-energy-pitch	34	LA-median-x
10	ACC-coefSum-x	35	LA-median-y
11	ACC-coefSum-y	36	LA-variance-x
12	ACC-min-y	37	LA-variance-m
13	ACC-min-z	38	LA-RMS-x
14	ACC-min-pitch	39	LA-energy-x
15	ACC-correl	40	LA-coefSum-x
16	ACC-absDif-z	41	LA-min-z
17	ACC-entropy-y	42	LA-min-m
18	ACC-entropy-z	43	LA-max-z
19	G-mean-m	44	LA-absDif-m
20	G-std-x	45	LA-entrop-m
21	G-std-y	46	M-energy-x
22	G-median-z	47	M-range-y
23	G-median-m	48	M-range-z
24	G-variance-y	49	M-range-m
25	G-energy-z	50	M-entrop-y

(b) Univariate Feature selection with Chi^2

	Selected Features		
1	ACC-mean-y	26	G-std-y
2	ACC-std-x	27	G-RMS-x
3	ACC-std-y	28	G-RMS-y
4	ACC-std-z	29	G-RMS-m
5	ACC-std-m	30	G-energy-x
6	ACC-std-roll	31	G-energy-y
7	ACC-variance-y	32	G-energy-m
8	ACC-variance-m	33	G-range-y
9	ACC-RMS-pitch	34	G-integ-m
10	ACC-energy-z	35	G-absDif-m
11	ACC-energy-pitch	36	LA-mean-m
12	ACC-range-x	37	LA-std-x
13	ACC-range-y	38	LA-std-y
14	ACC-range-z	39	LA-std-m
15	ACC-range-m	40	LA-median-m
16	ACC-range-pitch	41	LA-variance-x
17	ACC-range-roll	42	LA-variance-y
18	ACC-min-y	43	LA-RMS-x
19	ACC-min-m	44	LA-RMS-y
20	ACC-min-roll	45	LA-RMS-m
21	ACC-max-m	46	LA-energy-y
22	ACC-integ-y	47	LA-energy-m
23	ACC-absDif-z	48	LA-coefSum-m
24	G-mean-m	49	LA-range-x
25	G-std-x	50	LA-range-y

(c) Selection with Random Forest

	Selected Features		
1	ACC-energy-roll	26	G-mean-y
2	ACC-entropy-y	27	LA-min-y
3	G-absDif-y	28	ACC-energy-m
4	ACC-median-pitch	29	ACC-RMS-m
5	ACC-std-pitch	30	ACC-max-y
6	ACC-energy-pitch	31	LA-RMS-m
7	ACC-mean-pitch	32	G-integ-y
8	LA-median-m	33	ACC-max-pitch
9	ACC-variance-pitch	34	ACC-integ-m
10	LA-energy-y	35	ACC-RMS-roll
11	M-min-y	36	LA-variance-y
12	LA-energy-m	37	ACC-integ-z
13	G-range-m	38	G-median-y
14	ACC-variance-y	39	ACC-max-z
15	ACC-std-y	40	M-std-m
16	ACC-min-z	41	LA-coefSum-m
17	ACC-median-z	42	G-median-x
18	M-range-y	43	G-energy-x
19	ACC-RMS-pitch	44	M-variance-x
20	G-std-m	45	ACC-min-y
21	LA-absDif-m	46	ACC-absDif-pitch
22	G-median-m	47	ACC-RMS-z
23	G-variance-m	48	LA-median-y
24	LA-range-z	49	G-integ-x
25	ACC-median-x	50	ACC-range-z

Table 5.14: Feature selection for RPocket position

(a) Recursive Feature Elimination

	Selected Features		
1	ACC-mean-y	26	G-std-m
2	ACC-std-x	27	G-median-x
3	ACC-std-y	28	G-median-z
4	ACC-std-m	29	G-median-m
5	ACC-std-pitch	30	G-energy-x
6	ACC-median-z	31	G-energy-z
7	ACC-variance-y	32	G-range-x
8	ACC-RMS-z	33	G-range-m
9	ACC-RMS-pitch	34	G-max-y
10	ACC-energy-x	35	G-max-z
11	ACC-energy-z	36	G-integ-m
12	ACC-energy-pitch	37	G-absDif-z
13	ACC-energy-roll	38	G-absDif-m
14	ACC-range-roll	39	LA-mean-x
15	ACC-min-y	40	LA-std-y
16	ACC-min-z	41	LA-std-m
17	ACC-min-m	42	LA-median-m
18	ACC-integ-z	43	LA-variance-y
19	ACC-correl	44	LA-variance-m
20	ACC-absDif-z	45	LA-RMS-y
21	ACC-entrop-y	46	LA-energy-m
22	ACC-entrop-z	47	LA-min-y
23	G-mean-y	48	LA-min-z
24	G-mean-z	49	M-std-m
25	G-mean-m	50	M-range-m

(b) Univariate Feature selection with Chi^2

	Selected Features		
1	ACC-mean-y	26	ACC-integ-m
2	ACC-mean-m	27	ACC-absDif-m
3	ACC-std-x	28	ACC-entropy-y
4	ACC-std-y	29	G-mean-m
5	ACC-std-z	30	G-median-m
6	ACC-std-m	31	G-RMS-m
7	ACC-std-roll	32	G-energy-m
8	ACC-variance-x	33	G-range-x
9	ACC-variance-y	34	G-integ-m
10	ACC-variance-m	35	G-absDif-m
11	ACC-RMS-m	36	LA-mean-m
12	ACC-RMS-pitch	37	LA-std-x
13	ACC-energy-m	38	LA-std-y
14	ACC-energy-pitch	39	LA-median-m
15	ACC-range-x	40	LA-variance-x
16	ACC-range-y	41	LA-variance-y
17	ACC-range-z	42	LA-RMS-x
18	ACC-range-m	43	LA-RMS-y
19	ACC-range-pitch	44	LA-RMS-m
20	ACC-range-roll	45	LA-energy-x
21	ACC-min-y	46	LA-energy-y
22	ACC-min-m	47	LA-energy-m
23	ACC-min-roll	48	LA-coefSum-m
24	ACC-max-m	49	LA-range-x
25	ACC-integ-y	50	LA-range-y

