Human Physical Activity Recognition Using Smartphone Sensors

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The Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **"Human Physical Activity Recognition Using Smartphone Sensors"**, submitted by Sourabh Roy Biswes, ID No: 191-15-12354, Rieaj Uddin Fahad, ID No: 191-15-12624, Mirza Sadman Ahmed Swapno, ID No: 191-15-12374 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *23 January 2023*.

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We hereby declare that, this thesis has been done by us under the supervision of **Mr. Abdus Sattar, Assistant Professor, Department of CSE** Daffodil International University. We also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

In day-to-day existence, people act on many tasks. It is vital to record and analyze the daily presence of individual people. Hence it could assist with relieving a few medical conditions and different issues. Human Activity Recognizing is a key component research topics in computer vision for different sectors like security monitoring, healthcare and human-computer association, and sports. Nowadays, the smartphone has become popular and helpful for people. Because smartphone has many various and effective sensors, in this paper, we have used smartphone sensors: an accelerometer and gyroscope to detect human activity. In our research, we collected 30 study participants labeled datasets between ages nine-teen to four-ty-eight (19-48) years who have executed actions such as activities of daily life include sitting, walking, standing, walking up or down stairs, and lying down while using a smartphone equipped with such sensors. The objective is to do each of the six activities in the correct order. Two sets of the record dataset were randomly chosen, with 70% of participants 30% were chosen to produce test data, the remaining 70% to produce training data. The results were gained along with compared by supervised learning algorithms like Decision Tree Classifier, Random Forest, K Nearest neighbor method, Logistic Regression, and Support Vector Machines algorithms. By comparing those algorithms, we gained the best results accuracy from Logistic Regression which is 96.21%.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Nowadays, the most well-liked research topic is Human Activity Recognition (HAR). HAR can be used in a wide range of sectors like security monitoring, healthcare, sports, and human-computer association. In our daily life, we do many daily lives work including sitting, standing, laying down, and walking upstairs and downstairs. We need to monitor those daily activities because of analyses of our health condition. A person should walk daily because it helps to maintain healthy health or lose body fat. It also prevents or manages many serious health diseases like diabetes, stroke, high blood pressure, etc. In that way, a man should a minimum of time lying in bed. If a person lies in bed the whole day, it would be harmful to his/her health. Same way, a person also sits down a minimum time. If a person sits for a period of long, it would also be harmful to his health, such as back pain and neck pain can occur.

So, in our daily life, we need to perform each and every activity including sitting, standing, laying down, and walking upstairs and downstairs in a sufficient period of time to maintain our health and prevent and manage some serious health problems. In this research, we detect human activity recognition using smartphone sensors.

We all know in this generation, smartphone uses are broad. In our daily life, we can't live a moment without a smartphone. Smartphones are also helpful for people. It has many effective sensors like a heart rate sensor, an accelerometer, a magnetic field sensor, a gyroscope, a light sensor, a proximity sensor, a pressure sensor, etc. In this paper, we have used an accelerometer, gyroscope, and gravity sensor to recognize regular activities (ADL). We have collected 30 percipients of person-labeled datasets, and datasets are divided into two subsets where 30% of the test data set and 70% of the train data set. Every person performed six activities and collection of data by wearing android-based phone (Model: Samsung Galaxy S-II). This smartphone contains a gyroscope sensor and an accelerometer sensor with three-dimensional linear acceleration, 3-dimensional angular velocity, and a hertz rate is 50. The dataset was collected using an experiment by video capturing and manually labeling the data. The use of machine learning (ML) algorithms and other cognitive technologies in medical science is commonly referred to as "AI in healthcare."

We can define AI as a technique for learning, thinking, making decisions, and taking actions on computers and other machines that mimic human cognition. AI plays a significant role with using machine learning as well as other cognition branches in healthcare to aid in diagnosing diseases purposes. We used machine learning algorithms for comparison to choose the appropriate algorithm which gives us the best results. We apply supervised learning techniques including DecisionTreeClassifier, K-Nearest Neighbors, Random Forest, Support Vector Machine (SVM), and Logistic Regression as our dataset is labeled, with the greatest accuracy achieving from Logistic Regression.

1.2 Motivation

Considering the present universe, innovation is speedily changing and continuously turning into a more significant role. Information Communication Technologies (ICT) have changed the routines of people. From the viewpoint of the medical field and the biosciences, ICT is used in the health services industry for a variety of purposes, most of which have an impact on patient care. Thanks to ICT, we got smartphones. The invention of the smartphone has modernized our daily life. There is various type of effective sensor in a smartphone. These sensors are capable of monitoring the daily activities of humans. Instead of using a third-party product like a smartwatch, we would directly detect our daily activities using a smartphone. It would be helpful for unnecessary costs and saving money. We can easily gather data by smartphone by using smartphone sensors such as accelerometers and gyroscopes. Human activity recognition is also helpful in the sports sector. A player's daily activities can be recognized by our proposed system. Our proposed system gathers this data from these human activities. AI will help to detect human activities by using algorithm learning models, and then it could predict the activity and can aware of human health conditions.

1.3 Problem Definition

AI performs a significant role in the health sector. To develop our health sector, we need the application and implementation of AI. For a suitable solution, we must identify the issues and requirements in this area. In order to identify health-related issues, 30 study participants were recorded carrying out activities of daily living. These recordings were used to generate the Human Activity Recognition database, which AI was then used to categorize the actions into one of the six categories.

1.4 Research Questions

In this thesis the main question are focuses are given below:

- What approaches are used to analyze the data and identify human activity?
- What kinds of research are used to detect or analyze human activity?
- What specific type of sensors are utilized to gather data?

1.5 Research Methodology

We describe the experiment data set, exploratory data analysis, data pre-processing, and model architecture in this portion of our research article.

1.6 Research Objectives

The use of AI in human activity recognition has several advantages. AI is used for a variety of technological and health-related purposes.
The following list of technological goals includes some of them:

- Create a reliable model for recognizing human action.
- To motivate software developers to use the approach while working with AI.
- Include the model in mobile applications.

