Sensor-Based Human Activities Recognition and User's Authentication Using Machine Learning Algorithms

Author

RAB NAWAZ

MS-18-CE-00000276416

Supervisor

DR. ALI HASSAN

DEPARTMENT OF COMPUTER & SOFTWARE ENGINEERING

COLLEGE OF ELECTRICAL & MECHANICAL ENGINEERING

NATIONAL UNIVERSITY OF SCIENCES AND TECHNOLOGY

ISLAMABAD

JULY, 2021

Sensor-Based Human Activities Recognition and User's Authentication Using Machine Learning Algorithms

Author

RAB NAWAZ

MS-18-CE-00000276416

A thesis submitted in partial fulfillment of the requirements for the degree of

MS Computer Engineering

Thesis Supervisor

DR. ALI HASSAN

Thesis Supervisor's Signature: ______________________________________

DEPARTMENT OF COMPUTER & SOFTWARE ENGINEERING

COLLEGE OF ELECTRICAL & MECHANICAL ENGINEERING

NATIONAL UNIVERSITY OF SCIENCES AND TECHNOLOGY, ISLAMABAD

JULY, 2021

Declaration

I certify that this research work titled "*SensorBased Human Activities Recognition and User's Authentication Using Machine Learning Algorithms*" is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources has been properly acknowledged/referred.

Signature of Student

RAB NAWAZ

MS-18-CE-00000276416

Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical, and spelling mistakes. The thesis is also according to the format given by the university.

Signature of Student

RAB NAWAZ

MS-18-CE-00000276416

Acknowledgments

All praise and glory to Almighty Allah (the most glorified, the highest) who gave me the courage, patience, knowledge, and ability to carry out this work and to persevere and complete it satisfactorily. Undoubtedly, HE eased my way and without HIS blessings I can achieve nothing.

I would like to express my sincere gratitude to my advisor Dr. Ali Hassan for boosting my morale and for his continual assistance, motivation, dedication, and invaluable guidance in my quest for knowledge. I am blessed to have such a cooperative advisor and kind mentor for my research.

Along with my advisor, I would like to acknowledge my entire thesis committee: Dr. Farhan Riaz, Dr. Farhan Hussain, Dr. Umar Farooq and Dr. Ahsan Shahzad for their cooperation and prudent suggestions.

My acknowledgment would be incomplete without thanking the biggest source of my strength, my family. I am profusely thankful to my beloved parents who raised me when I was not capable of walking and continued to support me throughout every department of my life. I also want to say thanks to my supportive Brothers, Sister, and Wife who were with me through my thick and thin.

Finally, I would like to express my gratitude to all my friends and the individuals who have encouraged and supported me through this entire period.

Dedicated to my exceptional parents: ***in the memory of Haji Muhammad Ramzan who supported me throughout my life especially providing me a paved path in getting the best education & Manzoor Maai****, supportive brothers, Sister and my Wife whose tremendous support and cooperation led me to this accomplishment. At the end, this thesis is dedicated to all those who believe in the richness of learning*

Abstract

Human Activity Recognition is a significant zone of machine learning research because of its uses in many fields such as health care, flexible interfaces, and a smart world, human behavior detection is gaining a lot of interest. Activities are often more abstract than words, as they're more contextually symbolic of a human's daily life. Techniques for recognizing actions from sensor-generated data are well-developed. However, there have been few attempts to target sensor-based behavior detection. The present-age smartphone is exceptional with a cutting-edge processor, more memory storage, a long-lasting battery, and highly effective underlying sensors. This gives a chance to open up new areas of data mining for human activities recognition. The Internet of Things is a quickly developing worldview for keen urban communities that gives a way of correspondence, recognizable proof, and detecting capacities among actually circulated gadgets. With the development of the Internet of Things (IoTs), client reliance on savvy frameworks and administrations, for example, brilliant machines, cell phones, security, and medical services applications, has been expanded. This requests secure verification instruments to save the clients' protection while collaborating with savvy gadgets. In this paper, a framework has been proposed for activities recognition and user authentication. We worked out with three publically available datasets WISDM, MobiAct, and MobiAct_V2 for human activities recognition. For user authentication, we used WISDM dataset. The various feature extraction tools have been explored in this research. The performance of random forest and support vector machine classifiers was outstanding on features extracted from the Matlab tool. The highest accuracy achieved for activities recognition on WISDM, MobiAct, and MobiAct_v2 datasets was 99.50%, 98.50%, and 98.43% respectively. For user authentication, maximum accuracy achieved by utilizing the Matlab features was 95% on WISDM dataset. In comparison to current work for human activity identification and user authentication, the findings showed that the proposed conspire performed better.

Key Words: *Radio frequency identification (RFID), Center for Advanced Studies in Adaptive Systems (CASAS), Human Activities Recognition (HAR), Convolution Neural Network (CNN), Support Vector Machine (SVM), Random Forest (RF), Long Short Term Memory (LSTM), Decision Tree (DT), Auto-Regression (AR), K-Nearest Neighbour (KNN)*

Table of Contents

List of Figures

List of Tables

CHAPTER 1 : INTRODUCTION

1.1 Introduction for Human Activities Recognition

Those people who manage singular biometric signature, health monitoring, progressed figuring, and older consideration, etc are the numerous solicitations based on the foundation of Human Activity recognition [1, 2]. Based on the activities performed by users, the output is predicted, and the raw sensor data has been fed to models. in the zone of unavoidable registering, the HAR framework turns into an arising discipline in astute processing applications [3]. An answer for such an issue is a critical exploration area which is termed activity recognition. medical care, security, senior consideration, shrewd conditions, client interfaces are all the applications in this area. For instance, the installation of video cameras in the observing zones, they have restriction of generally require framework uphold, therefore image and video based human activity recognition has been concentrated since quite a while. Body-worn sensors or a smart telephone are alternative approaches that are available and have built-in sensors to perceive the daily living of human activity. Excluding a patient, a normal human cannot wear in any case such countless sensors on the body. Therefore, nowadays the core of the human world considers as Smartphones. GPS, accelerometer, cameras, compasses and closeness temperature, light, spinner, receivers are all the components of smartphones [4]. Recent studies show that by the accelerometer sensor human activity recognition utilizing information. Every day for human activity recognition by utilizing tri-axial accelerometer got awesome accuracy by the investigators [5]. In recognizing an activity of daily living, many researchers since the most recent decade, are utilized in recognizing [6]. By using mobile devices, in the zone of applications slight practical effort has been done yet. This framework is productive for medical health care, military purposes, and so forth because of the immediate sensor readings utilized in Human Activity Recognition. For the daily life activities, the vast majority utilize smart devices like following rest hours, covering tabs, checking walk steps, buying things, getting medical services-related data, following calories, discovering headings and the list goes on. These devices with no extra expense can give exceptional examples of every individual's daily life activities and can create bunches of individual information. Incidentally, strange activities may likewise happen, other than the previously mentioned ordinary daily activities. Strange and abrupt activities of an individual's active work schedule can be ordered as falls. Consequently, in an activity recognition framework, the recognition and discovery of falls is important especially when this is applied for observing of older folks [7]. Different activities performing by different users are shown in Figure 1.

Figure 1.1: Different kind of human activities are performed by different users.

To assemble numerous valuable applications with the assistance of underlying sensors, there is an awesome chance to consider human activity recognition. Now a day the detection of daily living human activities becomes an interesting research area. In perceiving an action of everyday living numerous scientists are working since the most recent decade. By utilizing cell phones there has been minimal viable work yet at the same time that has been done by nearby applications [8].

1.2 Introduction for User's Authentication

Whenever, at any place cell phones, particularly smartphones can be utilized viably which join a wide assortment of sensors. In the fields of business, smart home environment checking, virtual education and amusement, individual medical care it has wide application possibilities [9,10]. Data is gathered and put in smartphones for examination increasingly closer to home information is only possible with the boundless utilization of smartphones [11]. For ensuring the individual information from unauthorized access, it turns out to be increasingly more significant subsequently. For cell phone users protected control, a critical authentication procedure is carried out by a typical test. To distinguish the genuine user of the framework authentication is the way toward it [12]. User authentication can be extensively grouped into three classifications [13]:

1. Objective-based includes users that keep the token number, keys, id card, etc.

2. Biometric-based involves behavioral characteristics such as the face, fingerprint, iris, etc.
3. Knowledge-based includes user obligations know like id number or password etc.

For user authentication, systems require the dynamic support of the user, PIN codes and Passwords are the customary techniques utilized. Moreover, there is a danger of data exposure if the straightforward passwords can be effectively recalled and can be speculated too if the secret key is some helpful data identified with the user. Henceforth, against speculating assaults, passwords are powerless and helpless [14]. By deciding the screen taps area, complex passwords can likewise be acquired utilizing the gyroscope and accelerometer sensor readings [15]. The long passwords sometimes create a problem for users to memorize them, but they are secured. Rather than passwords, PINs are simpler to recall. They can be guessed more rapidly, and they are less forgotten. For brilliant gadgets and shrewd frameworks, biometric authentication has likewise been utilized which can be divided into two classifications: physiological and behavioral. Face lock, iris acknowledgment, and finger impression examine are the authentication included in the physiological biometric incorporate termed as ordinarily utilized techniques. For authentication design of utilizing physiological biometrics, these physiological qualities can be copied and changed as the fundamental downside. Fingerprints and hand calculations can be reproduced in plastic [16]. Various stances of the face can make disarray in the face acknowledgment framework and Scars and wounds can change the fingerprints [17]. Unique finger impression and iris acknowledgment utilized by the physiological biometric strategies which need the help of some extra equipment for input. For gaining admittance to any framework these techniques require the user to effectively take part in the framework as it is a dynamic verification strategy that gets irritating and dreary to the users. Users like to utilize fewer protection hindrances at the end. Therefore, we need a strong mechanism which preserves the privacy of user with the development of the Internet of Things (IoTs). So, in this research, a sensor-based user authentication mechanism is also proposed. For constantly monitoring the user, sensors are placed on different positions of the body. A lot of work is done for user authentication and inhuman activities recognition.

1.3 Motivation

In interpersonal relations and human-to-human interaction, human activity recognition plays a significant role. It is difficult to extract because it provides information about the identity of a person, their personality, and psychological state. To recognize another person's activities of computer vision and machine learning the human ability is one of the main subjects of study of the scientific areas. User dependence on smart systems and services, such as smart appliances, smartphones, security, and healthcare applications has been increased with the evolution of the Internet of Things (IoTs). To preserve the users' privacy this demands secure authentication mechanisms when interacting with smart devices. That is why this topic (Sensor-Based Human Activities Recognition and User's Authentication Using Machine Learning Algorithms) is selected by us.

1.4 Problem Statement

A lot of work has been done in user authentication and human activities recognition. Many researchers for recognizing human activities applied different methodologies. Some authors used different machine learning models for activity recognition. Some of them extracted statistical feature sets and applied the classification on them. Traditionally methods for activity recognition have limitations in terms of their range. In vision base, human activities recognition, cameras are deployed at a specific location for activities recognition but outside of the camera's range, they are unable to recognize the activities. Therefore, we need to develop a mechanism to recognize the activities continuously at any place. By using sensors, we can recognition activities without the limitation of range. The same thing can be applied to user authentication.

1.5 Objectives

The key objectives of the research are as follow.

- To validated and compare the performance of the purposed method with published methods.
- To evaluate the performance of the proposed approach using the real data sets.
- To create machine learning models for the recognition of human activities using sensor data.
- To evaluate the performance of the different feature extraction tools for human activity recognition and user authentication
- To build the activities-based user recognition models for user authentication.

1.6 Structure of Thesis

The following is the structure of this research.

Chapter 2 presents the previous work that has been done for human activities recognition and user authentication.

Chapter 3 discusses selected different datasets which are used in our research work.

Chapter 4 describes the methodology that is used to evaluate this research.

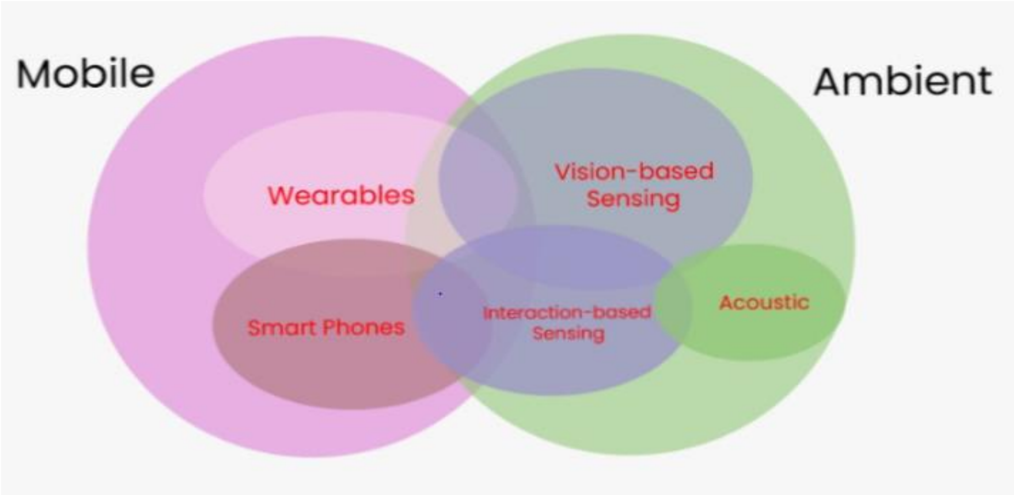
Chapter 5 discusses the experimental results in detail including coveted tables and figures.

Chapter 6 informs about the conclusion and discloses the future work of this research.

CHAPTER 2 : LITERATURE REVIEW

2.1 Literature Review for Human Activities Recognition

According to the sensor-based HAR, in terms of sensor deployment strategies approximately two key tracks are present. In the first track, sensors are deployed in an environment by creating them mostly stationary and ambient. In track second, humans carried out the sensors and considered them of nomadic or mobile nature. Into three subcategories, ambient sensing studies are additionally classified. Firstly, in the ambient track, we notice a vision-based HAR computerization domination. HAR has a wide background for vision-based computerized systems especially in public space, surveillance, and security applications. For the aim of health care just like the utilization of video cameras in secure surroundings like elegant house show concerns of privacy and it is not acknowledged by every individual. Therefore, utilization of miniaturized sensors is enhanced that is responsible to assess the situations of the surroundings and individual interactions with that. Long ago, the second track of ambient sensing has evolved and extended fastly just because of sensor and communication technology advancements and possess fewer issues of privacy. In acoustic sensing actions of elegant surroundings, there is an enhancing trend as the sound had wide data about these surroundings and the specific actions performed with it. As the natural means of communication and interaction is speech. For applications of healthcare, particularly in the cases of remote monitoring, understanding ambient sound and speech is helpful. For the use of human activity recognition purposes, smartphones that possess a huge quality of functions with sensing capacity are easy for mobile sensing track. Mobility is one of the major benefits that sensing-based smartphones had that make us able to enlarge the indoor as well as outdoor surroundings. Through this, complications occur in activity recognition that ends with the challenges on a limited capacity battery-operated device in the data processing. Recently, the unbearable growth of these devices gave an increase to a new path of applications that need recognition of activities automation. Ongoing with easy accelerometer-based sensing of the activity levels, this quantified-self paradigm has extended fastly that carry physiological signs with it just like oxygen saturation, heart rate, and blood pressure level. In the last decade, the researcher's hard work on wearable sensing also increased exponentially to meet the demand. In Figure 2.1 sensing-based classification overview of HAR literature is specified. There are several intersections studies in which general groups are prominent and use technology combinations. Therefore, we give a summary in the following part regarding the state-of-the-art and elaborate separately each major division of activity recognition research. Our main focus is on the recent trends, just because of the huge studies collection in each group specified.



. **Figure 2.1:** Sensing-based Classification of human activity recognition studies

2.1.1 Ambient Sensing

2.1.1.1 Human Activity Recognition through Vision-based

In vision-based computerization, activities of humans are recognized by setup the different selection of cameras, such as multiple cameras, single cameras, infrared cameras, and stereo system vision cameras. They are deployed at different places for activity recognition. Many researchers have done a lot of work in this field. A vision-based extensive literature survey for human activities recognition has been done in references [18-23]. A detailed review of publicly available datasets is given in reference [24]. In the past, three or four years, vision-based human activities recognition had been converted towards three-dimensional from two-dimensional (2D) having depth information provided by cameras. Particularly, when Microsoft Kinect senor was introduced [25]. The devices related to direct and single 3D imaging have turn into commercial and pervasive existing at little price. For mature monitoring appliances in the house, ergonomic form factors and fewer prices of depth video sensors have made human activity recognition feasible. In [26], to recognize the daily actions of older individuals, a depth-based life classification structure is proposed. Firstly, to confine depth outlines, a deepness imaging sensor is used. Human skeletons based on these outlines, with mutual information, are produced which are additionally used for action acknowledgment and creating their life logs. In two phases, the framework for life-logging is divided. For each activity separately, the researchers collected a dataset in the training phase by using a depth camera, separated features, and skilled a hidden Markov model (HMM). Through the subsequent level, the recognition engine confidential the learned actions and made life logs. By utilizing features for lifelogging, the framework was made against free part features and principal segment and get acceptable recognition rates on the elegant inside action datasets. With the help of a single camera, the system can be deployed easily without any difficulties. But it is very difficult to deploy the system by using multiple cameras because we must place cameras carefully and adjust them in a such way that they give good results. Alternatively, multi-view covers all the aspects of humans as contrasted to a single camera. Furthermore, these types of sensors have a restricted range, and expected data can be altered by dispersed light. Reference [27], the authors did a qualitative comparison of some methodologies by using two unique datasets. With the outcomes of datasets, they found that data collected from multiple views (three dimensions) provide the best results as contrasted to data gathered from two Dimensional counterparts. The main power of multi-view setups is the top-notch three-dimensional full-volume information that can be given from three-dimensional recreation shapes from refinements and outlines methods. Likewise, it assists with uncovering occluded activity locales from various views in the worldwide 3D information. A few researchers tended to copy the exploration outcomes on datasets that are documented in more uncontrolled conditions. The authors in [28] presented another human activity dataset in brilliant house surroundings which are explicitly gathered to assist us with breaking down human activities in house surroundings. Utilizing the given dataset, consideration of some existing activity of human recognition algorithms, that reflect brilliant execution on other datasets of straightforward nature. The authors [29] proposed a framework for home activity by addressing two main issues in a genuine application. In the first place, the data which belonged to different categories is exceptionally unbalanced, which cruelly reduces the performance of classification. Second, daily living activities are complemented by others, for example, walking nurses close by. It is unrealistic to predefine and mark every one of the perceivable activities of all the possible guests. By applying a strategy called subspace naïve-Bayesian mutual information maximization, they did partition the feature space into various spaces and permits the standardization parameters and kernel to alter among various spaces. Likewise, they suggested a filtering method to decrease the impacts of the involved scenarios related to many people. By assessing the proposed activity model, they saved the dataset of daily living activities and executed this model for eight unique categories.

2.1.1.2 Acoustic Human Activity Recognition

Regarding the actions, the ambient sound can give a consideration acted within an environment. A few examinations attempting to recognize the activities utilizing acoustic data. Regardless, the AuditHIS framework which performs constant sound investigation from eight receivers directs in an elegant house is introduced in [30]. Assessment of AuditHIS in various ways highlighted that sound methodology is providing to gain data that are not accessible with the help of other sensors of old-style. Sound preparation likewise possesses the capability to give a characteristic method of associations among individuals and the elegant surroundings. The outcomes were gotten from the data collected from different volunteers in the environment of smart homes; the accuracy of that data was 72%. The amount of dataset is produced publicly from this study [31]. In reference [32], they proposed a methodology for the classification of multiple daily living activities by using non-markovian voting. Their method did not bother with a quiet identification or sound stream division. The authors in [33] presented a framework for multi-modal HAR based on audio and video signals. The audio data consisted of twelve non-speech acoustic and five spoken commands. The specified alarms for audio and speech activities such as help, cry, cough, and fall, etc. that generate a sign of a crucial condition. The recognizer of non-discourse and discourse sound occasions depends on HMMs displaying or ascertains Melrecurrence cepstral coefficients through different channel sound signs. As per the outcomes, the most reduced exactness was noticed with 60% recognition rate for the non-speech sound occasion "Fall". The events mistaken for the "Means" are about 30%. The general recognition exactness of discourse occasions was 96.5% and the acoustic occasion was 93.8%. In reference [34] a mobile framework was proposed for indoor and outdoor. The system was operated by using sound from an environment which is precious information to detecting both social behaviors and individuals.