(c) Selection with Random Forest

	Selected Features		
1	ACC-absDif-pitch	26	LA-median-m
2	ACC-median-pitch	27	ACC-integ-z
3	G-absDif-y	28	M-max-z
4	G-min-x	29	ACC-median-z
5	ACC-entropy-y	30	LA-energy-m
6	ACC-RMS-pitch	31	ACC-variance-roll
7	LA-energy-x	32	LA-min-z
8	ACC-std-pitch	33	LA-mean-m
9	ACC-variance-pitch	34	ACC-energy-pitch
10	M-range-z	35	ACC-mean-pitch
11	ACC-RMS-y	36	LA-coefSum-m
12	ACC-max-y	37	G-mean-y
13	G-median-m	38	G-energy-x
14	ACC-min-pitch	39	M-std-m
15	ACC-std-y	40	LA-std-z
16	ACC-correl	41	LA-correl
17	M-range-m	42	ACC-variance-z
18	ACC-variance-y	43	ACC-mean-z
19	ACC-energy-y	44	M-variance-m
20	M-max-m	45	LA-integ-m
21	ACC-absDif-x	46	G-median-y
22	LA-energy-y	47	G-integ-m
23	ACC-std-roll	48	ACC-mean-x
24	M-range-x	49	LA-std-y
25	ACC-max-z	50	LA-RMS-m

Table 5.15: Feature selection for UArm position

(a) Recursive Feature Elimination

Selected Features			
1	ACC-std-y	26	G-max-x
2	ACC-std-m	27	G-integ-y
3	ACC-median-m	28	G-correl
4	ACC-variance-y	29	G-absDif-m
5	ACC-RMS-x	30	LA-mean-y
6	ACC-energy-x	31	LA-median-x
7	ACC-energy-z	32	LA-range-m
8	ACC-energy-roll	33	LA-min-x
9	ACC-range-pitch	34	LA-min-m
10	ACC-min-y	35	LA-max-x
11	ACC-min-m	36	LA-integ-m
12	ACC-min-pitch	37	LA-correl
13	ACC-max-x	38	LA-absDif-x
14	ACC-correl	39	LA-absDif-m
15	ACC-absDif-z	40	M-mean-x
16	ACC-entrop-x	41	M-std-x
17	ACC-entrop-y	42	M-std-m
18	ACC-entrop-z	43	M-median-x
19	G-mean-y	44	M-median-z
20	G-mean-m	45	M-coefSum-z
21	G-std-y	46	M-range-m
22	G-std-m	47	M-min-z
23	G-median-y	48	M-max-x
24	G-RMS-y	49	M-max-m
25	G-energy-y	50	M-entrop-z

(b) Univariate Feature selection with Chi^2

Selected Features			
1	ACC-std-x	26	G-std-m
2	ACC-std-y	27	G-variance-y
3	ACC-std-z	28	G-variance-m
4	ACC-std-m	29	G-RMS-y
5	ACC-std-pitch	30	G-RMS-m
6	ACC-std-roll	31	G-energy-y
7	ACC-variance-x	32	G-energy-m
8	ACC-variance-y	33	G-range-z
9	ACC-variance-z	34	G-integ-m
10	ACC-variance-m	35	LA-mean-m
11	ACC-variance-pitch	36	LA-std-y
12	ACC-RMS-m	37	LA-std-z
13	ACC-energy-m	38	LA-median-m
14	ACC-range-x	39	LA-variance-y
15	ACC-range-y	40	LA-variance-z
16	ACC-range-m	41	LA-RMS-y
17	ACC-range-pitch	42	LA-RMS-z
18	ACC-range-roll	43	LA-RMS-m
19	ACC-min-y	44	LA-energy-y
20	ACC-min-roll	45	LA-energy-z
21	ACC-max-m	46	LA-energy-m
22	ACC-max-pitch	47	LA-coefSum-m
23	ACC-integ-m	48	LA-range-y
24	G-mean-m	49	LA-max-y
25	G-std-y	50	LA-integ-m

(c) Selection with Random Forest

Selected Features			
1	ACC-median-m	26	ACC-median-x
2	G-correl	27	M-median-x
3	G-absDif-y	28	G-energy-z
4	LA-range-m	29	ACC-correl
5	LA-min-y	30	LA-max-z
6	ACC-median-y	31	G-variance-m
7	M-max-x	32	LA-RMS-m
8	LA-mean-x	33	LA-energy-z
9	ACC-absDif-m	34	G-energy-y
10	ACC-std-z	35	LA-median-m
11	ACC-mean-m	36	ACC-max-z
12	ACC-energy-x	37	G-RMS-z
13	LA-median-y	38	M-min-z
14	LA-std-y	39	M-max-m
15	ACC-RMS-x	40	ACC-max-m
16	G-max-z	41	M-integ-x
17	LA-max-m	42	LA-variance-m
18	ACC-variance-z	43	ACC-range-m
19	ACC-energy-z	44	LA-variance-y
20	LA-absDif-x	45	LA-median-x
21	ACC-max-x	46	G-max-y
22	ACC-RMS-y	47	G-RMS-y
23	G-range-z	48	ACC-min-y
24	ACC-std-m	49	ACC-RMS-m
25	LA-range-y	50	LA-RMS-z

