

Seeking Optimum System Settings for Physical Activity Recognition on Smartwatches

Muhammad Ahmad, *Member, IEEE*, Adil Mehmood Khan, *Member, IEEE*, ,

Abstract—Physical activity recognition (PAR) using wearable devices can provide valued information regarding an individual's degree of functional ability and lifestyle. In this regards, smartphone-based physical activity recognition is a well-studied area. Research on smartwatch-based PAR, on the other hand, is still in its infancy. Through a large-scale exploratory study, this work aims to investigate the smartwatch-based PAR domain. A detailed analysis of various feature banks and classification methods are carried out to find the optimum system settings for the best performance of any smartwatch-based PAR system for both personal and impersonal models. To further validate our hypothesis for both personal (The classifier is built using the data only from one specific user) and impersonal (The classifier is built using the data from every user except the one under study) models, we tested single subject validation process for smartwatch-based activity recognition.

Index Terms—Sensor, Smartphone, Smartwatch, Physical Activity Recognition, Personal and Impersonal Models.

I. INTRODUCTION

Last few years have witnessed a massive growth in consumer interest in smart devices [1]. These include smartphones, smart TVs, and recently smartwatches. Because of their increased penetration, smartwatches have claimed a handsome market share. A typical smartwatch contains a heart rate monitor, GPS, thermometer, camera, and an accelerometer. Thus, it can provide a variety of services. These services include temperature and pulse measurements, monitoring blood glucose level, and the number of calories consumed when performing a physical activity, such as walking, running, and cycling, and so forth.

Recently, smartwatches have emerged in our daily lives, and like their smartphone counterparts, smartwatches include gyroscope, magnetometer, and accelerometer sensors, so that they can support similar capabilities and applications such as health applications, i.e., calories consumption that require sensor based physical activity recognition. A number of calories consumed during physical activities vary from one activity to another; therefore, the first thing to do when estimating the number of calories is to recognize the activity. It is called physical activity recognition [2].

This work explores the idea of physical activity recognition on smartwatches using the embedded gyroscope, magnetometer, and accelerometer sensors (*The gyroscope, magnetometer, and accelerometer sensors are ideal for physical activity recognition.*), with a detailed analysis of various feature banks

and classification methods to seek the best settings for optimum performance on two different types of models such as impersonal and personal model. Personal models referred as the classifier is built using the data only from one specific user, whereas the impersonal model referred as the classifier is built using the data from every user except the one under study. To summarize, the main contributions of this work is towards answering the following questions:

- 1) Existing smartphone-based physical activity recognition studies have a number of features that were utilized for smartphone-based physical activity recognition; can they be used for smartwatch-based physical activity recognition as well?
- 2) Which of the most commonly used classifiers from the reference field provides the best recognition accuracy?
- 3) Does features permutation help to improve the accuracy?
- 4) Does features normalization help to improve the performance of the classifier?
- 5) Which model (Personal or Impersonal) works better for smartwatch-based physical activity recognition?
- 6) Does changing the window size affect the recognition accuracy?

Physical activity recognition in general, using motion sensors especially using smartphones has been studied in recent years [3-5], and currently being studied extensively [6-7], but there are a few studies on physical activity recognition using smartwatches [8-17], in which the authors studied the role of the smartwatch in physical activity recognition system for health recommendation purposes.

For instance, Guiry et al., proposed physical activity recognition system to recognize nine different activities using five different classifiers [8]. These activities include walking, standing, cycling, running, stair ascent, stair descent, and elevator ascent and elevator descent. However, the authors studied smartphone and smartwatch based activity recognition separately and did not combine the data from both devices. Furthermore, for real-time data collection, the author's used magnetometer, accelerometer, pressure, and gyroscope sensors for smartphone and accelerometer for a smartwatch.

S. G. Trost, et al., used sensors on hip and wrist to detect physical activities using logistic regression based classification method in [9]. In this work, the authors just focused on showing the potential of using the wrist position for physical activity recognition for health recommendation system.

S. Chernbumroong et al. used a single wrist-worn accelerometer to detect five different physical activities for recommendation system in [10]. These activities include standing, sitting, lying, running, and walking. However, F. G. Da-Silva, et al, used the same sensor to detect the eight different physical

M. Ahmad, and A.M. Khan are with Machine Learning and Knowledge Representation (MiKr) Lab, at the Department of Computer Science, Innopolis University, Innopolis, 420500, Russia.

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activities for recommendation system in [11]. In addition to the activities identified in [10], F.G. Da-Silva includes the activity of working on a computer.

The works [12] and [13] detect the eating activity using a Hidden Markov Model (HMM) with a wrist-worn accelerometer and gyroscope sensors. R. L. Ramos-Garcia, identify the eating activity by dividing it into further sub-activities in [12], which includes resting, drinking, eating, using utensil and others. Meanwhile, Y. Dong et al., proposed to differentiate eating periods from non-eating periods to identify the eating and not-eating activity in [13].

S. Sen, et al, used both accelerometer and gyroscope sensor data to recognize the eating and non-eating activities in [14]. Furthermore, the authors used smartwatch camera to take images of the food being consumed to analyze what a user is eating.

P. M. School et al. presented a feasibility study to detect and identify the smoking activity in [15] using accelerometer sensor, where the authors only reported a user specific accuracy for smoking activity. Whereas, A. Parade et al., used both accelerometer, magnetometer and gyroscope sensors to recognize smoking puffs in [16], where the authors just try to distinguished smoking activity from other activities. A similar work has been reported in [17], where the J. P. Varkey et al., used support vector machine (SVM) classifier to recognize six different physical activities. These activities include standing, walking, writing, jacks, smoking, and jogging.

H. Kim et al. proposed the collaborative classification approach for recognizing daily activities using smartwatches [18]. The authors exploit a single off-the-shelf smartwatch to recognize five daily activities namely, eating, watching TV, sleeping, vacuuming, and showering. For fair comparisons, the authors suggested using single and multiple sensors based approaches to compare with their proposed approach with the overall accuracy of 91.5% with the improved recall rate up to 21.5% for each activity.

G. M. Weiss et al. showed that accelerometers and gyroscopes sensors that sense users movements and can help identify the user activity [19]. The authors propose to compare the smartphone and smartwatch based user activity recognition, in which smartwatch have the ability to recognize hand based activities namely eating which is not possible through a smartphone. They showed that the smartwatch is able to recognize the drinking activity with 93.3% accuracy while smartphones achieve only 77.3%.

F. Nurwanto et al. proposed a daily life light sport exercise activities, and these activities include squat jump, push up, sit up, and walking [20]. This study focuses only on accelerometer-based signal captured by left-handed persons, and the obtained signals were processed through sliding window approach with the k-nearest neighbor method and dynamic time warping as the main classifier. They proved that k-NN together with dynamic time warping method is an efficient method for daily exercise recognition, with the accuracy of 76.67% for push up, 96.69% for squat jump and 80% for sit up activity. They intentionally exclude the walking activity for their experimental process because of the random patterns.