The following list includes some of the discovering health issue targets:

- Help the people or athletics to know about there health condition.
- Make the people or athletics self-dependent.
- Reduce the time and cost of check health condition.
- Increase the accuracy rate.
- Solve overfitting model.

1.7 Research Layout

Chapter 1: In this section, we'll talk about our project's introduction, inspiration, problem definition, research question, research methodology, and research objective.

Chapter 2: We’ll talk about the history of study, its connected activities, and its present position from the viewpoint and within the rules of Bangladesh.

Chapter 3: We would explain about Research Methodology and Architecture of this research.

Chapter 4: We will discuss about Performance of the Proposed Model, Classification and Confusion Matrix.

Chapter 5: The focus is on the comparison and analysis of the results.

Chapter 6: It will describe the Final Thoughts and Future Directions of this research.

Chapter 7: The sources we used for this study are all listed below.

CHAPTER 2

BACKGROUND

2.1 Introduction

As reported in many studies integrating the detection of human activity using smartphone sensors has been accomplished. To determine the best accuracy, they use several algorithms. Several of them also compared various algorithms.

2.2 Related Works

A particularly common issue is the use of smartphones to recognize human activities. A strong method to identify and categorize everyday living activities (ADLs) is to control artificial intelligence to recognize human activity. Researchers are trying to classify activity and use numerous algorithms, and only few professionals succeeded in this related area. Our study focuses on methods for identifying human activity that make use of a particular wearable sensor platform: the smartphone. The smartphone is gradually gaining acceptance as a platform for wearable sensors. It has a wide range of uses, such as tracking human activity as well as tracking traffic and road conditions, trade, health-monitoring, and environmental factors.

In paper [1] ,The accelerometer has been used extensively in some key HAR studies since the late 1990s. The most often referenced experiment, however, used a variety of sensors placed on a variety of body areas combined with a variety of data mining methods to get good findings. In this study, smartphone sensors were utilized to recognize human behaviors by using convolutional neural networks as an autonomous feature extractor and classifier. The proposed strategy produced results with a 93.75% accuracy.

In paper [2] proposes the use of the Average Combining Extreme Learning Machine (ACELM), a reliable and effective classification method, to identify activities using data from mobile phone accelerometer sensor. The Extreme Learning Machine (ELM) classifier's generalization performance and stability have both increased.

In paper [3], Using J48 and a multilayer perceptron, the results for walking, jogging, moving upstairs, and moving downstairs were achieved with 75.3% and 73.95% accuracy, respectively.

In the paper, [4] for the purpose of activity recognition, it was recommended that six distinct classification algorithms-the J48 decision tree, Bayes Net, Naive Bayes, K-Star, KNN and Random Forest-as well as two feature selection algorithms-OneRAttributeEval and ReliefFAttributeEval-be compared. These classifiers' precision was evaluated using a ten-fold cross-validation approach. They presented the result achieved as the highest average accuracy of KNN was 94%. Respectively, the average accuracy achieved by Random Forest was 93%, the average accuracy achieved by k-star was 93%, the average accuracy achieved by J48 decision tree was 91%, the average accuracy achieved by Bayes net was 88%, and the average accuracy achieved by Naive Bayes was 81%.

In the paper, [5] enhanced support vector machines (SVM), and regularized logistic regression (RLogReg), decision stumps (AdaBoost) based on three distinct validation situations, were presented as three separate classifiers (specifically, subject dependent, subject adaptive, and subject independent). The three scenarios had 89.82%, 81.94%, and 92.81% accuracy on average.

In the paper, [6] an instance-based learning (IBL) or closest neighbor approach, a C4.5 decision tree, and naive Bayes classifiers were used to execute the suggested Activity recognition. The choice-based algorithms used in decision tree classifiers had the highest recognition accuracy, correctly identifying laying, standing, and locomotion and sitting with a precision of 89.30%. In this aspect, Bao & Intille's work is the most successful and exhaustive (2004).

In the paper, [7] proposed a k-nearest neighbor (KNN) algorithm for classifying human activities. The average accuracy achieved by KNN was 96.70%.

The paper [8] proposed fundamental machine learning methods such Gradient Boosted, K-Nearest Neighbor, Decision Tree, Random Forest, Logistic Regression, and Support Vector Machine. With a linear kernel, both SVM and logistic regression achieved 98% accuracy, and the accuracy of hyperparameter adjustment is the same for both techniques.

The paper [9] shows a performance comparison of the machine learning techniques SVM, KNN, and Random Forest. Based on SVC and RBF kernels, the result obtains the greatest accuracy and recall, respectively, of 87% and 85%. The processing time is quickest for support vector machines using stochastic gradient descent. However, Random Forest has the best performance. Within 0.45 minutes, the Random Forest approach can achieve an accuracy of 96% with a depth of 100 and 300 trees.

The paper[10] use the Random Forest classifier machine learning approach to identify human activity using the fundamental accelerometer characteristics. The method has a 77.34% accuracy rate. When fundamental data are paired with angular information estimated from the phone's orientation, the accuracy ratio rises to 85%.

The paper [11] a six-activity classification system was created for the Nokia N95, with categories for sitting, standing, walking, running, driving, and cycling. They evaluate several classifiers, including C4.5 Decision Trees (DT), Naive Bayes (NB), K-Nearest Neighbor (KNN), and Support Vector Machine (LibSVM). The C4.5 Decision Tree method has produced the best recognition accuracy rate in this research, which is 90.6%. In accordance with their degrees of accuracy, Naive Bayes (NB), K-Nearest Neighbor (KNN), and the Support Vector Machine (LibSVM) have attained 68.7%, 77.9%, and 84.3%, respectively.

In paper [12], To identify the activity, they suggested machine learning classifiers such as Naive Bayes, Decision Tree, K-Nearest Neighbor, and Support Vector Machine classifiers and validated using 10-fold cross-validation. The C4.5 Decision Tree classifier, which has a true positive rate of 95.2%, a false positive rate of 1.1%, a precision of 94.4%, and a recall rate of 94.2%, is the best and surpasses the other classifiers on average, according to their findings.

