A

PROJECT REPORT

ON

HUMAN ACTIVITY RECOGINATION

For Partial Fulfillment of Award of the

B. Tech Degree in Information Technology

Under the supervision of

<u>**Prof. Pushpa Choudhary**</u>

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Submitted by:

Arpit Maheshwari (1719213025)

Dhiraj Kumar Singh (1719213038)

GL BAJAJ INSTITUTE OF TECHNOLOGY AND MANAGEMENT,

GREATER NOIDA

(Affiliated to AKTU University, Lucknow)

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INTRODUCTION

1.1 INTRODUCTION

As more sensors are being used in mobile phones to measure our positioning, movements and orientation, the opportunity to understand this data and make improvements in our daily lives increases. Our project scope consists of analyzing mobile phone sensor data in the context of activity recognition. Our objective is to build a model that accurately classifies whether an individual is walking, sitting, standing or laying using sensor data.

Studying activity recognition offers various benefits and enables many new applications. Mobile health applications that track a user's activities over time can be beneficial for elderly assistance or personal health monitoring. In addition to providing personal support, this research also has links to various fields of study including medicine, human-computer interaction, sociology, etc.

1.2 OBJECTIVE

Although smartphone devices are powerful tools, they are still passive communication enablers rather than active assistive devices from the user's point of view. Our aim is to introduce intelligence into such types of platforms to allow them to automatically assist users in their everyday activities. One of the methods of accomplishing this is by integrating situational awareness and context recognition into electronic devices. Smartphones provide an attractive platform for activity recognition, providing powerful processing units and built-in sensors. These devices are capable of detecting complex everyday activities of the user or the device and they are able to exchange information with other devices and systems using a large variety of data communication channels.

Mobile phone sensing is still in its infancy. There is some or no consensus for the sensing architecture for the phone. Common methods for collecting and sharing data should be developed. Mobile phones can't be overloaded with continuous sensing commitments that decreases the performance of the phone. It is not clear which architectural components should run on the phone.

CHAPTER 2

EXISTING SYSTEM

Device sensors record activities of persons doing in real-time. Knowing the activity of different users allows, for example, to interact with them through an application. Nowadays, collecting this type of data is an easy task. With the growth of the IoT, almost everyone has some gadget that monitors their various movements. It can be a smartwatch, a smartphone, or even a pulsometer.

Monitoring is performed using a fixed-length sliding window approach for the features extraction where two parameters have to be fixed i.e. the size of the shift and window.

This data we could use:

- Body acceleration.
- Gravity acceleration.
- Body angular speed.
- Body angular acceleration.
- Etc.

The machine learning model used for activity recognition is built on top of the available sensors in devices. Because of the complexity of human activities and the existing differences between two individuals, analyzing this data is a challenge.

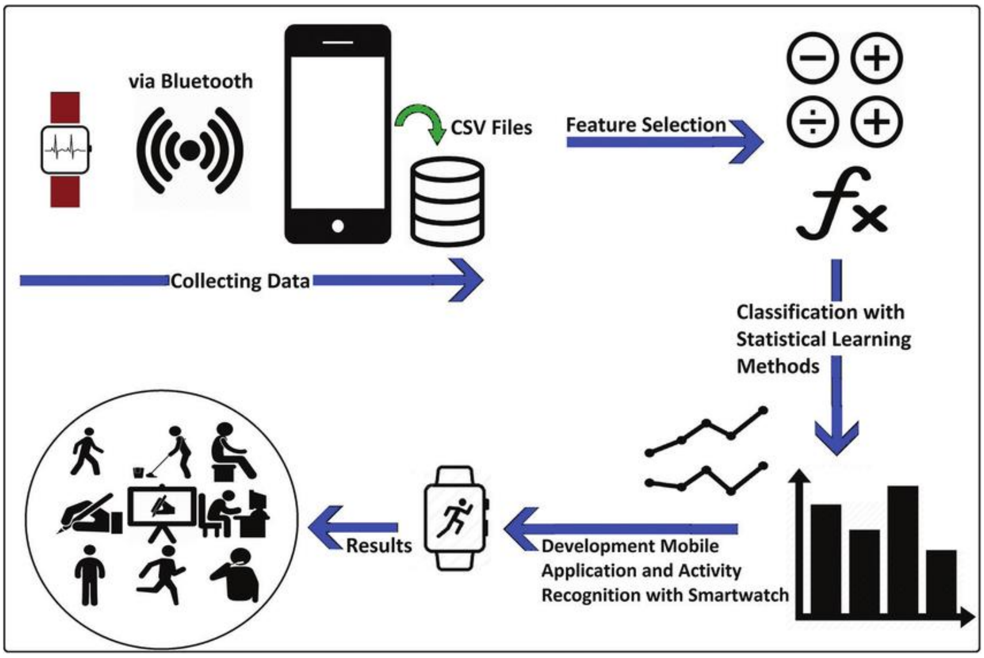

Figure 2.1 – Process of HAR

Here we have created a flow chart for the project to understand it in an easy way. It represents steps in a sequential way and is widely used in presenting the flow of algorithms.

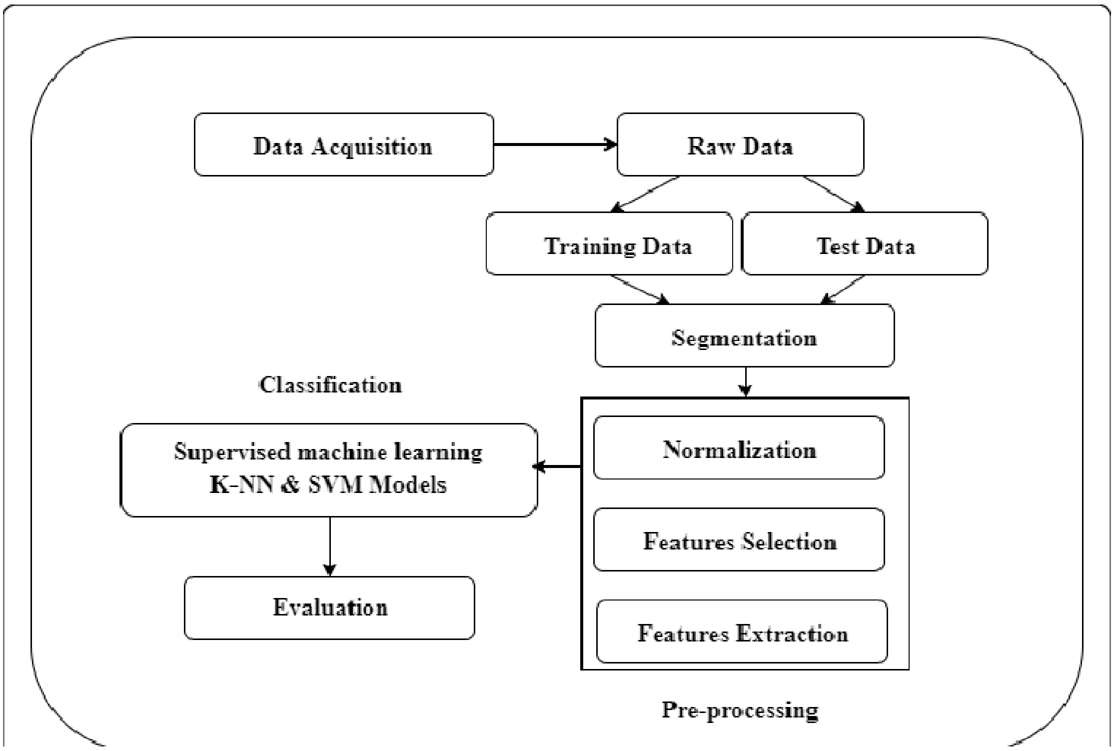

Figure 2.2- HAR Flow Chart

The use case diagram is the main building block of object-oriented modelling. It is used for general conceptual modelling of the structure of the application, and for detailed modelling, translating the models into code.