N. Al-Naffakh et al. proposed the usefulness of using smart-watch motion sensor namely gyroscope and accelerometer to perform user activity recognition in [21]. They proved the natures of the signals captured are sufficiently discriminative to be useful in performing activity recognition.

Different activities can be recognized using motion sensors at the wrist position, i.e., drinking, eating, smoking, walking, walking down stairs, walking up stairs, running, jogging, elevator up, elevator down, doing regular exercises, writing, etc. However, there is no study that discusses these activities all together with the recommendations of optimum system settings.

Therefore, to extend the existing works, we evaluate the combination of different feature banks and classification techniques for the reliable recognition of various activities. We also evaluate three different built-in motion sensors. Moreover, unlike the current trends, we also evaluate the effect of window size on each activity performed by the individual user, and its impact on the recognition performance of simple and complex activities. Although the effect of window size on physical activity recognition has been studied by T. Huynh et al., in [22], but the windowing effect on complex activities is yet not fully explored. Moreover, unlike the recent researches, we explore the use of both *personal* and *impersonal* models individually for each activity. Personal model means the classifier is trained using the data only from one specific individual while the impersonal model means the classifier is built using the data from every user except the one under study, and for both models, one subject cross validation process is adopted. Finally, our study suggests the optimum system settings for any activity recognition system based on smartwatches.

This work analyzes the effects of combining gyroscope, magnetometer, and accelerometer sensors data for activity recognition for different size of windows varying from one second to 12 seconds long window. We further analyze the effect of various sampling rates on the recognition performance in different scenarios.

However, in our current study, we still have room for further improvement. For example, our current dataset is not balanced (as shown in Fig. 1) for all performed activities, which might lead to the biased results towards majority classes. To handle the said problem to some extent, we used one subject cross validation process for different models (personal and impersonal) which somehow overcome the class imbalance issue.

This study also overcomes the limitations of overlapping while segmenting the raw data, which forcefully improve the recognition performance because this overlap cause using some part of data in both training and testing which limiting the use of such techniques in real time environment. Moreover, we proposed and suggest some methods, which helps to improve the recognition performance for those activities that have low recognition performance.

The rest of the paper has the following organization. Section II describes the material and methods. Section III contains experimental settings. Section IV presents the results and discussion, and finally, Section V concludes the paper with possible future directions.

II. MATERIALS AND METHODS

Today's smartwatches are equipped with a variety of motion sensors that are useful for monitoring device movements like tilt, rotate, and shake. Some of these sensors are the ambient light sensor, accelerometer, compass, gyroscope, and GPS sensors. To this end, we collected the raw signals (*as explained below*) using three different sensors, such as an accelerometer, magnetometer, and gyroscope sensors.

A. Data Collection

We collected raw signals for five physical activities from six healthy subjects (three male and three female) having the mean age of twenty-five years old. The criterion for selecting the subjects is based on the gender because different genders exhibit different patterns when performing the same activity. These activities include walking upstairs, walking downstairs, walking, running, and jogging.

All subjects performed these activities twice on each day for more than a month. Therefore, we collected data from the same user for same activity but performed on different days. Fig.1 shows three-dimensional raw signals collected from a single subject for each activity.

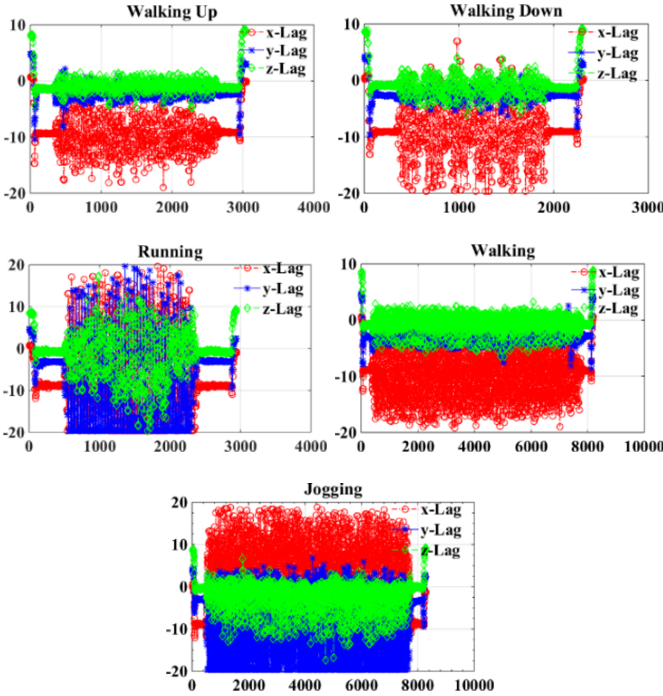


Fig. 1: Raw Signal obtained through accelerometer sensor for individual activity.

B. Feature Extraction

Embedded sensor generates three-dimensional time series signals, which are highly fluctuating and oscillatory in nature. The oscillation and fluctuations make the physical activity recognition more difficult than other applications in nature. These raw signals are shown in Fig. 1 for individual activity performed by the single user. Therefore, it is compulsory to gather the nontrivial signals from raw data through a feature extraction process.

The raw signals are divided into several equal sized windows to control the flow rate and pass fewer data to the system to extract the meaningful information. In [23] A. M. Khan et al., has presented a detailed analysis of using different kinds of features with a different number of samples per windows for smartphone-based physical activity recognition.

From these raw signals, the extracted features are divided into two different feature banks: first feature bank include the features obtained by taking; average, median, variance, standard deviation, interquartile, autocorrelation, partial autocorrelation, coefficients of autoregressive model, coefficients of moving average model, coefficients of autoregressive moving average model, wavelet coefficients.

Second feature bank includes the features obtained by taking; average acceleration, average absolute difference, standard deviation, average resultant acceleration, and the average difference between peaks and finally, we also calculate the binned distribution in which we determine what fraction of reading fall in a ten equal sized bins. This function generates ten features. Every feature except average resultant acceleration is extracted for each axis.

These features are extracted from each axis of the three-dimensional acceleration signal and in total, for each window of acceleration data, 43 (first-feature-bank) and 70 (second-feature-bank) features are extracted respectively, and prior to the feature extraction process, moving average filter of order three is used for noise reduction.

C. Classifier's

A. M. Khan et al., and T. R. D. Saputri et al., showed that support vector machines (SVM) and artificial neural networks (ANN) are superior to other traditional classification methods for user independent physical activity recognition system in [23-25]. K-nearest neighbor (KNN) is also one of the most popular classification method used for smartphone-based physical activity recognition [26]. ELM [27], Naive Bayes [28], Adaptive learning/Ensemble learning (BAG) [29], and Decision tree [30] classifiers are also famous for smartphone-based physical activity recognition system. All these classification methods have shown several advantages in several fields most probably in their respective domains. Once again, given that ours is an exploratory study and the fact that each of these classifiers has shown a good performance in their respective studies, instead of choosing one we decided to explore the use of all of these classifiers except neural networks in this work.

III. EXPERIMENTAL SETTINGS

The following experimental studies are performed using all the data to create both personal and impersonal models. In our first study, using a fixed size of 75 samples per window, the performance of five classifiers are compared to the following three cases on both feature banks and for both *personal* and *impersonal* models as stated in the previous sections.