2.1.1.3 Interaction-based Sensor Human Activity Recognition

For home automation, utilization of ambient sensors of interaction nature in an understanding way was premier introduced within the last part of the 90s [35]. The households a few elegant appliances furnished with smart cooler sensors for food screening only. Georgia Institute of Technology created the AwareHome comparative task [36]. For confinement purposes, they exploited a few ceil installed labels for radio and camera frequency identification (RFID). With the help of these undertakings, among the main instances of existing research centers and thus pointed building up evidence of a plan. As far as a purpose for the recognition of activities, Massachusetts Institute of Technology among the spearheading contemplates created the project and house. The authors in [37] introduced piezoelectric switches and reed switches on entryways, ovens, windows, sinks, showers, cupboards, microwaves, fridges, ovens, sinks, latrines, light switches, drawers, lights, a few compartments, and electronic machines in two unique houses to identify different activities. By using software that was executed on the personal digital assistant, the gathered data was marked by subjects. They used a naïve Bayes classifier to evaluate the research study. The performance of the classifier was 25% to 89% depending on evaluate metric. A few scientists utilized radio and camera frequency identification for identifying the associations with the surroundings through the item utilization. They recognized the activities by utilizing the information from RFID readers. RFID provides information on whether the subject is present in the environment or not [38, 39]. RFID-based frameworks expect inhabitants to one or the other wear a convenient RFID per user on their bodies or wearing extraordinary RFID tags. In any case, extra weight on the occupants is brought other than the higher electromagnetic openings. Thus, low-power frameworks that can quantify the communications without the extra weight have gotten more mainstream. The datasets for the Center for Advanced Studies in Adaptive Systems (CASAS) were introduced in [40]. The authors observed fifteen different activities with the help of an elegant house testbed. That was embedded with monitor sensors and temperature sensors. The framework was established in the environment. By utilizing the testbed, eleven distinct sensor datasets were collected. With the help of this dataset, the research work was evaluated by using HMM, NBC, and a CRF model with a comparison of performance among them. The accuracy of recognition by utilizing NBC was 74.87%, HMM was 75.05% and CRF was 72.16% with three cross-validations [41].

2.1.2 Mobile Sensing

The accelerometer sensor is extensively utilized for daily living activities recognition. Authors in [42] developed a system by using five accelerometers on different positions of the body such as, arm, ankle, and hip to evaluate twenty various activities. Activities were containing ambulation, and daily living such as working on the computer, watch television, scrubbing, and vacuuming, etc. In a home environment, gathered data was labeled by the user. The c4.5 decision tree classifier was used to classify the activities by utilizing the time, and frequency domain features. The accuracy of the classifier to recognize the ambulation activities was 95%, and on other activities, such as vacuuming, watching television, etc. was 84%. With different acceleration patterns, many researchers utilized the accelerometer for recognizing human activities for instance standing, walking, jogging, etc. These daily living human activities are outstanding to defining people's activities levels as we can see in reference [43], however, they do not deliver sufficient information regarding daily living activities for example they cannot be distinguished with high-level accuracy from eating to reading activity. Authors in [44] introduced a system that recognized activities such as stairs down, standing, sitting, jogging, and walking, etc. based on sensor data of the accelerometer. Data was collected by performing activities with five different volunteers while keeping the smartphone in their front pocket. They applied a 10s moving window for feature extraction by setting the sample frequency rate of 20 Hz. They utilized two algorithms for feature selection one was ReliefF AttributeEval, and the second was OneRAttributeEval. The research was evaluated by using six classifiers' algorithms random forest, naïve Bayes, Bayes net, j48, KNN, and k-star with 10-fold cross-validation. The performance of KNN classifier was outstanding among other classifiers. The accuracy of KNN was 94% for recognition. In reference [45] the authors proposed an activities recognition system by utilizing a smartphone sensor. They used a publicly available dataset [46,47], which consists of six activities such as upstairs, laying, running, walking, downstairs, and standing. Data was gathered by 30 volunteers while keeping a sample frequency rate of 50 Hz. They applied a 50% overlapping window of 2.56s. They extracted 45 features from the dataset and applied different machine learning classifiers for the instant decision tree, support vector machine, and logistic regression, etc. the performance of the logistic regression classifier was excellent among other classifiers. The accuracy of logistic regression was 96%. In reference [48], the authors utilized the publicly available WISDM dataset. The data was gathered with the help of thirty-six volunteers while keeping the smartphone in their pocket. Dataset consists of six activities such as sitting, jumping, jogging, walking, stairs-up, and stairs-down. They applied a 10s non-overlapping window with a sample rate of 20 hertz. They extracted 43 statistical features from the dataset. Different classifiers were applied to evaluate the research. The classifiers were RF, SVM, KNN, NB, DT, and JRIP. The comparison had been done among the classifiers. The performance of the RF classifier was outstanding. The accuracy of RF was 95% for activities recognition. The authors in [49] performed different algorithms to recognize human daily living activities. They used two publicly available datasets such as WISDM and UCI HAR. Both datasets consist of six activities for instance walking, jogging, jumping, sitting, upstairs, and downstairs. They utilized ANN, CNN, LSTM, logistic regression, SVM, DT, and RF for activities recognition. The comparison had been done among the algorithms and as well as between the datasets. The performance of LSTM was good on WISDM dataset. The accuracy of LSTM model was 95.45%. The performance of CNN model was excellent on UCI HAR dataset. The accuracy of CCN was 96.42%. In reference [50], the authors introduced Deep Convolutional Neural Network and Gramian Angular Field model for activities recognition. They utilized three publicly available datasets such as UCI, opportunity, HAR, and WISDM. The different models had been evaluated for activity recognition. The combined performance of GAF+Fusion-Mdk-ResNet was outstanding. The accuracy of the combined model on WISDM, uci har, and opportunity datasets was 97%, 89.5%, and 97.27% respectively. The authors in [51] utilized a non-linear support vector machine to classify human activities. They used MobiAct dataset which consists of nine different daily activities and four types of fall activities. They utilized the auto-regression model for generating the signals with the help of auto-regression co-efficient values instead of statistical features. They used the walker method to evaluate the auto-regression model. With the help of the SVM machine, classification had been done. The accuracy of walking, jogging, upstairs, downstairs, and standing was, 100%,98.40%,93%, 94.42%, 98.60%, and 100% respectively. The average accuracy of SVM+AR was 97.45%. They did a comparison with already published methods. They obtained good results as contrasted with other methods. In reference [52] the author's utilized different machine learning classifiers to evaluate two publicly available WISDM and MobiAct datasets. They extracted the statistical features from datasets, applied the classifiers IBK, and J48 to recognize the activities. The accuracy of activities walking, jogging, sitting, and standing was 100% by utilizing IBK classier on features extract from MobiAct dataset. In the case of features extract from WISDM dataset, the accuracy of activities walking, jogging, upstairs, downstairs, sitting, and standing was 100%, 99%, 99%, 99%, 99%, and 99% respectively. The average accuracy of IBK and J48 on MobiAct dataset was 99.88%, and 99.30% respectively. The average accuracy of IBK, and J48 on WISDM dataset was 99.79%, and 98.63% respectively. In reference [53] authors used MobiAct dataset for activities recognition. The data was gathered by using a smartphone. They utilized six activities out of nine daily living activities. The SAX-based features were used for classification. The proposed general and personal models to evaluate the results. The comparison had been done with other classifiers such as logistic regression, multi-layer perceptron, and J48. Personal model performance was outstanding. The average accuracy of walking was 97.30%, for jogging was 97.20%, for upstairs was 94.5%, for downstairs was 94.30%, for standing 97.60%, and for sitting was 98% by using the personal model. The average accuracy of the personal model was 96.7%. The authors proposed CNN model-based system to recognize human daily living activities. They used the publicly available MobiAct_v2 dataset for activities recognition. The MobiAct_v2 dataset consists of eleven different daily living activities and four types of fall activities. The deep neural network was utilized to evaluate the dataset. They applied eight models to recognize the activities. The average accuracy of model 1 was 97.66%, model 2 was 95.24%, model 3 was 94.13%, model 4 was 98.89%, model 5 was 97.64%, model 6 was 98.48%, model 7 was 99.11%, and model 8 was 98.36%.

2.2 Literature Review for User's Authentication

Some researchers have explored that whether unpretentious ID or implies subjects do not have to play out a specific activity. The authors in [45] utilized the versatile telephone-based accelerometer for unpretentious biometric. They utilized the straw man strategy in the neural network as a learning algorithm. For all five subjects, they obtained 100% positive and negative authentications [54]. The authors in [55] proposed a user's authentication system by using accelerometer, orientation, and magnetometer sensors. They explored that outstanding results can be achieved with multiple sensors. They obtained good precision up to 95%. In reference [56] the authors introduced gait-based authentication. They researched that how the position of the phone at different place influence authentication. The authors in [57] intended a biometric authentication by utilizing the movement of a user when he was calling on the phone. With the help of orientation and accelerometer sensors, the movement of a user was exposed. In reference [58], the authors explored the fusion technique. They investigated that how the various sensors which are built-in smartphone influence authentication. Their research technique was implicated different sensors for instance accelerometer, camera, and gyroscope sensors. The experiment had been done by merging both gyroscope and accelerometer sensors, and they found by using a single accelerometer sensor alone gave outstanding authentication instead of combining both sensors. The combining sensors led to erroneous results. In [59] the authors utilized three datasets for user authentication. Each dataset has a different number of users and various activities. That data was gathered by utilizing smartphone sensors and wearable sensors. They extracted the statistical features in time and frequency domains. Then they recognized human daily living activities by utilizing different machine learning classifiers. Based on activity recognition, users were authenticated. The average accuracy of user authentication on HAR, mobile, and pamap2 datasets was 94.96%, 99.81%, and 96.54% respectively. In reference [60], they proposed gait-based use's authentication. They used two datasets for recognition of activities and based on those activities users were authenticated. They utilized different machine learning algorithms for activity recognition and user authentication. The accuracy of user authentication based on walking activity was 95%. In this study, we have utilized three datasets. We used three datasets for activities recognition that is a major part of this research, and minor work has been done in user authentication by utilizing the wisdom dataset.

CHAPTER 3 : DATASETS

There are many publicly available datasets for human activities recognition and user authentication. Each dataset has different characteristics such as the different number of activities, different types of sensors used to collect data, and different time duration of activities, etc. The names of some datasets are following.

1. MOBIACT
2. MOBIACT_V2
3. WISDM
4. HAR (Human activity recognition by utilizing smartphone dataset)
5. PAMAP2(Monitoring the physical activity datasets)
6. OPPORTUNITY
7. MOBIFALL

We used the first three datasets in this research. All three datasets have been utilized for human activities recognition and WISDM dataset has been used for user authentication. The complete description of the datasets is given below.

3.1 MobiAct Dataset

3.1.1 Description of Dataset

MobiAct dataset consists of different daily living activities and fall activities as well. The data was gathered while performing various activities by different users with help of the smartphone. This dataset depends on the earlier released MobiFall dataset [61]. The MobiFall dataset contained different everyday activities, which led to research in human activities recognition. It includes four unique kinds of falls and nine distinctive daily living human activities performed by fifty-seven subjects with more than 2500 preliminaries while caught with a cell phone. The following criteria are utilized for chosen daily living activities.

a) The first fall-like activities are incorporated, in which the user is near to stopped at different positions for instance step in and set out from the car.
b) Jumping and jogging activities are incorporated in the dataset which is mostly like the falls.
c) Other daily living activities are standing, walking, upstairs, and downstairs.

These activities are important in research for human activity recognition. Table 3.1 and Table 3.2 illustrate fall activities, and daily living activities, respectively. Which include their trial counts, a short description of each activity, and time duration. The data can be downloaded from the given link: https://bmi.hmu.gr/the-MobiFall-and-MobiAct-datasets-2/

Table 3.1: Fall activities in MobiAct dataset.

Sr No.	Name of activity	Trials of each activity	Duration of activity	Description
1	Back sitting chair	3	10s	Falling backward while sitting on the chair
2	Front-knees lying	3	10s	Falling forward while standing on knee
3	Sideward lying	3	10s	Falling sideward while standing with bending legs
4	Forward lying	3	10s	Falling forward while standing

Table 3.2: Daily living activities in MobiAct dataset.

Sr. No	Name of activity	Trials of each activity	Duration of activity	Description
1	Jumping	3	30s	Jumping continuously
2	walking	1	5m	Walking in a normal way
3	Jogging	3	30s	Jogging
4	Standing	1	5m	Standing with an ingenious way
5	Sitting on chair	6	6s	Sitting on chair
6	Upstairs	6	10s	Stairs-up (ten stairs)
7	Downstairs	6	10s	Downstairs (ten stairs)
8	Step out from car	6	6s	Step out from a car
9	Car step in	6	6s	Step in from a car

3.1.2 Details of Dataset Acquisition

Three sensors were utilized to gathering the MobiAct dataset. The sensors are the accelerometer, gyroscope, and orientation. These sensors are built-in smartphones. By using geomagnetic, and accelerometer sensors, the data of the orientation sensor was obtained owing to a software-based orientation sensor. With the help of an integrated tool for gathering data, the prior gyroscope was adjusted. By utilizing acceleration, orientation, and angular velocity, the raw data was recorded with the help of introducing the android application [62]. The highest sampling rate was achieved by enabling sensor delay fastest. In the end, in nanoseconds form each sample was put in storage.

3.1.3 Number of Participants in Collecting Dataset.

There were fifty-seven participants in collecting the dataset. There were forty-two men and fifteen women performing daily living activities. The age of participants was between twenty to forty-seven and the average age was twenty-six. The height range was 160 cm to 187 cm, and the average weight was seventy-six.

3.2 MobiAct_v2 Dataset

3.2.1 Description of Dataset

A MobiAct_v2 dataset is an extended form of MobiAct dataset. The MobiAct_v2 dataset consists of twelve different daily living activities performed by sixty-six subjects. More than 3200 trials were performed. The daily living human activities were chosen based on the below criteria.

a) The first fall-like activities are incorporated, in which the user is near to stopped at different positions for instance step in and set out from the car.
b) Jumping and jogging activities are incorporated in the dataset which is mostly like the falls.
c) Other daily living activities are standing, walking, upstairs, and downstairs.

Three extra daily living activities are added to this dataset such as laying, car step in, and car step out. The remaining falling and daily living activities can be seen in table 3.1, and table 3.2, respectively. With the help of the sensor delay fastest' parameter, a sampling rate was obtained. In the end, data is stored in a nanosecond. Data can be obtained via the given link: https://bmi.hmu.gr/the-MobiFall-and-MobiAct-datasets-2/.

3.2.2 Details of Data Acquisition

Three sensors were utilized to gathering the MobiAct_v2 dataset. The sensors are the accelerometer, gyroscope, and orientation. These sensors are built-in smartphones. By using geomagnetic, and accelerometer sensors, the data of the orientation sensor was obtained owing to a software-based orientation sensor. With the help of an integrated tool for gathering data, the prior gyroscope was adjusted. By utilizing acceleration, orientation, and angular velocity, the raw data was recorded with the help of introducing the android application. The highest sampling rate was achieved by enabling sensor delay fastest. In the end, in nanoseconds form each sample was put in storage.

3.2.3 Number of Participants in Collecting Dataset.

There were sixty-six participants for the gathering dataset, in which fifty-one were men and fifteen women. For daily living activities, data were collected with the help of fifty-nine subjects. The age of subjects lied between twenty to forty-seven. The height ranged was 160 cm to 193 cm. The weight of subjects was between 50kg to 120 kg. The complete description of the dataset can be seen in reference [63].

3.3 WISDM Dataset

3.3.1 Description of Dataset

The WISDM dataset consists of six daily living activities such as walking, jogging, sitting, upstairs, downstairs, and standing. Each activity has a different number of samples. The total number of examples is 1098207. There are no missing values in the dataset. Table 3.3 illustrates the dataset.

Table 3.3: Daily living activities in WISDM dataset

Sr. no	Activity name	Total sample	Percentage
1	Walking	424,400	38.6%
2	Jogging	342,177	31.2%
3	Sitting	59,939	5.5%
4	Upstairs	122,869	11.2%
5	Downstairs	100,427	9.1%
6	Standing	48,395	4.4%

3.3.2 Details of Data Acquisition

The accelerometer sensor was utilized for collecting the data, which is a built-in android smartphone. While carrying the smartphone, they performed daily living activities. They had kept the cell phone in their pants leg pockets. The data was collected at a rate of 20 samples in one second. The sampling frequency was 10 Hz. The complete details about the dataset are given in reference [64].

3.3.3 Number of Participants in Collecting Dataset

Thirty-six subjects were included in collecting the dataset. They had different ages and various weights. The id number was given against each subject. The dataset was collected with the help of both men and women. The dataset can be obtained through the given link. https://www.cis.fordham.edu/WISDM/dataset.php.

CHAPTER 4 : METHODOLOGY

In the proposed methodology, we have utilized the sensors data for daily living human activities recognition. The data was in raw form. Before utilizing this raw data, the preprocessing step has been done. In preprocessing step, labels were assigned against each class, and a segmentation technique was applied to the data. After preprocessing, Statistical features were extracted by utilizing various feature extracted tools. Then data was split into training and testing. The model was constructed based on the training dataset and stored the data. Based on the trained model, evaluation has been done. Figure 4.1 illustrates the proposed methodology.

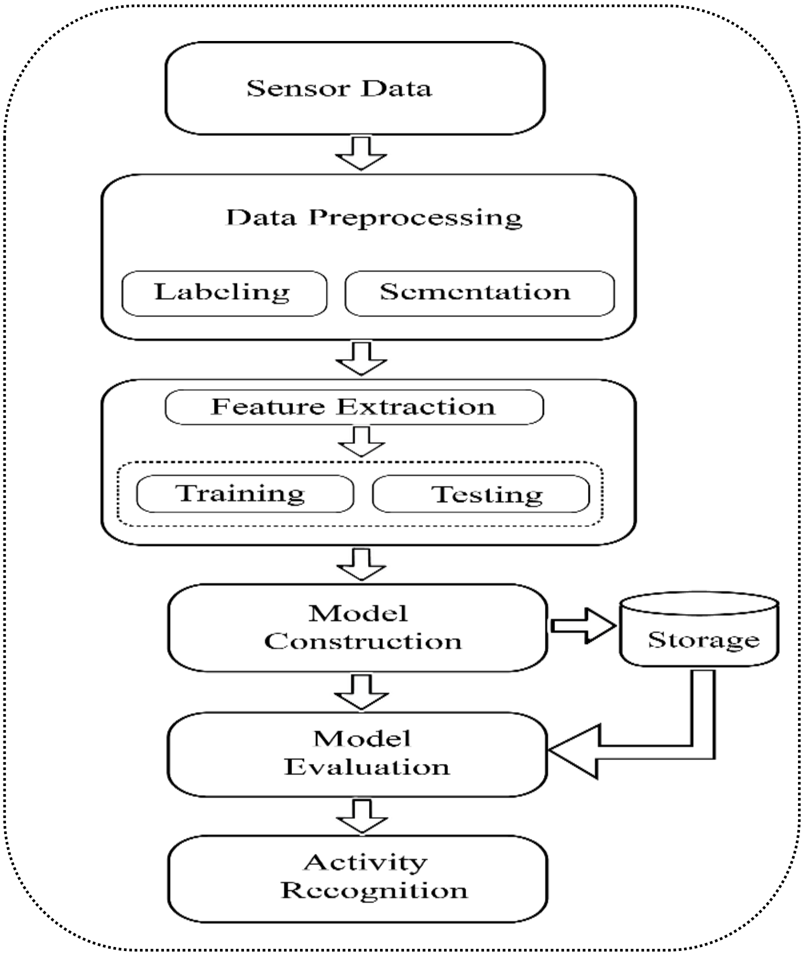


Figure 4.1: Proposed methodology for activities recognition

The methodology is discussed in detail.

4.1 Characteristics of Selected Datasets

We had utilized six activities from WISDM and MobiAct datasets, and eleven activities from MobiAct_v2 dataset. The purpose of utilizing selected activities was to compare the results with other published methods. The eminent features of selected activities are shown in table 4.1. In the below table, we can see that activities are divided into three categories: static, dynamic, and transitions. The activities in MobiAct, and WISDM datasets lie in static and dynamic categories. Some activities in MobiAct_v2 lie in the transition category.

Table 4.1: Salient features of selected datasets

Datasets	Type of sensor	No. of activities	Activities		
			Static	**Dynamic**	**Transitions**
MobiAct [62]	Accelerometer Gyroscope Orientation	6	Sitting and Standing on chair	Walking Jogging Walking stairs up Walking stairs down	-
MobiAct_v2 [63]	Accelerometer Gyroscope Orientation	11	Sitting and Standing on chair	Walking Jogging Walking stairs up Walking stairs down Jumping Car step in Car step out	Sit to stand Stand to sit.
WISDM [64]	Accelerometer	6	Sitting Standing	Walking Jogging Walking stairs up Walking stairs down	-

4.2 Data Preprocessing

The raw data had been preprocessed into two steps: data labeling and data segmentation.

4.2.1 Data Labeling

The information profiles of each subject contain the sensor assessment of their devices. Each subject's profile is suitably named. The named information helps in the better organization of the information collection and concentrates subject-related features and improves execution [65]. Consequently, added the marks against every activity.

4.2.2 Data Segmentation

The activities in all three datasets have a different time duration. Some activities have a 10s duration. Some of them have greater than 10 s duration. Therefore, we applied a window of 10 seconds on those activities which were greater than 10 s duration and kept all those activities as it which were less than or equal to 10 s duration in MobiAct, and MobiAct_v2 datasets. In the 10 s window, 2000 samples were taken at a rate of 100Hz from MobiAct, and MobiAct_v2 datasets. In WISDM dataset 200 samples were taken in a 10s window with a sampling frequency of 10Hz.

4.3 Features Extraction Tools

The aim of feature extraction is to reduced data by dropping the number of unimportant features. Extract those features from data that help take further decisions. Good features can help to recognize human activities in a better way. We utilized two tools for statistical features extraction: Matlab tool and OpenSmile tool. The fourteen statistical features were extracted by using the Matlab tool and 384 statistical features were extracted by utilizing OpenSmile module. The details are given below for statistical features extraction from different tools.