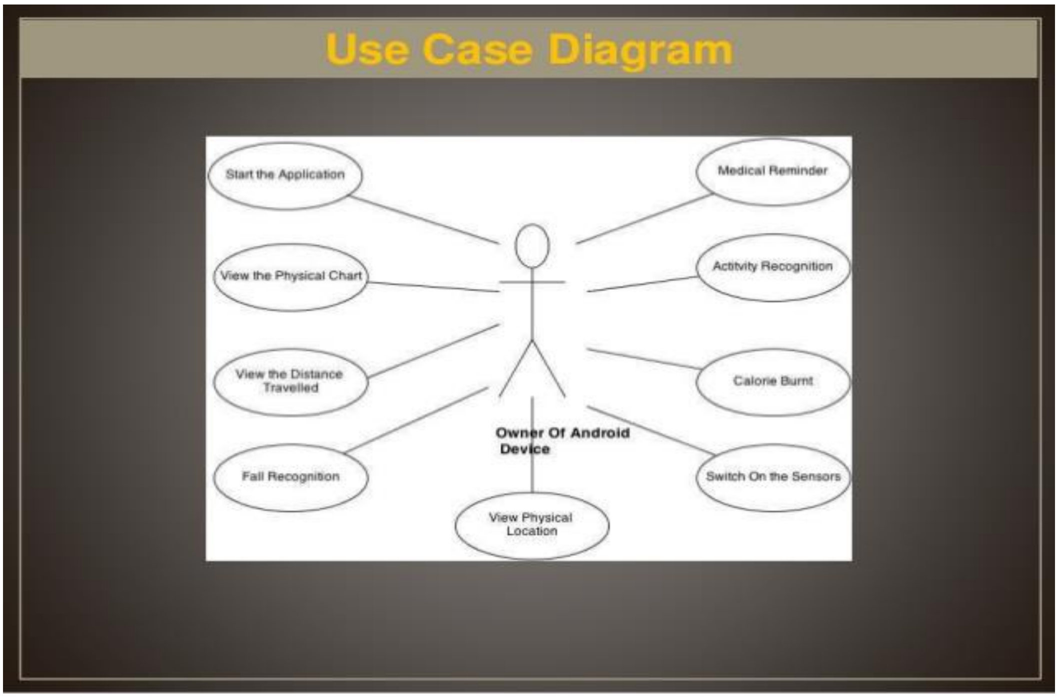

Figure 2.3- Use-Case Diagram for HAR

EXISTING METHORDS

Health Monitoring Instruments

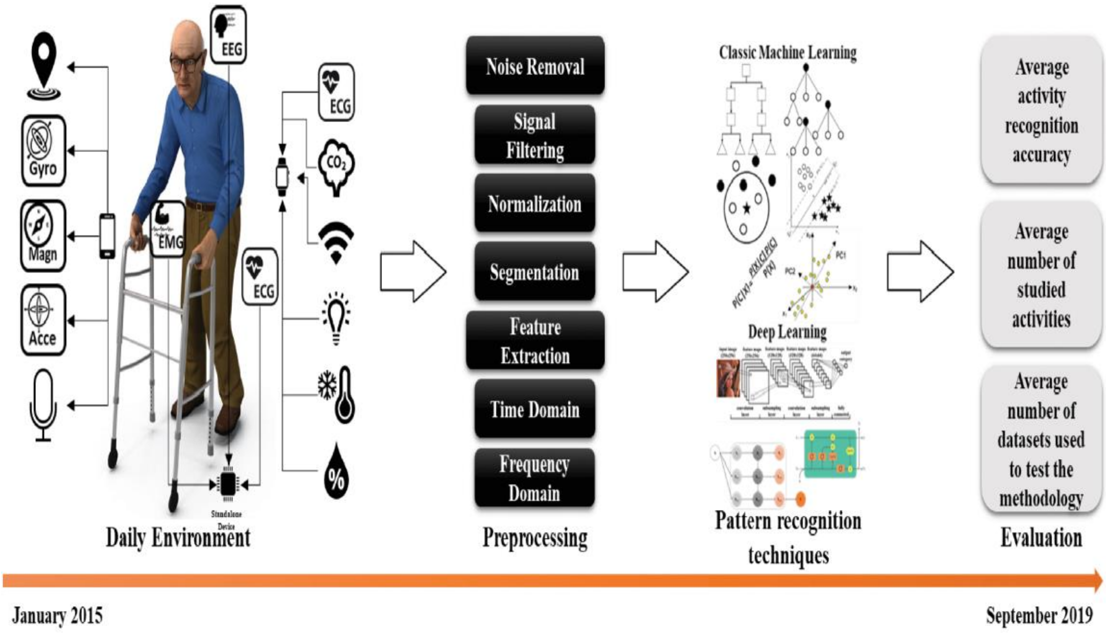

Figure 2.4- Working of Health Monitoring Instruments

Figure 2.5 - Heart Beat Analysis in various positions

Health monitoring consists of activities undertaken to maintain a system in an operable condition which is limited to an observation of current system states, with some maintenance and repair being prompted by these observations. Various sensors are used for providing a real-time, structural integrity assessments health management system.

Smart Watches

Figure 2.6- Smart Watches

Smartwatches are the most widely used wearable devices. HAR using wearable devices has been actively analyzed for a wide range of applications, including healthcare, sports, and abnormal behavior detection.

CHAPTER 3

PROPOSED WORK

3.1 PROPOSED WORK WITH INTRODUCTION

Activity recognition is used to research problems related to the successful development of intelligent environments. It is the process by which an actor's behavior and environment are monitored and analyzed to get results from the activities. Activity recognition consists of activity modelling, behavior and environment monitoring, data processing, pattern recognition etc. Activity recognition systems have 3 components: -

- Low-level sensing module gathers relevant information about activities using light sensors, microphones, etc.
- Feature processing and selection module that processes the raw sensor data into features that help discriminate between different activities.
- Classification module uses the features to infer what activity an individual or group of individuals is engaged
- For example, cooking, walking or having a conversation.

There are various approaches for activity recognition as described as follows -

A. **Vision-Based Activity Recognition**

   It uses camera-based surveillance systems to monitor an actor's behavior and the changes in its environment. This composed of four steps: human detection, activity recognition, behavior tracking and activity evaluation. Other research approaches used different methods such as: single camera and infrared to capture activity context.

B. **Sensor-Based Activity Recognition**

   Sensor network technologies are used to monitor an actor's behavior along with its environment. In this sensor are attached to humans. Data from the sensors are collected and analyzed using machine learning algorithms to build activity models and perform activity recognition.

C. **Human-Sensing Taxonomy**

It is the process of extracting any information regarding the people in any environment. This describes the inference of spatiotemporal properties only. It consists of low-level components regarding the history and position of people in an environment.

3.2 STRUCTURE OF PROPOSED MODEL

We can achieve higher accuracy with fewer training labels if we choose the data from which we learn.

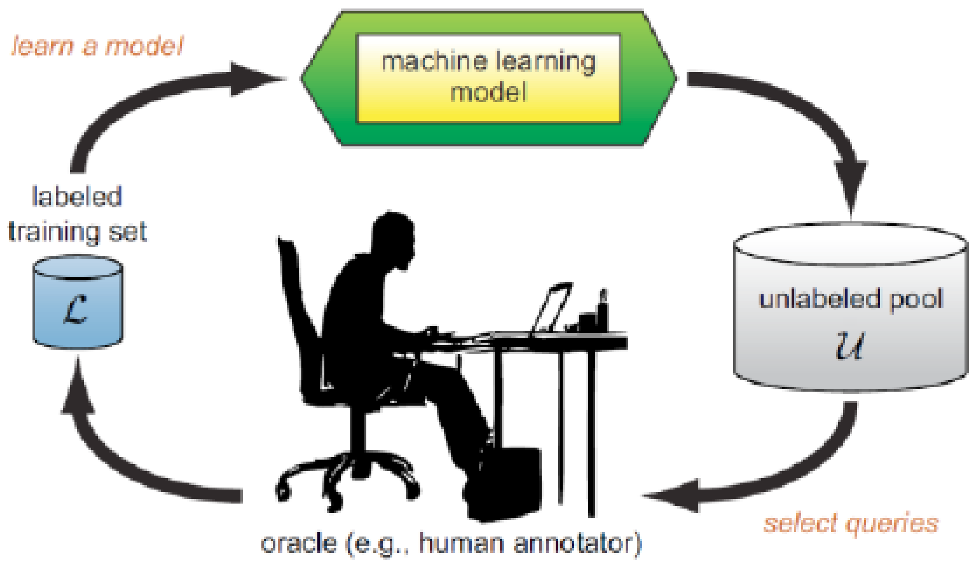

Figure 3.1 – 3-Machine Learning Model

Different methods to frame the provided data as a prediction problem is as follows:

- Predict activity for a time step of movement data.
- Predict activity for multiple windows of movement data.
- Predict activity sequence for multiple windows of movement data.
- Predict activity sequence for movement data for a pre-segmented activity.
- Predict activity cessation for transition given a time step of movement data.
- Predict a stationary or non-stationary activity for a window of movement data.

These framings may be challenging or easy. These framings provide an additional way to explore and understand the dataset.

3.3 TEST CASES

We have obtained our data from the UC Irvine Machine Learning Repository. For the original construction of the data, an experiment was performed out with 30 participants, having each person wear a Samsung Galaxy S2E smartphone containing an accelerometer and a gyroscope while performing the above six activities .

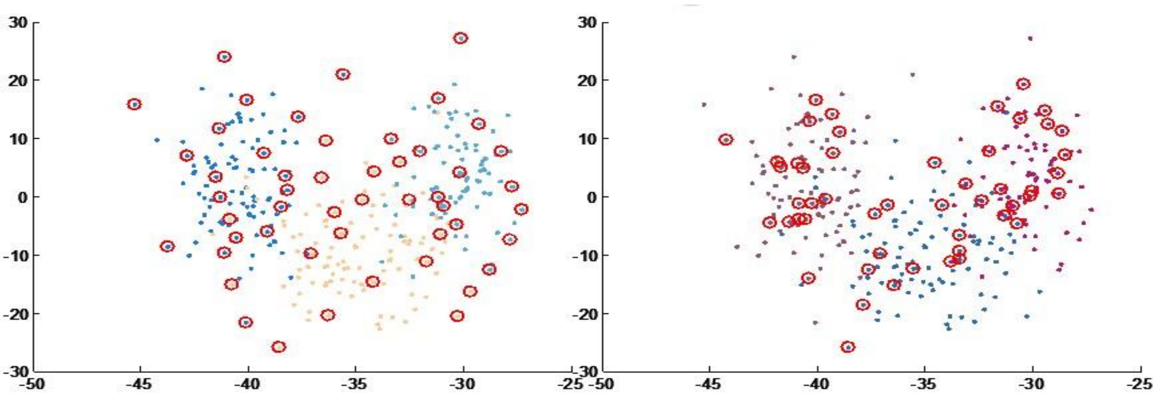

Figure 3.2- Active Learning

We have split our dataset into 70% training and 30% test data, with 21 of 30 participants in the train data and the remaining 9 participants in the test data. Disjoint nature of the training and testing split is most important. An effective model of recognizing activities should be able to predict the activities of new individuals.