In paper [13] proposed machine learning methods to identify the activity include Naive Bayes, Decision Trees, and Random Forest algorithms. The Random Forest algorithm has obtained the best recognition rate, which is 89.6%. Naive Bayes and C4.5 Decision Tree have achieved 86% and 85% accuracy, respectively.

2.3 Bangladesh Perspective

According to Bangladesh, the average person does not worry about health issues the way other contemporary cultures do. However, many people have been using smartphones for a while. So, regular people can learn about their health conditions using mobile phone sensors and our work.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

Described in this chapter the methods of how the prediction of human activity recognition takes place using accelerometers, gyroscopes, and gravity sensors.

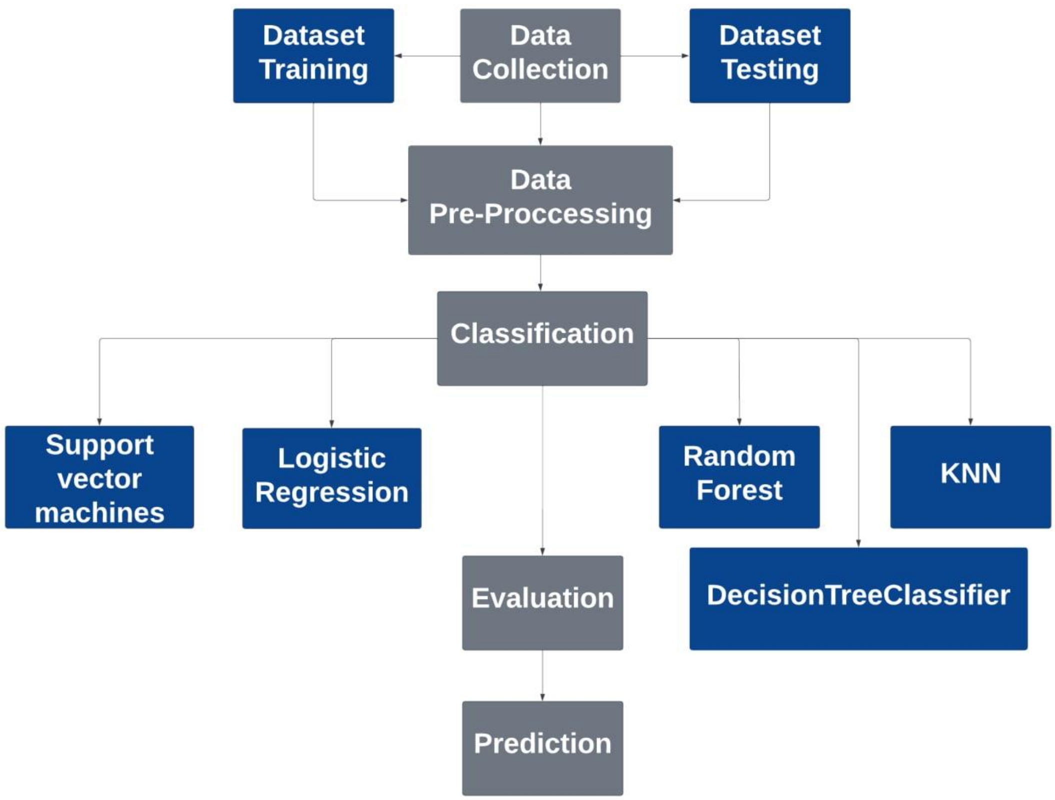

Figure 3.1 The workflow of this Research.

3.2 Data Collection

The datasets used for this paper are UCI human activity recognition that is publicly available with enough examples for training and testing the classifier. These are considered to find the features for recognizing human activities and classify the highest accuracy rate of the used classifiers. The data collected for this dataset is from accelerometers along with gyroscope sensors embedded in smartphones. The data collected for the input is the activities performed by the user. The output will be in the form of predicted human activity for user data. The HAR dataset comprises six activities of daily living Walking Upstairs, Walking Downstairs, Standing, Walking, Sitting, and Laying. These activities are usually performed many times a day by a human. The experiment for this dataset is performed with a team of 30 willing volunteers. They have an age bracket of about 19 to 48 years. Each volunteer completed the above six activities by wearing a smartphone containing accelerometer and gyroscope sensors on their waist. Three-axial linear acceleration and three-axial angular velocity measurements are recorded or obtained at a continuous rate of 50 Hz utilizing the implanted accelerometer and gyroscope data sensors. The data is then divided into two groups, with 70% of the individuals chosen for the training data and the remaining 30% chosen for the testing data.

3.3 Exploratory Data Analysis

EDA is the frequently crucial step prior to training any model since it allows us to learn much about our data and explains how to build a model. "EDA has no purpose without domain knowledge, just as a problem has no soul without EDA."

3.3.1 Stationary and Moving activities are completely different

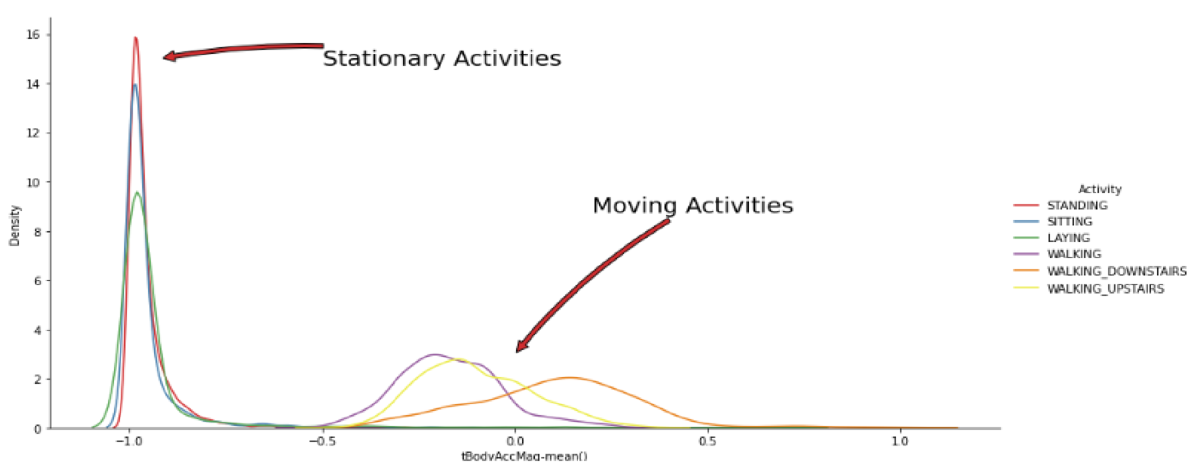

Figure 3.3.1 Stationary and Moving activities.