Table 5.16: Feature selection for Wrist position

(a) Recursive Feature Elimination

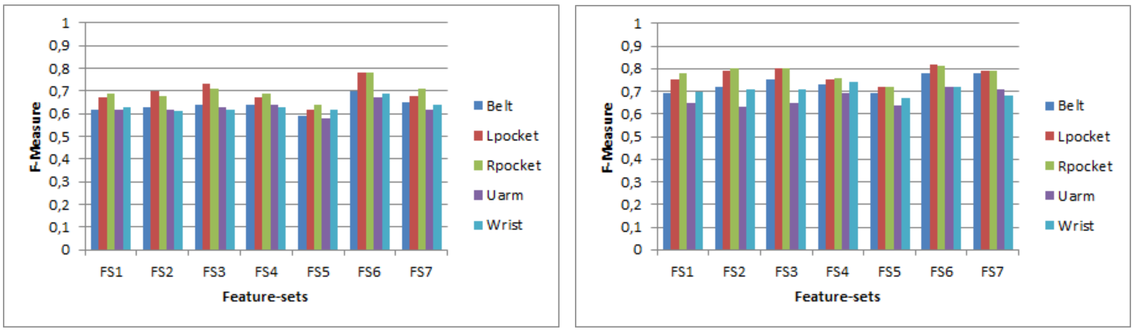
Selected Features			
1	ACC-mean-pitch	26	G-RMS-y
2	ACC-std-x	27	G-energy-z
3	ACC-median-y	28	G-coefSum-y
4	ACC-median-z	29	G-min-y
5	ACC-median-m	30	G-max-x
6	ACC-variance-m	31	G-integ-z
7	ACC-RMS-x	32	G-correl
8	ACC-RMS-pitch	33	G-absDif-z
9	ACC-energy-y	34	LA-std-x
10	ACC-energy-z	35	LA-std-y
11	ACC-range-m	36	LA-range-y
12	ACC-min-y	37	LA-min-y
13	ACC-min-z	38	LA-absDif-y
14	ACC-min-m	39	M-mean-x
15	ACC-max-x	40	M-std-x
16	ACC-max-pitch	41	M-std-m
17	ACC-absDif-z	42	M-RMS-x
18	ACC-absDif-pitch	43	M-RMS-z
19	ACC-entrop-x	44	M-energy-m
20	ACC-entrop-y	45	M-range-x
21	ACC-entrop-z	46	M-range-z
22	G-mean-x	47	M-range-m
23	G-mean-y	48	M-min-y
24	G-std-x	49	M-absDif-z
25	G-median-x	50	M-entrop-y

(b) Univariate Feature selection with Chi^2

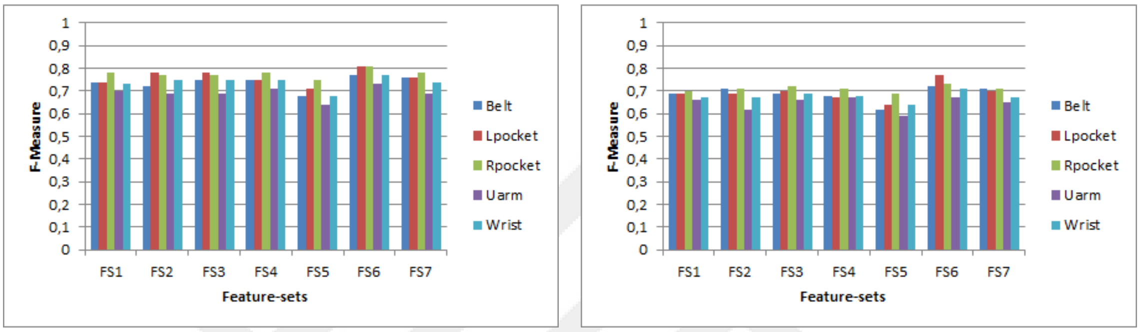
Selected Features			
1	ACC-std-x	26	G-variance-x
2	ACC-std-y	27	G-RMS-x
3	ACC-std-m	28	G-RMS-m
4	ACC-std-pitch	29	G-energy-x
5	ACC-variance-x	30	G-energy-z
6	ACC-variance-y	31	G-energy-m
7	ACC-variance-m	32	G-coefSum-m
8	ACC-variance-pitch	33	G-integ-m
9	ACC-RMS-x	34	G-absDif-m
10	ACC-RMS-m	35	LA-mean-m
11	ACC-energy-z	36	LA-std-x
12	ACC-range-x	37	LA-std-y
13	ACC-range-y	38	LA-std-m
14	ACC-range-m	39	LA-variance-x
15	ACC-range-pitch	40	LA-variance-y
16	ACC-range-roll	41	LA-variance-m
17	ACC-min-y	42	LA-RMS-x
18	ACC-max-x	43	LA-RMS-m
19	ACC-max-y	44	LA-energy-x
20	ACC-max-m	45	LA-energy-m
21	ACC-max-pitch	46	LA-range-x
22	G-mean-m	47	LA-range-y
23	G-std-x	48	LA-range-m
24	G-std-z	49	LA-max-x
25	G-median-m	50	LA-max-m

(c) Selection with Random Forest

Selected Features			
1	ACC-max-y	26	ACC-median-roll
2	ACC-median-pitch	27	ACC-integ-y
3	M-range-m	28	G-variance-x
4	G-median-y	29	ACC-RMS-z
5	LA-correl	30	ACC-RMS-roll
6	ACC-range-x	31	LA-variance-y
7	G-correl	32	ACC-median-m
8	G-energy-y	33	ACC-max-x
9	M-std-m	34	G-max-x
10	LA-range-y	35	ACC-entropy-x
11	M-variance-m	36	ACC-entropy-y
12	ACC-median-y	37	M-absDif-z
13	ACC-range-z	38	LA-max-y
14	LA-median-y	39	ACC-std-x
15	G-energy-x	40	LA-integ-x
16	ACC-energy-x	41	M-range-z
17	LA-min-y	42	ACC-std-m
18	M-RMS-x	43	G-min-y
19	LA-std-y	44	ACC-variance-pitch
20	ACC-mean-pitch	45	M-entrop-z
21	M-min-y	46	ACC-variance-m
22	ACC-absDif-y	47	ACC-std-y
23	ACC-mean-y	48	ACC-median-x
24	ACC-RMS-x	49	ACC-RMS-y
25	M-max-x	50	M-mean-x