4.3.1 Features Extraction through Matlab Tool

In this portion, fourteen statistical features were extracted by utilizing the sensor data. The features were extracted across three dimensions of sensor data (x, y, z). The size of the feature vector was (14 x 3) = 42. The explanation of each feature is given below in detail.

(i) **Mean:** The single value that describes the central position of data. It is also called the central tendency of data. The mean is adequate to the sum of all the values within the data set divided by the total samples within the data set. The below is the formula of the mean. S represents the signal value from the sensor and N total samples of data.

$$\text{mean}(\bar{S}) = \frac{1}{\mathrm{N}}\sum_{\mathrm{k}=1}^{N} \mathrm{S_k} \qquad (4.1)$$

The mean value represents a model of the dataset. The mean value that we calculate is not presented in real values of the dataset. But mean value is very important because it produces less error in contrast to other values in the dataset. The other main feature of the mean value is that it is incorporated every value being a part of data in the calculation.

(ii) **Median:** the value of median describes the middle value of the dataset. It is less effective from outlier value as compared to mean. The median value is calculated by arranging the data in ascending order and selected the middle value.

$$mdn = median(S) \qquad (4.2)$$

After calculating the median value is stored in 'mdn' variable.

(iii) **Variance:** the variance describes the flexibility of data. It reveals that how much data is spread from the mean of data. If a larger spread is present in data, it means that data has a larger value of variance. The variance is calculated by subtracting the data point from the mean value and then taking an average of the a square. The formula of variance is given below.

$$var(S) = \frac{1}{\mathrm{N}}\sum_{\mathrm{k}=1}^{\mathrm{N}} (\mathrm{S_k} - \bar{S})^2 \qquad (4.3)$$

S bar represents the mean of data and S_k is current point data, and N total numbers of samples in data.

(iv) **Standard Deviation:** Standard deviation could be a measurement that can examine how distant from the mean a bunch of numbers is, by using the square root of the change. The calculation of variance employments squares since it weighs exceptions more intensely than information closer to the mean. This calculation moreover anticipates contrasts over the mean from canceling out that underneath, which would result in a variance of zero. By finding the variance among the data points, the standard deviation is calculated by taking the square root of variance. The formula of standard deviation is given below.

$$\mathrm{std}(S) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(S_k - \bar{S})^2} \tag{4.4}$$

Standard deviation is one of the key strategies that investigators, portfolio supervisors, and advisors utilize to decide hazards. When the gather of numbers is closer to the mean, the investment is less hazardous; when the bunch of numbers is advance from the mean, the investment is of a more prominent chance to a potential buyer.

(v) **Skewness:** Skewness alludes to mutilation or asymmetry that goes astray from the symmetrical chime bend, or ordinary dissemination, in a set of materials. On the off possibility that the bend is shifted to the cleared out or to the proper, it is said to be skewed. Skewness can be defined as a representation of how far a dispersion deviates from a regular distribution. Typical dissemination features a skew of zero, whereas a lognormal dispersion, for illustration, would show a few degrees of right-skew. Its formula is given below.

$$\mathrm{skewness}(S) = \frac{\sum_{k}^{N}(S_k - \bar{S})^3}{N\sigma^3} \tag{4.5}$$

Whereas N is presented the total sample points. S bar is the mean value and S_k current data point.

(vi) Kurtosis: Kurtosis is a factual degree that explains how far the tails of distribution differ from the tails of a typical conveyance. In another way, kurtosis determines if a dispersion's tails contain exceptional values. Together with skewness, kurtosis is an imperative graphic measurement of information conveyance. In any case, the two concepts must not be befuddled with each other. Skewness measures the symmetry of the conveyance, whereas kurtosis decides the largeness of the conveyance tails. The below is the formula for kurtosis.

$$\mathrm{kurtosis}(S) = \frac{\sum_{k}^{N}(S_k - \bar{S})^4}{N\sigma^4} \tag{4.6}$$

(vii) Median absolute deviation: The MAD talks about the spread of data. The also standard deviation and variance are utilized to estimate the spread of data, but the

MAD performs outstandingly when the values are tremendously high or tremendously and ordinariness. When data is ordinary, then the best choice is to utilized standard deviation. If data is not ordinary, then the best choice is to utilized MAD. The below is a formula of MAD.

$$\mathrm{mad}(S) = \mathrm{median}(\,|(\mathrm{S_k} - \bar{S})|\,) \qquad (4.7)$$

Subtract the data points from the mean value of data and then takes the absolute value of that subtracted value.

(viii) **Interquartile range:** the mid spread is the second name of the interquartile range or it's also called the middle 50%. Its value is equal to the value of between 75th and 25th percentiles of difference or value that lies between lower and upper quartiles. Its formula is given below.

$$\mathrm{iqr}(S) = \mathrm{Q3(S)} - \mathrm{Q1(S)} \qquad (4.8)$$

The interquartile range estimates the flexibility in the data. The interquartile range is categorized int to three parts, the first part is called Q1, the second part is called Q2, and the third part is called Q3 that is the difference between Q1 and Q2.

(ix) **Autoregression Coefficient:** the AC belongs to the IIR filter's coefficients. It is treated as an IIR filter. The coefficients of the filter define that how the IIR filter works. The other filters such as the stop-band filter, and passband filter work on parameters of coefficient. They also depend on the order of the filter. The below is the formula of AC.

$$\mathrm{a} = \mathrm{arburg(S, 4)}, \quad \mathrm{a} \in \mathrm{R} \qquad (4.9)$$

It has an order of four. It means it gives four coefficients' values.

(x) **Energy:** the energy of signal defines that how enough signal is strong. It means we can find different characteristics of the signal by finding its energy. The different signals are categorized based on energy. The formula to calculate the energy of the signal is given below.

$$\mathrm{E_f(S)} = \Sigma|\mathrm{S}|\mathrm{f}\,||^2 \qquad (4.10)$$

(xi) **Sum of Peaks Value:** It calculates the peaks of the signal and then the sum of all peaks value into one value. It is also a good feature for the classification of signals because every signal has different peak values. Its formula is given below.

$$\mathrm{sum_{pv}} = \sum_{k=1}^{N} \mathrm{findpeaks}(S_k) \qquad (4.11)$$

4.3.2 Features Extraction through OpenSmile Module

4.3.2.1 Brief Introduction about OpenSmile

OpenSmile stands for The Munich open-Source Media Interpretation by Large feature-space Extraction. It is a toolkit that is utilized for flexible feature extraction. Owing to flexibility features extraction, it is very important for machine learning applications and signal processing. Its also used for signal analysis by utilizing the other modalities for instance visual signals, physiological signals, and values of physical sensors, etc. It has been written in C++ with effective architecture, it executes on a different platform for instance windows, Linux, Android, and macos, etc [66].

4.3.2.2 Data Input

It supports the following file formats for data reading.

- CSV file (comma-separated value)
- AREF file
- RIFF-wave file
- Video format by utilizing OpenCV.
- Audio file

Through the PortAudio library, live audio recording is done with the help of a PC sound card.

4.3.2.3 Audio Features in OpenSmile

The low-level descriptors can be computed via OpenSmile by utilizing audio files as input. The following are the low-level descriptors.

- Frame loudness
- Energy of frame
- Auditory spectra
- Auditory spectra via loudness
- Coefficient via perceptual linear predictive
- LPC (linear predictive coefficients)
- LSP (line spectra pairs)
- The fundamental frequency through the cepstrum
- Quality of voice such as jitter
- Bandwidths and formant frequencies
- Mean crossing and zero crossing
- Entropy, centroid, and roll-off pints are called spectral features.
- Energy normalizes.

There are some other descriptors as well.

4.3.2.4 Functionals in OpenSmile

The following functionals can be used to map curves of audio and video low-level descriptors against a vector of defined dimensionality:

- Jitter and Glitter in the Voice
- Frequencies and bandwidths of formants

- Rates of zero and mean crossing
- Spectral characteristics (arbitrary band powers, roll-off stages, centroid, entropy, and so on).
- Spectral harmonicity and psychoacoustic sharpness
- CENS (octave-warped semitone spectra) and CHROMA (octave-warped semitone spectra) features (energy-normalized and smoothed CHROMA)
- Chord and Key identification based on CHROMA functionality.
- Ratios of F0 Harmonics

4.3.2.5 Output Format

The following file formats are natively supported for writing data to files:

- WAVE-RIFF (PCM uncompressed audio)
- CSV (comma separate values)
- Parameter file for HTK
- File WEKA ARFF
- LIBSVM has a file format that it can use.
- Matrix format for binary floats

4.3.2.6 Built-in Configuration Files in OpenSmile

Many built-in configuration files present in OpenSmile module. Each configuration file gives various numbers of statistical features. The following are the names of some built-in configuration files.

- Avec2011
- Avec2013
- ComParE2016
- Emobase
- IS09_emotion
- IS10_paraling
- IS11_speaker_state
- IS12_speaker_trait
- IS13_ComParE
- prosodyAcf
- smileF0
- list_audio_devices

We utilized the IS09_emotion configuration file features extraction. It gives 384 statistical features.

IS09_emotion configuration file: It includes 384 statistical features that are added to low-level descriptor curvature. Arff format is used to store the features, which allows for the inclusion of new instances to an existing file. The following list documents the names of the 16 low-level descriptors as they emerge in the Arff file:

- The energy of the root-mean-square signal frame
- Cepstral coefficients of Mel-Frequency 1-12

- The rate at which a time signal crosses zero is called the zero-crossing distance (frame-based)
- The ACF was used to measure the voicing probability.
- The Cepstrum was used to calculate the fundamental frequency.
- The suffix _sma added to the names of the low-level descriptors indicates that they were smoothed using a three-window moving average filter. The suffix _de appended to the _sma suffix means that the present function is a smoothed low-level descriptor's 1st order delta coefficient (differential). The names of the 12 functionals as they exist in the Arff file are listed below:
- The contour's maximum worth.
- The contour's minimum value.
- Range value (max-min)
- The highest value's absolute location (in frames)
- The minimal value's absolute location (in frames)
- The contour's arithmetic mean
- A linear approximation of the angle of the curves
- The offset (t) of a linear contour approximation
- The quadratic error is determined by subtracting the linear approximation from the true contour.
- The magnitude of the contour's standard deviation
- The skewness moment of 3^{rd} order
- The kurtosis moment of 4^{th} order

4.4 Feature Selection and Analysis

After extracting the statistical features from openSMILE toolkit, the analysis of features has been done. We observed the most of the features are less effective as they are purely voice data. So, it is recommended features selection should be applied for removing the redundant features. The correlation method has been applied for features selection based on ranking. We selected the top 300 features and analyzed them. We found that most of the features were related to Mel Frequency Cepstral Coefficients and Root Mean Square Energy. Figure 4.1 illustrates the distribution of the top 300 features. We can see in the pie graph 74% of features are related to MFCC descriptor, 15% of features are related to RMS Energy, and 11% of features are related to voicing probability. Whereas features related to fundamental frequency and zero-crossing rate descriptors are zero because they are purely related to audio.

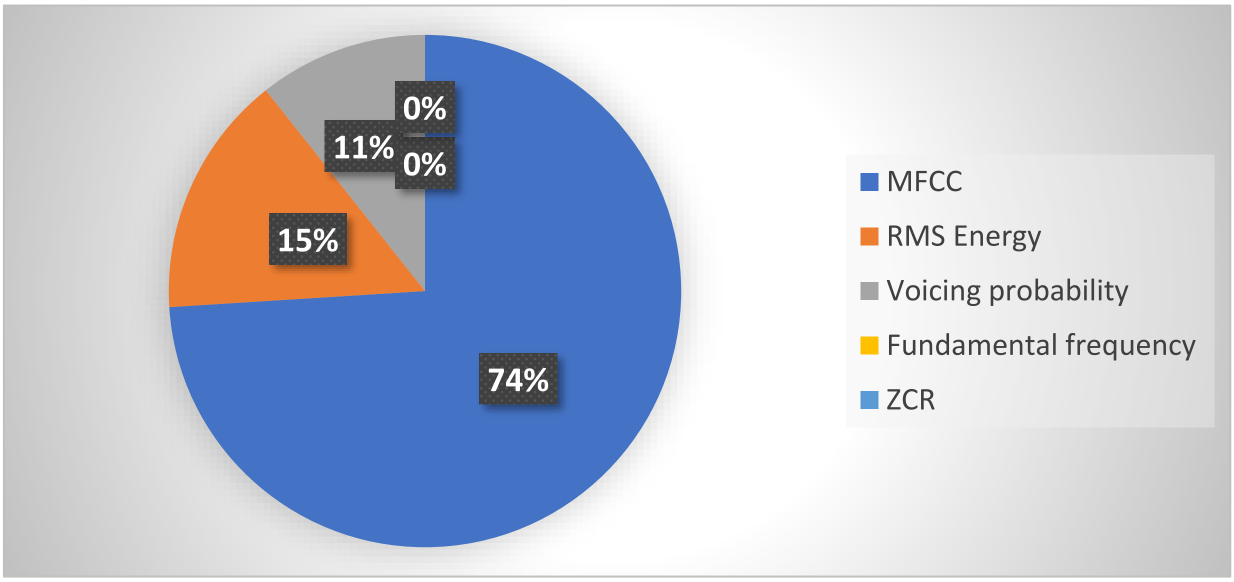


Figure 4.2: Distribution of top 300 features

4.5 Weka Tool

After extracting the statistical features from the Matlab tool and OpenSmile module, the features set fed into to Weka tool for implementation. Weka is a machine learning tool. It has been developed by the University of Waikato. It is discussed in detail.

4.5.1 Brief Introduction about Weka Tool

Weka is a series of data mining-related machine learning algorithms. The algorithms can be used to explicitly refer to a dataset or named from Java code. Data pre-processing, sorting, regression, clustering, correlation rules, and visualization are all available in Weka. Let's have a look at another data science platform called Weka in this age of data science where R and Python rule the roost. Weka has been around for a while and was built for academic purposes at the University of Waikato. The simple learning curve is what makes Weka so appealing. Weka's Interface makes it easier to step into the field of Data Science for someone who has not coded in a while. Since the library is written in Java, anyone with a working knowledge of the language will use it with their code [67].

4.5.2 Downloading and Installation

Weka is available in two versions: the latest stable release is Weka version 3.8. The development version is Weka 3.9. Once or twice a year, new versions of these two versions are released. It is also possible to download hourly snapshots of these two models for those who wish to remain on the cutting edge. The stable version receives only bug fixes and software upgrades that do not break compatibility with previous releases, whereas the development version will receive new features that break compatibility. Weka 3.8 and 3.9 provide a package management framework that helps the Weka group to quickly add additional features to the framework. To import and update packages, the package management system needs an internet connection. **Snapshots:** Any night, we take a snapshot of the Subversion repository containing the Weka source code, compile it, and package it in ZIP files. This exists in both the creation and stable divisions of the program. These snapshots are available to anyone who want the most recent bug fixes before the next official update. **Stable version:** Weka 3.8 is the most recent stable version. While major new features may become available in bundles, this branch of Weka only gets bug fixes and updates that do not interrupt compatibility with earlier 3.8 launches. There are some ways to import and install it on your computer. **Download the Weka tool for Windows:** Azul's 64-bit OpenJDK Java VM 11 is used as a self-extracting executable for 64-bit Windows (weka-3-8-5-azul-zulu-windows.exe, 124.6 MB), it can be downloaded in reference [67].

4.5.3 Requirements

Weka's most recent official releases require Java 8 or later. If you are running Windows and have a device with a high pixel density (HiDPI) display, you'll want to use Java 9 or later to prevent issues with Weka's graphical user interfaces scaling inappropriately. The built-in package manager has a list of packages for Weka that can be installed. A package's Javadoc can be found at https://weka.sourceforge.io/doc.packages/ accompanied by the package's name.

4.5.4 Data Format in Weka

The following point provides an overview of the ARFF format.

Stable attribute-relation file format (ARFF): ARFF files are split into two parts. The header information is shown first, followed by the data information. The name of the relation, a list of the attributes (data columns), and their forms are all found in the ARFF file's header. The header section can be defined in two ways. The reference declarations and attribute declarations are found in the ARFF header portion of the code. The **relation declaration** in the header: The first line of the ARFF file defines the relation's name. It can be written as @relation [relation-name]. [relation-name] is a string in this case. If the name comprises spaces, the string must be quoted. In addition, no reference or attribute names (see below) can begin with a character below \u0021, and '{', '}', ',', or '%'. Furthermore, it can only focus on one particular or double quote if the name ends with a matching quote. The **attributes declaration** is heard: A structured sequence of @attribute statements constitutes an attribute declaration. Each attribute in the data set has its @attribute declaration, which specifies the name and data form of the attribute in a specific way. In the data segment of the file, the order in which the attributes are declared determines the column location. Weka requires all of an attribute's values to be included in the third comma-delimited column if it is the third one declared. Any of the four forms provided by Weka can be used as the [datatype]:

- Data in numeric form
- Data in string form
- Numeric integers are treated as numeric reals.
- Data in nominal form
- For multi-instance data, relational is the way to go (for future use)

CHAPTER 5 : EXPERIMENTAL RESULTS

The Weka platform was used to carry out the implementation. The detailed discussion about Weka can be found in chapter 4. After extracting statistical features from Matlab and opnenSMILE module, the feature set was fed to the weka tool for human activities classification and user's authentication based on activities recognition. There are many classifiers available in the Weka tool. We used the RF classifier with default parameters and 10-fold cross-validation, as well as the SVM classifier with the polynomial kernel of degree 3 and 10-fold cross-validation in the Weka tool. We choose these two classifiers for the proposed method of assessment because they provide strong outcomes, as seen in References [68,69,70]. These two classifiers are discussed in detail.

5.1 Random Forest Classifier

Random forest is a scalable, easy-to-use machine learning algorithm that in most cases, produces excellent results even without hyper-parameter tuning.

5.1.1 Brief Introduction about RF Classifier

RF is a learning algorithm that is supervised. It creates a "forest" out of an ensemble of decision trees, which are normally educated using the "bagging" technique. The bagging method's basic premise is that combining different learning models improves the outcome.

5.1.2 Working of RF Classifier

Th working of the RF classifier can be presented in four steps [71].

- From given data, select random samples.
- Create a decision tree for each sample and use it to generate a prediction outcome.
- Making a vote for each expected outcome.
- As the final forecast, pick the prediction with the most votes.

In figure 5.1, we can see the working of the RF classifier.

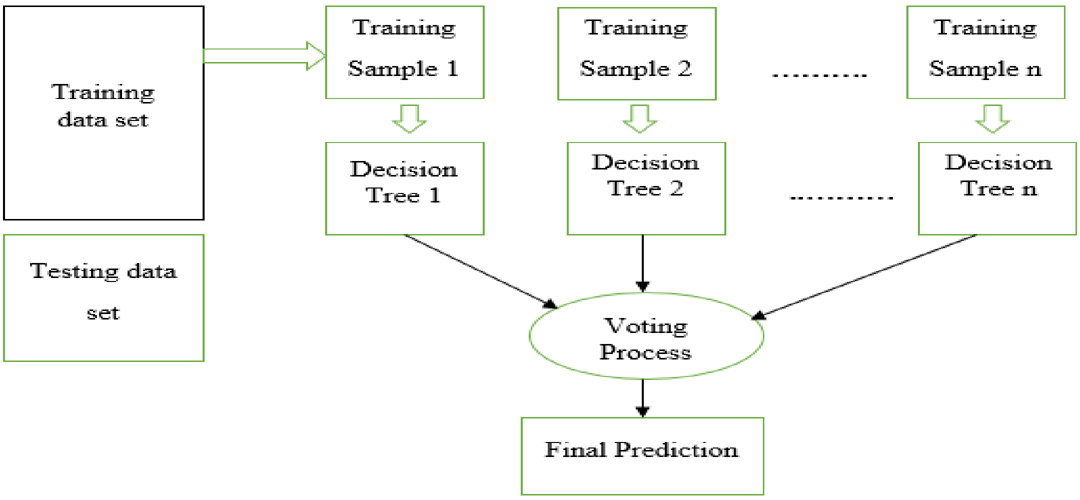


Figure 5.1: Working of RF classifier

5.1.3 Advantages of RF Classifier

- RF is an extremely reliable and robust method due to involving of a vast number of decision trees procedure.
- It is not impacted by the issue of overfitting. The biggest explanation for this is that it averages all the forecasts, canceling out any biases.
- It is utilized for regression and classification problems.
- The missing values can be managed by RF. In two ways RF handles the missing values by utilizing mean and median.

5.1.4 Disadvantages of RF Classifier

- Due to having multiple decision trees, RF takes a long time to generate predictions.
- Random forests are much more complex and time-consuming to create than decision trees.
- When we have a sufficient number of decision trees, it becomes less intuitive.

5.2 Support Vector Machine Classifier

While the Support Vector Machine is generally thought of as a classification tool, it can be used to solve both classification and regression problems. It is a supervised machine learning algorithm.

5.2.1 Brief Introduction about SVM Classifier

It can treat both continuous and categorical variables with ease. To distinguish various groups, SVM generates a hyperplane in multidimensional space. SVM iteratively produces a better hyperplane, which is then used to minimize an error. SVM aims to find a maximal marginal hyperplane (MMH) that divides a dataset into groups as evenly as possible [72].