There are two actions.

i. Static
ii. Dynamic

Motion information won't be particularly helpful during static activities (stand, lie down and sit). The dynamic activities will require a lot of information about motion. (Walking, walking upstairs, and walking downstairs).

3.3.2 The magnitude of acceleration can separate it well

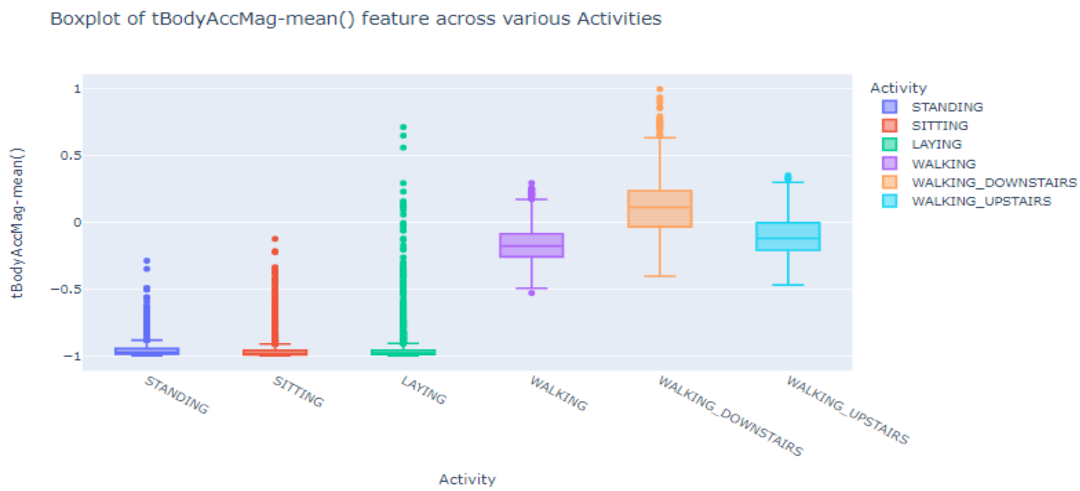

Figure 3.3.2 Boxplot of various activity.

Observations: If t-Acc Mean is -0.8, the activities are either standing, sitting, or lying down. If t-Acc Mean is larger than -0.6, the activities are either walking, walking downstairs, or walking upwards. If t-Acc Mean > 0.0, walking downward is the activity. We can classify 75% of the activity labels with only minimal errors.

3.3.3 Position of Gravity Acceleration Components also matters

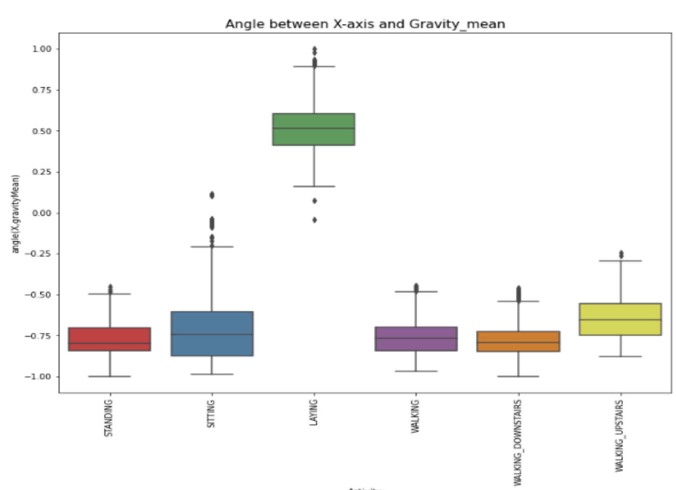

Figure 3.3.3 Angle between X-axis and Gravity mean.

Observations: Activity is lying if angle X, gravity mean is greater than 0. With only one "if else" phrase, we can group together all the data points related to laying activity.

3.3.4 Apply t-sne on the data

The t-SNE plot shows that the majority of activity are well separated, with the exception of the blue and red dots, which indicate that standing and sitting characteristics are overlapping. In this case, we are mapping 561 dim to 2 dim. Here, separating standing from sitting points is a major difficulty. All of our points, with the exception of standing and sitting, are effectively grouped when the perplexity is changed, and the summary remains the same. This demonstrates that even linear models will perform admirably.

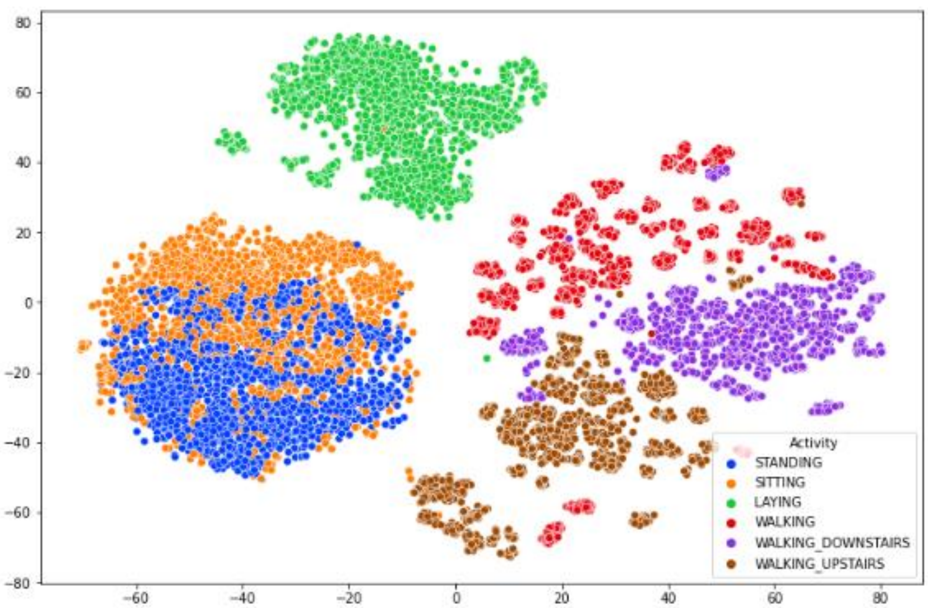

Figure 3.3.4 t-SNE plot of Activity.

