Mobile Sensors based Human Activity Recognition using Machine Learning with Explainable ML.

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A thesis submitted to the Department of Computer Science and Engineering
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B.Sc. in Computer Science

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Ethics Statement

We, Raihan Rahman, Shafin Jami Osdi, Sadia Sidran Till, consciously assure that for the thesis paper "Mobile Sensors based Human Activity Recognition using Machine Learning with Explainable ML" the following is fulfilled:
1. This is our original work, which has never been published before.
2. The paper is not being considered for publication anywhere at this time.
3. The report accurately and completely represents our own study and analysis.
4. All of our team members made significant contributions, which are duly acknowledged in the study.
5. The findings are adequately contextualized in light of previous and ongoing research.
6. All of the sources that were used are properly credited (correct citation). Quote marks and a relevant reference must be used to identify text that has been copied verbatim.
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Abstract

Based on the data collected from the sensors of smartphone a region that has garnered a lot of interest has a consequence of the growing popularity in the numerous variety for pertaining to applications(i.e. Real world implementations), of ambient intelligence, such of which includes from health care and sports to surveillance and even remote healthcare monitoring, is known to be HAR(i.e. Which stands for Human Activity Recognition). MThere are numerous studies that have, unraveled astounding discoveries upon the use of a diverse array of different sensors of contemporary smartphones in this context (examples of such sensors includes accelerometer, gyroscope etc). Despite the fact that there is a behaviour which is the same sensor motion wave form is varied to significant extent in a large number of enhanced mobile phone (i.e. smartphone), position. As a result the comprehension of actions to vast range would be strenuous to do with high accuracy and precision. Each of every distinct person their patterns of movements in comparison to one another substantially and recognizably vary. These are due to various different relevant parameters of assessments related to the analysis which includes each individual's gender, age, age band and behavioural habits, and their professions the diet, life style the region they live in which exacerbates the challenge of defining the boundaries of distinct activities. . 563 features were train and tested through supervised machine learning approach. Among the algorithms SVM came up with the highest number of accuracy. In our work we tried to bring the explainability of a machine learning model through LIME and SHAPE. We used SVM model for applying LIME and used SHAPE for Deep Neural Network. This two approach helped us to understand which features are the key features, how they changed and which features will be more effective.

Keywords: SHAPE(SHapley Additive exPlanation)); Machine Learning;
LIME(Local Interpretable Model-Agnostic Explanations);Neural Network;Explainable ML;

Dedication

We the group members are really grateful towards our co-supervisor Md.Golam Rabiul Alam, Phd for his valuable time and help to accomplish our work successfully.

Acknowledgement

Firstly, We cannot express our enough gratitude towards our Supervisor, Dr.Md Khalilur Rahman for His valuable time, support, help and encouragement .

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Chapter 1

Introduction

1.1 Introduction

The fast growing of the population in industrialized cultures necessitates the evolution of improved tools to continuously monitor people's activities. The objective of these instruments are mainly to promote active and healthy aging, as well as to detect potential health issues early on in order to live a healthy life.Though this systems work well in a supervised situations, their utility outside of the lab is restricted due to a variety of flaws in present methodologies. Day by day new technologies are coming to overcome these situations and researchers are trying to build improved applications to detect various types of human activities.

In the recent decade, Human Activity Recognition has been extensively researched.Now a days each and every smartphone have sensors in bulit in way so having these types of sensors many gadgets are coming day by day. Activity-aware computing covers a wide range of applications. For example, information obtained from accelerometers and other inertial sensors and gyroscope and other sensors can be used to perform recognition. These sensors are built-in to several smartphones. Signals from bodies are sent and processed through supervised machine learning models. In the previous related works they tried to proposed their models with different kind of dataset and approaches. But in our paper we tried to accomplish our work with different types of machine learning model and explainable machine learning with a better accuracy.On the other hand some of the papers also focused on only on accelerometer sensor data with only one classifier algorithm. But there we noticed some limitations.

But we worked with not only Machine Learning techniques but also Deep Learning techniques. We used CNN and LSTM in our work and for classification we used multiclass SVM classifier. We dealt with not only accelerometer data but also used gyroscope sensor's data for six type of activity recognition. For the explainability part we used two type of method which are SHAP and LIME which helps us to bring the explainability of the model what we have used in our works. We alo got the best accuracy by using multiclass SVM classifier which is around 95% and we got accuracy by CNN is 89% and by LSTM model we got accuracy around 89%.

1.2 Problem Statement

For the last twenty years, human activity recognition (HAR) has been a hot study area because of its potential applications in domains like health, remote monitoring, gaming, security and surveillance, and human-computer interaction. Due to its applicability in different industries such as health, security and surveillance, entertainment, and intelligent settings, human activity identification has risen in popularity in recent years.Human activity identification has received a lot of attention, and researchers have used a variety of ways to accomplish it, including wearable, object-tagged, and device less approaches.The capacity to recognize/detect present activity based on information collected from various sensors is known as activity recognition.The vision-based technique, in which a camera is used to record information about human behaviors, is one of the pioneering approaches in this field. Different activities can be recognized using computer vision techniques on this collected data.Because of the low cost and improvement in sensor technology, the majority of HAR research has turned to a sensor-based approach. Different sensors are employed in the sensor-based approach to capture human behavior while people do normal living tasks.Because there are so many options for recognizing activities, we must first define what we want to achieve in order to determine which arrangement is best and which actions are very much needed. In the previous works they used machine learning and deep learning techniques we also used these techniques in our work with a better accuracy and able to bring explainability and interpretability using explaninable machine learning.

1.3 Aim of Study

Predicting individuals' basic daily life activities is our aim of study. In our thesis we bring to manage the relation between sensor data and human activities. How a sensor data which is located in different axes can be represented as human activity. From the data set we picked up the best features which told us what activities are done by an individuals and also the different orientation of sensors data can be represented as a human activity.

1.4 Research Methodology

Though our main target is activity recognition, so having this objective first we needed to gather data from different sensors like accelerometer, gyroscope and other sensors.Tri-axial linear acceleration and angular velocity are the signals recorded by the accelerometer and gyroscope, respectively. In a tri-axial component, however, there is also a set of input signals derived from the other sensor.Then we needed to normalize the dataset and bring all the input signals into binary using label encoder because the values we got are all categorical values. Then we utilize various number of features to guarantee that each factor is contacted. To choose the most significant features we did feature engineering and also guideline component analysis(PCA). We used K-means clustering for PCA which helped us to understand the features and their distribution in dataset and how this features are changing and helped to pick the right features among all the features.Then we trained and tested our dataset by using a model which is multicalss SVM classifier. Then we used deep neural network which works in dense layer and tried to bring better accuracy by changing number of epochs along with some other parameters. We also used LSTM architecture.Lastly we bring LIME and SHAP approach in our machine learning models to bring the expalinability of that particular model and able to predict which features are effective and how these are changes.

1.5 Thesis Outline

This report puts influence on constructing a prediction model which would be beneficial in detecting six types of activities in primary stage. The aim of the authors is to formulate a data set based on mobile sensors which would be used for training existing supervised machine learning models to classify new observations. The overall report focuses on the steps that were followed by the researchers. Firstly, introduction part (Chapter 1) states the motivation behind research which inspired authors to address this particular problem statement. The goals of our research and summary of the work is briefly discussed here.

In Literature review section (Chapter 2), we have discussed about papers from computer science background which have addressed similar issue. In addition to that,The purpose of background study was finding out the short comings of previous researches. Moreover, we have stated our contribution and reasons behind primary data collection.

In the data collection phase (Chapter 3), we have explained why we have used this data set. This portion also included a description of data set. We also emphasized on the reliability and consistency of our generated data set. Feature selection argued how the huge number of features can be reduced to decrease time complexity.

Furthermore, Model Selection (Chapter 4) includes our proposed models and comparative study of the prediction rate among respective models.This section examines both classic and sophisticated algorithms in the context of our generated data set. In addition, the results are summarized with a visual representation to show which model performs best for our data set.

Chapter 2

Related Work

In one paper Activity identification utilizing ambient sensors and dedicated body-worn sensors has been extensively researched by Incel [1]. Lara[2] gave a complete guideline for rezognize the activities by sensors which are wearable. Motion sensors for activity recognition were investigated by the authors Bao[3] and Mantyjarv[4]. Their methods entail the use of wearable sensors at a variety of body regions. Author Bao collects bi-axial accelerometer data from four separate limb regions as well as a sensor at the right hip.