5.2.2. Working of SVM Classifier

The key goal is to stratify the provided dataset as efficiently as possible. The margin is the difference between the two points that are closest to each other. The aim is to find a hyperplane that has the largest possible margin between support vectors in the dataset. In the following stages, SVM looks for the highest marginal hyperplane:

- Create hyperplanes that effectively separate the groups.
- Select that hyperplane that can segregate maximum data points.

When data is non-linear, then kernel trick is being used by SVM. In kernel trick, data is transformed from lower dimensional to higher-dimensional space. Where data can be separated easily.

5.2.3 Kernel Tricks in SVM

A kernel is used to execute the SVM algorithm in operation. An input data space is transformed into the appropriate form by a kernel. The kernel trick is a method used by SVM. The kernel converts a low-dimensional input space into a higher-dimensional space in this case. To put it another way, it turns non-separable problems into separable problems by applying more dimensions to them. It is most useful in problems concerning non-linear separation. The kernel trick aids in the creation of a more reliable classifier. Many kernels are available such as linear kernel, polynomial kernel, and radial basis function kernel, etc.

5.2.4 Advantages of SVM Classifier

SVM Classifiers outperform as contrasted to Nave Bayes algorithm in terms of accuracy and prediction speed. They still use limited memory in the selection phase since they only use a subset of training points. With a large dimensional space and a clear separation margin, SVM fits well.

5.2.5 Disadvantages of SVM Classifier

Because of its long training period, SVM is not good for massive datasets, and it often takes longer to learn than Nave Bayes. It has problems with overlapping classes and is often influenced by the kernel type used.

5.3 Performance Criteria

For the assessment of the proposed process, the following success metrics were chosen.

- **Overall accuracy:** Overall Accuracy informs us what percentage of the reference locations is accurately mapped out of all of them. The total accuracy is generally calculated as a percentage, with 100 percent accuracy meaning that all reference sites were accurately identified. Overall accuracy is the simplest to measure and comprehend, but it only offers specific accuracy knowledge to map users and producers. It can be calculated as:

$$\boldsymbol{Overall\ accuracy} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FP + FN + TN}}$$

- **Precision:** Precision is a method of calculating how many accurate positive forecasts have been made. The percentage of correctly estimated positive examples divided by the overall number of positive examples predicted is used to quantify it. The sum of true positives divided by the combined number of true positives and false positives equals accuracy. It can be calculated as:

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

- **Specificity:** The true negative rating (TNR), also known as the accuracy of a result, is the percentage of tests that test negative using the test in question that is negative. It is calculated as:

$$\boldsymbol{Specificity} = \frac{\boldsymbol{TN}}{\boldsymbol{TN + FP}}$$

- **F-Measurement:** Precision and recall are also considered when calculating the F1 Score. It is the precision and recall's harmonic mean (average). The F1 Score is better when the machine has a good balance of precision (p) and recall (r). On the other hand, if one measure is increased to the detriment of another, the F1 Score is not as good. If P is 1 and R is 0, the F1 score is 0. It is calculated as:

$$\boldsymbol{F\_Masurement} = \boldsymbol{2} * \frac{(\boldsymbol{Recall} * \boldsymbol{Precision})}{(\boldsymbol{Recall} + \boldsymbol{Precision})}$$

Where as TN=True Negative, TP= True Positive, FP= False Positive, FN= False Negative.

5.4 Evaluation of WISDM Dataset

The WISDM dataset consists of six daily living activities such as jogging, walking, sitting, standing, walking upstairs, and walking downstairs. We applied two eminent classifiers random forest and support vector machine for the classification of different activities.

5.4.1 Results with Applying Window of 10 Second

We applied a window of 10 s with a sampling frequency of 20 Hz. The total samples in the 10s window were 200. The performance of the RF classifier was good as compared to the SVM classifier in the case of the Matlab features set. The accuracy of activities such as downstairs, jogging, sitting, standing, upstairs, and walking was 86%, 99.40%, 98.60%, 100%, 90.21%, and 99.40% respectively by utilizing RF classifier. By applying the SVM classifier, the accuracy of activities such as downstairs, jogging, sitting, standing, upstairs, and walking was 89.31%, 99%, 98%, 96.10%, 92.20%, and 98.60 % respectively. Figure 5.2 illustrates the performance of both classifiers.

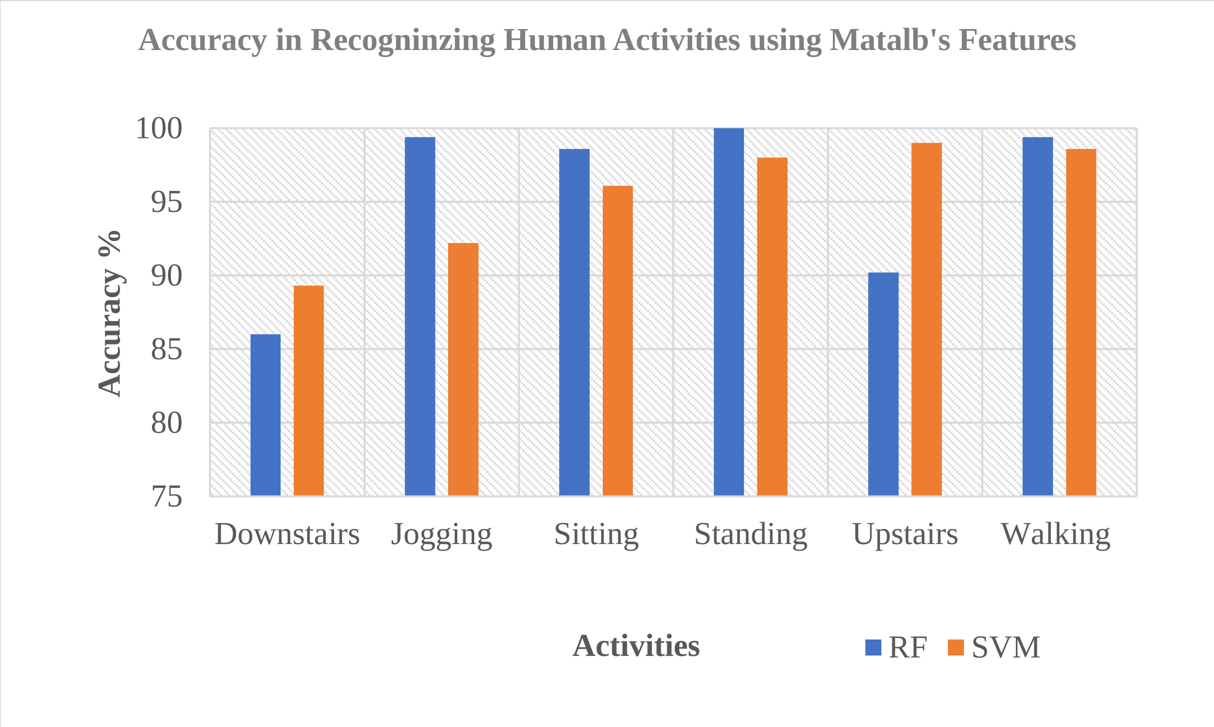


Figure 5.2: The accuracies achieved by RF and SVM by using Matlab features at WISDM dataset.

From the above figure, we can see that the accuracy of standing activity is 100% in the case of the RF classifier. Tables 5.1 and 5.2 show the confusion matrix of RF and SVM classifiers, respectively. Tables 5.3 and 5.4 illustrate the performance criteria of RF and SVM classifiers, respectively. The overall accuracy of RF and SVM classifiers was 97.15% and 97.02% respectively. The accuracy of the RF classifier is a little bit greater than the accuracy of the SVM classifier. In the case of OpenSmile features set, the accuracy of downstairs, jogging, sitting, standing, upstairs, and walking was 13.20%, 99.10%, 92%, 78.41%, 28%, and 97% respectively by applying the RF classifier. With applying the SVM classifier, the accuracy of downstairs, jogging, sitting, standing, upstairs, and walking was 45%, 97%, 88%, 74%, 51%, and 88% respectively. Figure 5.3 illustrates the performance of both classifiers.

Table 5.1: Confusion matrix of RF classifier by using Matlab features at WISDM dataset.

classified as	A	b	C	d	e	f
a=Downstairs	**418**	7	0	0	29	32
b=Jogging	2	**1685**	0	0	1	7
c=Sitting	1	0	**284**	3	0	0
d=Standing	0	0	0	**231**	0	0
e=Upstairs	17	22	0	0	**544**	20
f= Walking	3	0	0	0	10	**2090**

Table 5.2: Confusion matrix of SVM classifier by using Matlab features at WISDM dataset.

classified as	A	b	C	d	e	f
a=Downstairs	**434**	2	0	0	39	11
b=Jogging	5	**1678**	0	0	9	3
c=Sitting	0	0	**282**	5	1	0
d=Standing	0	0	9	**222**	0	0
e=Upstairs	30	6	0	0	**556**	11
f= Walking	12	1	0	0	17	**2073**

Table 5.3: Performance criteria for RF classifier by using Matlab features at WISDM dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
downstairs	0.860	0.005	0.948	0.860	0.902
jogging	0.994	0.008	0.983	0.994	0.989
Sitting	0.986	0.000	1.000	0.986	0.993
standing	1.000	0.001	0.987	1.000	0.994
upstairs	0.994	0.008	0.932	0.902	0.917
walking	0.994	0.018	0.973	0.994	0.983
Weighted Avg.	**0.972**	**0.011**	**0.971**	**0.972**	**0.971**

Table 5.4: Performance criteria for SVM classifier by using Matlab features at WISDM dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
downstairs	0.893	0.010	0.902	0.893	0.898
jogging	0.990	0.002	0.995	0.990	0.992
Sitting	0.979	0.002	0.969	0.979	0.974
standing	0.961	0.001	0.978	0.961	0.969
upstairs	0.922	0.014	0.894	0.922	0.908
walking	0.986	0.008	0.988	0.986	0.987
Weighted Avg.	**0.970**	**0.006**	**0.970**	**0.970**	**0.970**

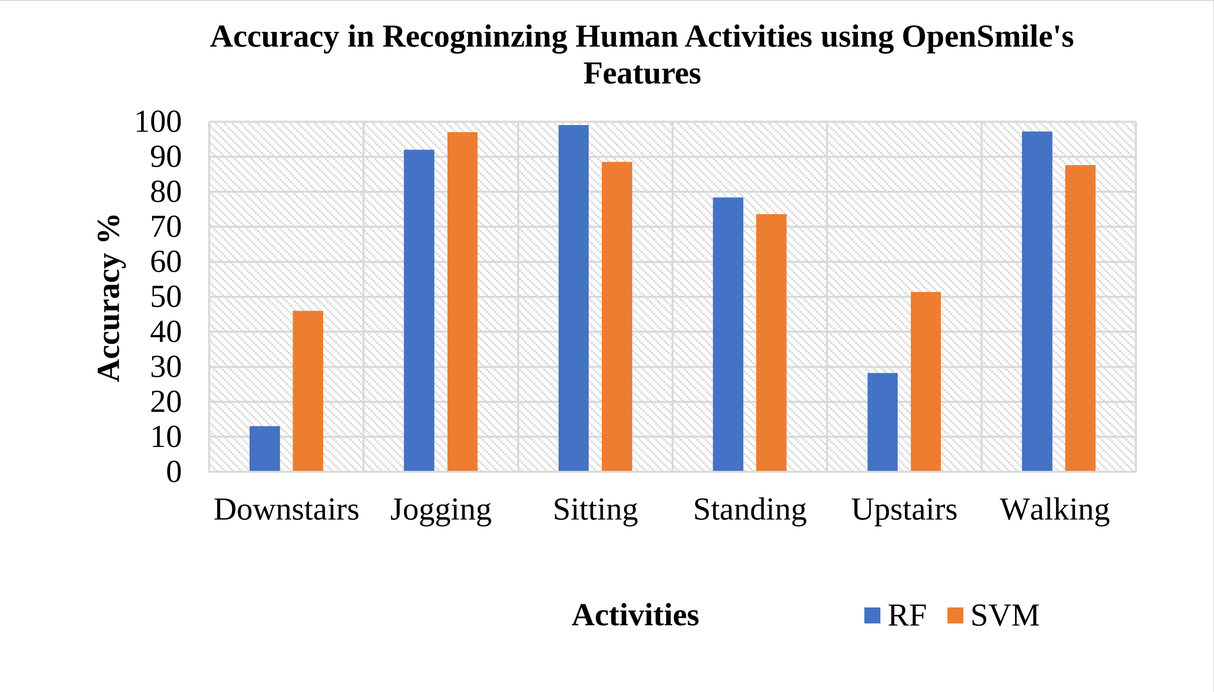


Figure 5.3: The accuracies achieved by RF and SVM by using OpenSmile features at WISDM dataset.

We can see in figure 5.3 the performance of classifiers is not good on OpenSmile features set as compared to the Matlab features set. The overall accuracy of RF and SVM classifiers is 81.46 % and 82.32 % respectively. Tables 5.5 and 5.6 show the confusion matrix and performance criteria of the RF classifier.

Table 5.5: Confusion matrix of RF classifier by using OpenSmile features at WISDM dataset.

classified as	a	b	C	d	e	f
a=Downstairs	**64**	37	0	4	40	341
b=Jogging	0	**1680**	0	0	0	15
c=Sitting	0	0	**265**	19	4	0
d=Standing	0	0	44	**181**	4	2
e=Upstairs	16	71	0	3	**170**	343
f= Walking	5	37	0	6	11	**2044**

Table 5.6 : Performance criteria of RF classifier by using OpenSmile features at WISDM dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
downstairs	0.132	0.004	0.753	0.132	0.224
jogging	0.991	0.039	0.921	0.991	0.955
Sitting	0.920	0.009	0.858	0.920	0.888
standing	0.784	0.006	0.850	0.784	0.815
upstairs	0.282	0.012	0.742	0.282	0.409
walking	0.972	0.212	0.745	0.972	0.843
Weighted Avg.	**0.815**	**0.097**	**0.811**	**0.815**	**0.775**

5.4.2 Results with Applying 80% Overlapping Window of 10 Second.

We achieved good results by applying overlapping window. The 80% overlapping window of 10s had been applied on WISDM dataset. After this, the statistical features had been extracted from Matlab and OpenSmile module. The statistical features had been fed to the weka tool and applied the RF and SVM classifiers for activities recognition. The performance of both classifiers was outstanding. The overall accuracy of RF and SVM classifiers was 99.55 % and 99.26% respectively. Figure 5.4 shows the accuracies of both classifiers.

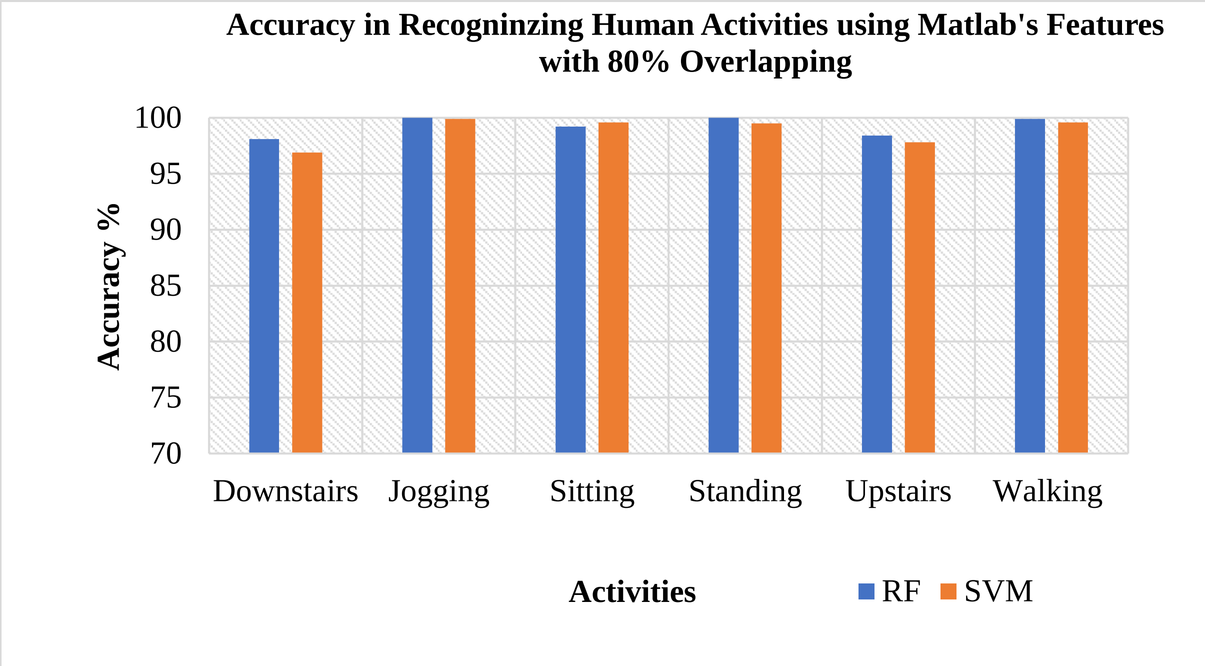


Figure 5.4: The accuracies achieved by RF and SVM by using Matlab features set with 80% overlapping window of 10 second at WISDM dataset.

The accuracy of the RF classifier was a little bit greater than the SVM classifier. The accuracy of jogging, standing, and walking activities was 100% in the case of applying the RF classifier. Tables 5.7 and 5.8 show the confusion matrix of RF and SVM classifies. Table 5.9 illustrates the performance criteria of the RF classifier for activities recognition.

Table 5.7: Confusion matrix of RF classifier by using Matlab features set with applying overlapping window at WISDM dataset.

classified as	a	b	C	d	e	f
a=Downstairs	**2323**	3	0	0	26	15
b=Jogging	0	**8404**	0	0	1	3
c=Sitting	1	0	**1384**	5	5	0
d=Standing	0	0	0	**1101**	0	0
e=Upstairs	14	18	0	0	**2879**	16
f= Walking	4	1	0	0	9	**10433**

Table 5.8 : Confusion matrix of SVM classifier by using Matlab features set with applying overlapping window at WISDM dataset.

classified as	a	b	C	d	e	f
a=Downstairs	**2293**	0	0	0	70	4
b=Jogging	2	**8402**	0	0	3	1
c=Sitting	0	0	**1389**	6	0	0
d=Standing	0	0	5	**1096**	0	0
e=Upstairs	52	0	0	0	**2862**	13
f= Walking	8	0	0	0	32	**10407**

Table 5.9: Performance criteria of RF classifier by using Matlab features with applying overlapping window at WISDM dataset

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
downstairs	0.981	0.001	0.992	0.981	0.987
jogging	1.000	0.001	0.997	1.000	0.998
Sitting	0.992	0.000	1.000	0.992	0.996
standing	1.000	0.000	0.995	1.000	0.998
upstairs	0.984	0.002	0.986	0.984	0.985
walking	0.999	0.002	0.997	0.999	0.998
Weighted Avg.	**0.995**	**0.001**	**0.995**	**0.995**	**0.995**

In the case of OpenSmile features set with applying 80% overlapping window, the performance of both classifiers was outstanding. The good results had been achieved as compared to without overlapping window. The individual accuracy of downstairs, jogging, sitting, standing, upstairs, and walking was 98.70%, 100%,99.51%, 93.70%, 99%, and 99.70% respectively by utilizing the OpenSmile features set with overlapping window. The overall accuracy of both classifiers on OpenSmile features set with applying 80% overlapping window of 10s was 99.37% and 98.96% respectively. Figure 5.5 illustrates the performance of both classifiers for daily living activities recognition.

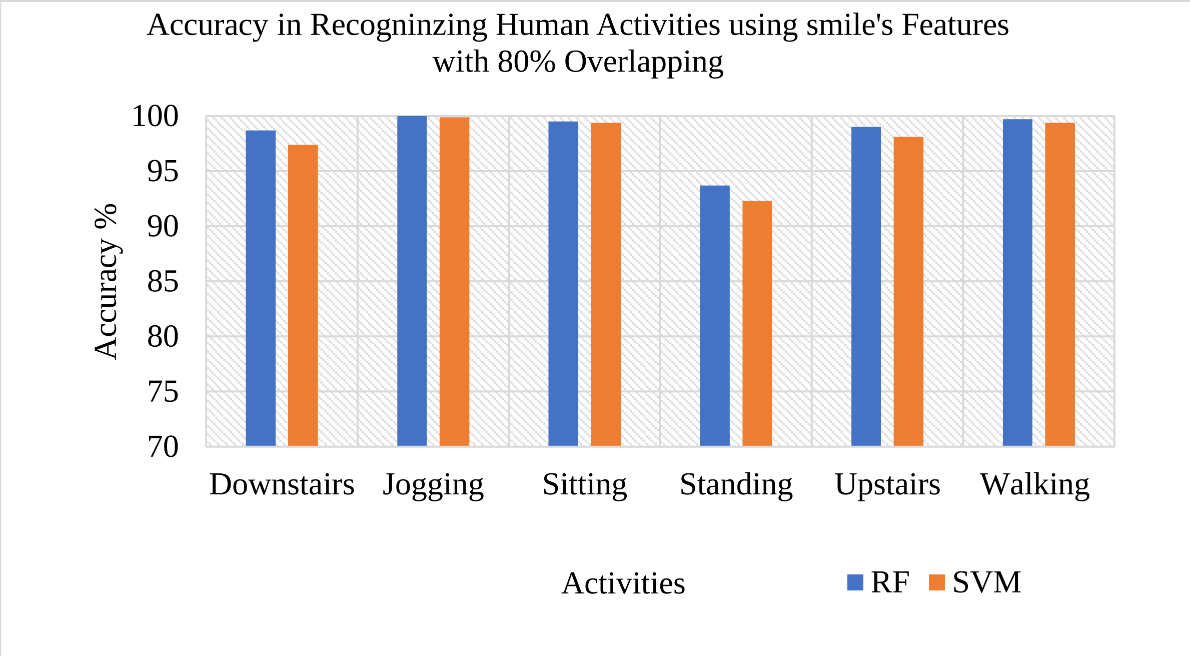


Figure 5.5: The accuracies achieved by RF and SVM by using OpenSmile features with 80% overlapping window of 10 second at WISDM dataset.