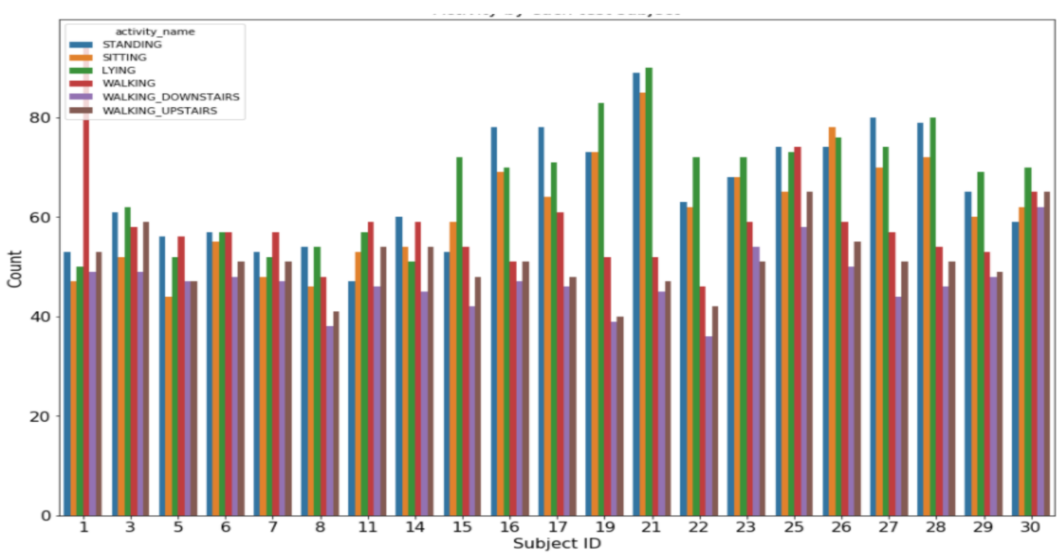

Figure 3.3 – Activity by Each Subject

3.4 PROJECT OUTPUTS

3.4.1 TSNE Output

t-SNE has the t-distribution on the Analyzed space. In t-SNE, context of the Gaussian classification used by normal SNE, this means that most times will repel each other, because t-SNE have 0 affinity in the briefing domain (gets zero quickly), it's >0 affinity in the return. Here, t-SNE forms cluster due to similarity in data points across various one, two and three dimensional. The perplexity of subject activity across different plots are generated using the t-SNE algorithm in jupyter Notebook.