For generating several features pre-processing is then applied to raw data [14] .

3.4 Data Pre-Processing

In order to preprocess the sensor signal data, noise filtering techniques were used. After that, data were instance in 2.56-second, movable windows with a set width and a 50% overlap (128 readings per window). Body motion and gravitational components of the sensor acceleration data were split into body acceleration and gravity using a Butterworth minimal filtering approach. 0.3 Hz of low frequency is employed because it is thought that the gravitational pull has low-frequency components. To obtain feature vectors from each window, frequency and time domain variables were calculated [14].

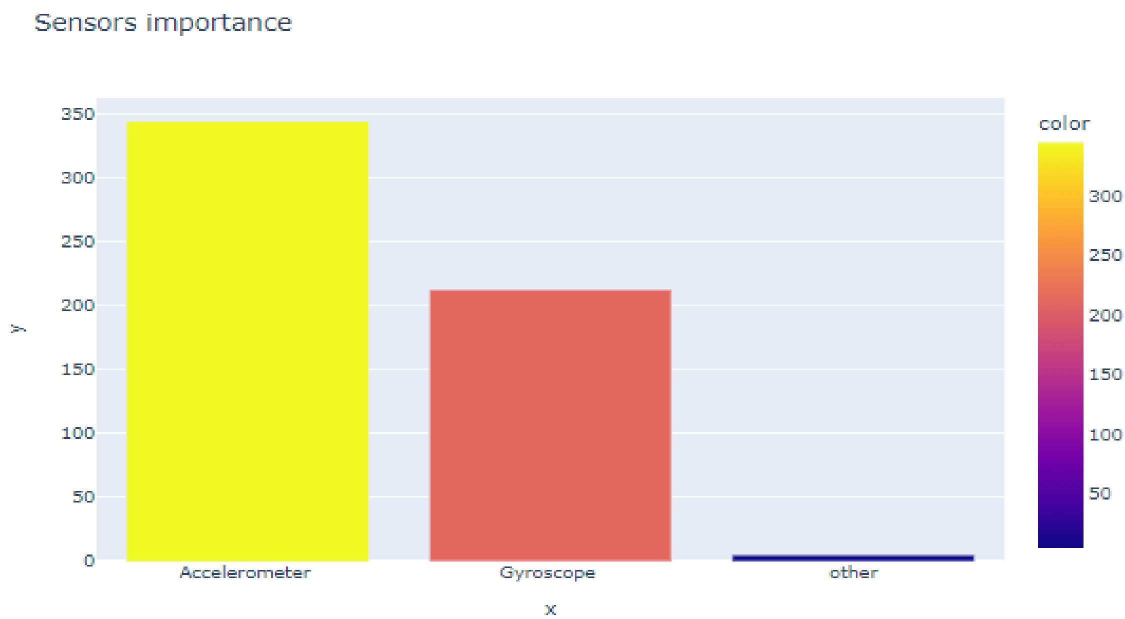

Figure 3.4 Sensor importance.

The 3-axial raw signals from the accelerometer and gyroscope contain the characteristics that were chosen for this database. (Acc=345 Geyro=213)

3.5 Feature Engineering

A data scientist or machine learning expert can benefit greatly from having a solid understanding of feature selection. A solid understanding of these techniques results in models that perform better, in a better comprehension of the underlying structure and properties of the data, and in a better intuitive understanding of the algorithms that underlie many machines learning models. Generally, feature selection is employed for the following two reasons:

1. Minimize the number of features to minimize overfitting and increase model generalization.
2. To comprehend the features and how they relate to the response variables better.

Univariate Feature selection: The strength of the relationship between each feature and the response variable is assessed using a univariate feature selection method. These techniques are straightforward to use and comprehend, making them generally excellent for better understanding data (but not necessarily for optimizing the feature set for better generalization). There are numerous options available for univariate selection.

Selecting Features with Best ANOVA F-Values: To choose the features with the best variance, we used SelectKBest. We passed two parameters: the scoring metric, f_classif, and the value of K, which denotes the number of features we want in the final dataset. The current dataset was fit and transformed into the desired dataset using fit transform.

3.6 Hyper Parameter Tuning

A mathematical model with a number of parameters that must be learned from the data is referred to as a machine learning model. Hyperparameters, on the other hand, are some parameters that cannot be learned directly. Prior to starting training, humans frequently choose them based on some intuition or trial and error. By enhancing the model's functionality, such as by increasing the model's complexity or learning rate, these parameters demonstrate their significance. Models may contain a large number of hyper-parameters, and determining the ideal set of parameters can be approached as a search problem.

Finding the best hyper-parameter for an SVM model is a very challenging task. These hyper-parameters include things like what C or gamma values to use. But it can be discovered by simply trying all possible combinations and observing which inputs are most effective. Its main principle is to build a grid of hyper-parameters and then simply test every possible combination of those parameters (hence the name Gridsearch for this technique, but don't worry! Scikit-GridSearchCV learn's incorporates this functionality, so we don't need to do it manually. GridSearchCV use a dictionary that contains a list of possible training parameter combinations in order to train a model. The settings to be tested are thought of as the values in a dictionary, with the parameters acting as the keys.

3.7 Architecture of The Model

To detect human activities, the categorization approach is utilized. Five machine learning classifiers are used in this work to group human activities. The performance of various classifiers is then contrasted in order to identify the one with the best accuracy rate. The classifiers employed were K-Nearest Neighbor, Random Forest, Logistic Regression, Support Vector Machines, and Decision Tree Classifier.