From figure 5.5, we can see that jogging activity is 100% correctly classified in the case of both classifiers. The performance of the RF classifier is better than the SVM classifier. Tables 5.10 and 5.11 depict the confusion matrix of RF and SVM for activities recognition.

Table 5.10: Confusion matrix of RF classifier by using OpenSmile features with applying overlapping window at WISDM dataset

classified as	a	b	C	d	e	F
a=Downstairs	**2337**	2	0	5	14	9
b=Jogging	1	**8406**	0	0	1	0
c=Sitting	0	0	**1388**	7	0	0
d=Standing	0	0	69	**1032**	0	0
e=Upstairs	8	10	0	0	**2899**	10
f= Walking	15	2	0	0	14	**10416**

Table 5.11: Confusion matrix of SVM classifier by using OpenSmile features with applying overlapping window at WISDM dataset

classified as	a	b	C	d	e	F
a=Downstairs	**2306**	0	0	2	26	33
b=Jogging	1	**8402**	0	0	4	1
c=Sitting	0	0	**1387**	8	0	0
d=Standing	1	0	84	**1016**	0	0
e=Upstairs	31	8	0	0	**2871**	17
f= Walking	37	0	0	0	22	**10388**

The performance criteria of both classifiers can be seen in tables 5.12 and 5.13.

Table 5.12: Performance criteria of RF classifier by using OpenSmile features with applying overlapping window at WISDM dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
downstairs	0.987	0.001	0.990	0.987	0.989
jogging	1.000	0.001	0.998	1.000	0.999
Sitting	0.995	0.003	0.953	0.995	0.973
standing	0.937	0.000	0.989	0.937	0.962
upstairs	0.990	0.001	0.990	0.990	0.990
walking	0.997	0.001	0.998	0.997	0.998
Weighted Avg.	**0.994**	**0.001**	**0.994**	**0.994**	**0.994**

Table 5.13: Performance criteria of SVM classifier by using OpenSmile features with applying overlapping window at WISDM dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
downstairs	0.974	0.003	0.971	0.974	0.972
jogging	0.999	0.000	0.999	0.999	0.999
Sitting	0.994	0.003	0.943	0.994	0.968
standing	0.923	0.000	0.990	0.923	0.955
upstairs	0.981	0.002	0.982	0.981	0.982
walking	0.994	0.003	0.995	0.994	0.995
Weighted Avg.	**0.990**	**0.002**	**0.990**	**0.990**	**0.990**

Table 5.14 illustrates the complete results on WISDM dataset. We can see that the maximum accuracy has been achieved by applying an 80% overlapping window of 10s. The maximum accuracy achieved with a non-overlapping window was 97.15% by utilizing the RF classifier and with an overlapping window the accuracy was 99.51% achieved by the RF classifier.

Table 5.14: The complete results on WISDM dataset.

	Applying window of 10s		**Applying 80% Overlapping window of 10s**	
Method	Accuracy on Matlab Features Set	Accuracy on OpenSmile Feature Set	Accuracy on Matlab Features Set	Accuracy on OpenSmile Feature Set
RF	97.15%	81.47%	99.55%	99.37%
SVM	97.02%	82.36 %.	99.26%	98.97%

5.5 Evaluation of MobiAct Dataset

The MobiAct dataset consists of nine different daily living activities such as walking, jogging, upstairs, downstairs, sitting, standing, jumping, car step in, and car step out. We selected 6 activities so that a comparison can be made with other published methods.

5.5.1 Results with Applying Window of 10 Second

We applied a window of 10 s with a sampling frequency of 100 Hz. The total samples in the 10s window were 1000. The performance of the RF classifier was good as compared to SVM classifier in the case of the Matlab features set. The accuracy of activities such as jogging, sitting, standing, downstairs, upstairs, and walking was 88%, 99.70%, 99.30%, 90.10%, 89.30%, and 99.30% respectively by utilizing RF classifier. By applying the SVM classifier, the accuracy of activities such as jogging, sitting, standing, downstairs, upstairs, and walking was 78.20%, 93.10%, 98.50%, 60%, 55.20%, and 97.30% respectively. Figure 5.6 illustrates the performance of both classifiers. From the figure, we can see that the accuracy of sitting activity is 100% in the case of the RF classifier. The performance of the RF classifier was outstanding in contrast to the SVM classifier. The overall accuracy of RF and SVM classifiers was 97.32%, and 91.92% respectively by utilizing the Matlab features set. Tables 5.15 and 5.16 show the confusion matrix of RF and SVM classifiers, respectively. Tables 5.17 and 5.18 illustrate the performance criteria of RF and SVM classifiers, respectively. In the case of OpenSmile features set, the accuracy of jogging, sitting, standing, downstairs, upstairs, and walking was 87.30%, 99.80%, 99.30%, 78.50%, 75.50%, and 100% respectively by applying the RF classifier. By applying the SVM classifier, the accuracy of jogging, sitting, standing, downstairs, upstairs, and walking was 87.50%, 97.30%,98.80%,70.9%, 73.60%, and 99.90% respectively. The overall accuracy of RF and SVM classifiers was 96.32% and 95.57% respectively. Figure 5.7 shows the performance of both classifiers for activities recognition.

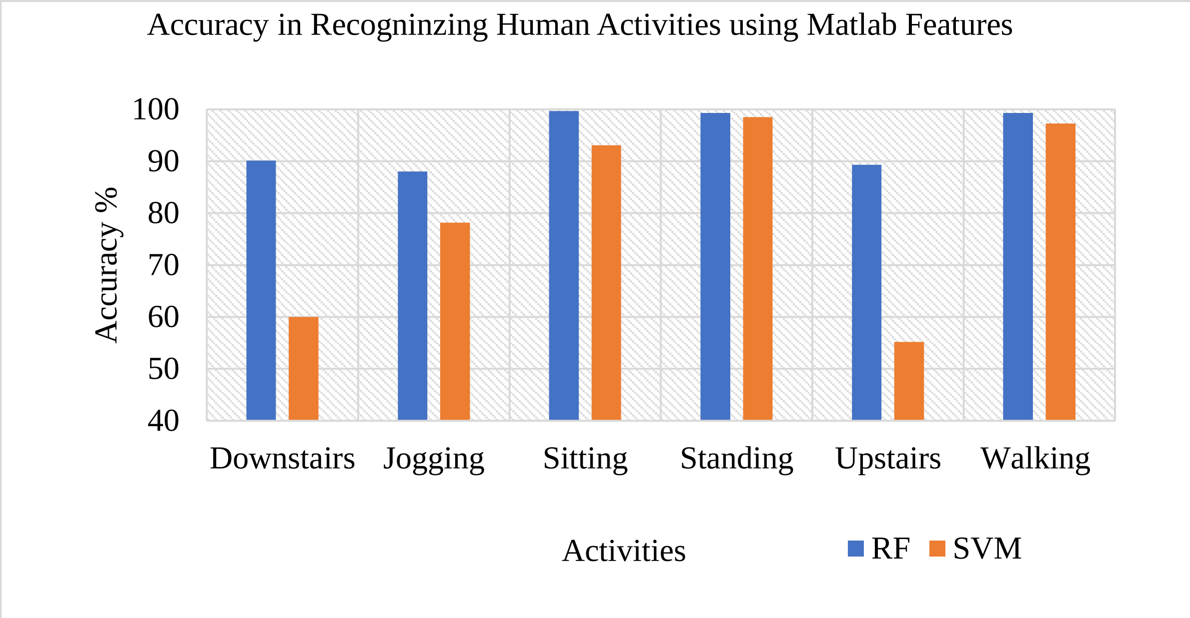


Figure 5.6: The accuracies achieved by RF and SVM by using Matlab features at mobiact dataset.

Table 5.15: Confusion matrix of RF classifier by using Matlab features at MobiAct dataset.

classified as	a	b	c	d	e	f
a= Jogging	**1585**	1	3	3	2	208
b= Sitting	1	**891**	1	0	0	1
c= Standing	7	7	**6899**	0	0	36
d=Downstairs	4	0	0	**808**	75	10
e=Upstairs	8	0	2	77	**796**	8
f= Walking	44	0	3	0	1	**7241**

Table 5.16 : Confusion matrix of SVM classifier by using Matlab features at MobiAct dataset.

classified as	a	b	c	d	e	F
a= Jogging	**1410**	1	10	8	12	361
b= Sitting	9	**832**	38	7	6	2
c= Standing	4	51	**6848**	8	6	32
d=Downstairs	21	19	9	**537**	123	188
e=Upstairs	16	8	14	113	**492**	248
f= Walking	162	4	27	10	6	**7090**

Table 5.17: Performance criteria of RF classifier by using Matlab features at MobiAct dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
Jogging	0.880	0.004	0.916	0.880	0.919
Sitting	0.997	0.000	0.991	0.997	0.994
Standing	0.993	0.001	0.999	0.993	0.996
Downstairs	0.901	0.004	0.910	0.901	0.905
Upstairs	0.893	0.004	0.911	0.893	0.902
Walking	0.993	0.023	0.965	0.993	0.979
Weighted Avg.	**0.973**	**0.010**	**0.973**	**0.973**	**0.973**

Table 5.18: Performance criteria of SVM classifier by using Matlab features set at MobiAct dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
Jogging	0.782	0.013	0.869	0.782	0.824
Sitting	0.931	0.005	0.909	0.931	0.920
Standing	0.985	0.007	0.987	0.985	0.986
Downstairs	0.599	0.008	0.786	0.599	0.680
Upstairs	0.552	0.009	0.763	0.552	0.641
Walking	0.973	0.073	0.895	0.973	0.932
Weighted Avg.	**0.919**	**0.033**	**0.916**	**0.919**	**0.915**

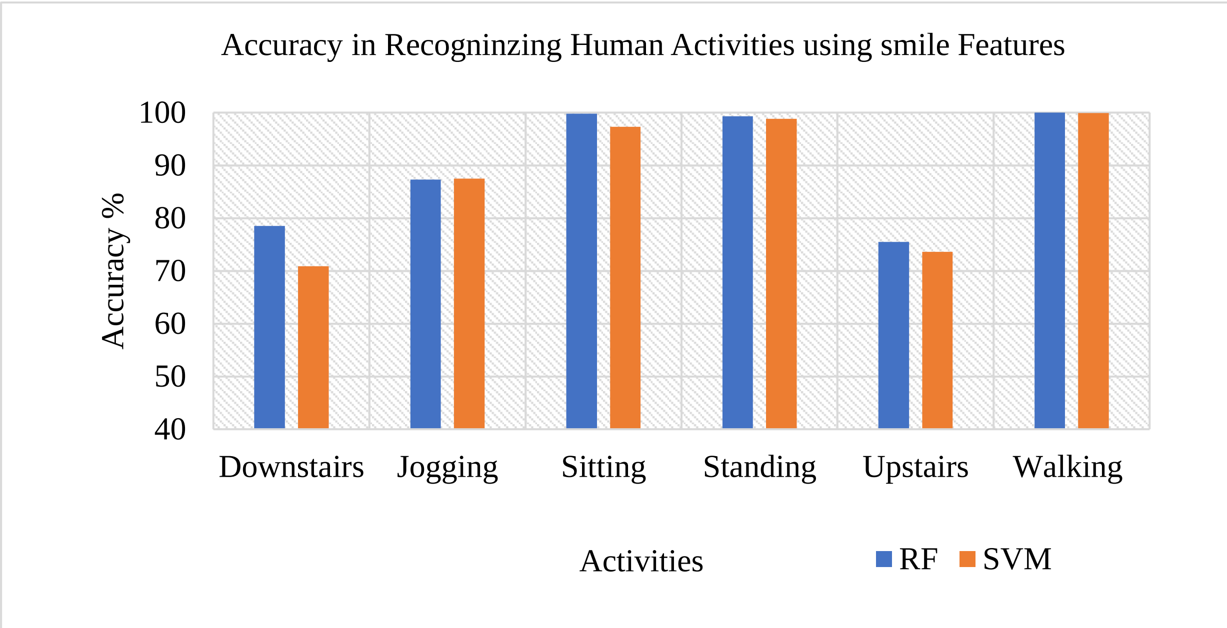


Figure 5.7: The accuracies achieved by RF and SVM by using smile features at mobiact dataset.

Tables 5.19 and 5.20 show the confusion matrix of RF and SVM classifiers, respectively. Tables 5.21 and 5.22 illustrate the performance criteria of RF and SVM classifiers, respectively.

Table 5.19: Confusion matrix of RF classifier by using smile features at MobiAct dataset.

classified as	a	b	c	d	e	f
a= Jogging	**1573**	4	205	0	3	17
b= Sitting	0	**892**	2	0	0	0
c= Standing	29	9	**6903**	0	0	8
d=Downstairs	4	3	0	**704**	185	1
e=Upstairs	6	0	2	210	**673**	0
f= Walking	0	0	0	0	0	**7289**

Table 5.20: Confusion matrix of SVM classifier by using smile features set at MobiAct dataset

classified as	a	b	c	d	e	f
a= Jogging	**1577**	3	220	0	0	2
b= Sitting	5	**870**	17	0	0	2
c= Standing	45	28	**6869**	1	1	5
d=Downstairs	3	1	0	**636**	257	0
e=Upstairs	1	0	0	234	**656**	0
f= Walking	1	2	1	0	0	**7285**

Table 5.21: Performance criteria of RF classifier by using OpenSmile features at MobiAct dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
Jogging	0.873	0.002	0.976	0.873	0.921
Sitting	0.998	0.001	0.982	0.998	0.990
Standing	0.993	0.018	0.971	0.993	0.982
Downstairs	0.785	0.012	0.770	0.785	0.777
Upstairs	0.755	0.011	0.782	0.755	0.768
Walking	1.000	0.002	0.996	1.000	0.998
Weighted Avg.	**0.963**	**0.009**	**0.963**	**0.963**	**0.963**

Table 5.22: Performance criteria of SVM classifier by using OpenSmile features at MobiAct dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
Jogging	0.875	0.003	0.966	0.875	0.918
Sitting	0.973	0.002	0.962	0.973	0.968
Standing	0.988	0.020	0.967	0.988	0.977
Downstairs	0.709	0.013	0.730	0.709	0.719
Upstairs	0.736	0.014	0.718	0.736	0.727
Walking	0.999	0.001	0.999	0.999	0.999
Weighted Avg.	**0.956**	**0.010**	**0.956**	**0.956**	**0.955**

5.5.2 Results with Applying 80% Overlapping Window of 10 Second

We achieved a few good results by applying overlapping window. The 80% overlapping window of 10s had been applied on selected activities in MobiAct dataset. After this, the statistical features had been extracted from Matlab and OpenSmile module. The statistical features had been fed to the weka tool and applied the RF and SVM classifiers for activities recognition. The performance of both classifiers was outstanding. The overall accuracy of RF and SVM classifiers was 98.49% and 95.89% respectively. Figure 5.8 shows the accuracies of both classifiers. The individual accuracy of jogging, sitting, standing, downstairs, upstairs, and walking was 96.70%, 99%, 99.80%, 78.30%, 74.70%, and 99.80% respectively in case of applying RF classifier. By applying the SVM classifier the accuracy of jogging, sitting, standing, downstairs, upstairs, and walking was 85.60%, 91.20%, 99.50%, 52%, 52.40%, and 99% respectively.

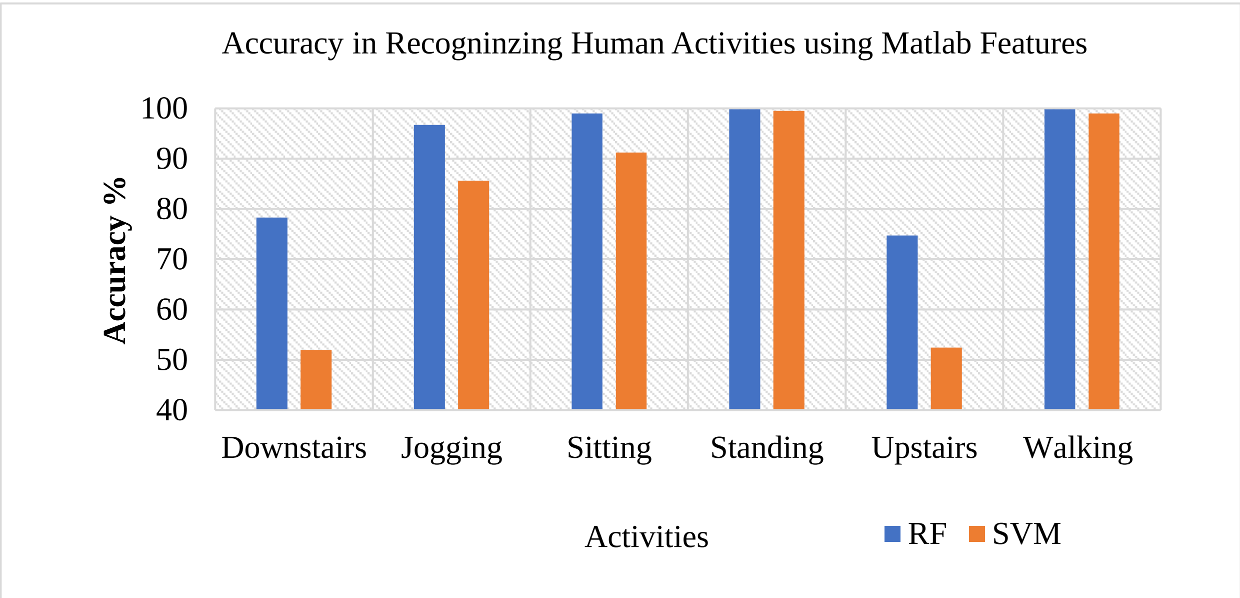


Figure 5.8: The accuracies achieved by RF and SVM by using Matlab features with applying 80% overlapping window at mobiact dataset.

Tables 5.23 and 5.24 illustrate the confusion matrix for RF and SVM classifiers by applying 80% overlapping window of 10 s. The correct instances of jogging, sitting, standing, downstairs, upstairs, and walking activities are 3267, 885, 16879, 702, 666, and 17775 respectively as we can see in table 5.23. In downstairs and upstairs activities, maximum instances are misclassified. In table 5.24, the correct instances of jogging, sitting, standing, downstairs, upstairs, and walking activities are 2893, 815, 16839, 446, 467, and 17635 respectively. Again, maximum instances are misclassified in downstairs and upstairs activities. Tables 5.25 and 5.26 show the performance criteria of both classifiers by applying an 80% overlapping window of 10s.

Table 5.23: Confusion matrix of RF classifier by using Matlab features set with applying overlapping window at MobiAct dataset.

classified as	a	b	c	d	e	f
a= Jogging	**3267**	0	1	11	5	96
b= Sitting	0	**885**	5	0	0	4
c= Standing	4	2	**16879**	2	0	29
d=Downstairs	40	0	7	**702**	56	92
e=Upstairs	28	0	3	60	**666**	134
f= Walking	22	0	0	8	5	**17775**

Table 5.24: Confusion matrix of SVM classifier by using Matlab features set with applying overlapping window at MobiAct dataset.

classified as	a	b	c	d	e	f
a= Jogging	**2893**	1	9	21	13	443
b= Sitting	1	**815**	58	6	10	4
c= Standing	5	38	**16839**	7	1	26
d=Downstairs	45	11	25	**466**	86	264
e=Upstairs	23	8	19	92	**467**	282
f= Walking	122	1	14	20	18	**17635**

Table 5.25: Performance criteria of RF classifier by using Matlab features with overlapping window at MobiAct dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
Jogging	0.967	0.003	0.972	0.967	0.969
Sitting	0.990	0.000	0.998	0.990	0.994
Standing	0.998	0.001	0.999	0.998	0.998
Downstairs	0.783	0.002	0.897	0.783	0.836
Upstairs	0.747	0.002	0.910	0.747	0.821
Walking	0.998	0.015	0.980	0.998	0.989
Weighted Avg.	**0.985**	**0.007**	**0.984**	**0.985**	**0.984**

Table 5.26: Performance criteria of SVM classifier by using Matlab features with overlapping window at MobiAct dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
Jogging	0.856	0.005	0.937	0.856	0.894
Sitting	0.912	0.001	0.932	0.912	0.922
Standing	0.995	0.005	0.993	0.995	0.994
Downstairs	0.520	0.004	0.761	0.520	0.618
Upstairs	0.524	0.003	0.785	0.524	0.629
Walking	0.990	0.044	0.945	0.990	0.967
Weighted Avg.	**0.959**	**0.022**	**0.956**	**0.959**	**0.956**

In the case of OpenSmile features set with applying overlapping window, the overall accuracy of RF and SVM classifiers was 97.55% and 95.79% respectively. That is a little bit higher accuracy than OpenSmile features without applying an overlapping window of 10s. Tables 5.27 and 5.28 show the confusion matrix and performance criteria for RF classifier by applying an overlapping window of 10s on OpenSmile's features. We can see in table 5.27 the sitting activity is 100% correctly classified. In downstairs and upstairs activities maximum instances are misclassified. Table 5.29 illustrates the complete results of selected activities in MobiAct dataset.