Author Tapia[5]introduced to us a real time activity recognition system which are built with heart rate sensors and five tri axial accelerometer sensors. In general, systems that employ many wearable sensors provide high activity identification accuracy.There is no comfort to wear this type of sensors for a huge amount of time.They also showed the use of inertial sensors for activity recognition. Bieber et al. [6] created a mobile phone application that uses the built-in accelerometer to detect everyday physical activities.Kwapisz et al. [7]used accelerometer data from a smartphone to perform activity recognition. The participants kept their phones in the front pocket of their trousers when walking, running, ascending. Dernbach et al [8]looked at the utility of accelerometer and gyroscope sensor values to categorizing basic and complex activities. Their method for classifying complicated tasks does not appear to be very effective.

Kwon et al. [9]introduced an activity recognition system based on unsupervised machine learning.Chen and Shen [10]recently used data from smartphone accelerometer and gyroscope sensors to classify five different activities. For activity recognition, the authors looked at time, frequency, and wavelet domain characteristics, as well as dimensionality reduction using the Kolmogorov-Smirnov test.Shoaib et al. [11] used hand and leg movement data obtained from the pocket and wrist positions to perform smartphone-based activity detection. The authors took into account behaviors such as typing, smoking, and eating in addition to regular physical activity.Standing, sitting, laying, walking, downstairs, and upstairs were all considered by Anguita et al. [12]. The tri-axial accelerometer and gyroscope sensor readings yielded a hard and fast of 27 greater indicators. on a dataset of 7352 training and 2947 check samples, their method, which uses statistical traits and an svm classifier, received 96.33 percent common class accuracy.

Wu et al. [13]looked at a fixed of time and frequency domain variables, as well as a k-nn classifier for recognizing phone-based activities. On a dataset with 2807 sensor indicators belonging to nine unique activities, 10-fold move-validation of their method, acquired 90.2 percent common classification accuracy. Since the aforementioned studies proved the functionality of identifying sports with the use of the integrated sensors of smartphones or different comparable devices with promising consequences on big datasets, there's a pressing want to create methodologies that deliver relatively accurate and trustworthy consequences. Furthermore, for the phone-based technique to be a superior option to committed body-worn sensor-based totally solutions in actual-international packages, performance should be improved. This caused us to create a method for spotting interest in smartphones primarily based on two revolutionary characteristic sets.

Wang, J., and colleagues[14](2019) conduct an overview of the literature primarily based on 3 standards: sensor modality, dl models, and application scenarios, and offer thorough information at the works studied. Wang, and associates describe the most up-to-date sensor modalities in har, focusing on the processes linked with every section of the har process in phrases of sensors, information preprocessing, characteristic studying, classification, and interest, including both traditional and dl strategies. In addition, they display ambient sensor-based totally har, Inclusive of digital camera-primarily based systems, in addition to systems that integrate wearable and ambient sensors.

Lester[15], Choudhury, and Borriello's experience constructing an autonomous physical activity recognition system. They address critical topics such as where sensors should be placed in a person, whether variance among users helps to increase activity categorization accuracy, and which modalities are optimal for recognizing activities in their research.They come to the conclusion that it doesn't matter where the users put the sensors; variance across users does aid improve classification accuracy, and accelerometers and microphones are the best modalities for recognizing physical activity. Human behaviors are learned in a controlled atmosphere once again.In prior research, we used a prototype of a wearable device that was completed by a camera. People acting in two constrained situations were asked to provide data on five routine activities.

The 5 activities had been categorized using a gentle boost classifier, which had an accuracy of 83 percent for every pastime. face-to-face social sports had been detected with high confidence the use of an aggregate of a bodily activity classifier and a face detector.in evaluation, on this paper, we ask how a long way we are able to cross in spotting human behaviors the usage of totally wearable statistics. Anguilla et al.citeanguita2007hardwareproposed the idea of a hardware-pleasant SVM (hf-SVM). Thefeed-forward phase of the SVM classifier is used using constant-factor mathematics on this approach, permitting it for use in hardware-restrained devices. this version is prolonged for the multiclass category on this study

Chapter 3

Data Collection and Feature Selection

A sensor network is made up of a large number of sensors that are densely placed inside or very close to the phenomenon. As a result, the function of a sensor network is to gather specific signals or events that represent the phenomenon of interest in order to draw conclusions about the phenomenon. This leads to challenges such as a continually changing architecture as sensors are added and removed, power consumption and processing capacity constraints, and sensor failure. We will first describe the sensor types that will be considered in this study, as well as our phenomenon of interest, i.e., the location where the sensor network will be deployed and the type of activity that should be performed, because there are numerous sensor types and areas of application (e.g., health, military, and home) and, as a result, multiple different settings.

3.1 Sensor Types

There are various kinds of sensors available these days, along with movement, physiological, proximity, and environmental sensors, all of which can be used to monitor a human in their entirety. We consciousness on movement sensors on this study due to the fact they're unobtrusive, require little energy, and guard users' privateness through no longer recording video, audio, or physiological statistics.certainly, motion sensors capture a ramification of motions and movements, in addition to the sensors' orientation or adjustments in orientation. Only sensors that are taken into consideration in this paper, whether for experiments or discussion, are discussed in the following sections. We're going to undergo the accelerometer, gyroscope, and magnetometer, which might be now discovered in practically each wearable smart machine.please notice that we always talk over with the sensors being carried out in 3 dimensions. because we'll be focusing on the accelerometer,gyroscope and we will cross over it in extra intensity to reveal how we use it.

Overall, the explanations are tool-unbiased and should resource comprehension of our arguments and conclusions. The accelerometer is a form of inertial sensor that measures the acceleration of a frame based on a alternate in pace over a period of time. from a bodily viewpoint, isaac newton's legal guidelines of motion define acceleration (a) as the amount of pressure (f) required to transport each unit of mass.Mechanical, capacitive, piezoelectric, resistive, and piezo-resistive accelerometers are all examples of distinct types of accelerometers.

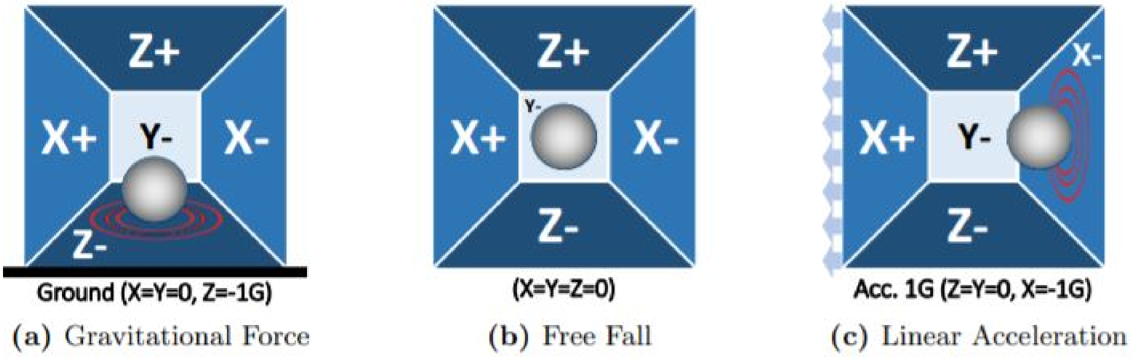

Figure 3.1: Three axis orientation of accelerometer

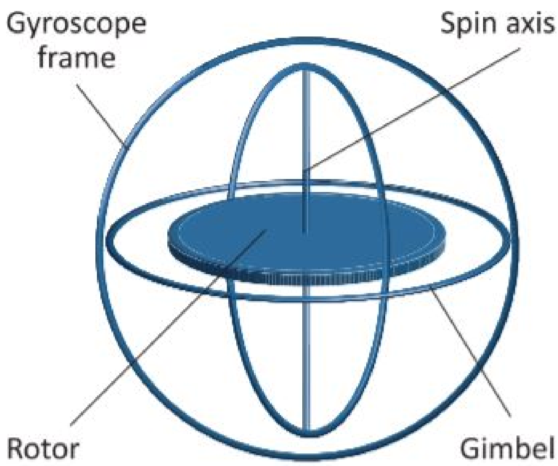

Figure 3.2: Gyroscope orientation

The gyroscope is part of the inertial sensor family and monitors angular velocity. This reflects the rate at which an angle around an axle varies over time and allows for the capturing of a body's rotation, which aids in determining orientation. The wheel has a high persistence due to angular momentum conservation, which means that when the gyroscope's orientation changes, the wheel's orientation practically stays the same.While pressure operates on the gyroscope, affecting its orientation and, as a result, trying to tilt the spinning wheel, the axis of rotation tilts perpendicular to the active pressure as a way to hold overall angular momentum. The gyration, or angular or rotational motion, is measured by way of measuring the rotation speed among the spinning wheel and the gyroscope's body. to be clean, while the wheel spins at a fast and steady velocity and a person grabs the gyroscope frame and starts strolling around, the orientation of the wheel is unaffected, i.e., the orientation of the wheel stays nearly consistent. The spin axis and gimbal, then again, respond to the variations in orientation as a result of walking about. the angular velocity is calculated by means of measuring the shift of those additives.