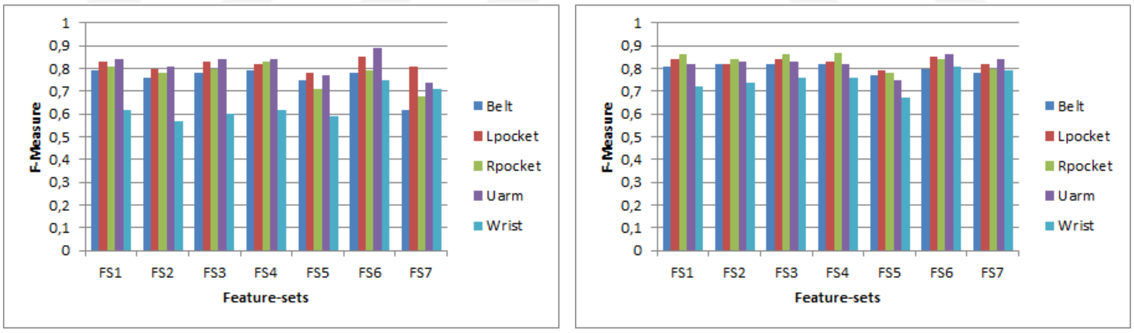


(a) GNB classifier (b) SVM classifier

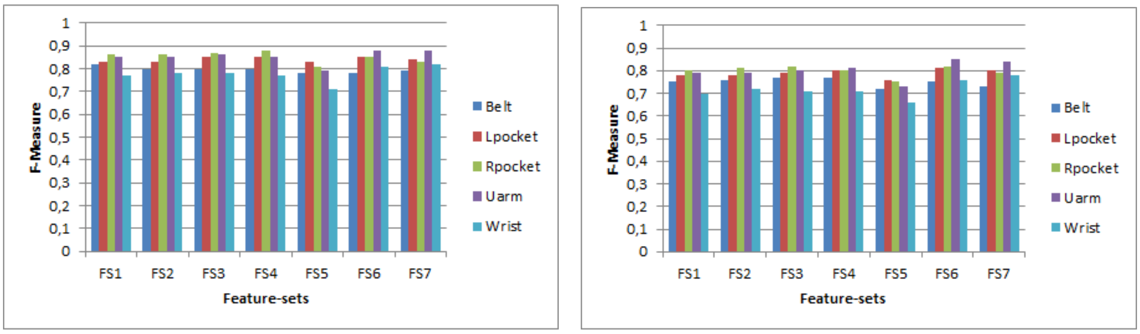


(c) RF classifier (d) DT classifier

Figure 5.1: Impact of using different feature-sets with four classifiers for Gyroscope

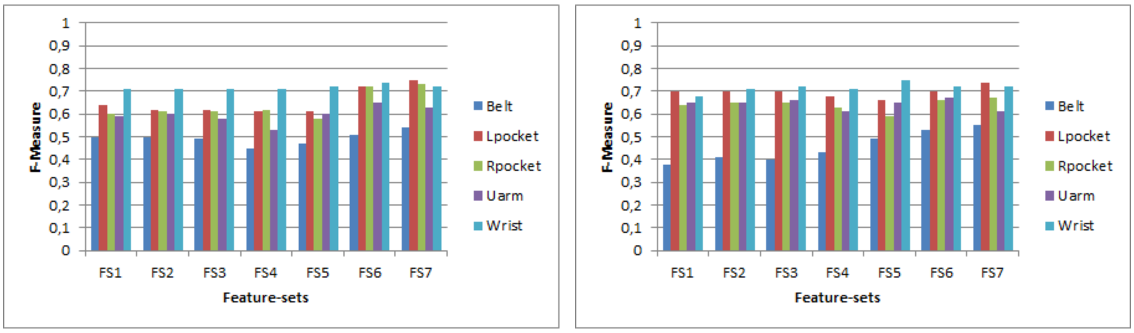


(a) GNB classifier (b) SVM classifier



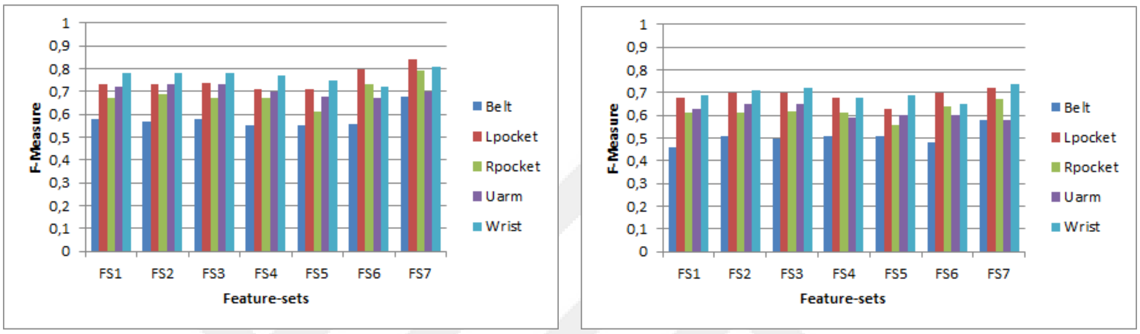
(c) RF classifier (d) DT classifier

Figure 5.2: Impact of using different feature-sets with four classifiers for Linear Acceleration



(a) GNB classifier

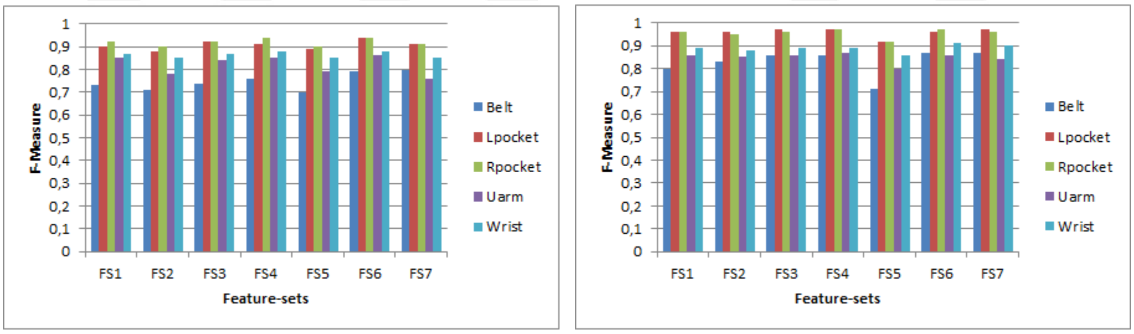
(b) SVM classifier



(c) RF classifier

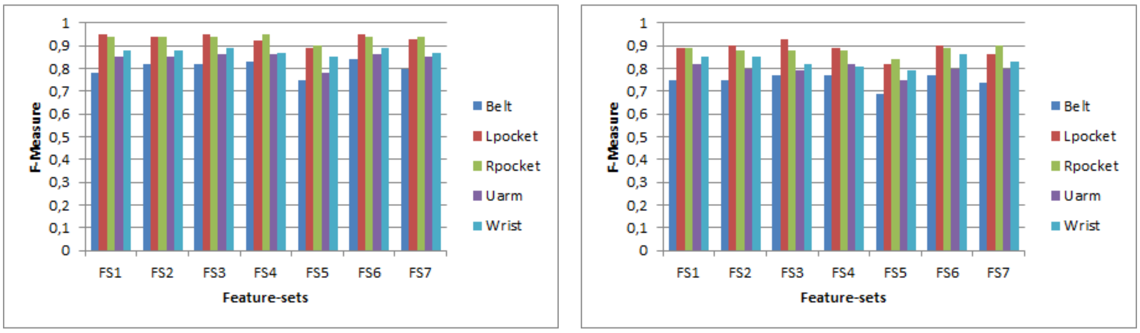
(d) DT classifier

Figure 5.3: Impact of using different feature-sets with four classifiers for Magnetometer