3.7.1 Support Vector

Support vector machines implement nonlinear class boundaries using a linear model. The fundamental concept is to separate the target classes using support vectors (lines or hyperplanes). The model trains a linear SVM model to classify the data in this new, higher-dimensional feature space after performing a number of transformations on the data using a mapping function to solve a nonlinear problem. Raschka and Mirjalili [15] claim that one issue with the mapping approach is the computational expense of creating new features, particularly when working with high-dimensional data. SVM approaches make use of a kernel function to avoid these costs. We build our model using the kernel function of the radial basis function (in Equation (1)).

$$k\left(x^{(i)}, x^{(j)}\right) = exp\ (-\frac{||x^{(i)} - x^{(j)}||^2}{2\sigma^2}) \quad (1)$$

3.7.2 Random Forest

Breiman [16] defined a "random forest" as a group of classifiers like a tree structure. {h(x, θ_k), k = 1,...} where {θ_k} are independent distributed random vectors, and each tree casts one unit of a vote for the most well-liked class at input x. In this context, one can think of a "random forest" as the bagging of decision trees. Multiple decision trees are used in a random forest to create a more robust model with better generalization performance, improved stability, and reduced susceptibility to overfitting. When splitting a node, the random forest algorithm looks for the best feature among a random subset of features rather than the most important feature. A better model is generally produced as a result of the wide diversity this causes. It is simple to measure the relative weighting of each feature on the prediction using the random forest method, which is another excellent feature of it. We use RF to confirm the effect of the evaluations of $\omega \in \Omega \forall \Psi \in \Psi$.

3.7.3 Logistic Regression

The probabilistic discriminative model of logistic regression. When Y stands for the target variable and X for the set of features, it simulates the posterior probability distribution $P(Y|X)$. They deliver a probability distribution over Y given an input of X. The logistic regression model's typical architecture is shown in Figure 3.6.3.1. In a binary classification problem, the output of the sigmoid function is interpreted as the likelihood that a specific sample will belong to a positive class, denoted by $\emptyset(z) = P(y = 1|x; \omega)$, where z is the linear combination of weights and sample features, denoted by $z = \omega^T x$.

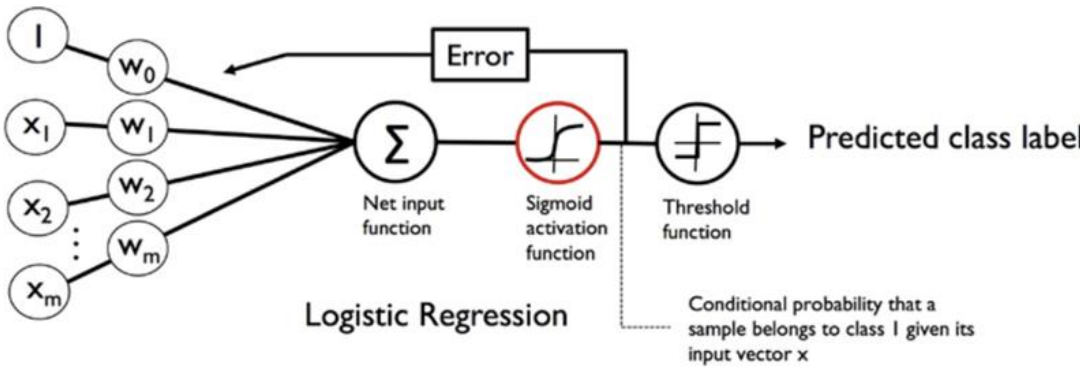

Figure 3.7.3 Logistic Regression Model [15].

3.7.4 K-Nearest Neighbors

KNN method, often known as K-nearest neighbors, is a non-parametric, supervised learning classifier that relies on proximity to provide classifications or predictions about the grouping of a single data point. Regression or classification problems may benefit from its use. However, because it depends on the notion that similar points may be found adjacent to one another, it is most usually used as a categorization tool.

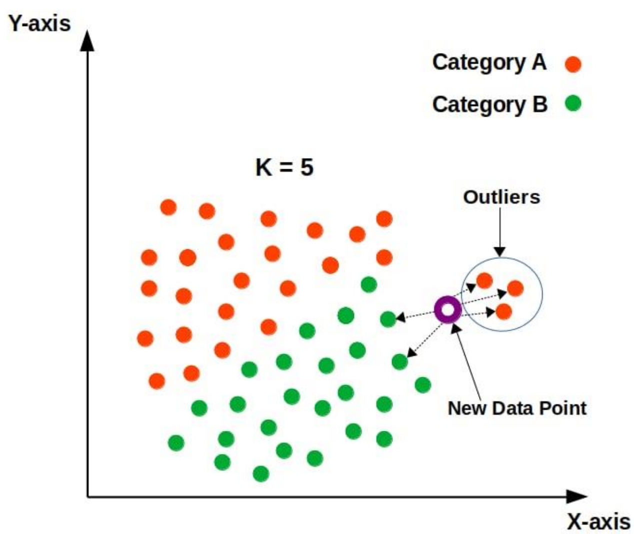

Figure 3.7.4 K-Nearest Neighbors.

3.7.4.1 Determine distance metrics:

To identify which data points are closest to a specific query point, the distance between the query point and the other data points must be calculated. These measures help define the decision boundaries, which separate the several zones at the query point. Voronoi diagrams are widely used to depict decision boundaries.