3.2 Data Collection

A group of 30 participants, ranging in age from 19 to 48 years old, participated in the experiments. The six activities were conducted by each participant while wearing their smartphone around their waist. The studies were videotaped to make data labeling easier. The acquired data was divided into two sets at random, with 70% of the patterns being used for training and 30% being used for testing. The test were conducted with a Samsung Galaxy S2 smartphone, which has an accelerometer and gyroscope capable of measuring 3-axial linear acceleration and angular velocity at a constant rate of 50Hz, which is sufficient for capturing human body motion. The recognition process starts with the acquisition of sensor signals, which are then preprocessed with noise filters before being sampled in 2.56 second fixed-width sliding windows with a 50% overlap.

Figure 3.3: Activity recognition process

Each window generates a vector of 17 characteristics after calculating variables using accelerometer data in the time and frequency domain (e.g.mean, standard deviation, signal magnitude area, entropy, signal-pair correlation, etc.).

3.3 Feature Extraction

In activity recognition feature extraction is the most important part because these features will determine the accuracy. So, there exist many features which deal with different types of activities. These features are derived from the many statistics models which include mean, median, standard deviation, correlation coefficient etc. For differentiating activities correlation is very useful. In our dataset these features are divided in time and frequency based domain. For activity recognition the main frequency lies between 1 and 18 Hz. We can say that if the accelerometer were placed in the hip so that the acceleration force would be lower from the ankle. So, the frequency measured at the hip will be lower. We know that lower frequencies cost lower computation cost as well as lower power consumption. Here both ac and dc components will be useful features for activity recognition. Static posture can be determined by a dc component which mostly influences gravity. Using a sliding window approach with 50% overlap, feature extraction is performed on data. One complete activity will be an observer in one particular window.

tBodyAcc.std.Z	tBodyAcc.mad.X	tBodyAcc.mad.Y	tBodyAcc.mad.Z	tBodyAcc.max.X	tBodyAcc.max.Y	tBodyAcc.max.Z	tBodyAcc.min.X	tB
-0.0801	-0.267	0.315	-0.124	-0.144	0.239	-0.108	-0.00806	
-0.1330	0.245	0.214	-0.169	0.623	0.258	-0.401	-0.08310	
-0.9690	-0.980	-0.964	-0.970	-0.929	-0.561	-0.797	0.82400	
-0.7920	-0.647	-0.615	-0.788	-0.526	-0.160	-0.696	0.58800	
-0.2350	-0.362	-0.031	-0.223	-0.110	-0.138	-0.378	0.23100	

Figure 3.4: Few features from dataset

From the above figure we can see some features which are contained by our dataset.The 3-axis raw data tAcc-XYZ and tGyro-XYZ from the accelerometer and gyroscope were used for this project. At a constant rate of 50 Hz, these time domain signals (prefix 't' to represent time) were collected. To reduce noise, they were filtered with a median filter and a 3rd order low pass Butterworth filter with a 20 Hz corner frequency. Using a low pass Butterworth filter with a corner frequency of 0.3 Hz, the acceleration signal was separated into body and gravity acceleration signals (tBodyAcc-XYZ and tGravityAcc-XYZ). The body linear acceleration and angular velocity were then calculated in time to provide Jerk signals (tBodyAccJerk-XYZ and tBodyGyroJerk-XYZ). The Euclidean norm was also used to calculate the magnitude of these three-dimensional signals (tBodyAccMag, tGravityAccMag, tBodyAccJerkMag, tBodyGyroMag, tBodyGyroJerkMag). Finally, some of these signals were subjected to a Fast Fourier Transform (FFT), yielding fBodyAcc-XYZ, fBodyAccJerk-XYZ, fBodyGyro-XYZ, fBodyAccJerkMag, fBodyGyroMag, fBodyGyroJerkMag. (The 'f' stands for frequency domain signals.)

Because the effectiveness of a classification algorithm is highly dependent on the dimensions of the feature space or vector, it is vital to minimize and diminish dimensionality's impacts.Feature selection methods are used to find and reject characteristics that make a minor contribution to the effectiveness of the classifier, which is one technique to minimize dimensionality.Sequential search techniques like branch bound searches and the Pudil algorithm are commonly used in feature selection algorithms. Because some characteristics may bias the classifier model, feature selection is also an effective way to avoid biasing while training.The following are two general ways to feature selection.

1.Filter approaches, which use a search algorithm to score and order features. The ordered list of attributes demonstrates which features have the greatest impact on the model.

2.Wrapper approaches assess outcomes for a particular classifier using several combinations of features; this information is then used to determine which feature combinations result in the most accurate model. This method takes a long time to complete and demands a lot of computing power.
We used K means clutering in our work. We checked the null values in our dataset and we didnt find any null values in our dataset.

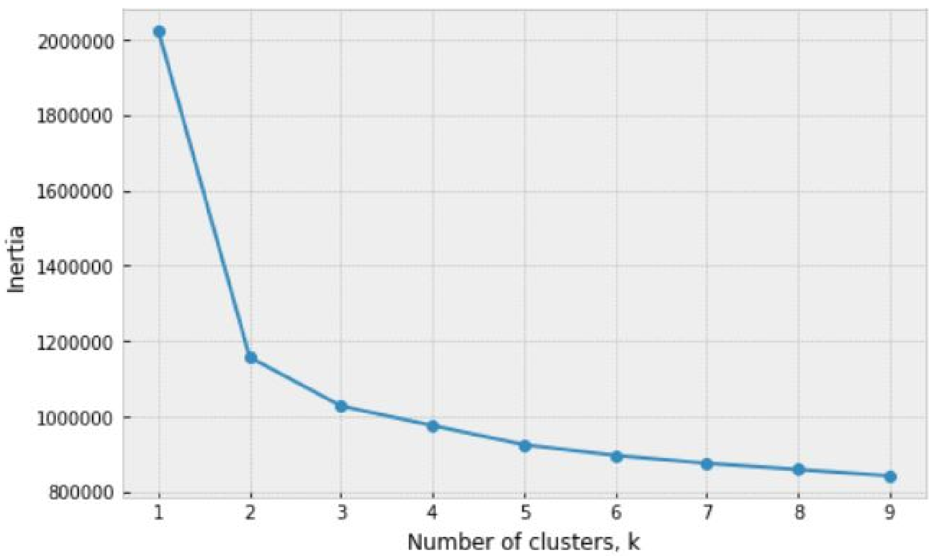

Figure 3.5: Clusters vs Inertia

From the above picture we can see that we got the highest value of inertia for cluster number 1 and the lowest value of inertia for cluster number 9. From cluster number 2 the changes are happening in a certain way. We fixed the optimal value of k which is 2.

orig_label	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	WALKING_UPSTAIRS
clust_label						
0	680	622	668	0	0	6
1	1	1	0	603	493	535

Figure 3.6: Labeling into two cluster

From the above figure we can see that we divided the labels in two clusters which is 0 and 1. From cluster 0 we can see that the values of Laying is 680 , for sitting is 622 and we didn't find any values for walking, walking-downstairs and walking-upstairs in cluster 0. But we found values for these activities in cluster 1.

orig_label clust_label	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	WALKING_UPSTAIRS
0	554	21	0	0	0	0
1	0	0	0	248	311	97
2	1	0	0	329	107	438
3	20	445	479	0	0	0
4	0	0	0	26	75	4
5	106	157	189	0	0	2

Figure 3.7: Labeling into six cluster

We made six clusters in above figure where number of activites count per cluster are shown. For example we find 554 for laying in cluster 0 which is the highest compairing to another five clusters. For sitting cluster number three containg the highest value.

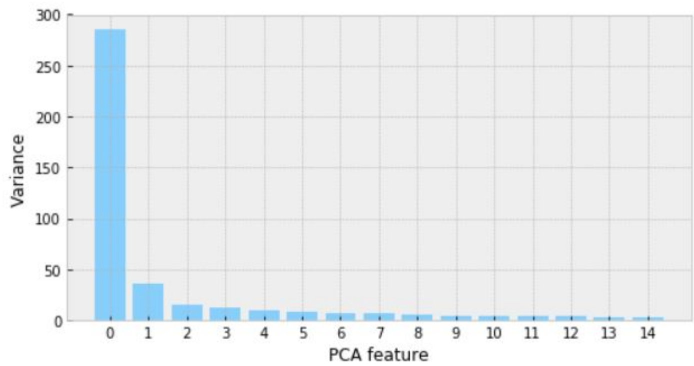

Figure 3.8: PCA vs Variance

From the above figure we got the highest variance for PCA feature 0 and from there the variance is decreasing.