- Randomly permuted features with normalization.
- Without random permutation and normalization.
- Randomly permuted features without normalization.

In the second study, the best setting for each classifier is chosen and tested multiple times while changing the number of samples in a window, *i.e.*, 25, 50, 75, 100, 125, 150, 175, 200, 225, 250, 275, 300 samples. The goal is to measure the effect of changing the window size on the performance of each classifier for *personal* and *impersonal* model respectively.

In our both studies, the training and testing data is randomly divided and classification results are obtained using 10-fold cross validation process. The values used for different parameters of classifiers are as follows, all these parameters are carefully tuned and optimized.

- SVM with quadratic kernel function is used.
- KNN with Euclidean distance is used, and K is set to 10.
- Adaptive Learning: Ensemble model (BAG) with tree model and the number of weak classifiers are set to 50.
- Decision Tree: The numbers of trees are set to 85

IV. EXPERIMENTAL RESULTS AND DISCUSSION

This section contains the obtained results for smartwatch-based physical activity recognition system. To validate our system we conduct different experiments. Our first experiment is both personal and impersonal model based physical activity recognition analyses. In this experiment, we conduct a detailed comparison of two different feature banks and five classifiers for both personal and impersonal models. Our second experiment explains the physical activity recognition process behavior with a different number of samples per window within the best settings obtained in our first experiment. Finally, the third experiment presents the single subject cross-validation recognition for each activity for both personal and impersonal models individually.

All these experiments are based on 10-fold cross validation process. All the experiments are carried out using Matlab R2014b, installed on core i5 and 8GB of RAM machine.

In the introduction section, we stated some important research questions which our explanatory study seeks to provide the basis of answers. The answers to those questions, based on the obtained results, are as follows: Based on our findings, yes, the features used in existing smartphone-based physical activity recognition studies can also be used for the smartwatch-based physical activity recognition.

If we consider normalized and random permutation feature space, classifiers perform better opposed to the case of without normalization and random permutation in several cases.

Table I to **Table IV** present the 98% confidence intervals about overall physical activity recognition rate. Using pairwise T-tests between groups of normalized/randomly permuted and unnormalized/non-permuted data at the 98% confidence level.

Statistically significant results are in boldface, shows decision trees and SVM classifiers are statistically better when normalized and randomly permuted features are used. This increase was as much as almost 50% (from 40% to 90% for the impersonal model and 94% to 98% for the personal model) looking at **Table I** and **Table II** with 43 number of features. Other classifiers are also statistically better using normalized features in a number of cases. For 70 number of feature-bank,

we again used pairwise T-tests between groups of normalized/randomly permuted and unnormalized/non-permuted data at the 97% - 98% confidence level.

Statistically significant results are in boldface, shows in all cases again decision trees, and SVM classifiers are statistically better when normalized features are used. This increase was as much as almost 10% (from 87% to 97% for the personal model) looking at **Table III** and **Table IV**. **Table V** to **Table VIII** shows single subject cross-validation process for each activity recognition.

Examining the overall and single subject cross validation accuracy of all classifiers, each personal, and the impersonal model becomes statistically significant in a number of cases. This leads us to prefer the use of normalization and random permutation in future applications of this method and in practical implementations.

All of our chosen classifiers provide acceptable performance but decision tree and SVM are found to be better than other classifiers and have a number of other attractive features to their applicability.

In terms of the applicability of the smartwatch system, decision tree and SVM have smaller confidence intervals implying that they have more reliability in their training than other classification models. In terms of the applicability of the smartwatch system, the personal model has smaller confidence intervals implying that personal model has more reliability overall accuracies for both numbers of feature banks.

Looking at **Table I** to **Table IV**, KNN, Decision trees, and SVM perform much better in the personal model for both number of features with normalization and for overall accuracy prospect; decision trees outperformed then KNN and SVM. The highest obtained accuracies are in bold face. For further analysis, the best-recommended system settings are 70 features normalized and randomly permuted used by Decision tree and SVM classifier to recognize the individual's activity on a smartwatch.

Given a fixed amount of data, the performance of KNN and SVM decreases significantly, when the window size is increased as it reduces the number of training samples. Interestingly, this does not affect decision tree classifier. Since decision tree, KNN and SVM classifiers trained, using 70 normalized and randomly permuted features happens to be the best setting for smartwatch based physical activity recognition system; it is chosen and tested multiple times while changing the size of samples per window as explained above.

Results are summarized in **Fig. 2**, which presents the overall classification accuracy with 98% confidence interval. According to these results, decision tree classifier shows higher accuracy for every size of the window. The performance of SVM and KNN through good but is relatively less than that of the decision tree in all cases.

Overall, decision trees performance happens to be best followed by SVM, as their performance did not much degraded when changing the size of samples per window. On the other hand, the performance of KNN reduced significantly as the window size is increased. We think that it is because we have a fixed amount of data, so a bigger window size results in a smaller number of training samples. To confirm this, the

TABLE I: Overall Classification Accuracy and Confidence Interval for **Impersonal Model** with **43 Features** extracted using **75 samples per window**. Where *NR* = *Normalized*, *UNR* = *Unnormalized*, *RP* = *Randomly Permuted*, and *NRP* = *Non Randomly Permuted*.

Classifiers	Walking			Walking Up			Walking Down			Running			Jogging		
	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP
Decision Tree	0.90±0.08	0.89±0.09	0.41±0.26	0.90±0.07	0.90±0.09	0.46±0.20	0.87±0.12	0.87±0.12	0.60±0.13	0.82±0.18	0.82±0.18	0.61±0.15	0.93±0.06	0.94±0.06	0.85±0.10
Naive Bayes	0.86±0.06	0.86±0.06	0.63±0.18	0.78±0.12	0.78±0.12	0.36±0.15	0.76±0.16	0.76±0.16	0.42±0.11	0.55±0.18	0.55±0.18	0.59±0.17	0.86±0.02	0.86±0.02	0.86±0.04
KNN	0.86±0.08	0.86±0.08	0.71±0.08	0.62±0.07	0.62±0.07	0.18±0.07	0.70±0.13	0.70±0.13	0.38±0.12	0.61±0.17	0.61±0.17	0.56±0.13	0.91±0.06	0.91±0.06	0.88±0.04
SVM	0.94±0.07	0.94±0.06	0.65±0.32	0.91±0.04	0.91±0.04	0.25±0.27	0.81±0.10	0.81±0.10	0.43±0.20	0.76±0.13	0.76±0.13	0.55±0.16	0.92±0.03	0.92±0.03	0.88±0.05
BAG	0.91±0.08	0.90±0.08	0.43±0.24	0.89±0.09	0.89±0.09	0.42±0.19	0.87±0.12	0.87±0.12	0.60±0.13	0.81±0.18	0.81±0.18	0.60±0.16	0.94±0.05	0.93±0.06	0.85±0.09

TABLE II: Overall Classification Accuracy and Confidence Interval for **Personal Model** with **43 Features** extracted using **75 samples per window**