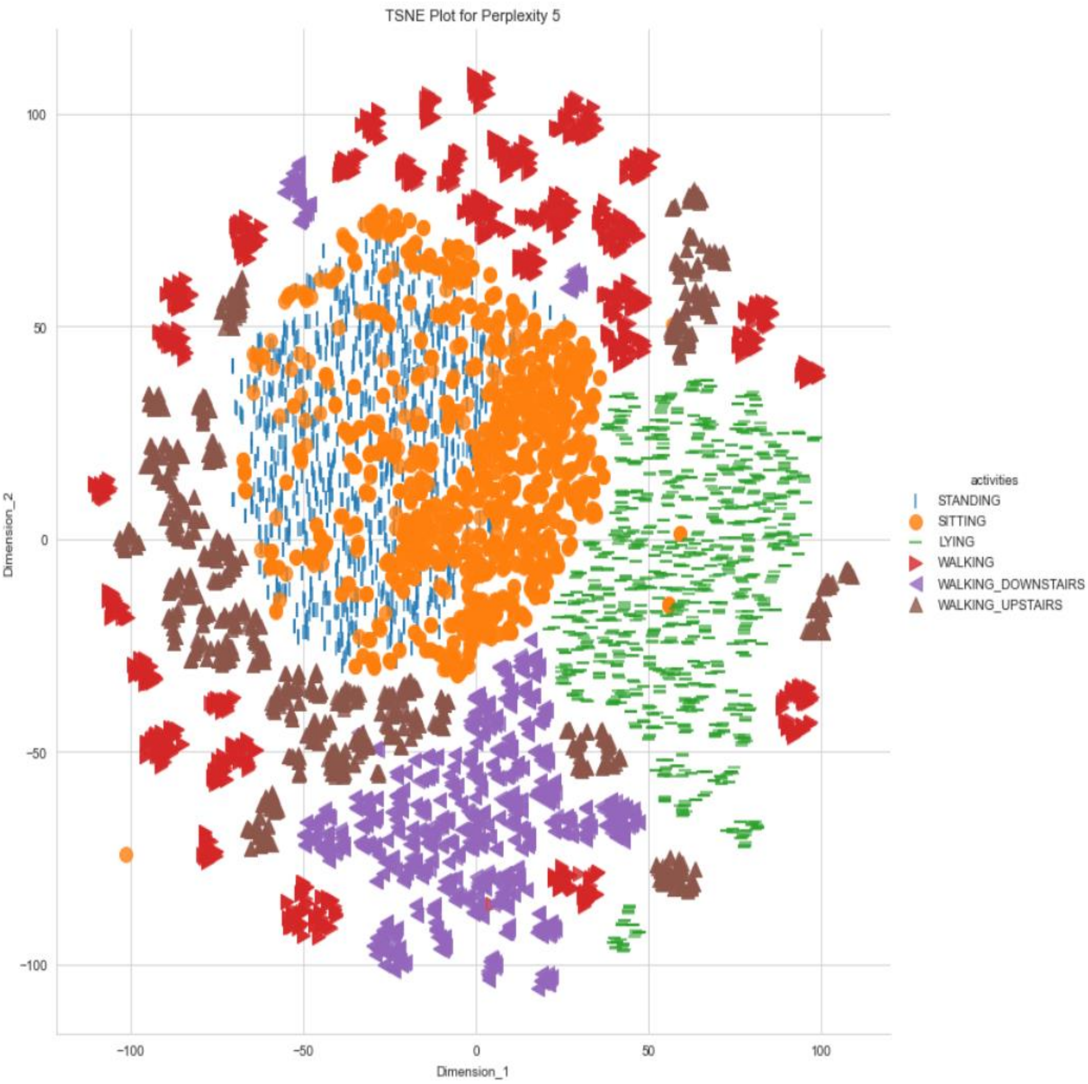

Figure 3.4 TSNE Perplexity Plot 1

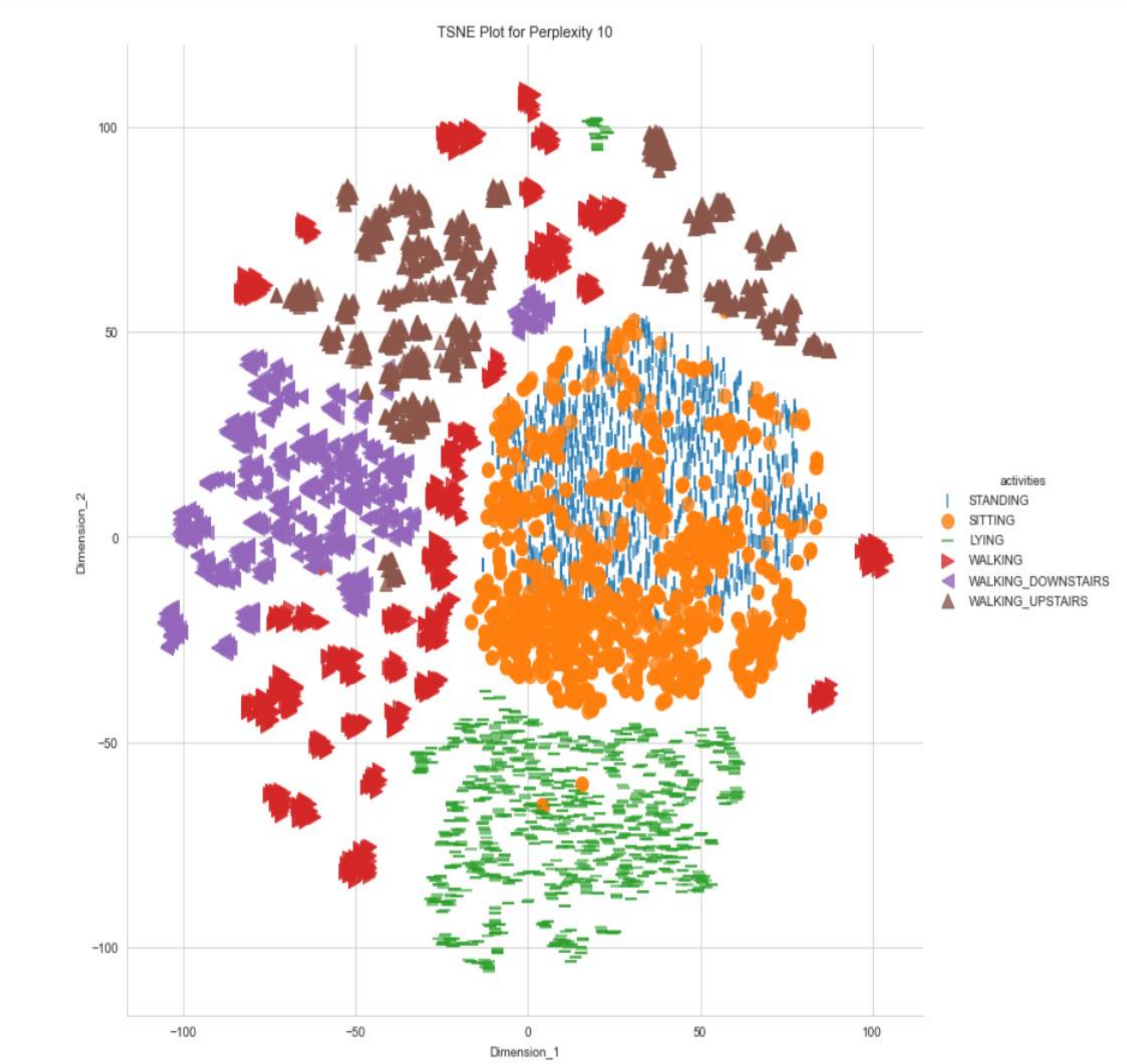

Figure 3.5 TSNE Perplexity Plot 2

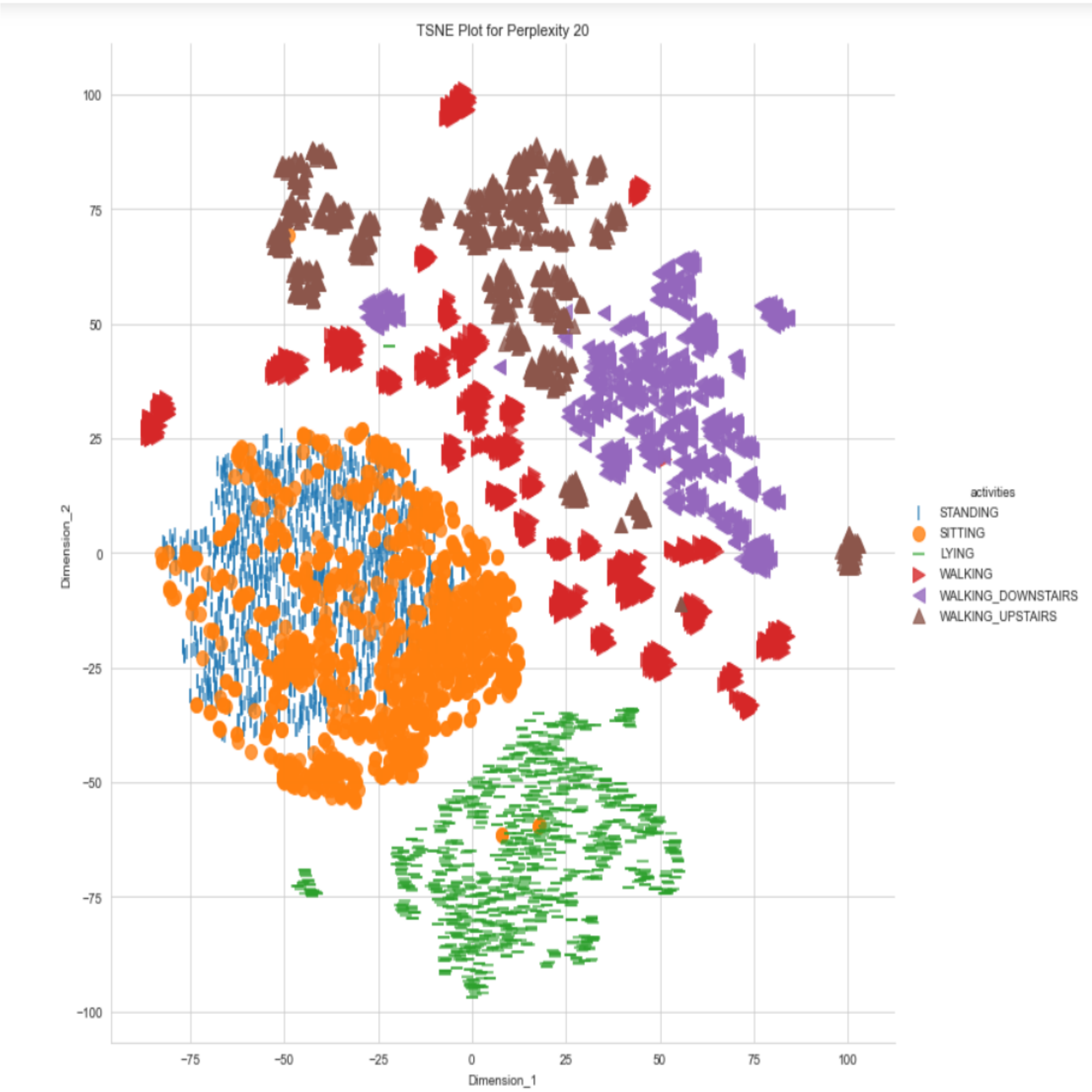

Figure 3.6 TSNE Perplexity Plot 3

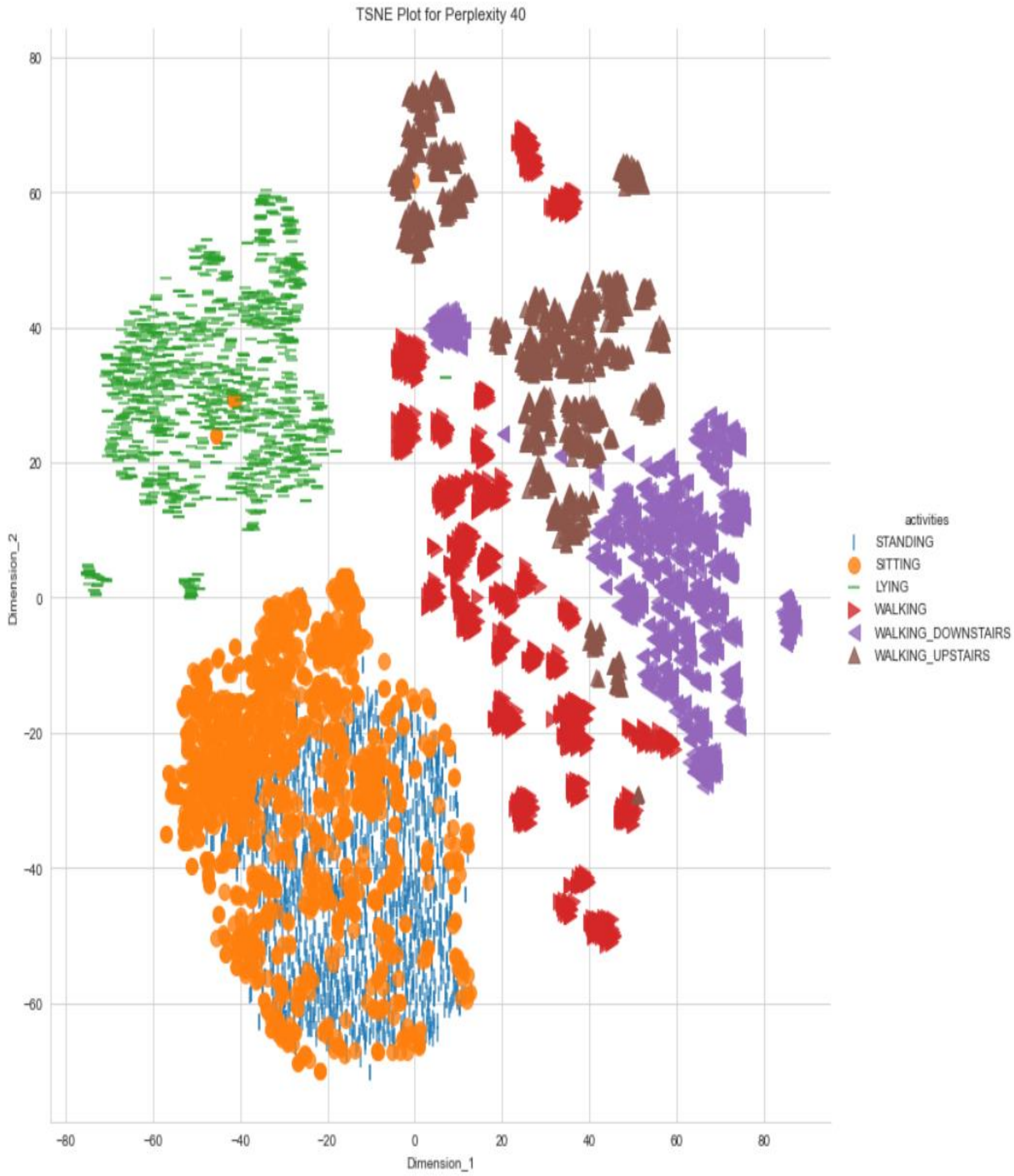

Figure 3.7 TSNE Perplexity Plot 4

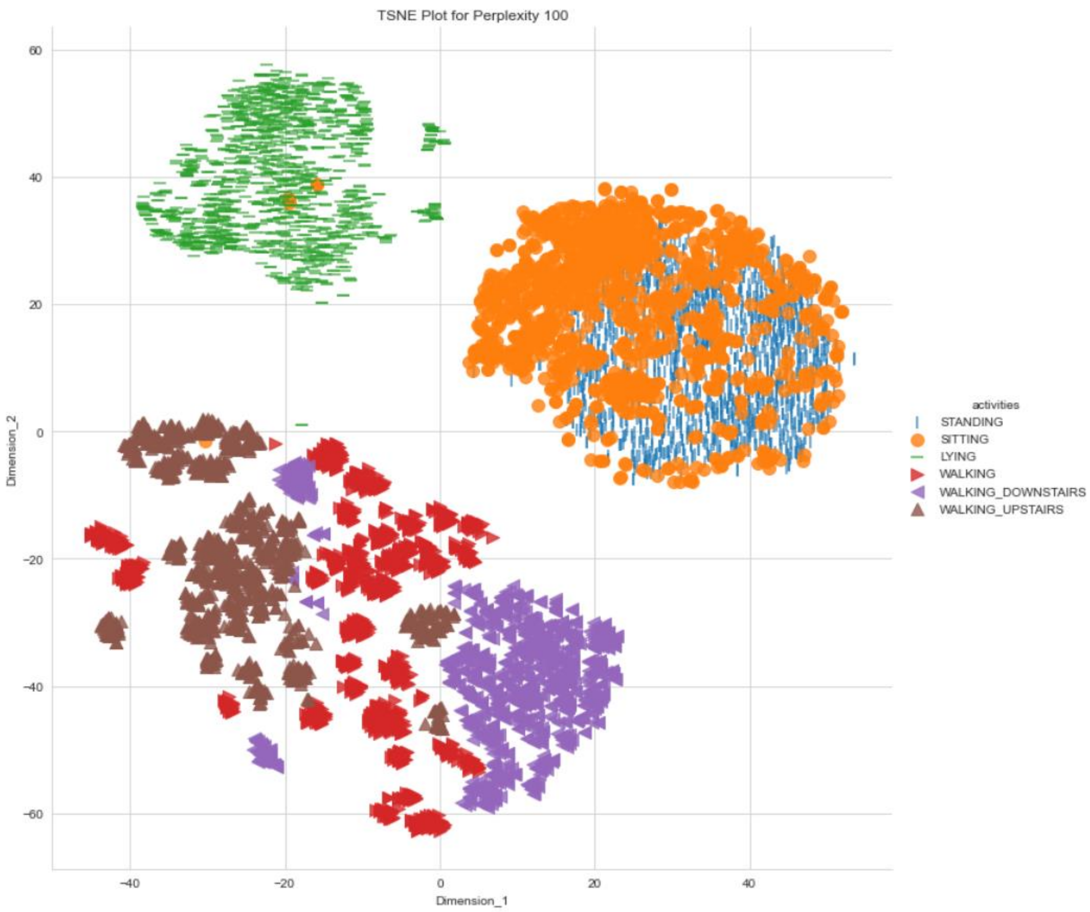

Figure 3.8 TSNE Perplexity Plot 5

3.4.2 Logistic Regression Output

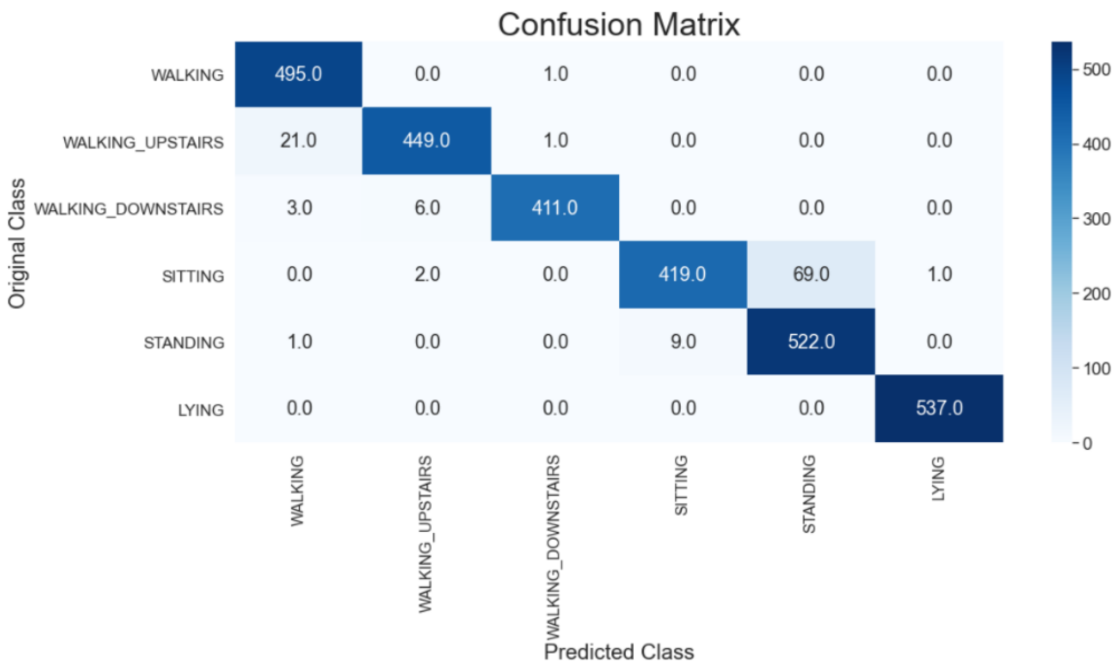

Figure 3.9 – Logistic Regression Confusion Matrix

Confusion matrix depicts the different ways in which our classification model is confused when it makes predictions i.e., it compares actual