Chapter 4

Model Selection and Result Analysis

4.1 Machine Learning

Arthur Samuel[16] coined the phrase "machine learning" in 1959 . The systematic learning of algorithms and statistical models is known as machine learning. A computer uses Machine Learning to successfully complete a task without the use of explicit commands, instead relying on patterns and interpretation. It falls under the umbrella of Artificial Intelligence. "With respect to a class of tasks T and performance measure P, a computer program is said to learn from experience E if its performance at tasks in T, as measured by P, improves with experience E," writes author Tom Mitchell. It is included in the field of Artificial Intelligence. [17]Algorithms for machine learning are utilized in a wide range of applications. It is employed in all areas of Artificial Intelligence, including Image Processing and Computer Vision. Where it is impossible to design an algorithm of explicit instructions for accomplishing the job, Machine Learning is usually preferred.In many ways, Machine Learning is similar to computational statistics, which is used to make predictions with computers. In our research, we used a machine learning methodology to predict drug addiction vulnerability.

There are several types of machine learning. For instance, supervised learning, unsupervised learning, and reinforcement learning are all examples of different types of learning. Because our problem had both input and output, we applied supervised learning in our research. In supervised learning [18], a mathematical model is constructed that includes both input and desired output. In the mathematical paradigm of supervised learning, each training data is a matrix, and each training example is an array or vector. Iterative optimization of a function aids in determining the best strategy to learn the task and predict the outcome [19].

Finally, the system predicts an input from outside the training data that was not included in the training data. This is how supervised learning determines a problem's forecast.Unsupervised learning algorithms, on the other hand, work with data that simply considers inputs and uncover various types of structures in the data, such as data grouping or clustering.The objective of reinforcement learning, once again, is to determine how software agents will respond in a situation in order to fully exploit some concept of cumulative return. Our task was to determine whether a test data set falls into the addicted or non-addictive category.

4.2 Neural Network Implementation

Multilayer perceptions were utilized since the model was intended to make complex judgements based on 563 features, which required more than a linear separation across classes. Hidden units have been proposed as a means of simplifying classification jobs. There are six classes in our dataset. where y = C was the transformation function (x). A hidden unit should be retained for every sample xi belonging to Ci so that the weight is identical to the pattern of class Ci. When the neuron in the previous layer returns value '1', the output layer should be chosen with an activation function that classifies outcome xi C1. Because the technique is well-suited to deal with numerical data, we mapped the responses to numeric values.

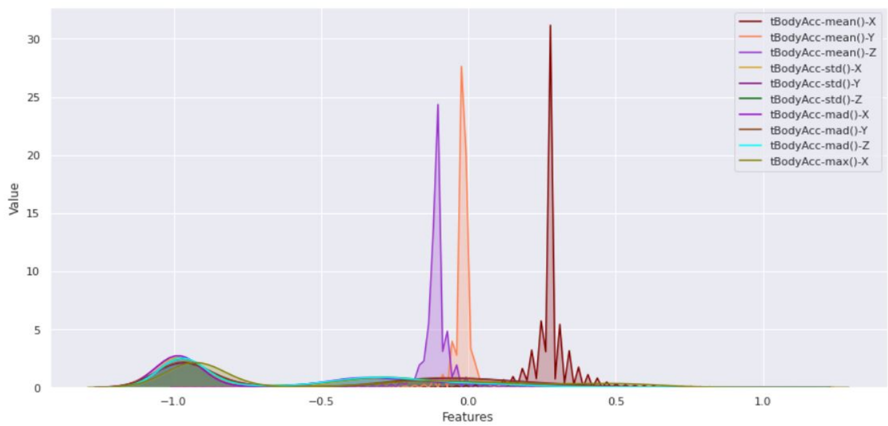

Figure 4.1: Features vs Value (1)

From the abovce figure we can see the features distribution along two axis. The test set was chosen from 70% of the data frame, containing 7352 samples from the whole dataset. After multiplying the feature values with the weights that served as input to the activation functions, the feature values were added. The formula for calculating the weighted sum is as follows. On the other hand, we implemented fully connected layers using dense layers, with the first layer having a dense value of 64. In the first layer, the relu activation function was utilized, together with 64 hidden units, to allow the network to learn more complex associations. Rectified linear units solve the vanishing gradient problem since they have a faster convergence feature. . Secondly, for the second and third layers, we employed the identical arrangement, with hidden units of 128 and 62, respectively. For the second and third layers, we utilized the same relu activation function.

We utilized 6 as our units in the fourth layer because our overall activity was 6, and we utilized softmax as the activation function. Our model was trained for 10 epochs in the first round to optimize it and ensure that the error on the training data was kept to a reasonable level. We examined the model's performance using test data after it was built. As a result, we estimated an accuracy score of 94.91 percent. We utilized the optimizer "Adam" and the loss "Categorical crossentropy" in this case. We went through the identical steps as before, but tweaked a few details. The number of epochs has been raised to 115. We modified the dense units to 128,64,32,6 and used "RMSprop" as an optimizer in this layer, and "Sigmoid" as a function in the last layer such that the value could fall between 0 and 1. We assessed the model on test data once it was built, and we obtained an accuracy of 80%. Finally, we modified the optimizer to "Adadelta," increased the epoch number to 303, and used the "Sigmoid" activation function to get an accuracy of about 89 percent.

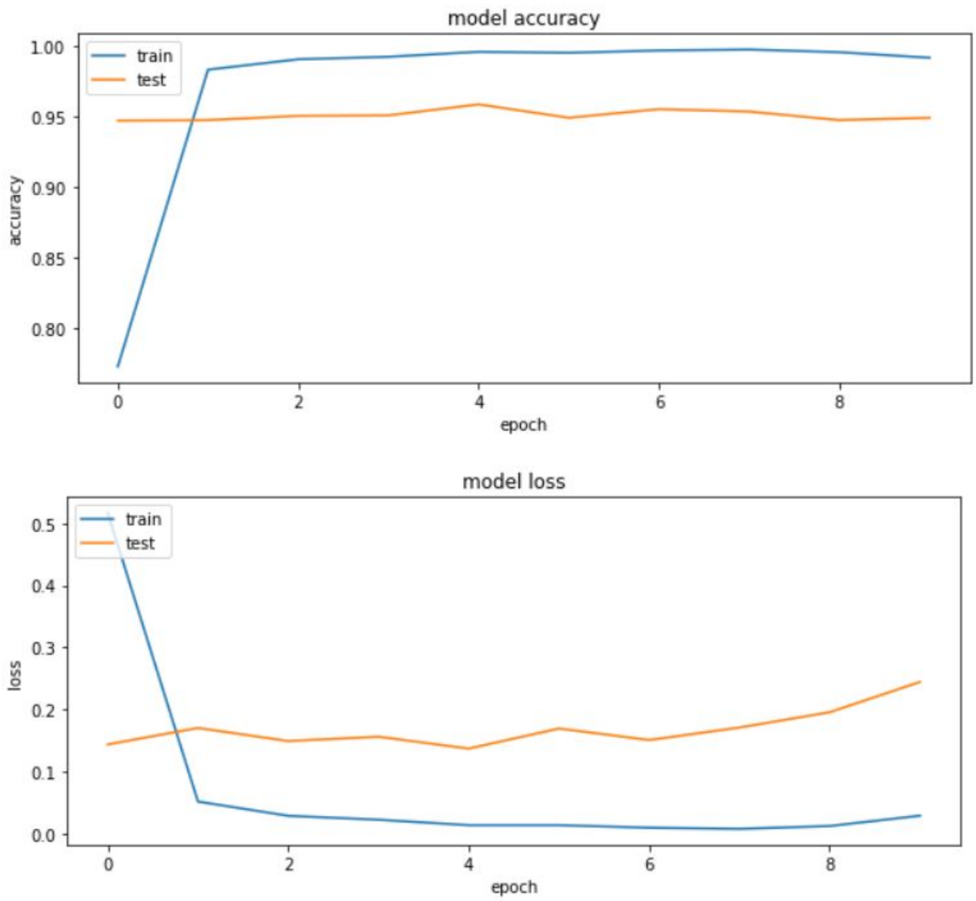

Figure 4.2: Model accuracy and Model loss

Here we can easily visualize that the model accuracy for training and test data for epochs and along with the model loss for each epoch for training and test data.

4.3 RNN

RNN is a type of neural network that is both powerful and robust, and it is one of the most promising algorithms now in use because it is the only one with an internal memory. Recurrent neural networks, like many other deep learning techniques, are still in their infancy. They were first developed in the 1980s, but we didn't appreciate their full potential until lately. The advent of long short-term memory (LSTM) in the 1990s, combined with an increase in computer power and the vast amounts of data that we now have to deal with, has really propelled RNN to the forefront.