Classifiers	Walking			Walking Up			Walking Down			Running			Jogging		
	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP
Decision Tree	0.98±0.01	0.88±0.09	0.94±0.01	0.93±0.02	0.78±0.06	0.69±0.10	0.98±0.05	0.75±0.03	0.75±0.07	0.95±0.01	0.95±0.01	0.78±0.09	0.98±0.01	0.95±0.06	0.94±0.01
Naive	0.91±0.02	0.72±0.02	0.87±0.08	0.77±0.11	0.61±0.09	0.55±0.07	0.81±0.07	0.60±0.08	0.64±0.12	0.61±0.19	0.67±0.13	0.65±0.07	0.87±0.08	0.73±0.07	0.87±0.06
KNN	0.92±0.07	0.79±0.07	0.87±0.07	0.64±0.09	0.45±0.11	0.22±0.05	0.62±0.12	0.53±0.10	0.44±0.10	0.77±0.07	0.72±0.12	0.71±0.08	0.91±0.08	0.88±0.09	0.92±0.03
SVM	0.93±0.07	0.76±0.01	0.93±0.01	0.79±0.09	0.74±0.07	0.56±0.16	0.90±0.03	0.68±0.04	0.6±0.10	0.87±0.06	0.83±0.09	0.74±0.07	0.97±0.01	0.94±0.06	0.94±0.01
BAG	0.98±0.01	0.88±0.09	0.87±0.09	0.85±0.09	0.80±0.08	0.66±0.06	0.89±0.07	0.75±0.04	0.72±0.09	0.95±0.02	0.95±0.02	0.72±0.10	0.99±0.01	0.92±0.08	0.94±0.01

TABLE III: Overall Classification Accuracy and Confidence Interval for **Personal Model** with **70 Features** extracted using **75 samples per window**

Classifiers	Walking			Walking Up			Walking Down			Running			Jogging		
	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP
Decision Tree	0.98±0.01	0.87±0.09	0.90±0.08	0.84±0.09	0.67±0.04	0.62±0.13	0.79±0.11	0.74±0.12	0.74±0.04	0.86±0.07	0.87±0.06	0.72±0.07	0.97±0.01	0.94±0.07	0.93±0.01
Naive	0.88±0.02	0.75±0.08	0.77±0.09	0.65±0.16	0.51±0.10	0.53±0.12	0.62±0.15	0.47±0.09	0.60±0.08	0.58±0.12	0.55±0.06	0.65±0.14	0.88±0.02	0.68±0.02	0.83±0.07
KNN	0.96±0.01	0.93±0.07	0.79±0.09	0.60±0.10	0.46±0.08	0.19±0.11	0.49±0.16	0.46±0.10	0.17±0.06	0.58±0.14	0.59±0.16	0.26±0.14	0.95±0.02	0.95±0.02	0.90±0.02
SVM	0.98±0.01	0.91±0.08	0.87±0.07	0.89±0.08	0.77±0.08	0.52±0.07	0.86±0.08	0.76±0.08	0.54±0.08	0.91±0.02	0.85±0.09	0.66±0.09	0.97±0.01	0.90±0.10	0.92±0.01
BAG	0.97±0.01	0.87±0.09	0.90±0.07	0.86±0.07	0.69±0.04	0.68±0.10	0.84±0.05	0.65±0.09	0.65±0.06	0.90±0.03	0.86±0.05	0.72±0.08	0.97±0.01	0.87±0.10	0.91±0.07

TABLE IV: Overall Classification Accuracy and Confidence Interval for **Impersonal Model** with **70 Features** extracted using **75 samples per window**.

Classifiers	Walking			Walking Up			Walking Down			Running			Jogging		
	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP
Decision Tree	0.91±0.07	0.91±0.07	0.50±0.21	0.82±0.09	0.81±0.09	0.45±0.19	0.64±0.12	0.64±0.12	0.57±0.10	0.62±0.21	0.63±0.21	0.54±0.18	0.86±0.07	0.86±0.07	0.85±0.094
Naive	0.76±0.09	0.73±0.08	0.39±0.11	0.54±0.08	0.14±0.03	0.50±0.07	0.53±0.11	0.13±0.03	0.46±0.07	0.42±0.10	0.16±0.07	0.54±0.17	0.81±0.05	0.80±0.11	0.80±0.08
KNN	0.89±0.05	0.89±0.05	0.73±0.08	0.54±0.08	0.54±0.08	0.14±0.03	0.42±0.13	0.42±0.13	0.13±0.03	0.31±0.11	0.31±0.11	0.16±0.07	0.86±0.06	0.88±0.09	0.80±0.11
SVM	0.97±0.02	0.97±0.02	0.84±0.12	0.90±0.04	0.90±0.04	0.12±0.07	0.82±0.06	0.82±0.06	0.50±0.1	0.80±0.09	0.80±0.09	0.60±0.06	0.94±0.03	0.94±0.03	0.87±0.06
BAG	0.90±0.07	0.90±0.08	0.51±0.20	0.80±0.09	0.80±0.10	0.44±0.18	0.63±0.12	0.63±0.12	0.57±0.09	0.61±0.21	0.61±0.21	0.54±0.18	0.86±0.07	0.86±0.07	0.85±0.09

same experiment is repeated for each activity individually. The entire results are summarized in **Table I** to **Table IV** and **Fig. 2**, which confirms our hypothesis. The additional experiments on single subject cross-validations are presented in **Table V** to **Table VIII** for both feature banks and both personal and impersonal models respectively.

V. CONCLUSION

Feature banks created by different smartphone-based physical activity recognition studies can be used for physical activity recognition on smartwatches because smartphone also uses accelerometer sensor, and hence the same set of features is acceptable for a smartwatch. Decision trees, SVM and KNN showed the best results with a minor difference; additionally, Naive Bayes and ensemble learning with Bag classifiers also produce a good performance.

Additionally, feature normalization and random permutation processes significantly improves the classification performance in several cases. In addition to above, without any doubt, changing window size affects the recognition accuracy.

From results, we observed that every activity and for every classifier results of activity recognition are highly correlated with window size. In general, every classifier performs well when features are extracted using 25-to-125 samples per window. Personal models perform better for smartwatch physical activity recognition providing an average accuracy of 98%. Furthermore, the impersonal model produces 94% and 90% accuracy respectively with the same settings of the personal model.