(a) GNB classifier

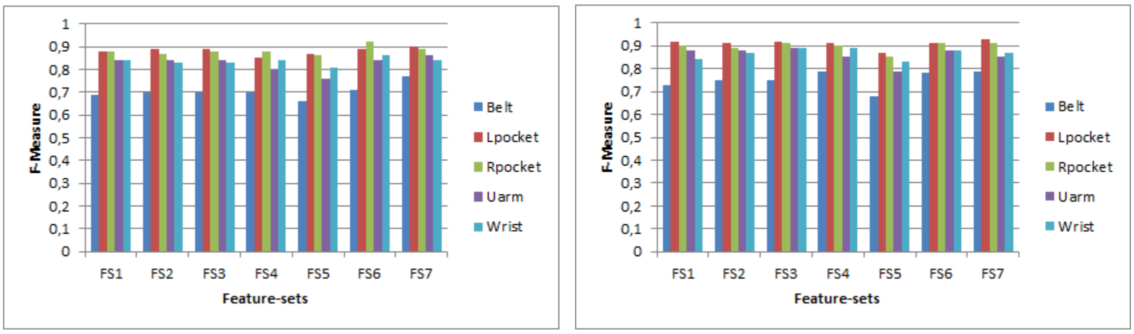
(b) SVM classifier



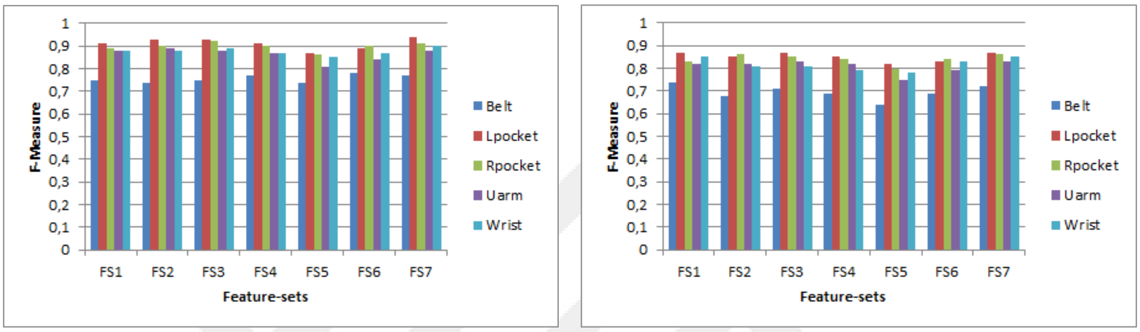
(c) RF classifier

(d) DT classifier

Figure 5.4: Impact of using different feature-sets with four classifiers for Accelerometer-Gyroscope

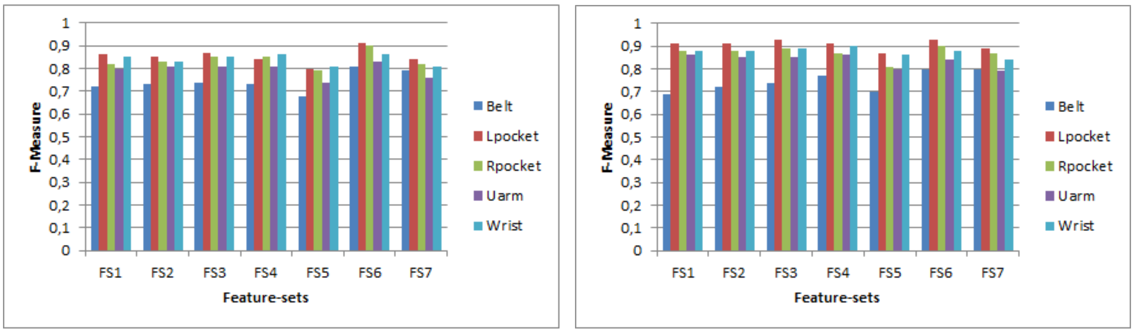


(a) GNB classifier (b) SVM classifier

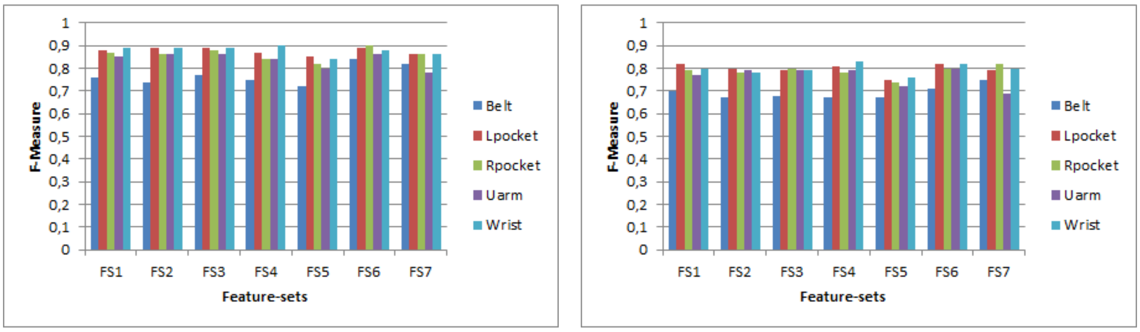


(c) RF classifier (d) DT classifier

Figure 5.5: Impact of using different feature-sets with four classifiers for Accelerometer-Magnetometer