3.7.4.2 Distance Function:

$$\text{Euclidian} = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{2}$$

$$\text{Manhattan} = \sqrt{\sum_{i=1}^{k}|x_i - y_i|} \tag{3}$$

$$\text{Minkoski} = \sqrt{\left(\sum_{i=1}^{k}(|\, x_i - y_i|)^q\right)^{\frac{1}{q}}} \tag{4}$$

$$\text{Hamming Distance, } D_H = \sum_{i=1}^{k}|x_i - y_i| \tag{5}$$

3.7.5 Decision Tree Classifier

A decision tree is made up of leaf nodes, branches that represent the results of the testing nodes, and several layers of testing nodes (testing an attribute). In classification problems, the class label is represented by the leaf nodes. Rules are represented by the path from the root to the leaf. Predictive models based on trees are highly accurate, stable, and simple to understand. If interpretability is important to us, decision trees are appealing models to consider. Information gain executes the data split (testing node) in a tree (IG). In order for the samples at each node to all belong to the same class, IG splits the nodes at the most informative features. The computation of the IG of a binary tree is shown in equation (2). Here, D_p, D_{left}, and Dright are the data sets for the parent node, the left child node, and the right child node, respectively, while f is the feature to perform the split and I is the impurity measure. N_{left} and N_{right} are the numbers of samples in the left and right child's nodes, and N_p is the total number of samples at the parent node.

$$IG(D_p, f) = I(D_p) - \frac{N_{left}}{N_p} I(D_{left}) - \frac{N_{right}}{N_p} I(D_{right}) \tag{6}$$

CHAPTER 4

PERFORMANCE OF THE PROPOSED MODEL

4.1 Evaluation

The evaluation techniques used for this paper are:

i) Classification report.

ii) Confusion matrix.

4.2 Classification Report

The recall, F1 score, precision, and support for the model are all displayed in the classification report.

Recall: The total number of correctly positive classes that the model correctly identified is known as recall.

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (1)$$

Precision: It is the percentage of correctly identified positive cases among all predicted positive cases.

$$\text{Precision} = \frac{True\ Positive}{False\ Positive + True\ Positive} \quad (2)$$

F1 Score: The F1 is the harmonic mean of recall and precision.[17].

$$\text{F1 Score} = \frac{2 \times True\ Positive}{2 \times True\ Positive + False\ Positive + False\ Negative} \quad (3)$$

Support: The number of trials overall in the class serves as support.

Accuracy: The total number of the model's accurate predictions, both positive and negative, is known as accuracy.

$$\text{Accuracy} = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \quad (4)$$

To compare the classification models, use the classification report.

Training accuracy for SVC Model: 94.43%

Testing accuracy for SVC Model: 93.72%

	precision	recall	f1-score	support
LAYING	1.00	1.00	1.00	597
SITTING	0.91	0.88	0.90	563
STANDING	0.89	0.91	0.90	547
WALKING	0.97	0.95	0.96	539
WALKING_DOWNSTAIRS	0.91	0.96	0.94	420
WALKING_UPSTAIRS	0.94	0.92	0.93	424
accuracy			0.94	3090
macro avg	0.94	0.94	0.94	3090
weighted avg	0.94	0.94	0.94	3090

Figure 4.2.1 Classification Report of SVC Model.

Training accuracy for Random Forest Model: 84.86%

Testing accuracy for Random Forest Model: 84.14%

	precision	recall	f1-score	support
LAYING	1.00	1.00	1.00	597
SITTING	0.86	0.58	0.69	563
STANDING	0.68	0.91	0.77	547
WALKING	0.85	0.94	0.89	539
WALKING_DOWNSTAIRS	0.93	0.79	0.85	420
WALKING_UPSTAIRS	0.80	0.82	0.81	424
accuracy			0.84	3090
macro avg	0.85	0.84	0.84	3090
weighted avg	0.85	0.84	0.84	3090

Figure 4.2.2 Classification Report of Random Forest Model.

Training accuracy for Logistic Regression Model: 97.29%

Testing accuracy for Logistic Regression Model: 96.21%

	precision	recall	f1-score	support
LAYING	1.00	1.00	1.00	597
SITTING	0.91	0.91	0.91	563
STANDING	0.91	0.91	0.91	547
WALKING	0.98	0.99	0.99	539
WALKING_DOWNSTAIRS	0.99	0.99	0.99	420
WALKING_UPSTAIRS	0.98	0.98	0.98	424
accuracy			0.96	3090
macro avg	0.96	0.96	0.96	3090
weighted avg	0.96	0.96	0.96	3090

Figure 4.2.3 Classification Report of Logistic Regression Model.

Training accuracy for KNN Model: 98.37%

Testing accuracy for KNN Model: 95.92%

	precision	recall	f1-score	support
LAYING	0.99	1.00	1.00	597
SITTING	0.90	0.89	0.89	563
STANDING	0.89	0.90	0.90	547
WALKING	0.99	1.00	0.99	539
WALKING_DOWNSTAIRS	1.00	0.99	0.99	420
WALKING_UPSTAIRS	0.99	0.99	0.99	424
accuracy			0.96	3090
macro avg	0.96	0.96	0.96	3090
weighted avg	0.96	0.96	0.96	3090

Figure 4.2.4 Classification Report of KNN Model.

Training accuracy for Decision Tree Classifier Model: 94.31%

Testing accuracy for Decision Tree Classifier Model: 89.15

	precision	recall	f1-score	support
LAYING	0.99	1.00	0.99	597
SITTING	0.81	0.85	0.83	563
STANDING	0.84	0.80	0.82	547
WALKING	0.91	0.94	0.93	539
WALKING_DOWNSTAIRS	0.92	0.87	0.90	420
WALKING_UPSTAIRS	0.87	0.88	0.87	424
accuracy			0.89	3090
macro avg	0.89	0.89	0.89	3090
weighted avg	0.89	0.89	0.89	3090

Figure 4.2.5 Classification Report of Decision Tree Classifier Model.

4.3 Confusion Matrix

The classification outcomes are summarized in the confusion matrix, which provides a comprehensive overview. The confusion matrix tabulates the predicted and actual values to display the individual results for each class. The confusion matrix and its elements are depicted in the following figure.

Predictive Values		Actual Values: Positive (1)	Actual Values: Negative (0)
	Positive (1)	TP	FP
	Negative (0)	FN	FP

Figure 4.3.1 Representation of confusion matrix.

True Positive (TP): The number of correct records that the model correctly identified as correct is shown by a true positive.

True Negative (TN): A true negative represents the number of negative records that the model correctly identified as negative.

False Positive (FP): The number of negative records that the model incorrectly interpreted as positive is known as a false positive.