values with the predicated values. Also, it displays the number of instances of two classes collide with each other.

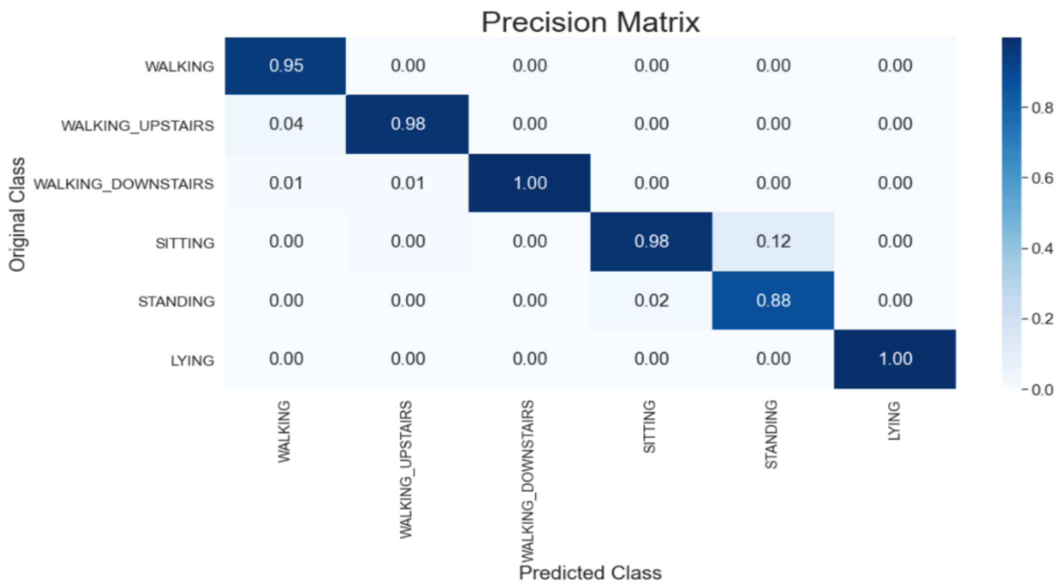

Figure 3.10 – Logistic Regression Precision Matrix

Precision matrix shows us how many of the correctly predicted cases actually turned out to be positive. To calculate precision of a model, we need the positive and negative numbers from the confusion matrix.

Precision = TP/(TP + FP)

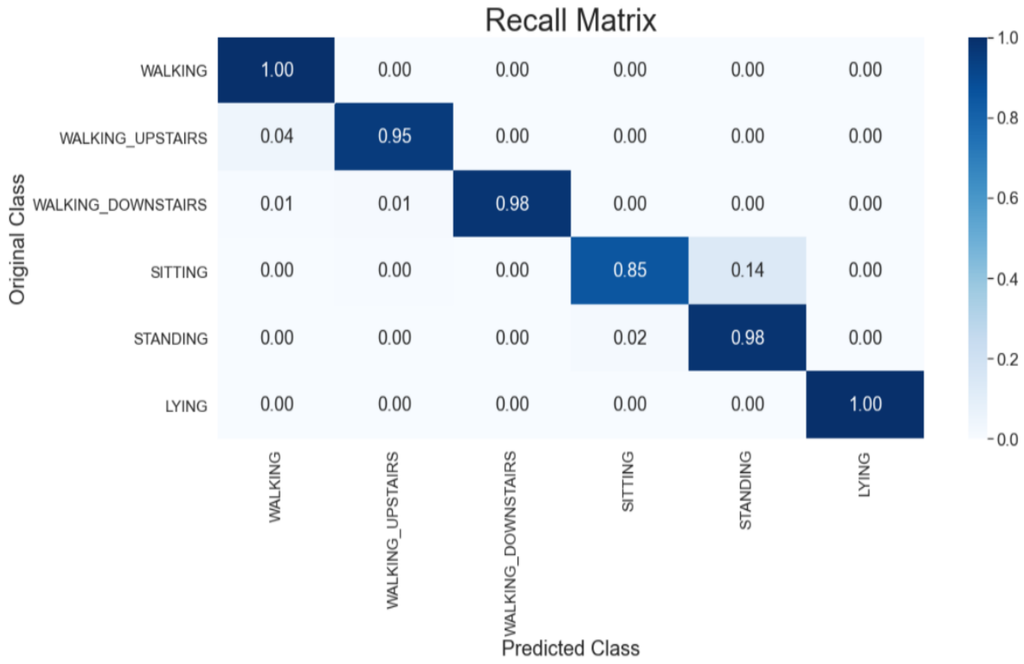

Figure 3.11 – Logistic Regression Recall Matrix

Recall matrix shows us how many of the actual positive cases we were able to predict correctly using our model.