Finally, the recommended combination for smartwatch-based physical activity recognition system is decision tree classifier trained using 25-to-125 samples per window of

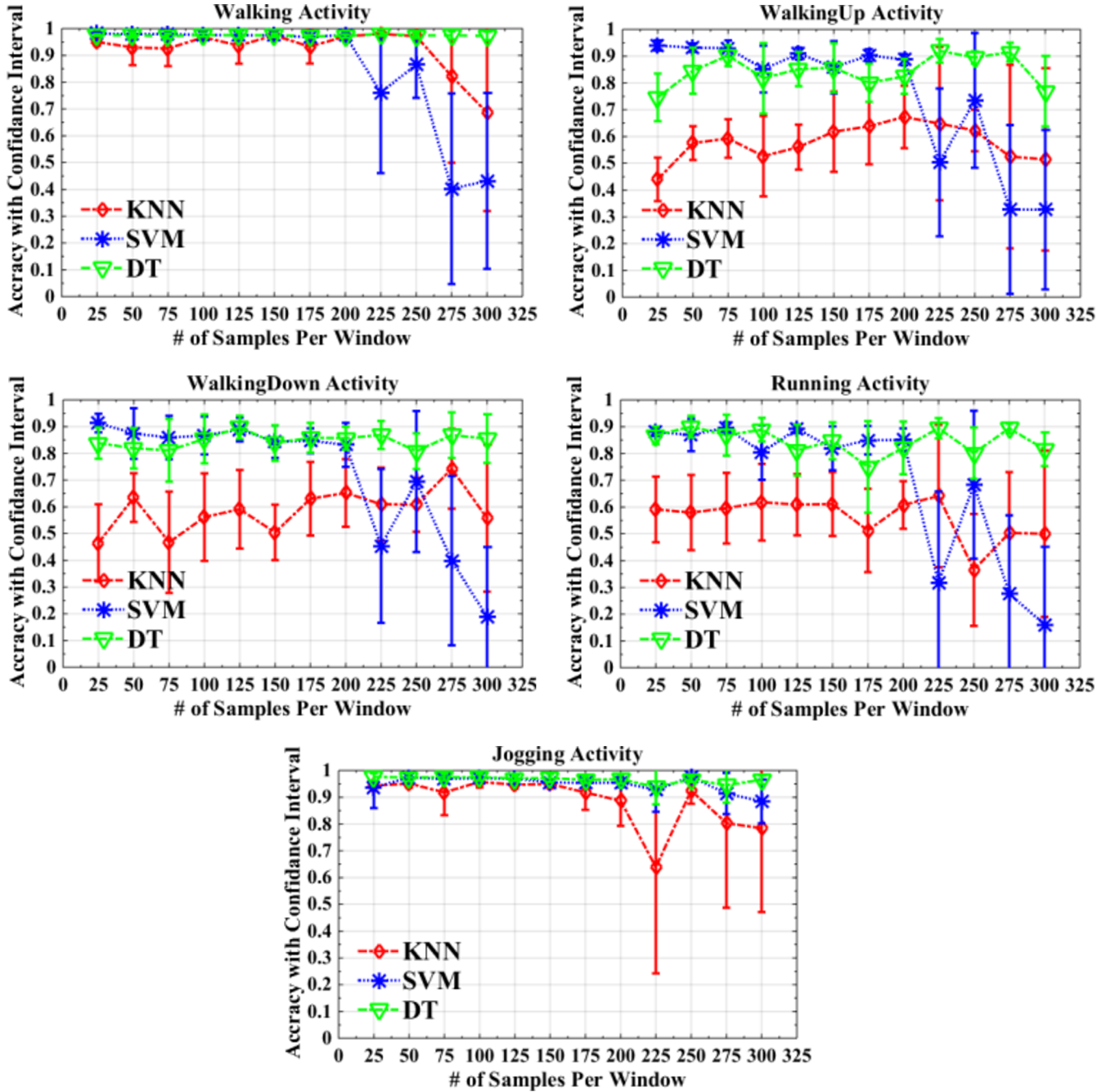


Fig. 2: Overall Accuracy for different Activities with different number of samples per window.

normalized and randomly permuted features. In our future work, we will investigate the effects of several linear/non-linear supervised/semi-supervised/unsupervised feature selection methods.

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TABLE V: Single Subject cross-validation based accuracy analysis for **Impersonal Model with 43 Features** extracted using 75 samples per window.

Users	Walking			Walking Up			Walking Down			Running			Jogging		
	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP
Decision Trees Classifier															
User 1	0.8706	0.8617	0.0595	0.9714	0.9689	0.4646	0.7909	0.7942	0.8123	0.6807	0.6922	0.5766	0.9759	0.9765	0.9175
User 2	0.7145	0.6961	0.0839	0.9768	0.9794	0.7112	0.9944	0.9940	0.7330	0.9724	0.9688	0.7371	0.9844	0.9871	0.8945
User 3	0.9757	0.9761	0.3730	0.7431	0.7000	0.7931	0.9497	0.9492	0.4230	0.9274	0.9259	0.7513	0.8691	0.8864	0.6500
User 4	0.9935	0.9894	0.5847	0.9380	0.9390	0.2432	0.9277	0.9312	0.4050	0.4287	0.4201	0.2616	0.9911	0.9941	0.9410
User 5	0.8998	0.8825	0.8987	0.9500	0.9442	0.2238	0.9690	0.9665	0.6171	0.9164	0.9126	0.7327	0.9687	0.9646	0.9400
User 6	0.9563	0.9518	0.4594	0.8450	0.8462	0.2972	0.6004	0.6025	0.6017	0.9804	0.9812	0.5938	0.8039	0.7993	0.7626
Naive Bayes Classifier															
User 1	0.7597	0.7597	0.2070	0.8883	0.8883	0.3495	0.6883	0.6883	0.5390	0.2448	0.2448	0.4323	0.8522	0.8522	0.8595
User 2	0.7979	0.7979	0.6905	0.9270	0.9270	0.3863	0.9742	0.9742	0.6137	0.7647	0.7647	0.7235	0.8855	0.8855	0.8909
User 3	0.9179	0.9179	0.6589	0.6373	0.6373	0.6961	0.8907	0.8907	0.3060	0.7411	0.7411	0.7614	0.8287	0.8287	0.7832
User 4	0.9369	0.9369	0.8342	0.8545	0.8545	0.2723	0.7525	0.7525	0.2624	0.3171	0.3171	0.2317	0.8614	0.8614	0.9242
User 5	0.8667	0.8667	0.5657	0.7791	0.7791	0.2500	0.8734	0.8734	0.4430	0.6918	0.6918	0.7673	0.9038	0.9038	0.8308
User 6	0.8847	0.8847	0.8176	0.5663	0.5663	0.1847	0.4017	0.4017	0.3473	0.5134	0.5134	0.6205	0.8256	0.8256	0.8479
KNN Classifier															
User 1	0.7523	0.7523	0.6728	0.5680	0.5680	0.1359	0.6299	0.6299	0.4416	0.4688	0.4688	0.5365	0.9179	0.9179	0.8942
User 2	0.7370	0.7370	0.6279	0.7854	0.7854	0.2017	0.8970	0.8970	0.3605	0.7765	0.7765	0.6882	0.9655	0.9655	0.9091
User 3	0.9661	0.9661	0.8268	0.6618	0.6618	0.3235	0.7814	0.7814	0.1913	0.7310	0.7310	0.6853	0.8759	0.8759	0.8444
User 4	0.8901	0.8901	0.6811	0.6150	0.6150	0.1878	0.7030	0.7030	0.2327	0.2317	0.2317	0.2378	0.9778	0.9778	0.9298
User 5	0.9371	0.9371	0.8495	0.5698	0.5698	0.0698	0.7848	0.7848	0.5190	0.6667	0.6667	0.5723	0.9615	0.9615	0.9269
User 6	0.8985	0.8985	0.6127	0.5422	0.5422	0.1606	0.4184	0.4184	0.5565	0.7813	0.7813	0.6339	0.7658	0.7658	0.8051
SVM Classifier															
User 1	0.9760	0.9760	0.1257	0.9223	0.9223	0.3204	0.8377	0.9657	0.6883	0.4740	0.4740	0.4792	0.9398	0.9380	0.9033
User 2	0.7710	0.7710	0.8497	0.9742	0.9742	0.0172	0.9657	0.8361	0.6695	0.8706	0.8706	0.7059	0.9164	0.9164	0.9073
User 3	0.9679	0.9679	0.1304	0.8137	0.8137	0.8971	0.8361	0.7277	0.2787	0.8985	0.8985	0.6954	0.8654	0.8654	0.7815
User 4	0.9874	0.9874	0.9550	0.9061	0.9061	0.0329	0.7277	0.8608	0.2772	0.7378	0.7378	0.1707	0.9464	0.9464	0.9575
User 5	0.9600	0.9600	0.9448	0.9302	0.9302	0.0814	0.8608	0.6109	0.5823	0.6792	0.6792	0.6604	0.9788	0.9788	0.9192
User 6	0.9776	0.9776	0.8864	0.9197	0.9197	0.1365	0.6109	0.9657	0.0669	0.8839	0.8839	0.5848	0.8991	0.8974	0.8308
Ensemble Learning-BAG Classifier															
User 1	0.8784	0.8656	0.0980	0.9694	0.9670	0.3529	0.7805	0.7864	0.7968	0.6734	0.6786	0.5661	0.9763	0.9748	0.9224
User 2	0.7086	0.7038	0.1243	0.9712	0.9721	0.6236	0.9944	0.9953	0.7416	0.9641	0.9647	0.7429	0.9827	0.9811	0.8982
User 3	0.9757	0.9759	0.3900	0.6730	0.6985	0.7902	0.9475	0.9497	0.4240	0.9279	0.9228	0.7472	0.8692	0.8764	0.6458
User 4	0.9894	0.9874	0.5782	0.9376	0.9366	0.2531	0.9292	0.9233	0.4183	0.3988	0.4073	0.2317	0.9930	0.9904	0.9442
User 5	0.8989	0.8970	0.9006	0.9517	0.9448	0.2017	0.9614	0.9608	0.6253	0.8994	0.9031	0.7409	0.9677	0.9662	0.9448
User 6	0.9546	0.9497	0.4305	0.8454	0.8426	0.2924	0.6167	0.6079	0.6004	0.9772	0.9777	0.5960	0.8373	0.8113	0.7576