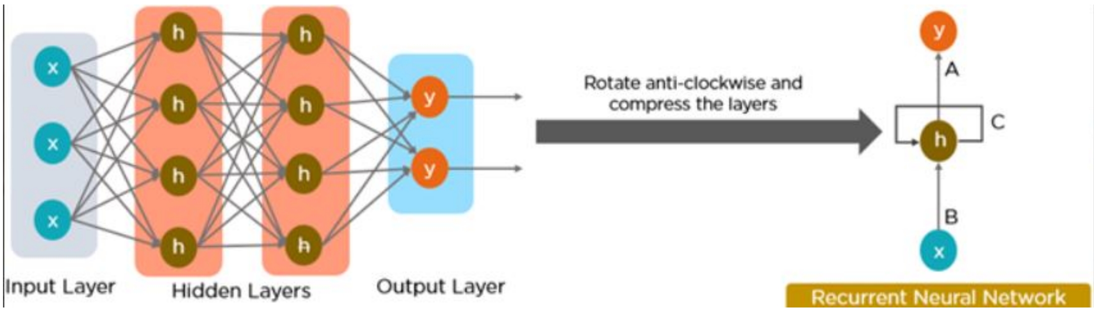

Figure 4.3: RNN architecture

RNNs may use their internal memory to recollect important data about the input they receive, allowing them to predict what will happen next with excellent accuracy. This is why they're the algorithm of choice for time series, speech, text, financial data, audio, video, weather, and a variety of other sequential data types. Recurrent neural networks, in compared to other algorithms, can learn a lot more about a sequence and its context.

4.4 LSTM based RNN

Long short-term memory networks are a type of recurrent neural network that expands the memory capacity. As a result, it is highly suited to learning from significant experiences separated by lengthy periods of time. The units of an LSTM have been used to build the layers of an RNN, also known as an LSTM network. Because of LSTMs, RNNs can remember inputs for a long time. Because LSTMs store information in a memory comparable to that of a computer, this is the case. The LSTM can read, write, and delete information from its memory. This memory can be thought of as a gated cell, with gated signifying that the cell decides whether or not to store or erase data (i.e., whether or not to open the gates) dependent on the data value. The algorithm also learns weights, which are used to assign importance. This essentially means that it learns over time what information is important and what information isn't. An LSTM has three gates: input, forget, and output. These gates regulate whether new input should be allowed (input gate), deleted (forget gate), or have an impact on the output at the current timestep (impact gate) (output gate). The gates of an LSTM are analog, in the form of sigmoids, and range from zero to one. They can conduct back propagation since they are analog. LSTM overcomes the problem of fading slopes by keeping the slopes steep enough, resulting in a short training period and high accuracy.

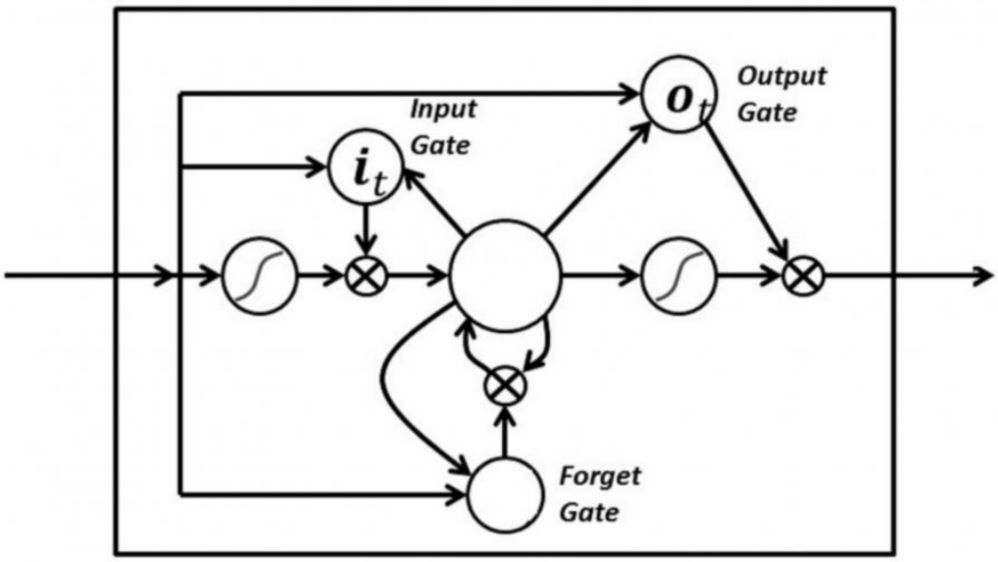

Figure 4.4: LSTM architecture

We used LSTM based RNN where we brought 7352 training series where 50% overlap between each series along with 2947 testing series. There are 128 timesteps per series and 9 input parameters per timestep. In our Lstm network there are 64 hidden layers and 6 classes. We used learning rate 0.0015 here and fixed the loop 300 times on dataset along with batch size1500.In our model number of multicell is 2.

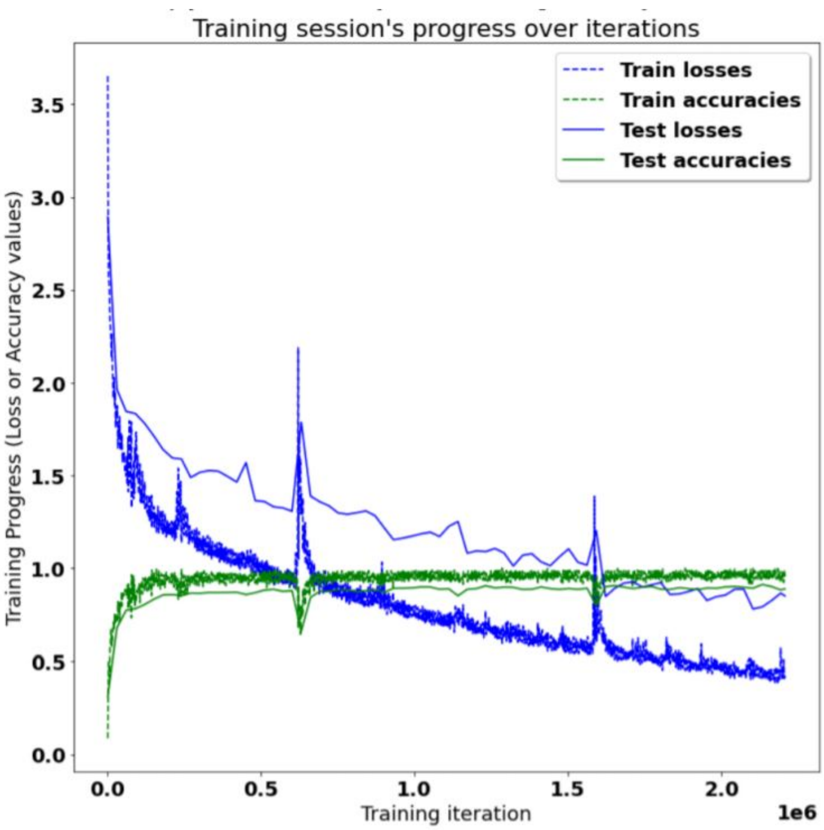

Figure 4.5: Training iteration vs training progress

Here we are not using any epochs so that when our model will get any test data it will not delete that particular data and will keep it in that model. From the above figure we can see that train losses , train accuracies, test losses, and test accuracies in different color.

4.5 Support Vector Machine

Support Vector Machines (SVM) are a well-known technique for binary classification problems in machine learning. Multi-class SVMs (MCSVMs) are frequently generated by combining multiple binary SVMs. SVM classification is based on the concept of decision hyperplanes, which establish decision boundaries in input space or high-dimensional feature space. SVM generates linear functions from a set of labeled training datasets (hyperplanes in either input or feature space). This hyperplane will try to tell the difference between positive and negative samples.

In general, the linear separator is built with the largest distance between the hyperplane and the nearest negative and positive samples. This results in correct categorization of training data that is comparable to, but not identical to, testing data. SVM employs a data matrix as input data during the training phase and classifies each sample as belonging to a given class (positive) or not (negative). SVM treats each sample in the matrix as a row in an input space or high-dimensional feature space, with the space's dimensionality determined by the number of characteristics. The goal of SVM design is to create a decision border that is as far away from any data point as possible, despite the fact that there are several linear separators. There is a pair (w,b) that says: if the training data can be split linearly.

$$\begin{aligned} \boldsymbol{w}^{\mathrm{T}} \boldsymbol{x}_i + b \geq 1 \text{ if } y_i = 1, \\ \boldsymbol{w}^{\mathrm{T}} \boldsymbol{x}_i + b \leq -1 \text{ if } y_i = -1 \end{aligned} \tag{4.5.1}$$

The linear classifier's definition is as follows:

$$f(x) = \operatorname{sign}\left(w^{\mathrm{T}} x + b\right) \tag{4.5.2}$$

For a given dataset and decision hyperplane, the functional margin of the i'th sample xi with respect to a hyperplane (w, b) is defined as:

$$\gamma_i = y_i \left(\boldsymbol{w}^{\mathrm{T}} \boldsymbol{x}_i + b\right) \tag{4.5.3}$$

A decision boundary dataset's functional margin is then doubled for any sample in the dataset with the smallest functional margin.