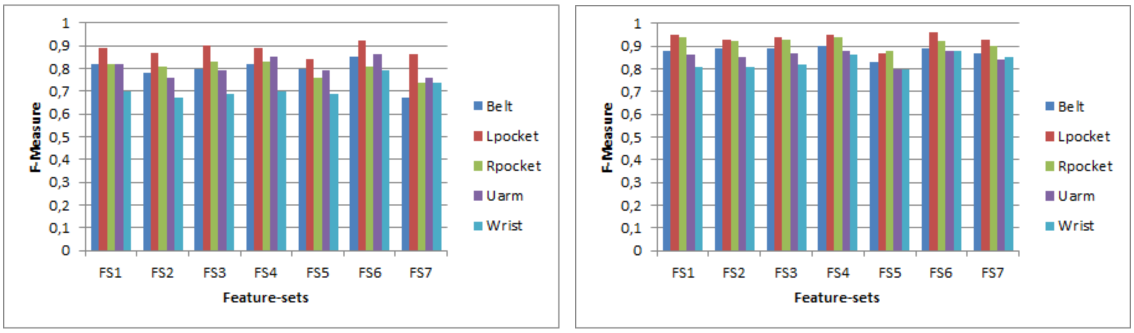


(a) GNB classifier (b) SVM classifier

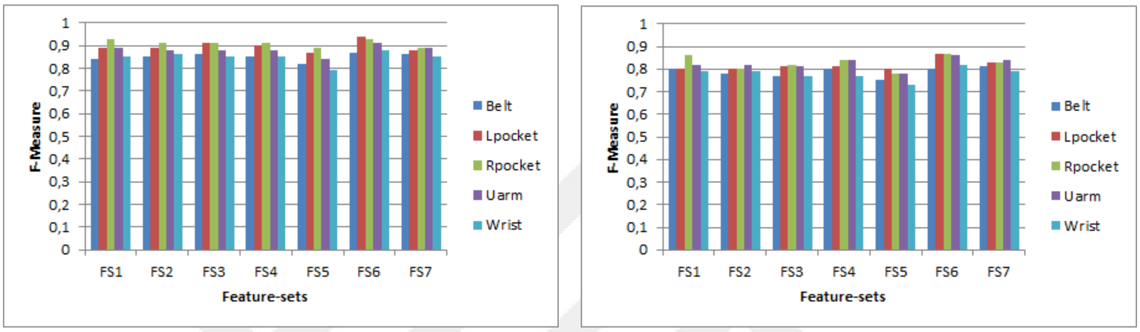


(c) RF classifier (d) DT classifier

Figure 5.6: Impact of using different feature-sets with four classifiers for Gyroscope-Magnetometer

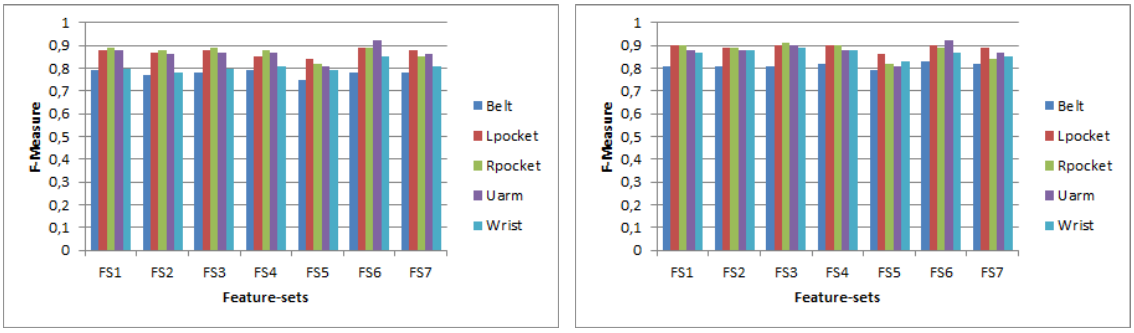


(a) GNB classifier (b) SVM classifier

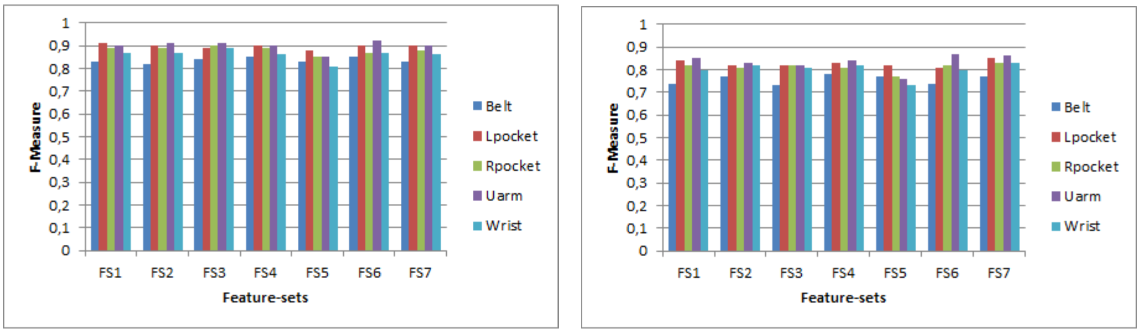


(c) RF classifier (d) DT classifier

Figure 5.7: Impact of using different feature-sets with four classifiers for Gyroscope-Linear Acceleration