TABLE VI: Single Subject cross-validation based accuracy analysis for **Personal Model with 43 Features** extracted using 75 samples per window.

Users	Walking			Walking Up			Walking Down			Running			Jogging		
	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP
Decision Trees Classifier															
User 1	0.9815	0.7889	0.9500	0.9073	0.7366	0.8000	0.9067	0.7067	0.5867	0.9632	0.9368	0.7895	0.9908	0.9945	0.9633
User 2	0.9820	0.9802	0.9604	0.8957	0.7348	0.8217	0.7870	0.7826	0.8043	0.9471	0.9647	0.8765	0.9836	0.9873	0.9382
User 3	0.9786	0.7768	0.9214	0.9450	0.7500	0.6750	0.9278	0.7167	0.7611	0.9333	0.9128	0.5487	0.9772	0.9579	0.9193
User 4	0.9874	0.9946	0.9568	0.9714	0.7619	0.5000	0.9600	0.7400	0.8100	0.9500	0.9625	0.7875	0.9833	0.9815	0.9500
User 5	0.9867	0.9905	0.9314	0.9235	0.7412	0.7176	0.9226	0.7290	0.8129	0.9548	0.9484	0.8581	0.9865	0.7885	0.9519
User 6	0.9741	0.7741	0.9397	0.9102	0.9306	0.5959	0.8894	0.8000	0.6979	0.9636	0.9682	0.7955	0.9829	0.9846	0.9282
Naive Bayes Classifier															
User 1	0.9019	0.6981	0.9000	0.8049	0.6146	0.4732	0.6800	0.4467	0.3467	0.5000	0.6474	0.5421	0.8789	0.7046	0.8844
User 2	0.9099	0.7171	0.9027	0.7087	0.5087	0.5000	0.8174	0.6478	0.7391	0.8412	0.8412	0.6118	0.9109	0.9036	0.8982
User 3	0.9518	0.7571	0.6589	0.9250	0.7300	0.6950	0.8889	0.6778	0.7500	0.7846	0.5949	0.7897	0.8912	0.6421	0.8930
User 4	0.9279	0.7423	0.9261	0.9429	0.7381	0.4952	0.8750	0.6600	0.6050	0.7500	0.7312	0.7250	0.9296	0.7315	0.7278
User 5	0.9219	0.7200	0.9105	0.6176	0.6176	0.6294	0.8903	0.6710	0.7355	0.6194	0.8194	0.6258	0.9308	0.7231	0.9269
User 6	0.8741	0.6862	0.8931	0.6490	0.4735	0.4776	0.7319	0.4809	0.6723	0.1955	0.3955	0.6273	0.6735	0.6803	0.8906
KNN Classifier															
User 1	0.7333	0.7389	0.6852	0.7122	0.4732	0.2585	0.5800	0.3467	0.3667	0.8316	0.8211	0.6895	0.9450	0.9541	0.9376
User 2	0.9604	0.7477	0.9045	0.5217	0.2783	0.1826	0.8391	0.6087	0.4435	0.8059	0.8412	0.8059	0.9691	0.9691	0.9164
User 3	0.9643	0.7571	0.9054	0.5400	0.5900	0.2050	0.7222	0.5222	0.3389	0.8051	0.6103	0.7436	0.9561	0.9491	0.9316
User 4	0.9568	0.9658	0.9351	0.8333	0.6333	0.1333	0.4450	0.6250	0.6350	0.6813	0.4813	0.7688	0.8741	0.6889	0.8481
User 5	0.9638	0.7600	0.9219	0.6765	0.4118	0.3000	0.6452	0.6581	0.5032	0.6387	0.6645	0.7355	0.9769	0.7769	0.9558
User 6	0.9397	0.7466	0.8759	0.5673	0.3143	0.2408	0.5064	0.4340	0.3234	0.8773	0.8773	0.5318	0.7316	0.9350	0.9009
SVM Classifier															
User 1	0.7481	0.7370	0.9315	0.8049	0.6732	0.6000	0.8400	0.6200	0.7333	0.7263	0.9158	0.7474	0.9688	0.9761	0.9431
User 2	0.9622	0.7658	0.9279	0.6522	0.6609	0.8261	0.9435	0.7565	0.7696	0.8824	0.6882	0.8059	0.9855	0.9855	0.9327
User 3	0.9714	0.7679	0.9089	0.7500	0.7250	0.7450	0.8556	0.6333	0.6889	0.8974	0.6769	0.7538	0.9719	0.9579	0.9246
User 4	0.9838	0.7892	0.9640	0.9238	0.7286	0.3095	0.9350	0.7150	0.7500	0.8500	0.8375	0.5938	0.9685	0.9685	0.9537
User 5	0.9581	0.7562	0.9067	0.9353	0.7235	0.5000	0.9226	0.6968	0.7484	0.8968	0.9161	0.8194	0.9673	0.7769	0.9596
User 6	0.9552	0.7638	0.9414	0.6939	0.9020	0.4082	0.8851	0.6638	0.4511	0.9636	0.9364	0.7045	0.9573	0.9607	0.9162
Ensemble Learning-BAG Classifier															
User 1	0.9870	0.7852	0.9481	0.7122	0.7317	0.7707	0.9133	0.7067	0.5933	0.9632	0.9421	0.7842	0.9872	0.7963	0.9486
User 2	0.9838	0.9874	0.9604	0.8870	0.7261	0.5652	0.9783	0.7826	0.8174	0.9588	0.9647	0.8706	0.9873	0.9909	0.9491
User 3	0.9786	0.7732	0.9179	0.9450	0.9500	0.6400	0.9278	0.7111	0.5556	0.9077	0.9026	0.8154	0.9807	0.9561	0.9105
User 4	0.9874	0.9964	0.9495	0.9619	0.7714	0.6762	0.9650	0.7400	0.8350	0.9375	0.9563	0.6000	0.9778	0.9778	0.9444
User 5	0.9867	0.9886	0.7276	0.9059	0.7235	0.7118	0.7290	0.7161	0.7871	0.9677	0.9548	0.6452	0.9942	0.7846	0.9462
User 6	0.9741	0.7724	0.7138	0.6980	0.9224	0.5918	0.8553	0.8255	0.7064	0.9727	0.9591	0.5955	0.9846	0.9897	0.9197