Recall = TP/(TP+FN)

3.4.3 Linear SVM Output

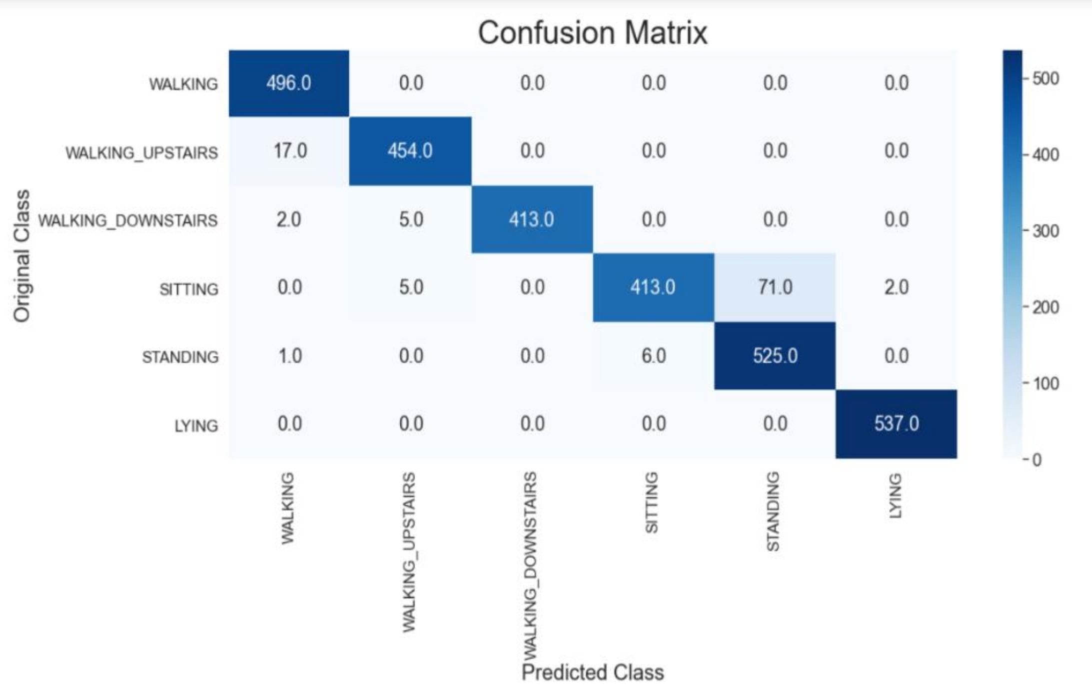

Figure 3.12 – Linear SVM Confusion Matrix

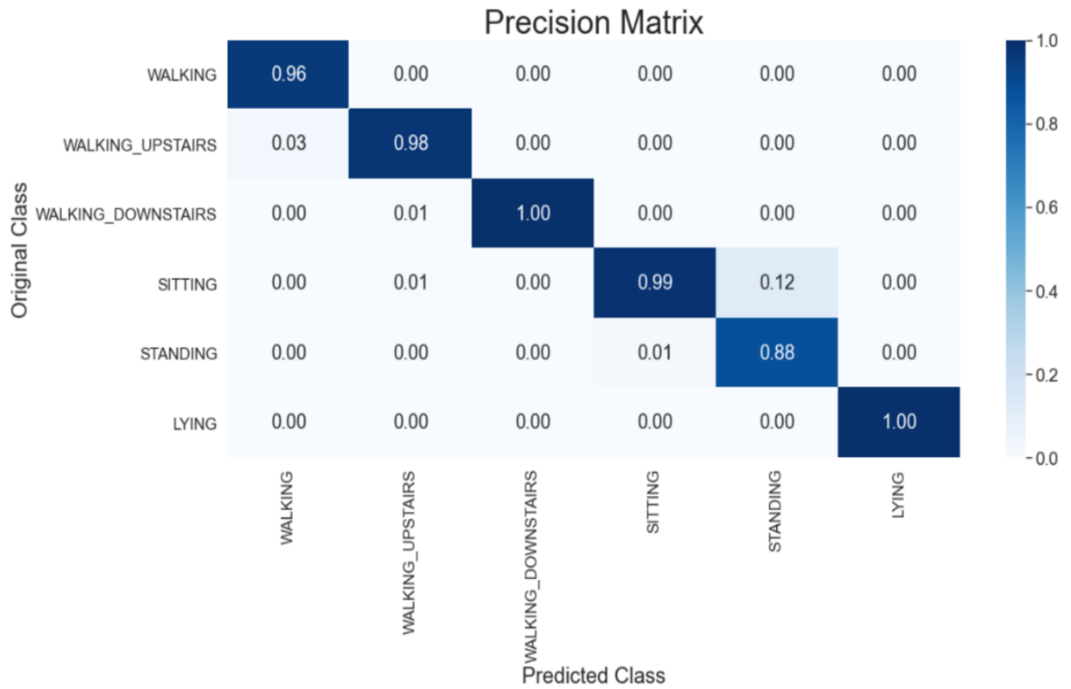

Figure 3.13 – Linear SVM Precision Matrix

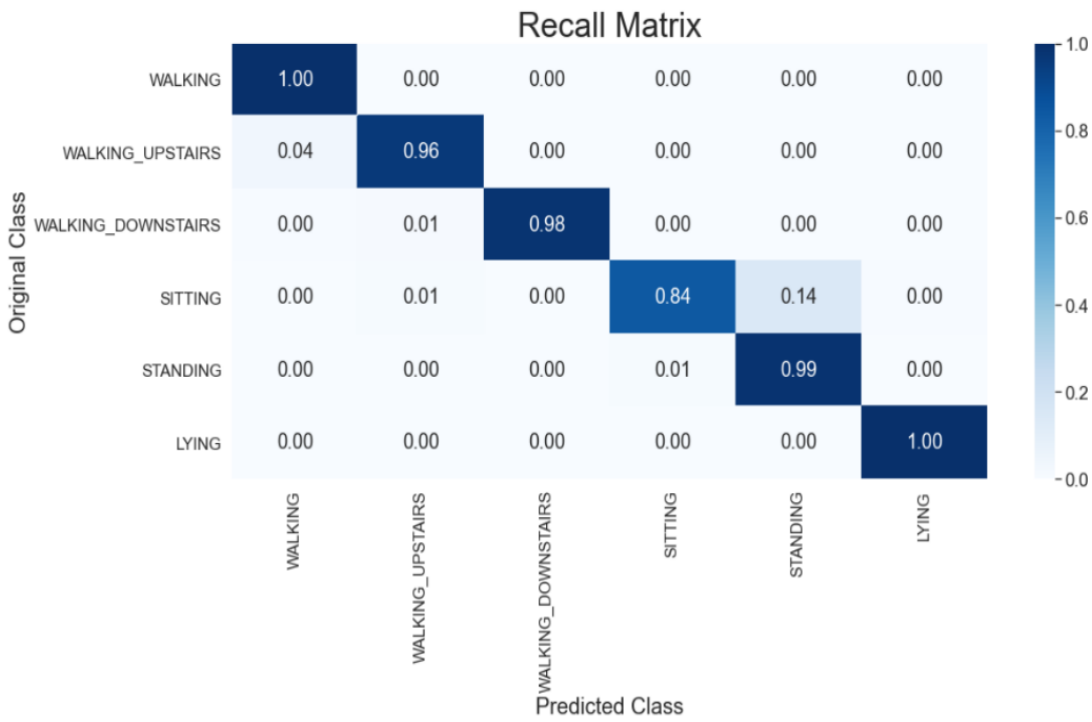

Figure 3.14 – Linear SVM Recall Matrix

3.4.4 Decision Tree Output

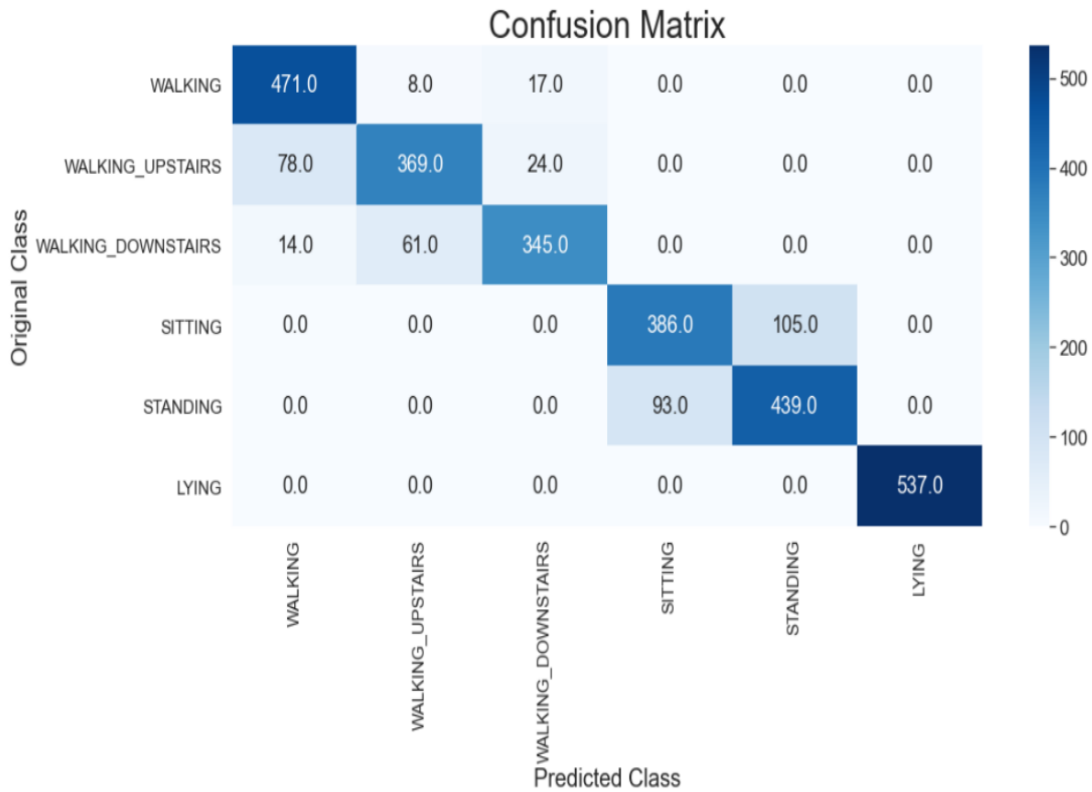

Figure 3.15 – Decision Tree Confusion Matrix

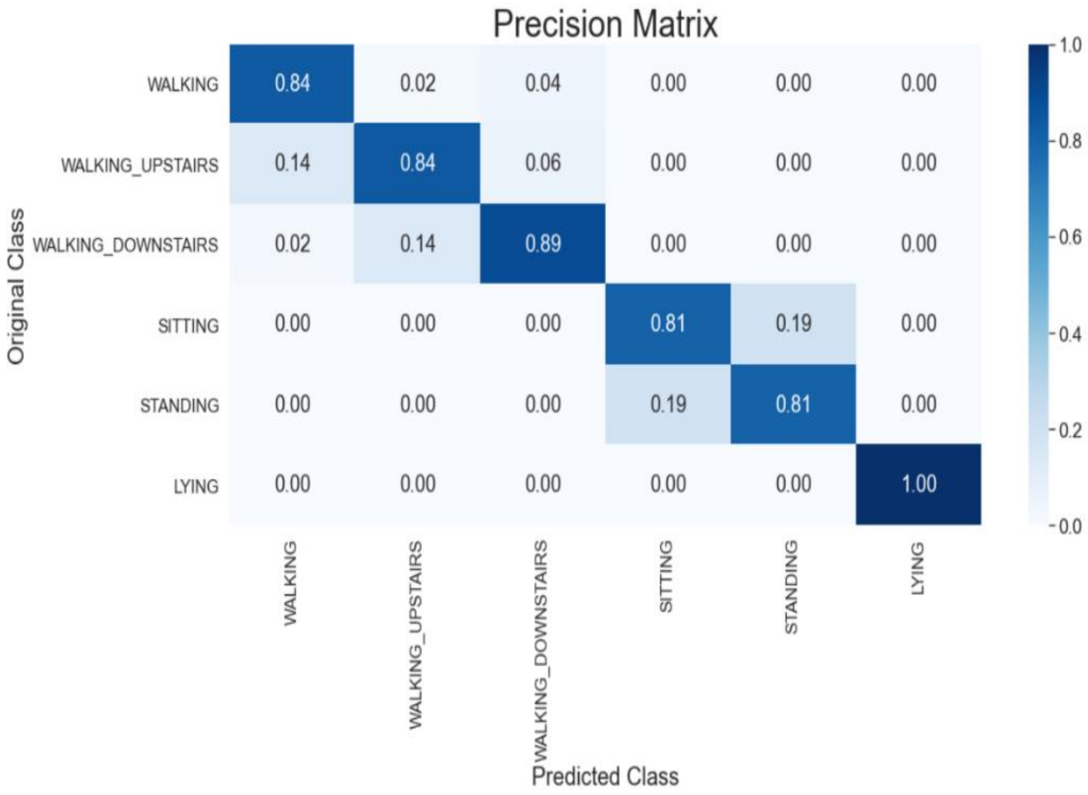

Figure 3.16 – Decision Tree Precision Matrix

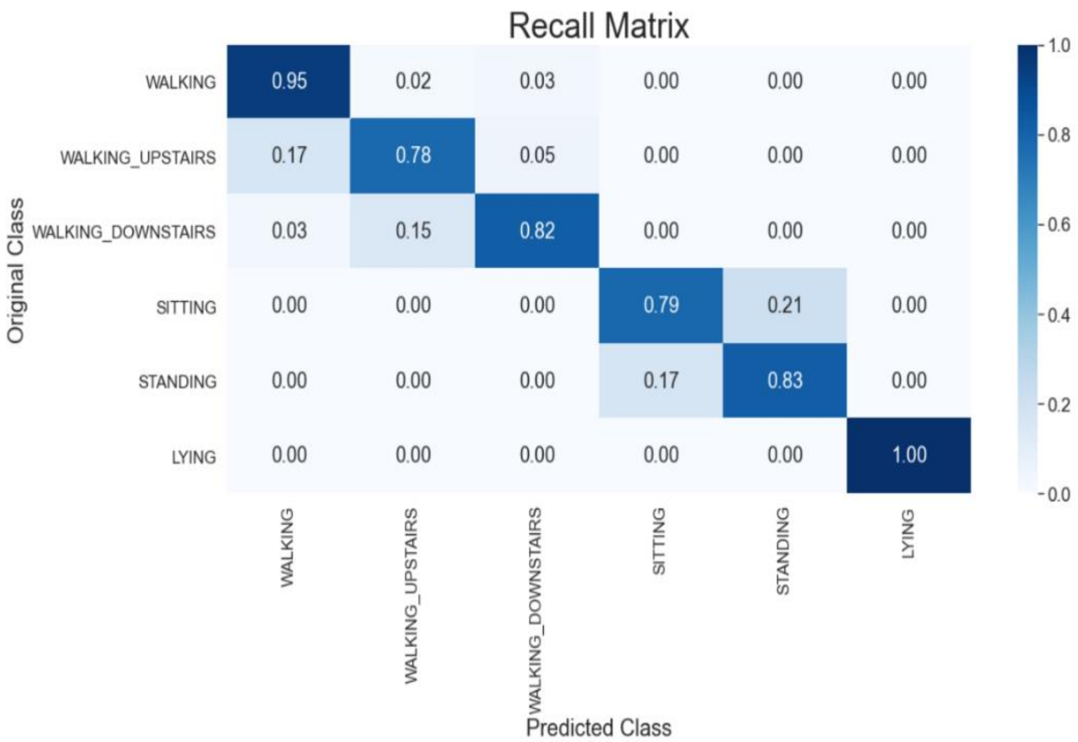

Figure 3.17 – Decision Tree Recall Matrix

3.4.5 Random Forest Output

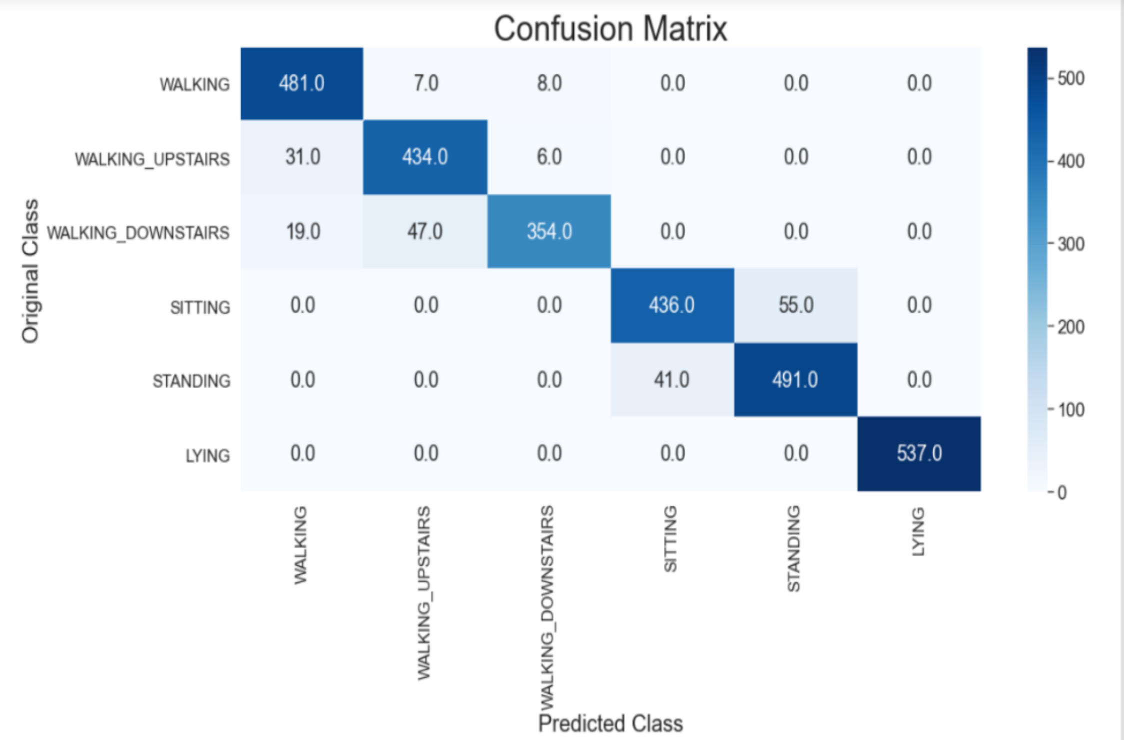

Figure 3.18 – Random Forest Confusion Matrix

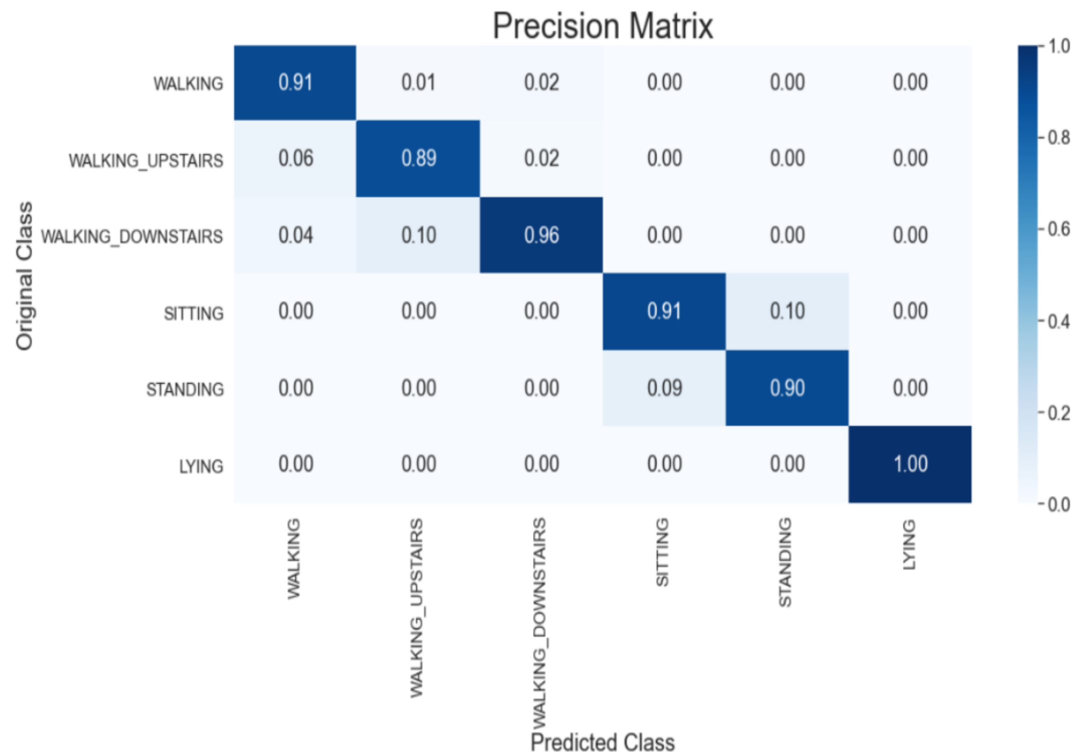

Figure 3.19 – Random Forest Precision Matrix

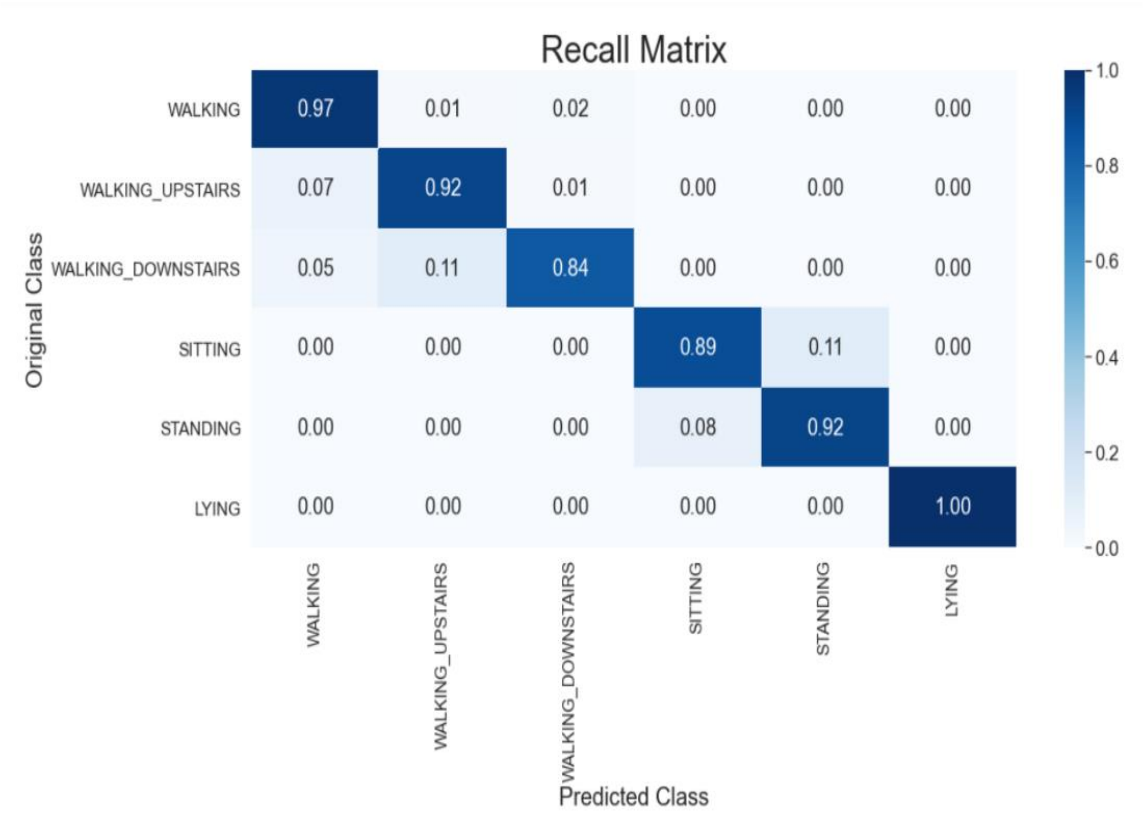

Figure 3.20 – Random Forest Recall Matrix

3.5 MODELS COMPARISION