We used the support vector machine technique to reduce misclassification errors since SVMs separate classes using an appropriate decision boundary. The data was preprocessed to segregate the attributes and class label, as well as divide it into train and test sets. 2947 samples were used in our testing, accounting for 30% of the total testing data. We chose a multiclass SVM classifier with a linear kernel because our goal was to classify data. The dot product of x and xi is used in linear kernels; x and xi represent the prediction input and each of the support vectors in that orde, respectively. There are four types of kernal
Linear Kernal:

$$K\left(x_i, x_j\right) = x_i^{\mathrm{T}} x_j \tag{4.5.4}$$

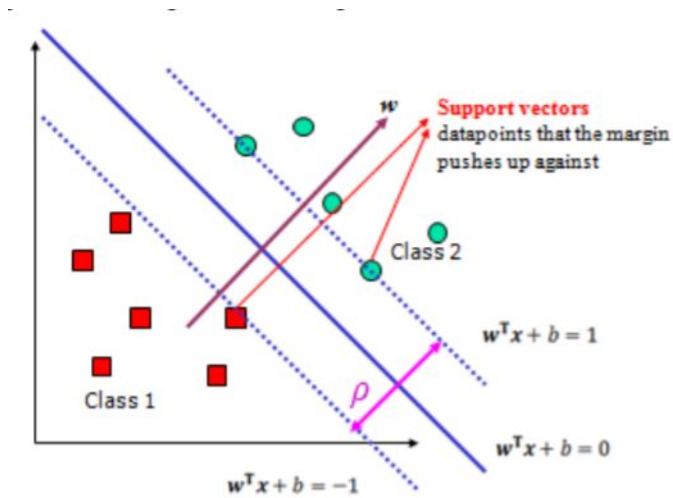

Figure 4.6: Decision boundary and margin of SVM

Polynomial Kernal with degree d:

$$K(x_i, x_j) = \left(x_i^{\mathrm{T}} x_j + 1\right)^d \tag{4.5.5}$$

Radial basis function(RBF) kernal:

$$K(x_i, x_j) = \exp\left(-\|x_i - x_j\|^2 / 2\sigma^2\right) \tag{4.5.6}$$

Sigmoid Kernal:

$$K(x_i, x_j) = \tanh\left(\delta x_i^{\mathrm{T}} x_j + r\right) \tag{4.5.7}$$

Our average precision, recall, F1 score is 0.96, 0.96, 0.96 respectively. So, we can say that our model is successfully able to predict the six activities.We got training set score for SVM is 1.00 and testing set score is 0.95.

4.6 Explainable Machine Learning

Explainable AI (XAI) is a type of artificial intelligence (AI) in which the solution's findings may be comprehended by humans. It contrasts with machine learning's "black box" approach, in which even the designers are unable to explain why an AI made a certain decision. The societal right to know could be manifested in XAI. XAI can improve the user experience of a product or service by supporting end users in trusting that the AI is making appropriate decisions, even if no legal right or regulatory requirement exists. The goal of XAI in this manner is to explain what has been done, what is being done now, and what will be done next, as well as to reveal the knowledge on which the actions are based. These features allow you to I confirm what you already know, (ii) dispute what you already know, and (iii) produce new assumptions.

White-box and black-box machine learning (ML) algorithms are the two types of algorithms utilized in AI. Machine learning models that give results that are understandable by domain experts are known as white-box models. Black-box models, on the other hand, are extremely difficult to describe and comprehend, even for domain experts. XAI algorithms are stated to follow three concepts: transparency, interpretability, and explainability. "If the method designer can define and motivate the techniques that extract model parameters from training data and construct labels from testing data," then transparency is granted. The ability to comprehend the ML model and provide the underlying reason for decision-making in a human-understandable manner is referred to as interpretability. Explainability is a term that is widely acknowledged as vital, yet there is no agreed-upon definition.

Explainability in machine learning is defined as "the collection of features of the interpretable domain that have led to the production of a decision (e.g., classification or regression) for a particular example." If algorithms fulfil these criteria, they can be used to justify decisions, track and so verify them, improve algorithms, and investigate new facts. With a white-box ML method that is interpretable in and of itself, it is sometimes possible to produce a high-accuracy outcome. This is particularly significant in fields such as medical, defense, finance, and law, where it is critical to comprehend and trust algorithms.

4.7 LIME

Individual predictions of black box machine learning algorithms are explained using local surrogate models, which are interpretable models. According to the authors, the Local Interpretable Model-Agnostic Explanations (LIME) is a practical implementation of local surrogate models. Surrogate models are trained to approximate the underlying black box model's predictions. LIME focuses on training local surrogate models to explain individual predictions rather than building a global surrogate model. The premise is simple and straightforward. The LIME technique, which works by locally estimating the model around a given prediction, is used to understand individual model predictions.

First, forget about the training data and imagine you simply have a black box model with which you may input data points and get model predictions. You have complete freedom to inspect the box as much as you like. Your objective is to figure out why the machine learning model made the predictions it did. When diverse data sets are fed into a machine learning model, LIME analyzes what happens to predictions. LIME generates a new dataset containing the updated samples as well as the black box model's predictions. LIME then uses this additional dataset to build an interpretable model that is weighted by the sampled instances' proximity to the instance of interest. Tabular data is information presented in the form of

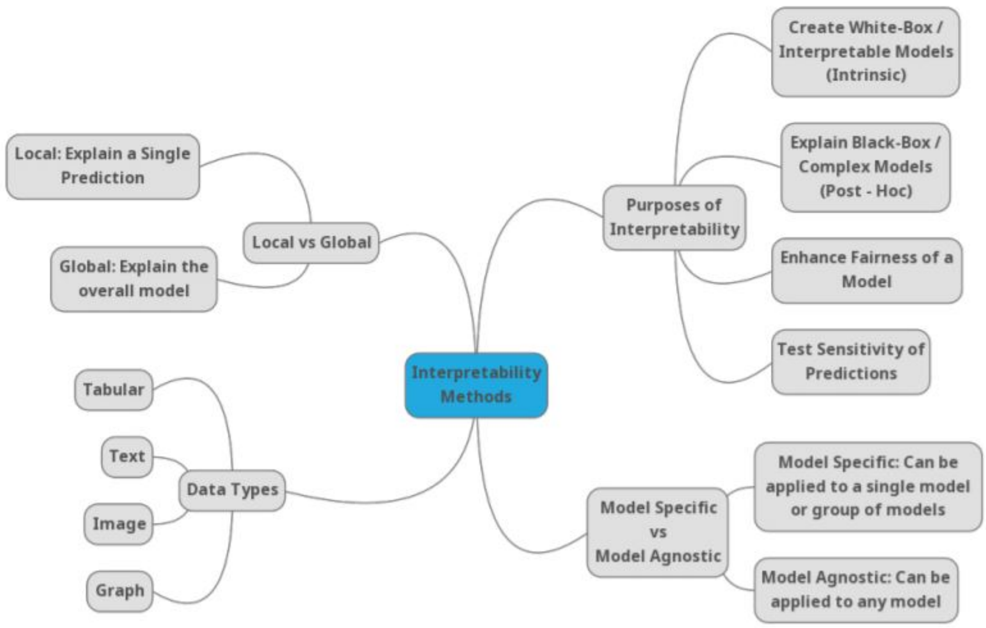

Figure 4.7: Interpretability methods

tables, with each row corresponding to an instance and each column to a feature. LIME samples are taken from the mass center of the training data rather than the instance of interest, which is inconvenient. It does, however, increase the chances that certain sample point predictions will differ from the data point of interest, and that LIME will be able to learn at least some of them.

$$\xi = \arg\min_{g\in\mathcal{G}} L\left(f, g, \pi_{x'}\right) + \Omega(g). \tag{4.7.8}$$

In our proposed model first we import the dataset and use crosstab to collect the values and put them according to the activities. And then print the dimension of the dataset which are (7352,561)for training set and for the testing set the dimension was(2947,561). We set the kernel into rbf and our kernel was linear and make the probability true.Then we set the final model to svm and we got the accuracy for training and testing is 100% and 93% respectively. Then we used Lime Tabular Explainer to explain the final model we used.We used tabular explainer here because our dataset contains values into table format. From the figure (4.13) we can see that predicted activities are walking downstairs,walking downstairs,standing and other. And the right side the two features are selected the two activities which is standing and other.So,that we can say these two feature are working here to explain this activity.And if we re-run the procudure again then we will be able to see some new features from dataset will be responsible for another type of activity.