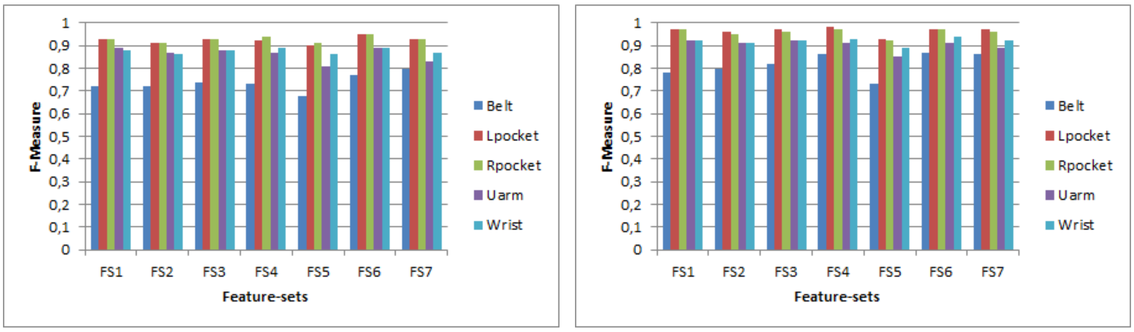


(a) GNB classifier (b) SVM classifier

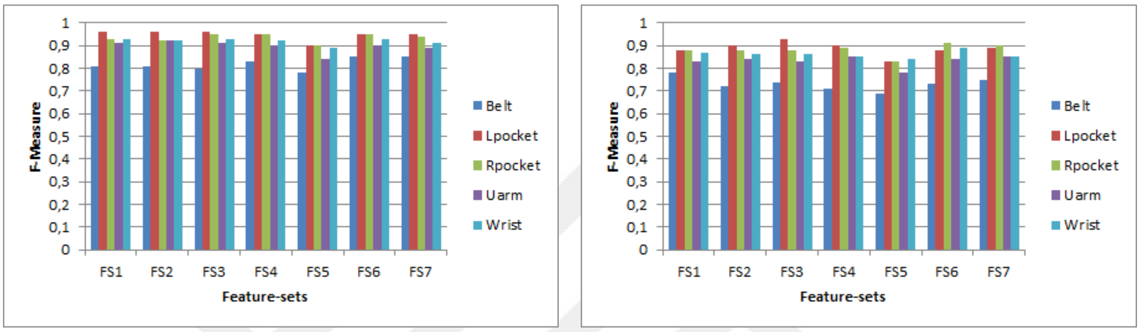


(c) RF classifier (d) DT classifier

Figure 5.8: Impact of using different feature-sets with four classifiers for Linear Acceleration-Magnetometer

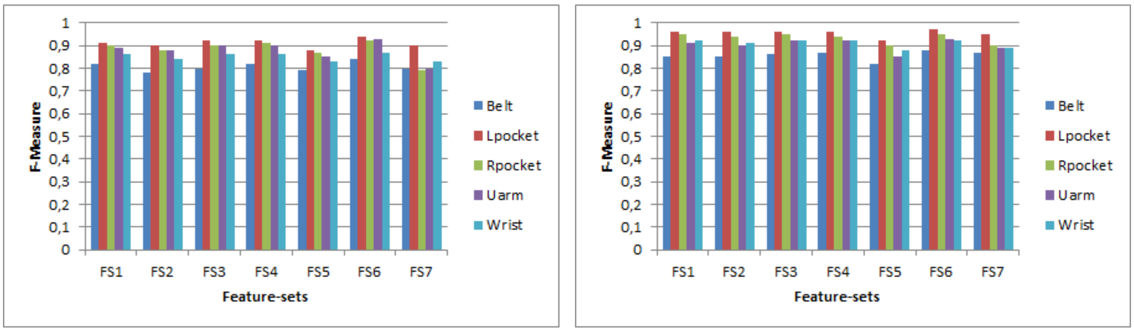


(a) GNB classifier (b) SVM classifier

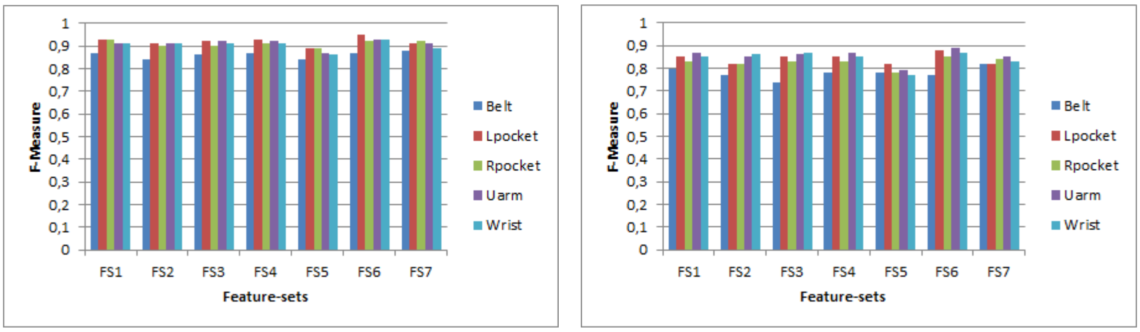


(c) RF classifier (d) DT classifier

Figure 5.9: Impact of using different feature-sets with four classifiers for Accelerometer-Gyroscope-Magnetometer