TABLE VII: Single Subject cross-validation based accuracy analysis for **Personal Model with 70 Features** extracted using 75 samples per window.

Users	Walking			Walking Up			Walking Down			Running			Jogging		
	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP
Decision Trees Classifier															
User 1	0.9593	0.9574	0.7074	0.6780	0.6780	0.7171	0.5800	0.5467	0.7000	0.6947	0.9053	0.7632	0.9908	0.9908	0.9541
User 2	0.9748	0.7640	0.9405	0.8913	0.7217	0.6130	0.9217	0.9522	0.7739	0.9235	0.7235	0.8176	0.9909	0.9873	0.9218
User 3	0.9821	0.7821	0.9357	0.9550	0.7500	0.4950	0.9389	0.7111	0.7167	0.8769	0.8872	0.7487	0.9421	0.9246	0.9105
User 4	0.9820	0.9856	0.9586	0.9286	0.7143	0.6762	0.8200	0.5950	0.8100	0.8562	0.9000	0.6062	0.9778	0.7741	0.9389
User 5	0.9790	0.7733	0.9257	0.8412	0.6235	0.8294	0.6903	0.8710	0.7548	0.9290	0.9419	0.6129	0.9750	0.9731	0.9462
User 6	0.9741	0.9810	0.9172	0.7265	0.7102	0.3673	0.7830	0.7489	0.6894	0.8727	0.8773	0.7773	0.9641	0.9675	0.9248
Naive Bayes Classifier															
User 1	0.8593	0.6333	0.7870	0.5073	0.4634	0.6537	0.5467	0.3733	0.6200	0.5368	0.5632	0.7211	0.8789	0.6642	0.8917
User 2	0.8757	0.8793	0.6505	0.3609	0.3826	0.5696	0.7478	0.5739	0.7739	0.7176	0.5529	0.7941	0.8636	0.6727	0.7000
User 3	0.9161	0.7179	0.6071	0.8750	0.6650	0.6300	0.7889	0.5722	0.4667	0.5333	0.6462	0.7590	0.8561	0.6614	0.8842
User 4	0.8955	0.6991	0.8541	0.8381	0.6524	0.6000	0.5050	0.4550	0.5400	0.6000	0.4063	0.4625	0.9130	0.7148	0.7333
User 5	0.8857	0.8800	0.8781	0.5765	0.3647	0.2588	0.8065	0.5613	0.6065	0.7613	0.5871	0.7677	0.9096	0.7135	0.9154
User 6	0.8638	0.6879	0.8448	0.7224	0.5429	0.4612	0.3362	0.3064	0.5745	0.3273	0.5318	0.3955	0.8598	0.6547	0.8838
KNN Classifier															
User 1	0.9648	0.9426	0.8944	0.4390	0.3951	0.1268	0.4267	0.4667	0.1600	0.7053	0.7158	0.1842	0.9835	0.9725	0.9138
User 2	0.9532	0.9532	0.8685	0.6565	0.5087	0.1391	0.5174	0.5174	0.2217	0.5118	0.7118	0.2000	0.9545	0.9600	0.8927
User 3	0.9625	0.9732	0.8536	0.7700	0.5950	0.4650	0.7389	0.5278	0.1444	0.4718	0.5795	0.2974	0.9263	0.9070	0.8526
User 4	0.9550	0.9568	0.7964	0.5048	0.4810	0.2048	0.3450	0.5200	0.2700	0.3250	0.2562	0.0938	0.9481	0.9574	0.9204
User 5	0.9771	0.7638	0.7048	0.5471	0.3176	0.1353	0.7161	0.5484	0.1613	0.7742	0.7935	0.5935	0.9635	0.9654	0.9058
User 6	0.9603	0.9759	0.6190	0.6898	0.4612	0.0980	0.2213	0.2043	0.0596	0.6955	0.4727	0.2182	0.9675	0.9556	0.8940
SVM Classifier															
User 1	0.9778	0.7759	0.8852	0.8634	0.7317	0.4000	0.8067	0.8067	0.5600	0.9000	0.9263	0.5105	0.9706	0.9725	0.9193
User 2	0.9946	0.9910	0.9297	0.9522	0.7652	0.4826	0.9348	0.7435	0.4870	0.9000	0.7294	0.5353	0.9909	0.9855	0.9200
User 3	0.9804	0.9839	0.8732	0.9150	0.7200	0.6150	0.9333	0.9389	0.4333	0.8718	0.8769	0.7231	0.9439	0.7175	0.9123
User 4	0.9820	0.9748	0.9063	0.9667	0.7619	0.6048	0.9100	0.7000	0.7100	0.9313	0.9437	0.7375	0.9667	0.7778	0.9241
User 5	0.9829	0.9752	0.6990	0.6882	0.6588	0.4765	0.8968	0.7032	0.4516	0.9097	0.6968	0.7677	0.9827	0.9808	0.9346
User 6	0.9759	0.7862	0.8983	0.9510	0.9633	0.5673	0.6851	0.6638	0.5872	0.9273	0.9545	0.7091	0.9675	0.9641	0.8872
Ensemble Learning-BAG Classifier															
User 1	0.9556	0.9500	0.9241	0.8780	0.6829	0.7317	0.7333	0.5133	0.6467	0.8947	0.8842	0.8000	0.9908	0.9890	0.9596
User 2	0.9658	0.7730	0.9405	0.8826	0.7087	0.8261	0.9087	0.7174	0.5696	0.9353	0.7529	0.8000	0.9873	0.9873	0.9364
User 3	0.9821	0.7804	0.9268	0.9500	0.7400	0.4700	0.8944	0.7056	0.5500	0.8667	0.8564	0.7487	0.9386	0.7228	0.9211
User 4	0.9874	0.9802	0.9532	0.6905	0.6952	0.6333	0.8250	0.5150	0.6650	0.8625	0.9000	0.6000	0.9741	0.7741	0.9444
User 5	0.9619	0.7695	0.9390	0.8235	0.6000	0.7941	0.8645	0.6903	0.7613	0.9032	0.9226	0.8065	0.9750	0.7750	0.9519
User 6	0.9741	0.9724	0.7241	0.9061	0.6939	0.6367	0.8170	0.7872	0.6936	0.9500	0.8409	0.5864	0.9761	0.9658	0.7231

TABLE VIII: Single Subject cross-validation based accuracy analysis for **Impersonal Model with 70 Features** extracted using 75 samples per window.