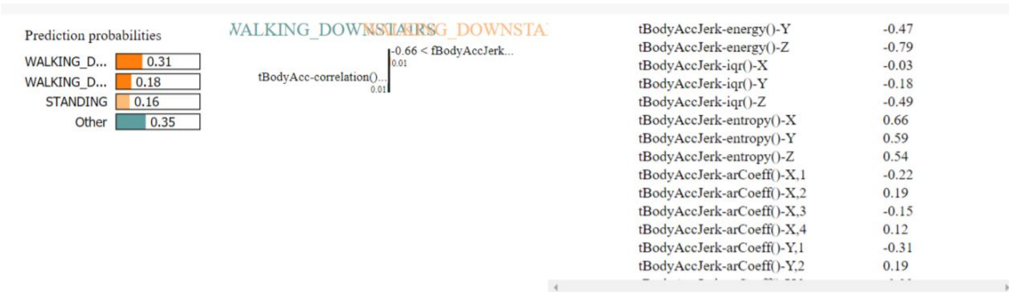

Figure 4.8: Interpretability through LIME

From the above image we can see that the prediction value of walking downstairs is 31% so that means that individuals are actually walking downstairs. On the otehr hand And this can vary in each run with the features because our model can work with one test data at a time.

4.8 SHAP

In many cases, understanding why a model generates a particular forecast is just as important as the accuracy of the prediction. Complicated models, such as ensemble or deep learning models, that even specialists struggle to understand, typically achieve the highest accuracy for large current datasets, creating a tension between accuracy and interpretability. As a result, several strategies for assisting users in interpreting the predictions of complicated models have recently been presented, although it is sometimes unclear how these methods are related and when one way is preferred to another. We propose SHAP, a unified framework for interpreting predictions, to resolve this issue (SHapley Additive exPlanations). SHAP (SHapley Additive exPlanations) is a game-theoretic methodology for explaining any machine learning model's output. It uses the traditional Shapley values from game theory and their related extensions to correlate optimal credit allocation with local explanations.

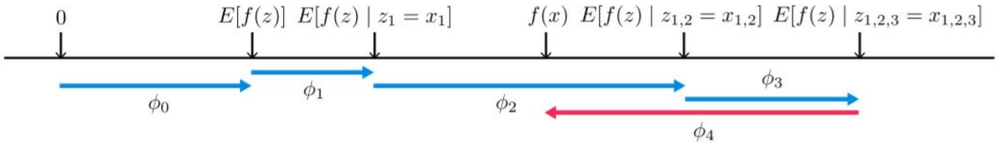

Figure 4.9: When a feature is conditioned on, SHAP (SHapley Additive exPlanation) values are assigned to it, and the change in the projected model prediction is assigned to it.

In the class of additive feature attribution methods, the existence of a single unique solution with three desirable attributes is an unexpected element of this class (described below). These characteristics were previously unknown in additive feature attribution methodologies, but are well-known in Shapley value estimation methods.

$$f(x) = g\left(x'\right) = \phi_0 + \sum_{i=1}^{M} \phi_i x_i' \tag{4.8.9}$$

The explanation model,

$$g\left(x'\right) \tag{4.8.10}$$

matches the original model f(x) when,

$$x = h_x\left(x'\right) \tag{4.8.11}$$

If,

$$f_x'\left(z'\right) - f_x'\left(z' \backslash i\right) \geq f_x\left(z'\right) - f_x\left(z' \backslash i\right) \tag{4.8.12}$$

Then only one possible model explanation model g follows,

$$\phi_i(f, x) = \sum_{z' \subseteq x'} \frac{|z'|! \, (M - |z'| - 1)!}{M!} \left[f_x(z') - f_x(z' \backslash i) \right] \tag{4.8.13}$$

In our proposed approach we tried to bring the explainability or interpretablity for a model we used in deep learning section.Where we fixed the optiimizer as "Adadelta" and loss as "mse" and we used "softmax" and "relu" for our activation function. We trained the modeel for 2000 epochs where we get the hightest value in 29'th number epoch which is 0.67.

here is the confusion matrix of six type of activities where we predicting laying and the actual number of laying is 169 or we predicting walking-upstairs and the actual number of this activity is 144.

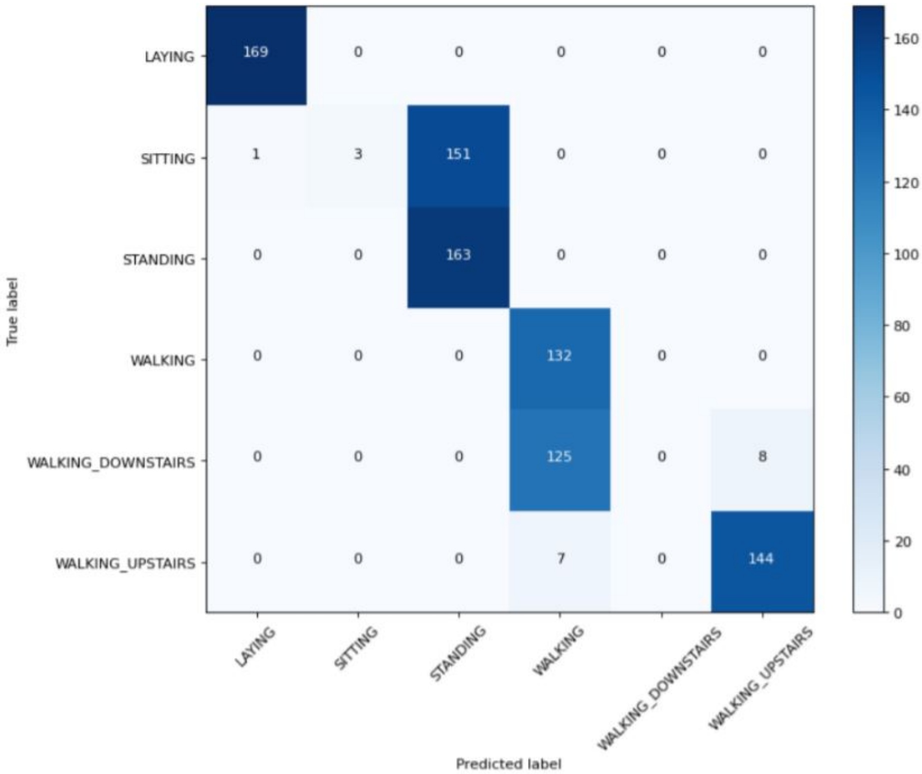

Figure 4.10: Confusion matrix,without normalization

From the figure (4.12)By generating summary charts, we can visualize the relevance of the features and their impact on the forecast. The one below sorts features by the total magnitude of SHAP values across all samples. It also use SHAP values to depict the distribution of each feature's impact.The color symbolizes the feature value, with red denoting a high value and blue denoting a lower value.From this figure we can specify the most importants features for our work which are in desenecding order.

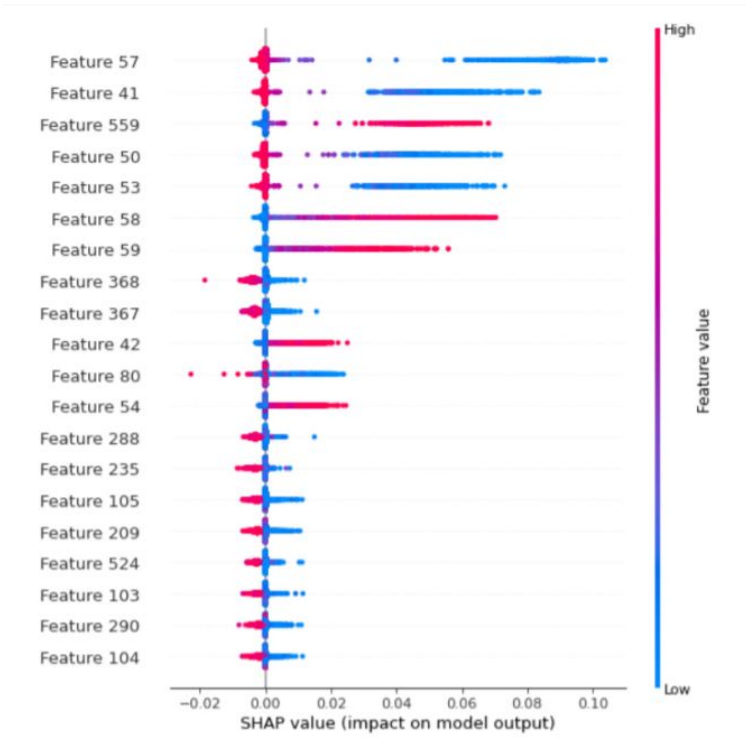

Figure 4.11: Interpretation of an entire model

So that, our feature 57 will get the highest priority and the rest of the features starting form feature 41 to feature 104 will get pritority according to their position.We can see from feature 57 has the lowest blue value so that it can tell that this will be something positive. And when the blue dots stay in the origin it cant give any prediction.On the other hand for red color in feature 58 it's predicting something positive.