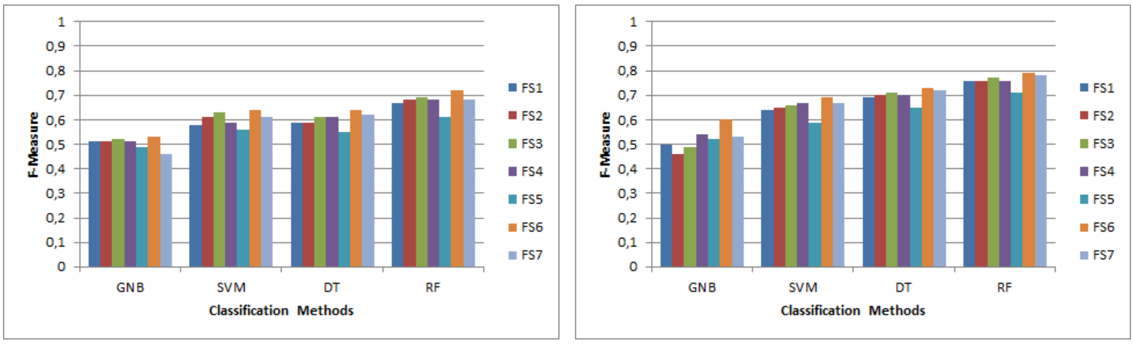


(a) GNB classifier (b) SVM classifier

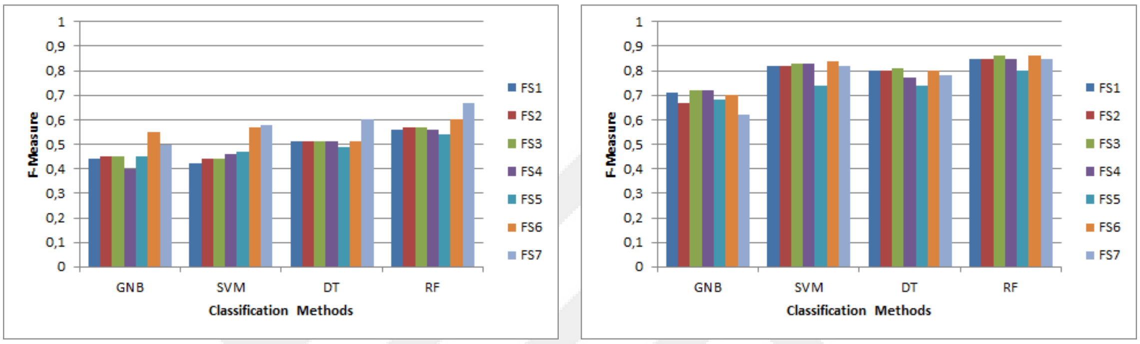


(c) RF classifier (d) DT classifier

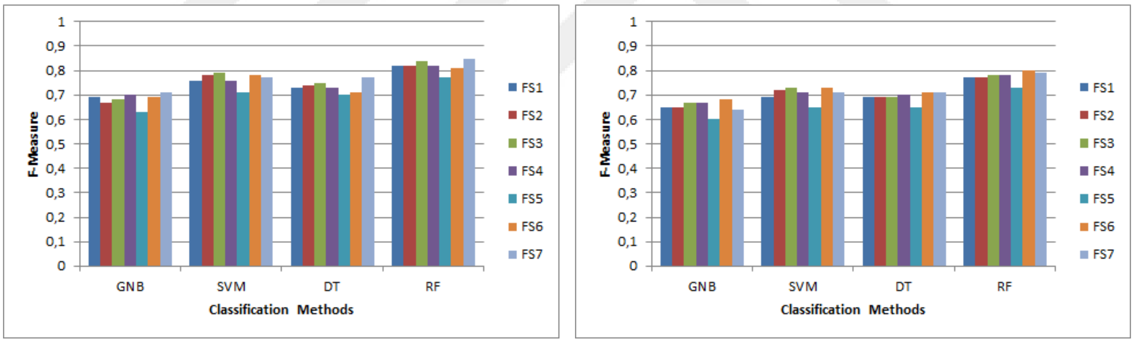
Figure 5.10: Impact of using different feature-sets with four classifiers for Gyroscope-Linear Acceleration-Magnetometer



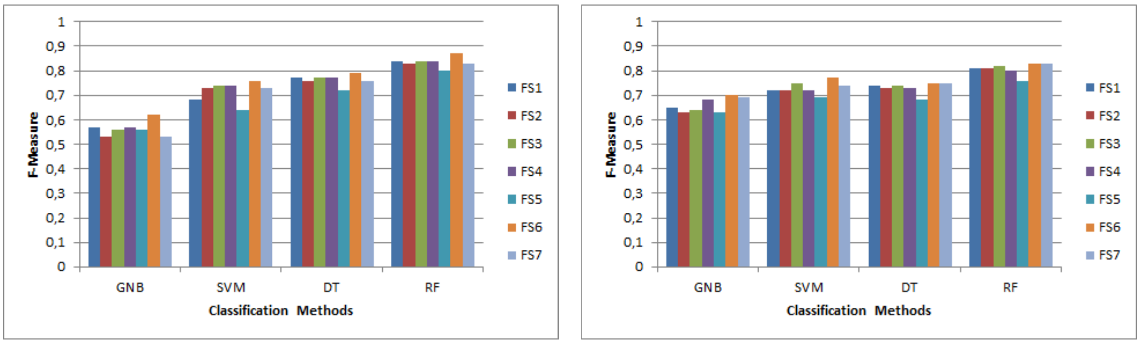
(a) Gyroscope (b) Linear Acceleration



(c) Magnetometer (d) Accelerometer-Gyroscope

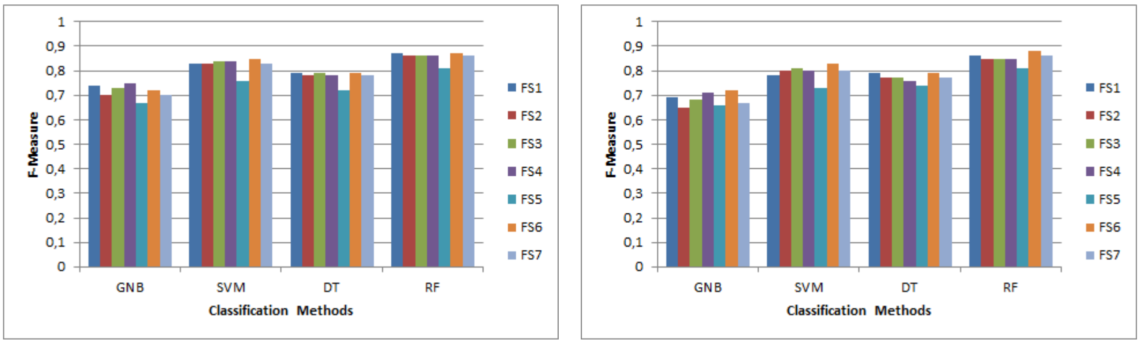


(e) Accelerometer-Magnetometer (f) Gyroscope-Magnetometer



(g) Gyroscope-Linear Acceleration (h) Linear Acceleration-Magnetometer

Figure 5.11: Impact of using different feature-sets with four classifiers for All Positions



(a) Accelerometer-Gyroscope-Magnetometer (b) Gyroscope-Linear Acceleration-Magnetometer

Figure 5.12: Impact of using different feature-sets with four classifiers for All Positions using triple combinations of sensors

BIOGRAPHICAL SKETCH

Berrenur Saylam was born on December 24, 1991 in Istanbul. After graduating from Beykoz Anatolian High School in 2009, she began studying Computer Engineering at Galatasaray University. She graduated from Computer Engineering Department in 2014 with getting second rank in her promotion and Industrial Engineering Department in 2015. In 2014, she enrolled in M.Sc. program in Computer Engineering at the same university. In 2015, she has gone to France to study on Complex Systems. After graduation from that specialization master program, she returned to Turkey to finish her master in Galatasaray.

She has one journal paper produced out of the master thesis, entitled as *The Parameter Space of Activity Recognition - The Impact on Performance with Mobile Devices* submitted to *Sensors* on July 2017.