Table 5.27: Confusion matrix of RF classifier by using OpenSmile features with applying overlapping window at MobiAct dataset.

classified as	a	b	C	d	e	f
a= Jogging	**3238**	0	57	34	31	20
b= Sitting	0	**894**	0	0	0	0
c= Standing	27	0	**16833**	8	24	24
d=Downstairs	20	2	5	**691**	172	7
e=Upstairs	4	0	1	197	**685**	4
f= Walking	149	0	175	13	25	**17448**

Table 5.28: Performance criteria of RF classifier by using OpenSmile features set with overlapping window at MobiAct dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
Jogging	0.958	0.005	0.942	0.958	0.950
Sitting	1.000	0.000	0.998	1.000	0.999
Standing	0.995	0.010	0.986	0.995	0.991
Downstairs	0.770	0.006	0.773	0.770	0.751
Upstairs	0.769	0.006	0.731	0.769	0.749
Walking	0.980	0.002	0.997	0.980	0.988
Weighted Avg.	**0.976**	**0.006**	**0.976**	**0.976**	**0.976**

Table 5.29: Results at selected activities in MobiAct data.

	With 10s window		**80% Overlapping window of 10s**	
Method	Accuracy on Matlab's Features	Accuracy on OpenSmile's Features	Accuracy on Matlab's Features	Accuracy on OpenSmile's Features
RF	97.32%	96.33%	98.49%	97.55%
SVM	91.92 %	95.32%	95.89%	95.79%

5.5 Evaluation of MobiAct_v2 Dataset

The MobiAct dataset consists of twelve different daily living activities such as walking, jogging, upstairs, downstairs, sitting, standing, jumping, laying, sit to stand, stand to sit, car step in, and car steps out. We selected 11 activities so that a comparison can be made with other published methods.

5.5.1 Results with Applying Window of 10 Second

We applied a window of 10 s with a sampling frequency of 100 Hz. The total samples in the 10s window were 1000. The performance of the RF classifier was good as compared to SVM classifier in the case of the Matlab features set. The accuracy of activities such as sit to stand, car step in, car step out, jogging, jumping, stand to sit, sitting, standing, downstairs, upstairs, and walking was 78.40%, 86%, 90%, 85.60%, 89.60%, 97.20%, 67.80%, 99.10%, 90%, 90.60%, and 99.20% respectively by utilizing RF classifier. Figure 5.9 shows the performance of the RF classifier for activities recognition. The overall accuracy of RF and SVM classifiers was 94.92% and 86.80% respectively. Tables 5.30 and 5.31 show the confusion matrix and performance criteria for the RF classifier. From table 5.30, we can see that maximum instances are misclassified in sitting and sit-to-stand activities and maximum instances are correctly classified in walking, standing, and stand to sit activities.

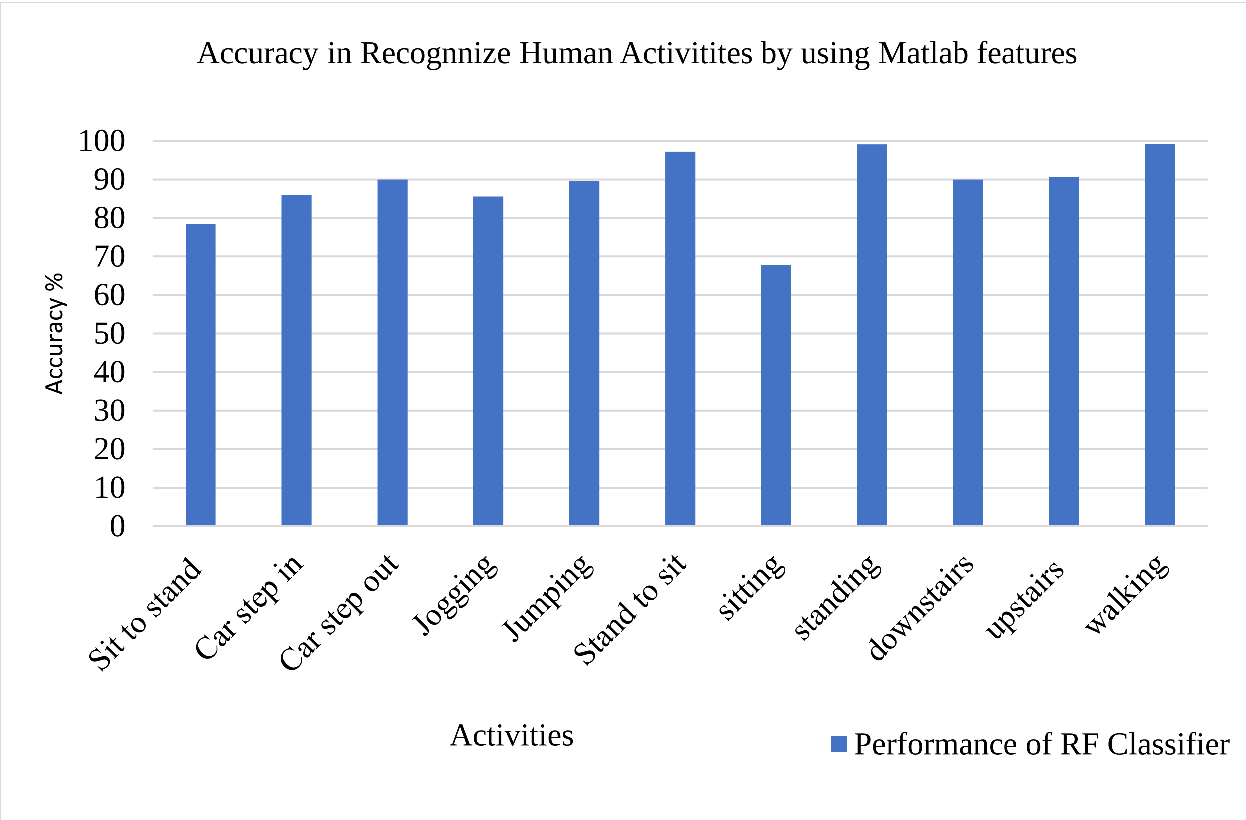


Figure 5.9: The accuracies achieved by RF classifier by using Matlab features at MobiAct_v2 dataset.

Table 5.30: Confusion matrix of RF classifier by using Matlab features set with applying window at MobiAct dataset.

classified as	a	b	c	d	e	f	g	h	i	j	k
a=Sit to stand	**268**	6	17	3	1	39	0	3	0	4	1
b=Car step in	0	**929**	100	2	1	34	0	0	2	0	6
c=Car step out	12	76	**974**	6	2	1	0	1	1	0	7
d=Jogging	0	1	9	**1881**	71	0	0	1	0	0	244
e=Jumping	0	1	3	129	**1970**	0	0	6	1	0	88
f= Stand to sit	2	23	3	0	0	**1061**	0	2	0	1	0
g= Sitting	0	0	0	0	7	13	**330**	136	0	0	1
h= Standing	1	0	4	6	15	5	12	**8264**	0	0	33
i=Downstairs	0	2	0	2	2	2	0	0	**987**	91	9
j=Upstairs	0	0	2	8	0	0	0	0	82	**987**	100
k=walking	0	3	4	49	15	0	0	2	0	0	**8822**

Table 5.31: Performance criteria of RF classifier by using Matlab features with applying window at MobiAct dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
Sit to stand	0.784	0.001	0.946	0.784	0.858
Car step in	0.865	0.004	0.892	0.865	0.878
Car step out	0.902	0.005	0.873	0.902	0.887
Jogging	0.856	0.008	0.902	0.856	0.878
Jumping	0.896	0.004	0.949	0.896	0.922
Stand to sit	0.972	0.004	0.919	0.972	0.944
Sitting	0.678	0.000	0.965	0.678	0.796
Standing	0.991	0.008	0.982	0.991	0.986
Downstairs	0.901	0.003	0.920	0.901	0.911
Upstairs	0.906	0.004	0.911	0.906	0.909
Walking	0.992	0.021	0.957	0.992	0.974
Weighted Avg.	**0.949**	**0.011**	**0.949**	**0.949**	**0.948**

In the case of OpenSmile features set, the accuracy of RF and SVM classifiers was 91.40% and 83.43% respectively. It shows that both classifiers perform outstandingly on the Matlab features set in contrast to OpenSmile features set. Table 5.32 illustrates the performance criteria of the RF classifier. In below table, we can see that accuracies of sit-to-stand, car-step-in, car-step-out, jogging, jumping, stand-to-sit, sitting, standing, downstairs, upstairs, and walking are 40.60%, 83%, 86.50%, 79%, 78.50%, 88.90%, 56.50%, 99.20%, 78.50%, 75.40%, and 99.70% respectively. Here we have shown the results of the RF classifier only.

Table 5.32: Performance criteria of RF classifier by using smile features with applying window at MobiAct dataset.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
Sit to stand	0.406	0.001	0.822	0.406	0.544
Car step in	0.830	0.006	0.856	0.830	0.843
Car step out	0.863	0.006	0.848	0.863	0.855
Jogging	0.790	0.016	0.808	0.790	0.799
Jumping	0.785	0.024	0.738	0.785	0.761
Stand to sit	0.889	0.008	0.827	0.889	0.857
Sitting	0.565	0.000	0.968	0.565	0.713
Standing	0.992	0.007	0.985	0.992	0.988
Downstairs	0.785	0.009	0.773	0.785	0.779
Upstairs	0.754	0.009	0.778	0.754	0.766
Walking	0.997	0.010	0.978	0.997	0.988
Weighted Avg.	**0.924**	**0.010**	**0.914**	**0.924**	**0.912**

5.5.2 Results with Applying 80% overlapping Window of 10 Second.

We achieved outstanding results by applying an overlapping window of 10s. The 80% overlapping window of 10s had been applied on selected activities in MobiAct_v2 dataset. The performance of both classifiers was outstanding. The overall accuracy of RF and SVM classifiers was 98.41% and 95.34% respectively. Figure 5.10 shows the accuracy of the RF classifier. sit to stand, car step in, car step out, jogging, jumping, stand to sit, sitting, standing, downstairs, upstairs, and walking was 73.70%, 86.10%, 88.40%, 96.50%, 97.60%, 97%, 86.30%, 99.70%, 88.70%, 88.60%, and 99.80% respectively. The recognition accuracy of standing and walking was greater than other activities. Table 5.33 illustrates the confusion matrix for the RF classifier. The maximum misclassification occurred in sit-to-stand activity. In the case of OpenSmile features set the accuracy achieved by RF and SVM machine was 96.32%, and 93.50% respectively. The complete results are given in table 5.34. We can see that the accuracy of recognition of activities is greater on the Matlab features set as a contrast to smile features set.

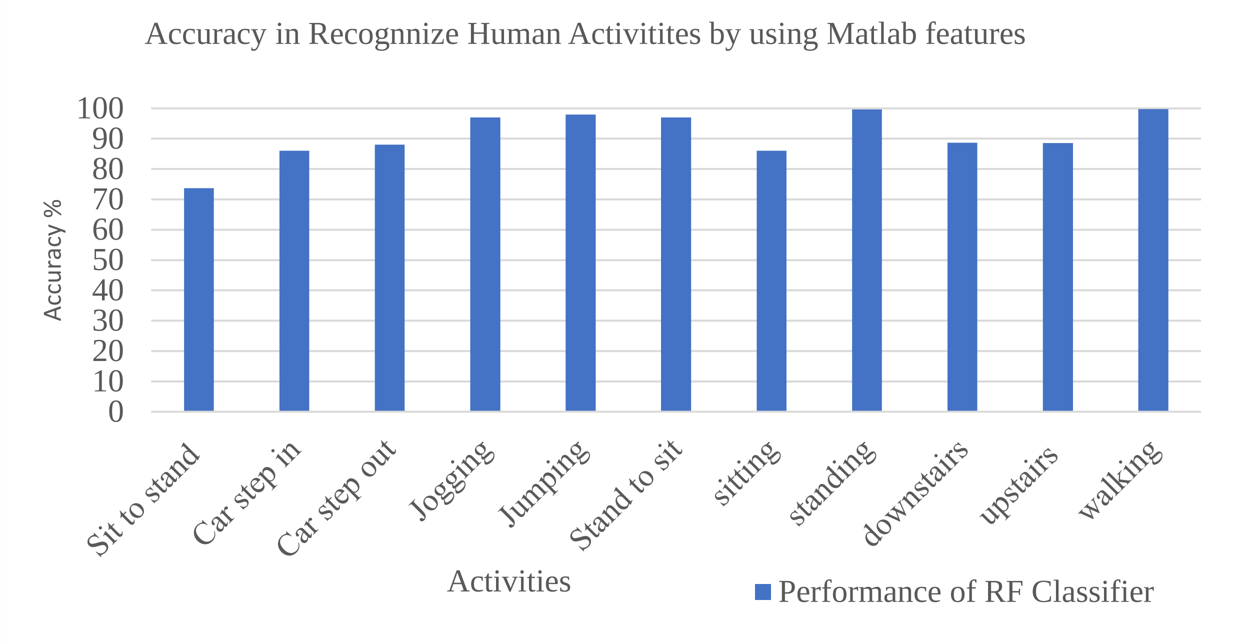


Figure 5.10: The accuracies achieved by RF classifier by using Matlab features with 80% overlapping window at MobiAct_v2 dataset.

Table 5.33: Confusion matrix of RF classifier by using Matlab features with applying window at MobiAct dataset.

classified as	a	b	c	d	e	f	g	h	i	j	K
a=Sit to stand	**252**	6	19	7	2	41	0	8	0	5	2
b=Car step in	0	**925**	92	3	4	34	0	0	2	2	12
c=Car step out	11	71	**955**	12	5	0	0	1	1	3	21
d=Jogging	0	0	7	**10516**	62	0	0	1	0	0	307
e=Jumping	0	4	1	164	**10567**	0	0	8	1	0	83
f= Stand to sit	4	22	1	2	2	**1059**	0	2	0	0	0
g= Sitting	0	0	0	0	6	8	**2062**	312	1	0	0
h= Standing	0	0	1	11	29	3	29	**41219**	0	0	72
i=Downstairs	0	1	0	9	10	2	0	2	**971**	86	14
j=Upstairs	0	1	0	11	3	0	0	0	87	**965**	22
k=walking	0	5	5	59	13	0	0	3	0	1	**44242**

Table 5.34: Results at selected activities in MobiAct_v2 dataset.

	Applying window of 10s		**Applying 80% Overlapping window of 10s**	
Method	Accuracy on Matlab Features Set	Accuracy on OpenSmile Features Set	Accuracy on Matlab Features Set	Accuracy on OpenSmile Features Set
RF	94.92%	91.41%	98.41%	96.32%
SVM	86.82%	83.43%	95.34%	93.51%

5.6 User Authentication based on Activities Recognition.

Authentication is the method of determining who the system's legitimate owner is. We identified or authenticated the user based on activity recognition. The same procedure is followed for user authentication as followed for activities recognition. Figure 5.11 illustrates the proposed methodology for user authentication.

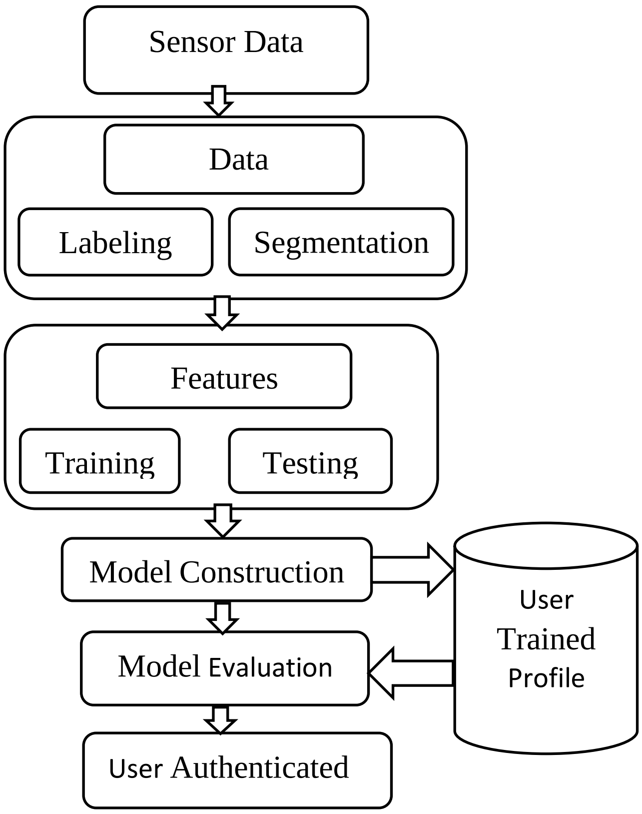


Figure 5.11: Proposed framework for user authentication.

5.6.1 Results for user authentication

We assessed WISDM dataset for user identification. The WISDM dataset consists of six activities: walking, jogging, sitting, standing, upstairs, and downstairs. These activities are performed by 36 various users. With the help of these activities, we can easily identify a user. In the case of Matlab features set, the outstanding performed by RF and SVM classifiers for user's authentication. The accuracy of RF and SVM was 98.80%, and 99.20% based on walking activity. Figure 5.12 shows the confusion matrix for user authentication based on walking activity.

```
=== Confusion Matrix ===

  a  b  c  d  e  f  g  h  i  j  k  l  m  n  o  p  q  r  s  t  u  v  w  x  y  z aa ab ac ad ae af ag ah ai aj   <-- classified as
 64  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  a = user1
  0 65  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  b = user10
  0  0 58  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0 |  c = user11
  0  0  1 52  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  d = user12
  0  0  0  0 65  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  e = user13
  0  0  0  0  0 69  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  f = user14
  0  0  0  0  0  0 57  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  g = user15
  0  0  0  0  0  0  0 62  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  h = user16
  0  0  0  0  0  0  0  0 48  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  i = user17
  0  0  0  0  0  0  0  0  0 62  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  j = user18
  0  0  0  0  0  0  0  0  0  0 86  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  2  0  0 |  k = user19
  0  0  0  0  0  0  0  0  0  0  0 57  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1 |  l = user2
  0  0  0  0  0  0  0  0  0  0  0  0 65  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  m = user20
  0  0  0  0  0  0  0  0  0  0  0  0  0 62  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  n = user21
  0  0  0  0  0  0  0  0  0  0  0  0  0  0 35  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  o = user22
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 32  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  p = user23
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 31  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  q = user24
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 34  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  r = user25
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 66  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  s = user26
  0  0  0  0  0  0  0  1  0  0  0  0  1  0  0  0  0  0  0 60  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  t = user27
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 69  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0 |  u = user28
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 62  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  v = user29
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 62  0  2  0  0  0  0  0  0  0  0  0  0  0 |  w = user3
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 62  0  0  0  0  0  0  0  0  0  0  0  0 |  x = user30
  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 83  0  0  0  0  0  0  0  0  0  0  0 |  y = user31
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 61  0  0  0  0  0  0  0  0  0  0 |  z = user32
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 74  0  0  0  0  0  0  0  0  0 | aa = user33
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 66  0  0  0  0  0  0  0  0 | ab = user34
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0 34  0  0  0  0  0  0  0 | ac = user35
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 31  0  0  0  0  0  0 | ad = user36
  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 29  0  0  0  0  0 | ae = user4
  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 60  0  0  0  0 | af = user5
  0  0  0  1  0  0  1  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 57  1  0  0 | ag = user6
  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  2  0  0  0  0  0  0  0  0  0  0 51  0  0 | ah = user7
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 85  0 | ai = user8
  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  1  0  1  0  0  0  0  0  0  0  0  0  0  0  0 61 | aj = user9
```

Figure 5.12: Confusion matrix for user authentication based on walking activity.