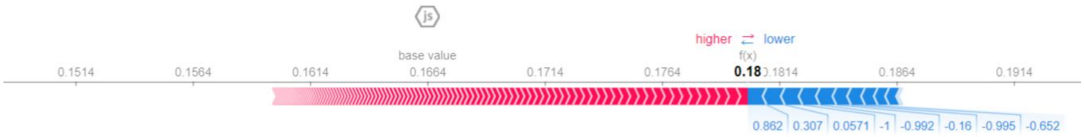

Figure 4.12: Interpretation for differnet featuresl

From the above figure we can see that there is a base value which is 0.18 and the red indicated features pushing righwards to the base value and the blue indicated features pushing leftwards to the base value.

4.9 Results Analysis and Performance Evaluation

4.10 Result analysis of SVM classifier

The model's performance was assessed after it was built to see how well it could forecast the future.The confusion matrix has four parameters, which we used to evaluate performance. TP, FP, TN, and FN were the parameters. The following equation was used to calculate the classifier's correct prediction rate:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.10.14}$$

$$\text{Sens } = \frac{TP}{TP + FN} \tag{4.10.15}$$

Precision also denoted the proportion of accurately predicted. Equation of the precision is:

$$\text{Precision } = \frac{TP}{TP + FP} \tag{4.10.16}$$

The sensitivity of the model determined how well it could predict sample outcomes when compared to all of the actual outcomes in the test set.The equation to compute sensitivity or recall is :

$$\text{Spec } = \frac{TN}{TN + FN} \tag{4.10.17}$$

Finally, the weighted average of precision and sensitivity was used to calculate the F1-score. It was thought to be a superior measure of performance because it worked even when the model's class distribution was uneven.

$$F1 - \text{ score } = \frac{2(\text{ Sensitivity } * \text{ Precision })}{\text{Sensitivity } + \text{ Precision}} \tag{4.10.18}$$

Activities	**Precision**	**Recall**	**F1_Score**	**Support**
Laying	**0.99**	**0.99**	**1**	**537**
Sitting	**0.98**	**0.89**	**0.93**	**491**
Standing	**0.92**	**0.98**	**0.95**	**532**
Walking	**0.96**	**0.98**	**0.97**	**496**
Walking_Downstairs	**0.98**	**0.93**	**0.95**	**420**
Waliking_Upstairs	**0.93**	**0.96**	**0.95**	**471**

Table 4.1: Multiclass SVM model accuracy

Though, we used precision, recall, f1-score, and support for our accuracy parameters so our average scores of these particular parameters are 0.96, 0.96, 0.96, 0.96 respectively. We can say that our model is predicting these six types of activities correctly.

4.11 Result analysis of LSTM based RNN

Here we also used precision, recall and f1-score for our accuracy purposes. We got the precision score 89.53 %. On the other hand we got recall and f1-score for our LSTM based architecture is 88.87% and 88.83% respectively. From the confusion

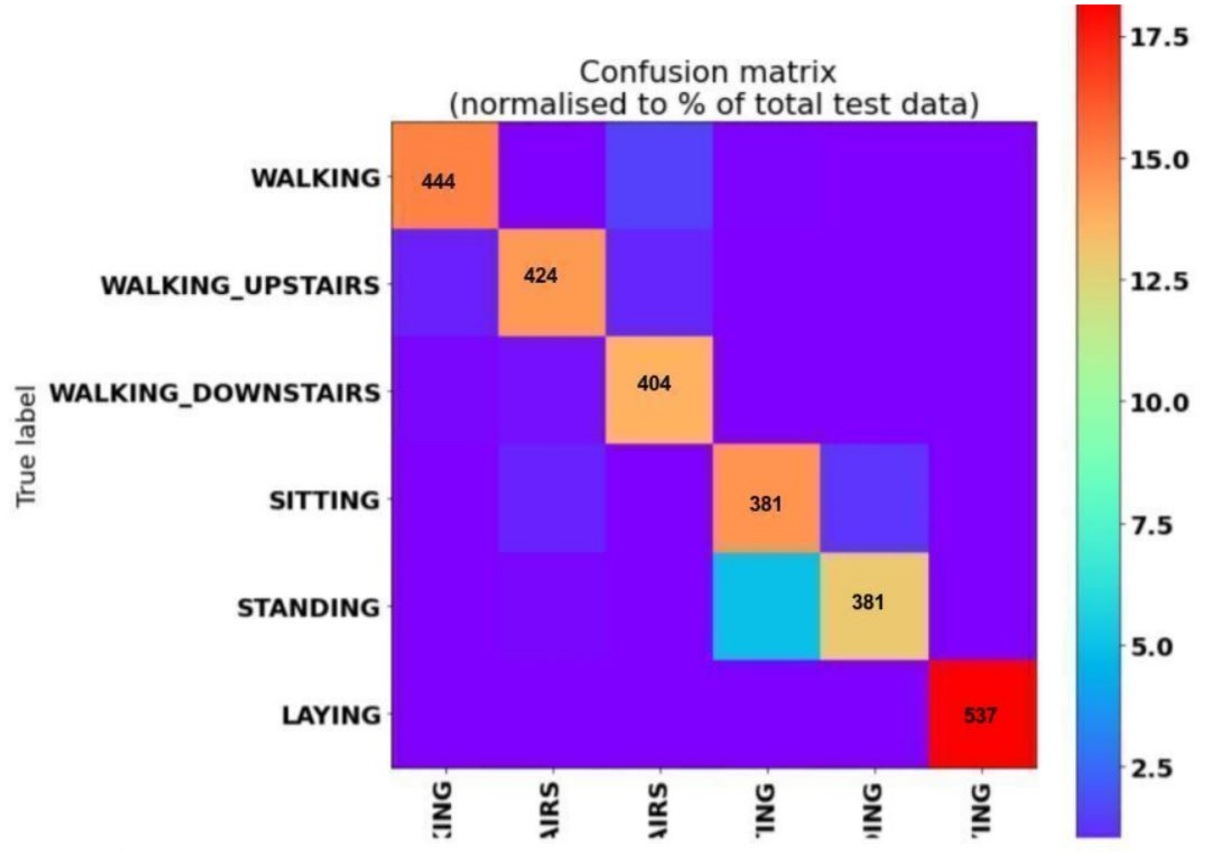

Figure 4.13: Confusion matrix of LSTM

matrix we can see that prediction for walking, walking up-stairs, walking-downstairs, sitting, standing, laying is 444, 424, 404, 381, 537

4.12 Result analysis of Deep Neural Network

In this part we used loss, accuracy, validation loss and validation accuracy for measuring the performance. We used Adam, Adagrad, RMS-prop different kind of optimizer and increased the epoch from 10 to 2000. We used different types of activation function which are sigmoid, sofmax, relu. Which actually helps tell the model in different types of probability. When we increased the epoch numbers the percentage

Epoch	Loss	Accuracy	Val_loss	Val_accuracy
1	0.517	0.7726	0.1438	0.9471
2	0.0516	0.9833	0.1703	0.9474
3	0.0287	0.9906	0.1492	0.9505
4	0.0224	0.9924	0.1562	0.9508
5	0.0136	0.9959	0.137	0.9586
6	0.0135	0.9952	0.1694	0.9491
7	0.0095	0.9969	0.1508	0.9552
8	0.0076	0.9976	0.171	0.9535
9	0.0122	0.9956	0.1956	0.9474
10	0.0288	0.9917	0.2445	0.9491

Table 4.2: DNN model analysis table

of accuracy from the model is a bit lower.From the above table we can see that the highest accuracy for our training dataset is 0.9917 and the highest accuracy for our testing dataset is 0.9491.

Chapter 5

Conclusion and Future Work

In our work we tried to recognize different types of activities using deep learning where we used different kinds of parameters and epoch numbers to evaluate our dataset and tried to figure out which features work perfectly and how it changes. We also build a model using LSTM architecture and and tried to keep it non biased and train the model such a way that it will update it's sef after every training and testing iteration. We also used SVM classifier in our dataset and obtained a better accuracy after working on training and testing set.In our work we bring explainable machine learning to predict a model and to express the explainability of a model. We applied on SVM model and able to bring the explainability and could able to explain a particular activity based on the best features. Our work is different from the previous works in many ways.In the previous most of them used Random Forest classifier, HF-SVM in their work. On the other hand We used SHAP on deep neural network to bring the expainability also. We experimented on six basic activities. We will try to add some more physical activities so that our model can work for a increase number of activities. For now we able to bring explainability for only one model which is Support Vector machine. Our plan is in future we will try to bring the explainability for other algorithms.

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