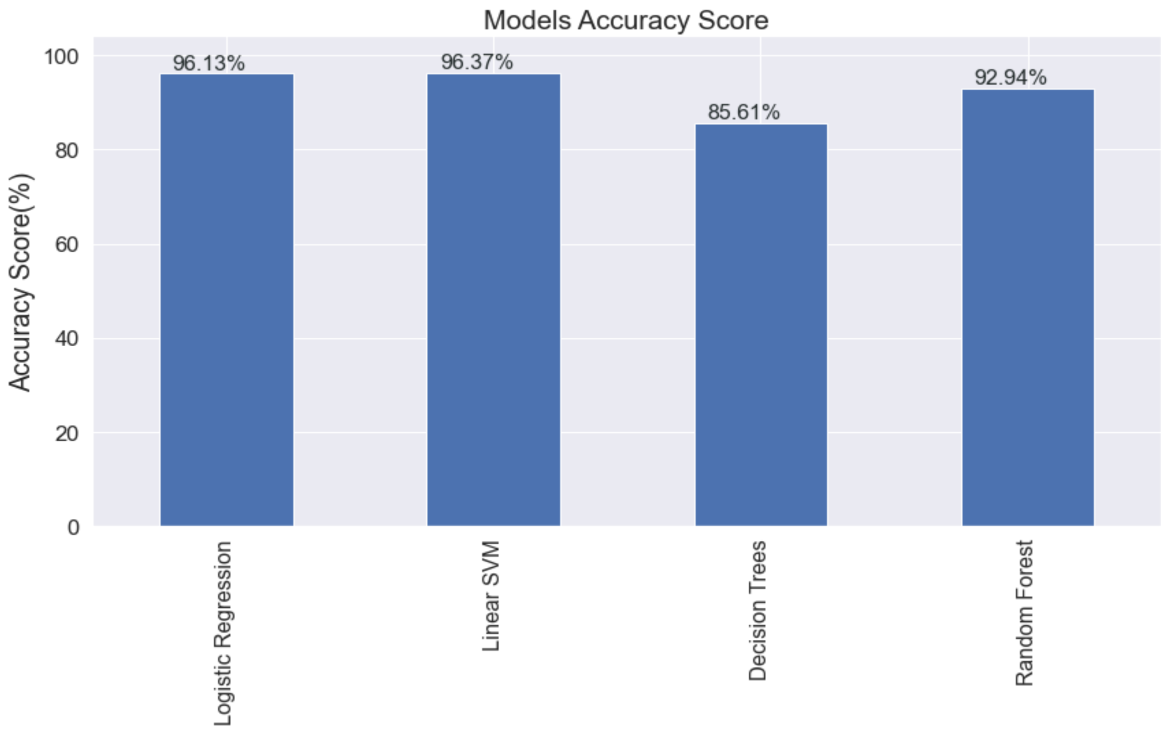

Figure 3.21 – Models Comparison

3.5 SOFTWARE REQUIREMENTS

Facilities required for proposed work:

For Desktop version –

- Jupyter Notebook
- Python
- Pandas
- Conda

3.6 HARDWARE REQUIREMENTS

- **Processor**: Minimum 1 GHz, Recommended 2GHz or more.
- **Hard Drive**: Minimum 128 GB, Recommended 256 GB or more.
- **Memory (RAM)**: Minimum 2 GB, Recommended 4 GB or above.

CHAPTER 4

FUTURE SCOPE AND CONCLUSION

4.1 CONCLUSION

Our set of classifiers has achieved relatively high performance. Different models displayed similar test errors, the accuracy for individual users and specific activities is varying. Sitting was the most difficult activity to classify. It often being misclassified as standing. So, additional features are required to distinguish sitting from standing could help in this aspect.

The linear kernel SVM has a higher misclassification rate when an individual was shifting from standing to sitting. The model that captures the time dependency in the data, such as a hidden Markova model, is useful in this case.

4.2 FUTURE SCOPE

Activity for Recognition is an important and difficult problem in computer vision parts. Its various application includes a wide variety of tasks including gaming, human-robot interaction, sports, health monitoring, robotics, etc. It is challenging due to the extremely difficult posture of humans.

Another possible area for HAR could be in processing and fusing data from multiple devices. There are a huge number of devices are available such as Actigraph, Microsoft Band, Empatica E4, Fitbit, Google Home, Amazon Echo. It is the case that a model that is developed using the data collection, using one device does not perform well with the other devices.

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