The accuracy of RF and SVM classifiers for user identification was 98%, and 98.70% based on monitoring jogging activity. While monitoring the downstairs activity, the accuracy of RF and SVM classifiers for identifying the users was 93%, and 96% respectively. Similarly, while monitoring the upstairs activity the accuracy of RF and SVM classifiers for user's authentication was 92% and 95% respectively. The accuracy of RF and SVM classifiers for user authentication based on sitting and standing activities was 98%, 88%, 93%, and 89% respectively. Figure 5.13 illustrates the confusion matrix of the RF classifier for user authentication while monitoring the upstairs activity.

```
=== Confusion Matrix ===

  a  b  c  d  e  f  g  h  i  j  k  l  m  n  o  p  q  r  s  t  u  v  w  x  y  z aa ab ac ad ae af   <-- classified as
 15  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  a = user1
  0 21  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  b = user10
  0  0 20  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0 |  c = user11
  0  0  0 13  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  d = user12
  0  0  0  0 22  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  e = user13
  0  0  0  0  0 39  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1 |  f = user14
  0  0  0  0  0  0  9  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0 |  g = user15
  0  0  0  0  0  0  0  6  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0 |  h = user16
  0  0  0  0  0  0  0  0 28  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  i = user17
  0  0  0  0  0  0  0  0  0 11  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1 |  j = user18
  1  0  0  0  0  0  0  0  0  0 18  0  0  0  0  0  0  0  0  0  0  1  0  1  0  0  0  0  0  0  0  0 |  k = user19
  0  0  0  0  0  0  0  0  0  0  0 24  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  l = user20
  0  0  0  0  0  0  0  0  0  0  0  0 23  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0 |  m = user21
  0  0  0  1  0  0  0  0  0  0  0  0  0 26  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  n = user22
  0  0  0  0  0  0  0  0  0  0  0  0  0  0 21  0  0  0  0  0  0  0  0  0  0  3  0  0  0  0  0  0 |  o = user23
  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0 11  1  0  0  0  0  1  0  0  0  0  0  0  0  0  0  1 |  p = user24
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1 17  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  q = user26
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 16  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  r = user27
  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0 11  0  0  0  0  0  0  0  2  0  0  0  0  0 |  s = user28
  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0 22  0  0  0  0  0  0  0  0  0  0  0  0 |  t = user29
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 17  0  0  0  0  0  0  0  0  0  0  0 |  u = user3
  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  1  2  0  0  0  1 16  0  0  0  0  0  0  0  0  0  0 |  v = user30
  0  0  1  0  0  0  0  0  0  0  0  0  2  0  0  0  0  0  0  0  0  0 20  0  0  0  0  0  0  0  0  0 |  w = user31
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 19  0  0  0  0  0  0  0  0 |  x = user32
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0 10  0  0  0  0  0  0  0 |  y = user33
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 19  0  0  0  0  0  0 |  z = user34
  0  0  0  0  2  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 25  0  0  0  0  0 | aa = user36
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  6  0  0  0  0 | ab = user4
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 16  0  0  0 | ac = user5
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  8  0  0 | ad = user6
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 18  0 | ae = user7
  0  0  0  2  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 19 | af = user8
```

Figure 5.13: Confusion matrix for user authentication based on upstairs activity.

Figure 5.14 shows the performance of RF and SVM classifiers for user authentication based on activities recognition. We can see that in the below figure the maximum users are authenticated based on walking and jogging activities. Almost both activities give 98% plus accuracy for users identifying. Its mean that these two activities are very helpful for user authentication. The performance of the SVM classifier is outstanding for user authentication in contrast to the RF classifier. But in sitting and standing activities, the performance of the RF classifier is outstanding in contrast to the SVM classifier. On based of pattern of walking, jogging, and sitting activities, users can be authenticated. The worst results are obtained for users' authentication by monitoring downstairs, upstairs and standing activities.

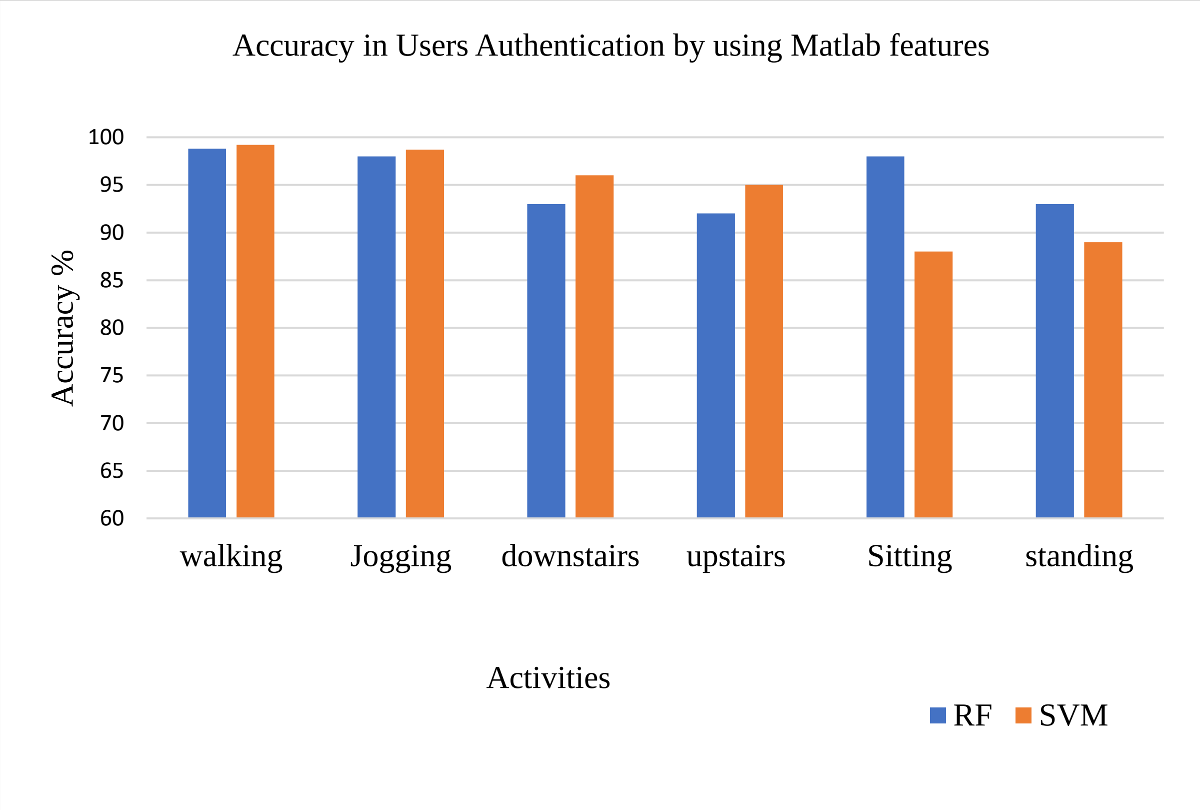


Figure 5.14: User authentication accuracy of RF and SVM classifiers based on activities recognition by using Matlab features.

In the case of OpenSmile features set, the accuracy of RF and SVM classifiers for user authentication was 76% and 75% while monitoring the walking activity. The OpenSmile features set is not got for user authentication as we can see that in the case of Matlab's features outstanding results were obtained. Figure 5.15 shows the confusion matrix of the RF classifier for user authentication while performing the walking activity. The accuracy of RF for user authentication was 80%, 50%, 58%, 37%, and 52% while performing jogging, downstairs, upstairs, sitting, and standing activities, respectively. The accuracy of SVM for user authentication was 78%, 50%, 54%, 34%, 35%, and 46% while performing jogging, downstairs, upstairs, sitting, and standing activities, respectively. We obtained the worst accuracy by utilizing the OpenSmile features set. Figures 5.16 show the performance of classifiers for user authentication based on activity recognition.

```
=== Confusion Matrix ===

  a  b  c  d  e  f  g  h  i  j  k  l  m  n  o  p  q  r  s  t  u  v  w  x  y  z aa ab ac ad ae af ag ah ai aj   <-- classified as
 46  0  0  0  2  2  0  4  0  0  0  0  1  0  0  0  0  0  0  0  2  0  0  0  1  3  0  1  0  0  0  0  0  0  2  0 |  a = user1
  0 62  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  2  0  0  0  0  0  0  0  0 |  b = user10
  0  0 38  0  0  0  0  0  2  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  8  0  2  0  0  0  0  0  0  0  2  7 |  c = user11
  0  0  0 39  2  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  5  0  0  0  0  0  0  0  0  0  0  0  4  2 |  d = user12
  0  0  0  0 63  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0 |  e = user13
  0  0  0  0  0 67  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  1  0  0  0  0  0  0  0  0  0  0 |  f = user14
  1  0  0  0  0  1 46  0  0  0  0  0  1  0  0  0  0  0  1  1  0  4  0  0  1  0  0  0  0  0  0  0  0  0  1  0 |  g = user15
  0  0  0  0  0  0  0 54  0  0  4  0  0  0  0  0  2  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0 |  h = user16
  0  0  4  0  0  0  0  0 38  0  0  2  0  0  0  0  0  0  0  0  0  0  0  0  3  0  0  0  0  0  0  1  0  0  0  0 |  i = user17
  0  1  0  0  0  0  0  0  2 55  0  0  1  0  0  0  0  0  0  0  0  1  0  0  1  0  0  0  0  0  0  0  0  0  1  0 |  j = user18
  0  0  0  0  0  0  0  3  0  0 72  1  0  0  0  0  2  0  0  3  0  0  3  0  3  0  0  0  0  0  0  0  0  1  0  0 |  k = user19
  0  0  1  0  0  0  0  0  2  0  6 39  0  0  0  0  0  0  0  0  0  0  4  0  0  0  3  0  1  0  0  1  0  0  1  0 |  l = user2
  2  2  0  0  1  3  1  0  0  0  3  0 36  0  0  0  0  0  0  3  0  0  0  0  4  0  2  0  0  0  0  1  0  1  6  0 |  m = user20
  0  0  0  0  0  0  0  0  0  0  0  0  0 57  0  0  0  0  0  0  4  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0 |  n = user21
  0  0  0  0  0  1  0  0  0  0  0  1  1  0 25  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  3  0  2  1  0 |  o = user22
  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0 31  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 |  p = user23
  0  0  0  0  0  0  0  1  0  0  3  0  0  0  0  0 24  0  1  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  1  0 |  q = user24
  3  4  0  0  1  2  1  0  0  0  0  0  0  0  0  0  0 14  0  0  1  0  0  0  0  4  0  2  0  0  0  0  1  0  1  0 |  r = user25
  0  0  0  0  0  0  1  0  0  0  1  0  0  0  0  0  1  0 57  0  0  3  0  0  0  0  0  0  0  0  0  0  0  1  2  0 |  s = user26
  1  0  1  0  0  1  4  4  1  0  6  0  0  1  1  0  0  0  0 34  0  0  0  0  1  1  2  0  0  0  0  0  1  1  2  0 |  t = user27
  0  0  1  0  1  1  0  0  0  0  0  0  0  7  0  0  0  0  0  0 48  0  0  0  1  0  6  0  0  0  3  1  0  0  1  0 |  u = user28
  2  0  0  0  0  4  5  0  0  0  3  0  0  0  3  0  0  0  2  2  1 36  0  0  0  0  0  0  0  0  0  2  2  0  0  0 |  v = user29
  0  0  0  0  0  0  0  1  1  0  5  3  0  0  0  0  0  0  0  0  0  0 49  0  2  0  0  0  0  0  0  2  0  0  1  0 |  w = user3
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 62  0  0  0  0  0  0  0  0  0  0  0  0 |  x = user30
  0  0  2  0  0  2  0  0  0  3  0  0  0  1  0  0  0  0  0  0  0  0  0  0 74  0  0  0  0  0  1  0  0  0  1  0 |  y = user31
  0  1  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 58  0  1  0  0  0  0  0  0  0  0 |  z = user32
  0  1  0  0  4  1  0  0  1  0  0  0  0  1  0  0  0  0  0  0  1  0  0  0  0  0 62  0  0  0  1  0  0  0  2  0 | aa = user33
  0  1  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  2  0 62  0  0  0  0  0  0  0  0 | ab = user34
  1  0  1  0  0  0  0  0  2  0  0  0  0  1  0  0  0  0  0  0  1  0  0  0  0  0  1  0 28  0  0  0  0  0  0  0 | ac = user35
  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  3  0  0  0  4  0  2  0  0 21  0  0  0  0  0  0 | ad = user36
  0  0  0  0  1  0  0  0  0  0  0  0  0  7  0  0  0  0  0  0  6  0  0  0  0  1  0  0  0  0 15  0  0  0  0  0 | ae = user4
  0  0  0  0  1  0  3  0  1  0  3  2  2  0  0  0  0  0  0  0  1  0  1  0  2  2  3  0  0  2  0 36  0  0  2  0 | af = user5
  1  3  0  0  1  4  4  0  0  0  7  0  1  3  0  0  0  0  0  3  6  1  1  0  8  3  5  0  0  1  0  0  5  1  3  0 | ag = user6
  0  0  0  0  0  0  0  0  0  0 10  0  0  0  0  0  0  0  0  0  0  0  2  0  0  0  0  0  0  0  0  0  0 43  0  0 | ah = user7
  5  1  0  0  2  1  0  0  0  0  2  0  0  0  0  0  0  0  4  0  0  0  0  0  1  0  3  0  0  0  0  2  0  1 63  0 | ai = user8
  0  0  4  0  0  1  0  0  0  0  0  1  0  1  0  0  0  0  0  0  2  0  1  0 15  0  5  0  0  0  0  0  0  0  2 32 | aj = user9
```

Figure 5.15: Confusion matrix for user authentication based on walking activity by utilizing smile’s features.

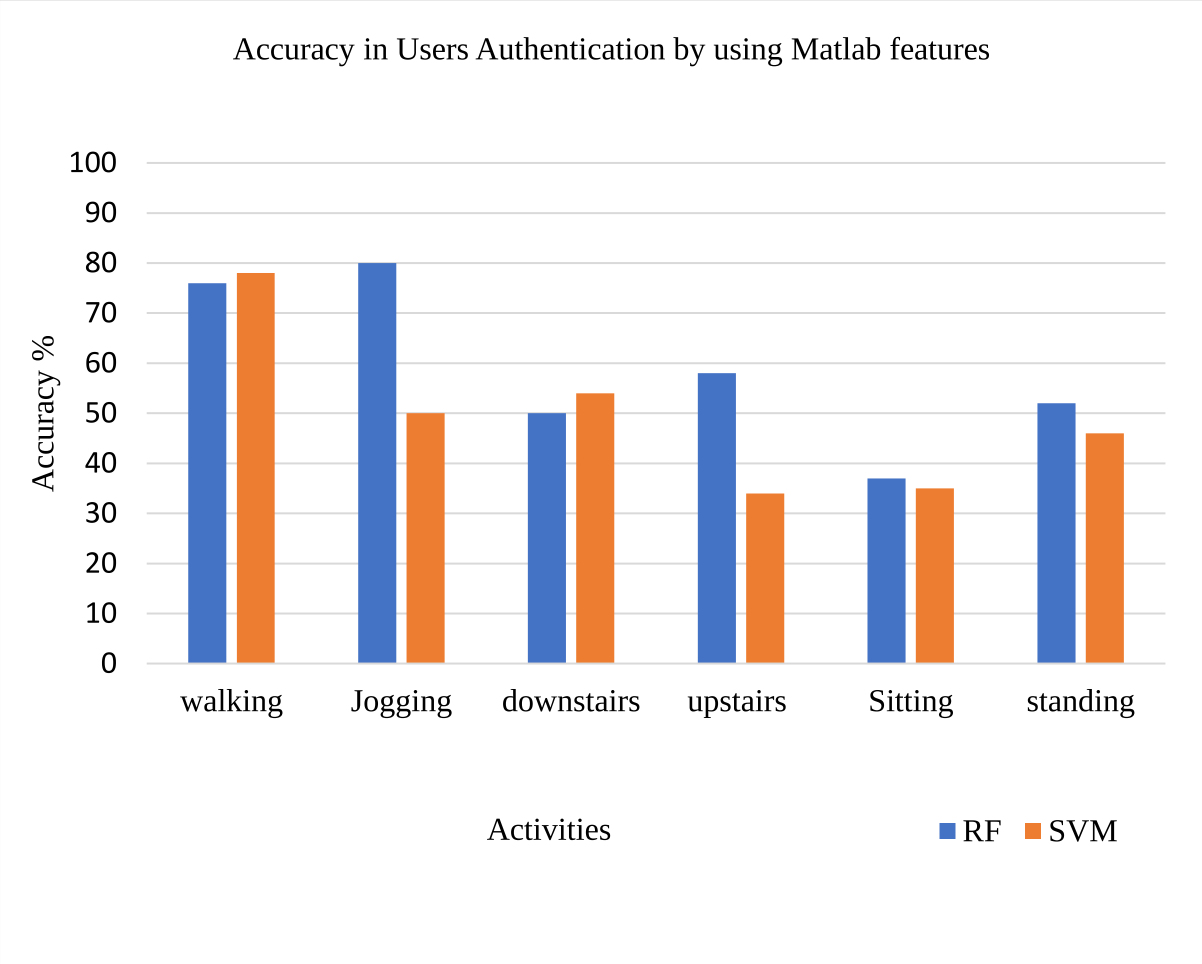


Figure 5.16: User's authentication accuracy of RF and SVM classifiers based on activities recognition by using OpenSmile features set.

Table 5.35 shows the complete results for user authentication based on activities recognition in WISDM dataset. The maximum accuracy is achieved by utilizing Matlab features set for user authentication while monitoring the walking activity. The performance of the SVM classifier is outstanding for user authentication in contrast to the RF classifier. But in the case of OpenSmile features set the RF classifier performed outstandingly.

Table 5.35: The complete results for user authentication at WISDM dataset.

Activates	Nos. Users	Matlab Features	Classifier	Accuracy	OpenSmile Features	Accuracy
Walking	36	14x3=42	RF SVM	98.51% 99.05 %	3x384=1152	75.65% 75.46%
Jogging	32	14x3=42	RF SVM	97.94% 98.70%	3x384=1152	79.65% 77.58%
Downstairs	32	14x3=42	RF SVM	92.39% 95.06%	3x384=1152	50% 49.79%
Upstairs	32	14x3=42	RF SVM	91.71% 94.36%	3x384=1152	56.05% 54.39%
Sitting	23	14x3=42	RF SVM	98.26% 88.19%	3x384=1152	37.50% 34.72%
Standing	24	14x3=42	RF SVM	92.21% 88.74%	3x384=1152	51.95% 46.32%

5.7 Comparison

The overall precision of the chosen classifier's display was evaluated. A comparison of opted classifiers was rendered based on accuracies obtained using Matlab features set and OpenSmile features set, revealing that Matlab features set accuracy was superior to OpenSmile features set accuracy. On three datasets, the efficiency of classifiers was compared, and it was found that the RF classifier achieved the highest classification accuracy as compared to the SVM classifier. The performance of classifiers on three datasets is shown in Figure 5.17. Table 5.38 shows a comparison of our methodology to previously published work. For activity detection, S. Khare et al used various models; the highest accuracy attained by LSTM was 96.42 percent on the WISDM dataset, and the highest accuracy obtained by CNN was 96.42 percent on the UCI HAR dataset. Some approaches used various methodologies to obtain different accuracies on different datasets. In the end, our proposed solution contrasts better with previous work. As seen in the table of comparisons. For user authentication, we obtained good results in contrast to the published approach at WISDM dataset. We found only one paper for user authentication at WISDM dataset. They achieved 95% accuracy for user authentication while monitoring the walking activity [60]. We obtained 99% accuracy for user authentication while monitoring the walking activity. It showed that without approach maximum accuracy achieved for user authentication.

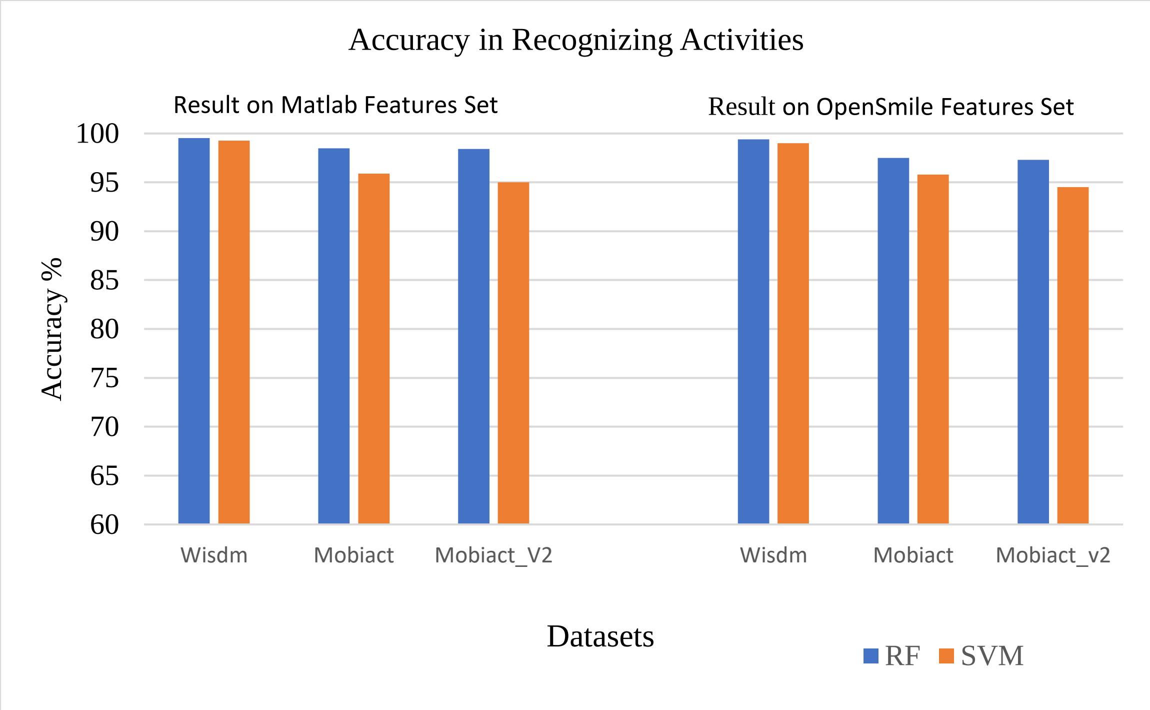


Figure 5.17: The average accuracy comparison between the classifiers based on Matlab features set and OpenSmile features set at the various datasets.