Users	Walking			Walking Up			Walking Down			Running			Jogging		
	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP	NR-RP	NR-NRP	UNR-RP
Decision Trees Classifier															
User 1	0.7455	0.7412	0.3338	0.9296	0.9286	0.3888	0.7896	0.7896	0.7383	0.3563	0.3677	0.3885	0.8648	0.8739	0.9086
User 2	0.9370	0.9458	0.1308	0.9682	0.9665	0.8129	0.7210	0.7223	0.6605	0.8600	0.8524	0.7094	0.8445	0.8320	0.8367
User 3	0.9846	0.9832	0.5609	0.7505	0.7471	0.6240	0.6268	0.6311	0.5557	0.8437	0.8508	0.7061	0.7346	0.7392	0.6330
User 4	0.9524	0.9532	0.6688	0.7906	0.7850	0.4028	0.6485	0.6470	0.3876	0.2348	0.2274	0.1835	0.9762	0.9773	0.9486
User 5	0.9617	0.9636	0.8874	0.8023	0.7849	0.1552	0.6791	0.6747	0.5766	0.7264	0.7157	0.7535	0.9442	0.9456	0.9133
User 6	0.8523	0.8491	0.4219	0.6711	0.6643	0.3040	0.3448	0.3552	0.5130	0.7254	0.7513	0.4955	0.7814	0.7879	0.8374
Naive Bayes Classifier															
User 1	0.6192	0.8429	0.4455	0.7087	0.1408	0.3883	0.5649	0.1039	0.5649	0.2396	0.1719	0.3646	0.7646	0.8102	0.8266
User 2	0.9123	0.7728	0.3953	0.5536	0.1330	0.5880	0.6609	0.1116	0.5536	0.5118	0.1294	0.7118	0.8582	0.8873	0.8273
User 3	0.8286	0.6982	0.5643	0.4216	0.1961	0.5392	0.5683	0.2022	0.4481	0.5736	0.2792	0.6954	0.7902	0.7115	0.7413
User 4	0.8342	0.5802	0.4432	0.5164	0.0845	0.5164	0.5149	0.1535	0.3960	0.3415	0.0183	0.2378	0.8965	0.9279	0.9205
User 5	0.6724	0.8114	0.1410	0.5291	0.1279	0.5756	0.6076	0.1266	0.4873	0.4969	0.1698	0.7610	0.7404	0.8769	0.6308
User 6	0.7126	0.6713	0.3270	0.4859	0.1767	0.3735	0.2594	0.0879	0.3347	0.3527	0.2188	0.4955	0.8222	0.5573	0.8393
KNN Classifier															
User 1	0.8096	0.8096	0.8429	0.6408	0.6408	0.1408	0.4026	0.4026	0.1039	0.2448	0.2448	0.1719	0.8029	0.8029	0.8102
User 2	0.9141	0.9141	0.7728	0.6438	0.6438	0.1330	0.5794	0.5794	0.1116	0.3235	0.3235	0.1294	0.9182	0.9182	0.8873
User 3	0.9143	0.9143	0.6982	0.5931	0.5931	0.1961	0.5683	0.5683	0.2022	0.5381	0.5381	0.2792	0.8759	0.8759	0.7115
User 4	0.9387	0.9387	0.5802	0.4131	0.4131	0.0845	0.2574	0.2574	0.1535	0.1037	0.1037	0.0183	0.9593	0.9593	0.9279
User 5	0.9733	0.9733	0.8114	0.4767	0.4767	0.1279	0.5380	0.5380	0.1266	0.3019	0.3019	0.1698	0.9231	0.9231	0.8769
User 6	0.8176	0.8176	0.6713	0.4618	0.4618	0.1767	0.2008	0.2008	0.0879	0.3705	0.3705	0.2188	0.7726	0.7726	0.5573
SVM Classifier															
User 1	0.9372	0.9372	0.6007	0.9417	0.9417	0.2233	0.7857	0.7857	0.5909	0.6146	0.6146	0.5313	0.9197	0.9197	0.8832
User 2	0.9517	0.9517	0.9660	0.9828	0.9828	0.0258	0.8712	0.8712	0.6266	0.9059	0.9059	0.6882	0.9655	0.9655	0.8909
User 3	0.9875	0.9875	0.8750	0.8578	0.8578	0.1716	0.8852	0.8852	0.5355	0.9137	0.9137	0.6802	0.8776	0.8776	0.7483
User 4	0.9928	0.9928	0.6883	0.8685	0.8685	0.2066	0.8861	0.8861	0.4208	0.8049	0.8049	0.5183	0.9778	0.9778	0.9482
User 5	0.9867	0.9867	0.9543	0.8663	0.8663	0.0291	0.8291	0.8291	0.5886	0.7358	0.7358	0.5849	0.9654	0.9654	0.9000
User 6	0.9639	0.9639	0.9466	0.8996	0.8996	0.0723	0.6820	0.6820	0.2176	0.8527	0.8527	0.5670	0.9573	0.9573	0.8256
Ensemble Learning-BAG Classifier															
User 1	0.7423	0.7240	0.3532	0.9194	0.9301	0.3888	0.7721	0.7825	0.7123	0.3219	0.3255	0.3906	0.8746	0.8611	0.9111
User 2	0.9331	0.9392	0.1644	0.9665	0.9597	0.7931	0.7120	0.7206	0.6652	0.8288	0.8253	0.7141	0.8393	0.8480	0.8349
User 3	0.9832	0.9852	0.5695	0.7333	0.7216	0.6039	0.6186	0.6235	0.5322	0.8376	0.8365	0.7015	0.7362	0.7392	0.6451
User 4	0.9450	0.9505	0.6701	0.7690	0.7643	0.3911	0.6416	0.6391	0.3856	0.2305	0.2329	0.1951	0.9758	0.9747	0.9444
User 5	0.9598	0.9577	0.8851	0.7628	0.7756	0.1651	0.6918	0.6842	0.5766	0.7182	0.7170	0.7440	0.9415	0.9463	0.9137
User 6	0.8522	0.8515	0.4389	0.6627	0.6514	0.2892	0.3477	0.3485	0.5188	0.7201	0.7076	0.4906	0.7805	0.7701	0.8487

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