Table 5.36: Comparisons of earlier published results with our methodology

Study	Year	Dataset	No of Performed Activities	Models/ Classifiers	Accuracy
S. Khare et al. [5]	2020	UCI HAR WISDM	6 6	CNN LSTM	96.42% 95.45%
H. Xu et al. [6]	2020	WISDM UCI HAR OPPORTUNITY	6 6 6	GAF+Mdk-ResNet	96.83% 89.48% 97.27%
Min et al. [42]	2020	WISDM	6	RF	94.68%
Ahmer M.et al. [3]	2017	MOBIACT	6	SVM+AR	97.45 %
Dao et al. [73]	2016	MOBIACT	6	Personal Model	96.48%
Chen et al. [74]	2019	MOBIACT_V2	11	CNN	99.10%
Our approach		WISDM MOBIACT MOBIACT_V2	6 6 11	RF RF RF	99.50% 98.50% 98.40%

CHAPTER 6 : CONCLUSION AND FUTURE WORK

6.1 Conclusion

The current project's key goal is to develop a reliable HAR and user authentication framework using data from smartphone sensors. Various feature extraction tools were investigated in this report, and a comparison was made between them. The suggested framework's robustness was also contrasted with other published research. The current work is unique in that it is the first to create a framework for recognizing human behaviors and user authentication using OpenSmile’s features and Matlab’s features. The suggested method was tested on the datasets: WISDM, MobiAct, and MobiAct v2 for activities recognition, and user authentication only WISDM dataset was utilized. The Weka tool was used for the implementation. Two ubiquitous classifiers, SVM and RF, were used to detect human behaviors from sensor data and as well for user authentication. On both the Matlab features set and the OpenSmile features set, the RF classifier outperformed the SVM classifier. The maximum accuracy at WISDM, MobiAct, and MobiAct_v2 was 99.50%, 98.50%, and 98.40% respectively by using Matlab features set for activities recognition. By using OpenSmile features, the maximum accuracy at WISDM, MobiAct, and MobiAct_v2 was 99.37%, 97.55%, and 97.32% respectively for activities recognition. Based on activity recognition, users were authenticated by utilizing the WISDM dataset. The performance of the SVM classifier was good for user authentication. The accuracy of user authentication based on walking, jogging, downstairs, upstairs sitting, and standing was 99%, 98.70%, 95%, 94%, 88%, and 89% respectively by utilizing the Matlab features set. In the case of OpenSmile feature set, the accuracy of user authentication based on walking, jogging, downstairs, upstairs sitting, and standing was 76%, 80%, 50%, 56%, 38%, and 51% respectively.

6.2 Contribution

- Built the model for user authentication.
- Explored various feature extraction tools.
- Made comparison among the feature’s extraction tools.
- Review & comparison of recent development techniques for activities recognition and user authentication.

6.3 Future Work

While the currently applied scheme provides acceptable results for smartphones sensors data it can be extended by carrying out on other available datasets such as UCI HAR and OPPORTUNITY datasets. Time-Frequency techniques can be helpful based upon results. The current study offers a foundational ideological principle for future researchers to investigate more configuration files for statistical feature extraction.

REFERENCES

[1] Zhao, Kunlun, Junzhao Du, Congqi Li, Chunlong Zhang, Hui Liu, and Chi Xu. "Healthy: A diary system based on activity recognition using smartphone." In 2013 IEEE 10th International Conference on Mobile Ad-Hoc and Sensor Systems, pp. 290-294. IEEE, 2013.

[2] Slim, Salwa O., Ayman Atia, and Mostafa-Sami M. Mostafa. "An experimental comparison between seven classification algorithms for activity recognition." In The 1st International Conference on Advanced Intelligent System and Informatics (AISI2015), November 28-30, 2015, Beni Suef, Egypt, pp. 37-46. Springer, Cham, 2016.

[3] Lara, Oscar D., and Miguel A. Labrador. "A survey on human activity recognition using wearable sensors." IEEE communications surveys & tutorials 15, no. 3 (2012): 1192-1209.

[4] Kwapisz, Jennifer R., Gary M. Weiss, and Samuel A. Moore. "Cell phone-based biometric identification." In 2010 Fourth IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS), pp. 1-7. IEEE, 2010.

[5] Khan, Adil Mehmood, Young-Koo Lee, Sungyoung Y. Lee, and Tae-Seong Kim. "A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical recognizer." IEEE transactions on information technology in biomedicine 14, no. 5 (2010): 1166-1172.

[6] Gallagher, Shaun. "Smartphone Sensor Data Mining for Gait Abnormality Detection." Fordham University, New York 2 (2014).

[7] Vavoulas, George, Matthew Pediaditis, Charikleia Chatzaki, Emmanouil G. Spanakis, and Manolis Tsiknakis. "The MobiFall dataset: Fall detection and classification with a smartphone." International Journal of Monitoring and Surveillance Technologies Research (IJMSTR) 2, no. 1 (2014): 44-56.

[8] J. W. Lockhart, T. Pulickal, and G. M. Weiss, “Applications of mobile activity recognition,” in Proceedings of the 2012 ACM Conference on Ubiquitous Computing - UbiComp ’12, 2012, p. 1054

[9] Tsai, Chang-Lung, Chun-Jung Chen, and Deng-Jie Zhuang. "Trusted M-banking Verification Scheme based on a combination of OTP and Biometrics." JoC 3, no. 3 (2012): 23-30.

[10] Majumder, Sumit, Tapas Mondal, and M. Jamal Deen. "Wearable sensors for remote health monitoring." Sensors 17, no. 1 (2017): 130.

[11] Teraoka, Teruhiko. "Organization and exploration of heterogeneous personal data collected in daily life." Human-Centric Computing and Information Sciences 2, no. 1 (2012): 1-15.

[12] Alzubaidi, Abdulaziz, and Jugal Kalita. "Authentication of smartphone users using behavioral biometrics." IEEE Communications Surveys & Tutorials 18, no. 3 (2016): 1998-2026.

[13] Delac, Kresimir, and Mislav Grgic. "A survey of biometric recognition methods." In Proceedings. Elmar-2004. 46th International Symposium on Electronics in Marine, pp. 184-193. IEEE, 2004.

[14] Kelley, Patrick Gage, Saranga Komanduri, Michelle L. Mazurek, Richard Shay, Timothy Vidas, Lujo Bauer, Nicolas Christin, Lorrie Faith Cranor, and Julio Lopez. "Guess again (and again and again): Measuring password strength by simulating password-cracking algorithms." In 2012 IEEE symposium on security and privacy, pp. 523-537. IEEE, 2012.

[15] Owusu, Emmanuel, Jun Han, Sauvik Das, Adrian Perrig, and Joy Zhang. "Accessory: password inference using accelerometers on smartphones." In proceedings of the twelfth workshop on mobile computing systems & applications, pp. 1-6. 2012.
[16] Tamviruzzaman, Mohammad, Sheikh Iqbal Ahamed, Chowdhury Sharif Hasan, and Casey O'brien. "ePet: when cellular phone learns to recognize its owner." In Proceedings of the 2nd ACM workshop on Assurable and usable security configuration, pp. 13-18. 2009.
[17] Jain, Anil K., Arun Ross, and Salil Prabhakar. "An introduction to biometric recognition." IEEE Transactions on circuits and systems for video technology 14, no. 1 (2004): 4-20.
[18] Weinland, D., R. Ronfard and E. Boyer, “A Survey of Vision-based Methods for Action Representation, Segmentation and Recognition”, Computer Vision and Image Understanding, Vol. 115, No. 2, pp. 224–241, 2011.
[19] Aggarwal, J. and M. Ryoo, “Human Activity Analysis: A Review”, ACM Computing Surveys, Vol. 43, No. 3, pp. 16:1–16:43, 2011
[21] Chaaraoui, A. A., P. Climent-P´erez and F. Fl´orez-Revuelta, “A Review on Vision Techniques Applied to Human Behaviour Analysis for Ambient-Assisted Living”, Expert Systems with Applications, Vol. 39, No. 12, pp. 10873 – 10888, 2012.
[22] Popoola, O. and K. Wang, “Video-Based Abnormal Human Behavior Recognition: A Review”, IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, Vol. 42, No. 6, pp. 865–878, 2012
[23] Xu, X., J. Tang, X. Zhang, X. Liu, H. Zhang and Y. Qiu, “Exploring Techniques for Vision Based Human Activity Recognition: Methods, Systems, and Evaluation”, Sensors, Vol. 13, No. 2, pp. 1635–1650, 2013
[24] Chaquet, J. M., E. J. Carmona and A. Fern´andez-Caballero, “A Survey of Video Datasets for Human Action and Activity Recognition”, Computer Vision and Image Understanding, Vol. 117, No. 6, pp. 633–659, 2013.
[25] Shotton, J., A. Fitzgibbon, M. Cook, T. Sharp, M. Finocchio, R. Moore, A. Kipman and A. Blake, “Real-time Human Pose Recognition in Parts from Single Depth Images”, IEEE Conference on Computer Vision and Pattern Recognition, CVPR ’11, pp. 1297–1304, 2011.
[26] Jalal, A., S. Kamal and D. Kim, “A Depth Video Sensor-Based Life-Logging Human Activity Recognition System for Elderly Care in Smart Indoor Environments”, Sensors, Vol. 14, No. 7, pp. 11735–11759, 2014.
[27] Holte, M., C. Tran, M. Trivedi and T. Moeslund, “Human Pose Estimation and Activity Recognition From Multi-View Videos: Comparative Explorations of Recent Developments”, IEEE Journal of Selected Topics in Signal Processing, Vol. 6, No. 5, pp. 538–552, 2012.
[28] Amiri, S., M. Pourazad, P. Nasiopoulos and V. Leung, “Non-intrusive Human Activity Monitoring in a Smart Home Environment”, IEEE 15th International Conference on e-Health Networking, Applications Services, HealthCom ’13, pp. 606–610, 2013.
[29] Cheng, H., Z. Liu, Y. Zhao, G. Ye and X. Sun, “Real World Activity Summary for Senior Home Monitoring”, Multimedia Tools and Applications, Vol. 70, No. 1, pp. 177–197, 2014.
[30] Vacher, M., F. Portet, A. Fleury and N. Noury, “Development of Audio Sensing Technology for Ambient Assisted Living: Applications and Challenges”, International Journal of E-Health and Medical Communications, Vol. 2, No. 1, pp. 35 – 54, 2011.
[31] Vacher, M., B. Lecouteux, P. Chahuara, F. Portet, B. Meillon and N. Bonnefond, “The Sweet-Home Speech and Multimodal Corpus for Home Automation Interaction”, 9th

International Conference on Language Resources and Evaluation, LREC ’14, pp. 4499–4506, 2014
[32] Stork, J., L. Spinello, J. Silva and K. Arras, “Audio-based Human Activity Recognition Using Non-Markovian Ensemble Voting”, 21st IEEE International Symposium on Robot and Human Interactive Communication, pp. 509–514, 2012.
[33] Karpov, A., L. Akarun, H. Yal¸cın, A. Ronzhin, B. Demir¨oz, A. C¸ oban and M. Zelezny, “Audio-Visual Signal Processing in a Multimodal Assisted Living Environment”, 15th Annual Conference of the International Speech Communication Association, INTERSPEECH ’14, pp. 1023–1027, 2014
[34] Zhan, Y. and T. Kuroda, “Wearable Sensor-based Human Activity Recognition from Environmental Background Sounds”, Journal of Ambient Intelligence and Humanized Computing, Vol. 5, No. 1, pp. 77–89, 2014.
[35] Mozer, M. C., “The Neural Network House: An Environment that Adapts to its Inhabitants”, AAAI Spring Symposium on Intelligent Environments, pp. 110–114, 1998.
[36] Abowd, G. D., A. F. Bobick, I. A. Essa, E. D. Mynatt and W. A. Rogers, “The Aware Home: A Living Laboratory for Technologies for Successful Aging”, AAAI02 Workshop Automation as Caregiver , 2002.
[37] Tapia, E. M., S. S. Intille and K. Larson, “Activity Recognition in the Home Using Simple and Ubiquitous Sensors”, International Conference on Pervasive Computing, Pervasive ’04, pp. 158–175, 2004.
[38] Philipose, M., K. P. Fishkin, M. Perkowitz, D. J. Patterson, D. Fox, H. Kautz and D. Hahnel, “Inferring Activities from Interactions with Objects”, IEEE Pervasive Computing, Vol. 3, No. 4, pp. 50–57, 2004.
[39] Fishkin, K., M. Philipose and A. Rea, “Hands-on RFID: Wireless Wearables for Detecting Use of Objects”, 9th IEEE International Symposium on Wearable Computers, ISWC ’05, pp. 38–41, 2005.
[40] Cook, D. J., M. Schmitter-Edgecombe, A. Crandall, C. Sanders and B. Thomas, “Collecting and Disseminating Smart Home Sensor Data in the CASAS Project”, Workshop on Developing Shared Home Behavior Datasets to Advance HCI and Ubiquitous Computing Research, 2009.
[41] Singla, G., D. J. Cook and M. Schmitter-Edgecombe, “Recognizing Independent and Joint Activities Among Multiple Residents in Smart Environments”, Journal of Ambient Intelligence and Humanized Computing, Vol. 1, No. 1, pp. 57–63, 2010.
[42] Bao, L. and S. S. Intille, “Activity Recognition from User-annotated Acceleration Data”, International Conference on Pervasive Computing, Pervasive ’04, 2004.
[43] Bulling, A., U. Blanke and B. Schiele, “A Tutorial on Human Activity Recognition Using Body-worn Inertial Sensors”, ACM Computing Surveys, Vol. 46, No. 3, pp. 1–33, 2014.
[44] Buber, E., Guvensan, A.M.: Discriminative time-domain features for activity recognition on a mobile phone. In: IEEE 9th International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), pp. 1–6, 21–24 April 2014
[45] Hung, W., Shen, F., Wu, Y.L., Hor, M.K., Tang, C.Y.: Activity recognition with sensors on mobile devices. In: Proceedings of the 2014 International Conference on Machine Learning and Cybernetics, Lanzhou (2014)
[46] Anguita, D., Ghio, A., Oneto, L., Parra, X., Reyes-Ortiz, J.L.: Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine. In: Bravo, J., Hervás, R., Rodríguez, M. (eds.) IWAAL 2012. LNCS, vol. 7657, pp. 216–223. Springer, Heidelberg (2012). doi:10.1007/978-3-642-35395-6_30

[47] Anguita, D., Ghio, A., Oneto, L., Parra, X., Reyes-Ortiz, J.-L.: A public domain dataset for human activity recognition using smartphones. In: ESANN 2013 Proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence, Bruges, Belgium (2013)
[48] Min, Ya, Yin Yin Htay, and Khin Khin Oo. "Comparing the Performance of Machine Learning Algorithms for Human Activities Recognition using WISDM Dataset." International Journal of Computer (IJC) 38, no. 1 (2020): 61-72.
[49] S. Khare, S. Sarkar and M. Totaro, "Comparison of Sensor-Based Datasets for Human Activity Recognition in Wearable IoT," 2020 IEEE 6th World Forum on Internet of Things (WF-IoT), New Orleans, LA, USA, 2020, pp. 1-6, doi: 10.1109/WF-IoT48130.2020.9221408.
[50] H. Xu et al., "Human Activity Recognition Based on Gramian Angular Field and Deep Convolutional Neural Network," in IEEE Access, vol. 8, pp. 199393-199405, 2020, doi: 10.1109/ACCESS.2020.3032699
[51] Muhammad Ahmer1 , M. Z. Abbas Shah2 , Syed M. Zafi S. Shah , Syed. M. Shehram Shah , Bhawani Shankar Chowdhry2 , Aunsa Shah and Khadim Hussain Bhatti, Using Non-Linear Support Vector Machines for Detection of Activities of Daily Living, Indian Journal of Science and Technology, Vol 10(36), DOI: 10.17485/ijst/2017/v10i36/119182, September 2017
[52] Vavoulas, George & Chatzaki, Charikleia & Malliotakis, Thodoris & Pediaditis, Matthew & Tsiknakis, Manolis. (2016). The MobiAct Dataset: Recognition of Activities of Daily Living using Smartphones. 143-151. 10.5220/0005792401430151.
[53] Dao, Minh-Son; Nguyen-Gia, Tuan-Anh; Mai, Van-Cuong (2017). Daily Human Activities Recognition Using Heterogeneous Sensors from Smartphones. Procedia Computer Science, 111(), 323–328. doi:10.1016/j.procs.2017.06.030
[54] Kwapisz, J.R.; Weiss, G.M.; Moore, S.A. Cell phone-based biometric identification. In Proceedings of the 2010 Fourth IEEE International Conference on Biometrics: Theory Applications and Systems (BTAS), Washington, DC, USA, 27–29 September 2010; pp. 1–7.
[55] Lee, W.-H.; Lee, R.B. Multi-sensor authentication to improve smartphone security. In Proceedings of the 2015 International Conference on Information Systems Security and Privacy (ICISSP), Angers, France, 9–11 February 2015; pp. 1–11.
[56] Primo, A.; Phoha, V.V.; Kumar, R.; Serwadda, A. Context-aware active authentication using smartphone accelerometer measurements. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, Columbus, OH, USA, 24–27 June 2014; pp. 98–105.
[57] Conti, M.; Zachia-Zlatea, I.; Crispo, B. Mind how you answer me: Transparently authenticating the user of a smartphone when answering or placing a call. In Proceedings of the 6th ACM Symposium on Information, Computer and Communications Security, Hong Kong, China, 22–24 March 2011; pp. 249–259
[58] Abate, A.F.; Nappi, M.; Ricciardi, S. I-am: Implicitly authenticate me person authentication on mobile devices through ear shape and arm gesture. IEEE Trans. Syst. Man Cybern. Syst. 2017, 99, 1–13.
[59] Malik, Maryam Naseer, Muhammad Awais Azam, Muhammad Ehatisham-Ul-Haq, Waleed Ejaz, and Asra Khalid. "ADLAuth: Passive authentication based on activity of daily living using heterogeneous sensing in smart cities." Sensors 19, no. 11 (2019): 2466.
[60] M. Zhang, "Gait Activity Authentication Using LSTM Neural Networks with Smartphone Sensors," 2019 15th International Conference on Mobile Ad-Hoc and

Sensor Networks (MSN), Shenzhen, China, 2019, pp. 456-461, doi: 10.1109/MSN48538.2019.00092

[61] Vavoulas, George, Matthew Pediaditis, Charikleia Chatzaki, Emmanouil G. Spanakis, and Manolis Tsiknakis. "The MobiFall dataset: Fall detection and classification with a smartphone." International Journal of Monitoring and Surveillance Technologies Research (IJMSTR) 2, no. 1 (2014): 44-56.

[62] Vavoulas, George, Matthew Pediaditis, Emmanouil G. Spanakis, and Manolis Tsiknakis. "The MobiFall dataset: An initial evaluation of fall detection algorithms using smartphones." In 13th IEEE International Conference on BioInformatics and BioEngineering, pp. 1-4. IEEE, 2013.

[63] Chatzaki, Charikleia, Matthew Pediaditis, George Vavoulas, and Manolis Tsiknakis. "Human daily activity and fall recognition using a smartphone's acceleration sensor." In International Conference on Information and Communication Technologies for Ageing Well and e-Health, pp. 100-118. Springer, Cham, 2016.

[64] Kwapisz, Jennifer R., Gary M. Weiss, and Samuel A. Moore. "Activity recognition using cell phone accelerometers." ACM SigKDD Explorations Newsletter 12, no. 2 (2011): 74-82.

[65] Chawla, Nitesh V., and Grigoris Karakoulas. "Learning from labeled and unlabeled data: An empirical study across techniques and domains." Journal of Artificial Intelligence Research 23 (2005): 331-366.

[66] Open smile Accessed: Nov 15, 2020. [online]. Available: https://www.audeering.com/OpenSmile/

[67] Weka tool Accessed: March 14, 2021. [online]. Available: https://www.cs.waikato.ac.nz/ml/weka/docs.html.

[67] Downlaod the Weka tool Accessed: March 14, 2021. [online]. Available: https://sourceforge.net/projects/weka/postdownload.

[68] Malik, Maryam Naseer, Muhammad Awais Azam, Muhammad Ehatisham-Ul-Haq, Waleed Ejaz, and Asra Khalid. "ADLAuth: Passive authentication based on activity of daily living using heterogeneous sensing in smart cities." Sensors 19, no. 11 (2019): 2466.

[69] Ahmer, Muhammad, MZ Abbas Shah, S. M. Z. S. Shah, Syed M. Shehram Shah, Bhawani Shankar Chowdhry, Aunsa Shah, and Khadim Hussain Bhatti. "Using Non-Linear Support Vector Machines for Detection of Activities of Daily Living." Indian J. Sci. Technol 10, no. 36 (2017): 1-8.

[70] Min, Ya, Yin Yin Htay, and Khin Khin Oo. "Comparing the Performance of Machine Learning Algorithms for Human Activities Recognition using WISDM Dataset." International Journal of Computer (IJC) 38, no. 1 (2020): 61-72.

[71] Random Forest classifier Accessed: March 25, 2021. [online]. Available: https://www.tutorialspoint.com/machine_learning_with_python/machine_learning_with_python_classification_algorithms_random_forest.htm.

[72] Support Vector Machine classifier Accessed: March 25, 2021. [online]. Available: https://www.datacamp.com/community/tutorials/svm-classification-scikit-learn-python.

[73] Salzberg, Steven L. "C4. 5: Programs for machine learning by j. ross quinlan. morgan kaufmann publishers, inc., 1993." (1994): 235-240.

[74] Gupta, Sarthak, and Ajeet Kumar. "Human Activity Recognition through Smartphone's Tri-Axial Accelerometer using Time Domain Wave Analysis and Machine Learning." International Journal of Computer Applications 975 (2015): 8887.