False Negative (FN): A false negative is the number of positive records that the model incorrectly predicted would be negative [17].

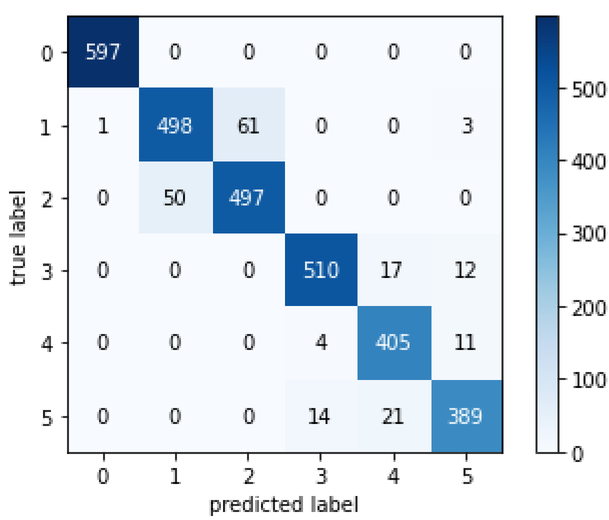

Figure 4.3.2 Confusion matrix for SVC Model.

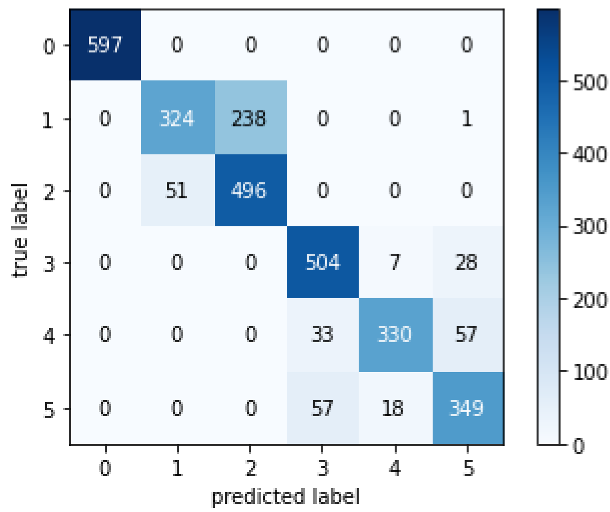

Figure 4.3.3 Confusion matrix for Random Forest Model.

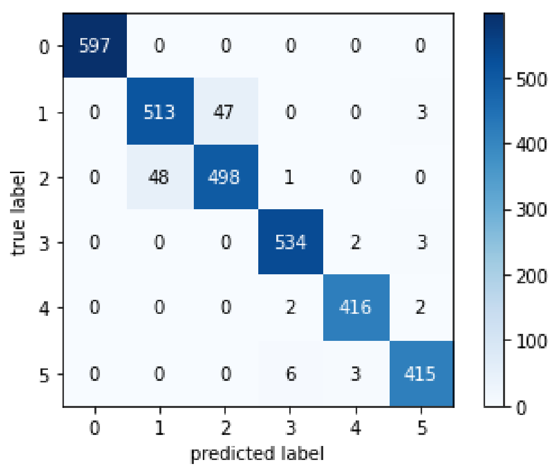

Figure 4.3.4 Confusion matrix for Logistic Regression Model.

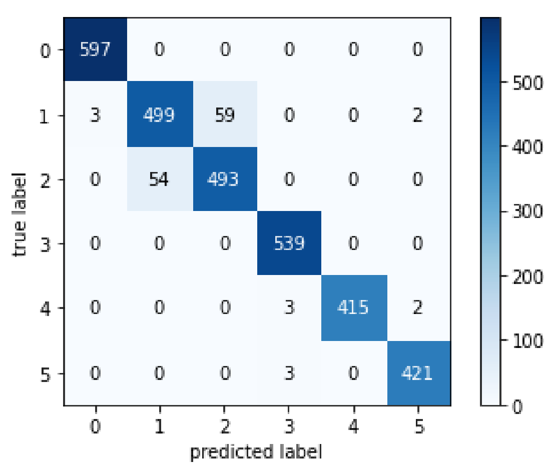

Figure 4.3.5 Confusion matrix for KNN Model.

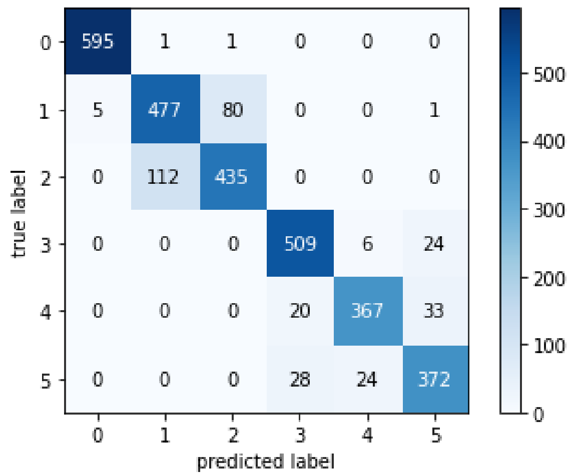

Figure 4.3.6 Confusion matrix for Decision Tree Classifier Model.

Observations: This confusion matrix shows actual class and predicted class for determine accuracy and errors.

Cross-validation: Cross-validation is a method for assessing models. Figuring out whether the trained model is generalizable that is, whether the predictive power we observe during training is also to be assumed on unseen data is the fundamental premise next to model evaluation.

CHAPTER 5

RESULT COMPARISON AND ANALYSIS

The outcomes of the experiments covered in the methodology section are discussed in this section of the paper 3.2. The UCI-HAR dataset, which the 30 volunteers collected, is used to detect human activity, and each volunteer participated in all six of the experiment's chosen activities. These include standing, sitting, moving around, moving up and down stairs, and lying down. They were using the smartphone to interact while carrying out these tasks. The gyroscope along with accelerometer data sensors, which are used for action recognition, were built into the smartphone. The comparison of the accuracy rates of the classifiers used in this study to predict human activities is shown in Figure 5.

To obtain the results in this study, all classifiers are tested on the same reduced dataset.

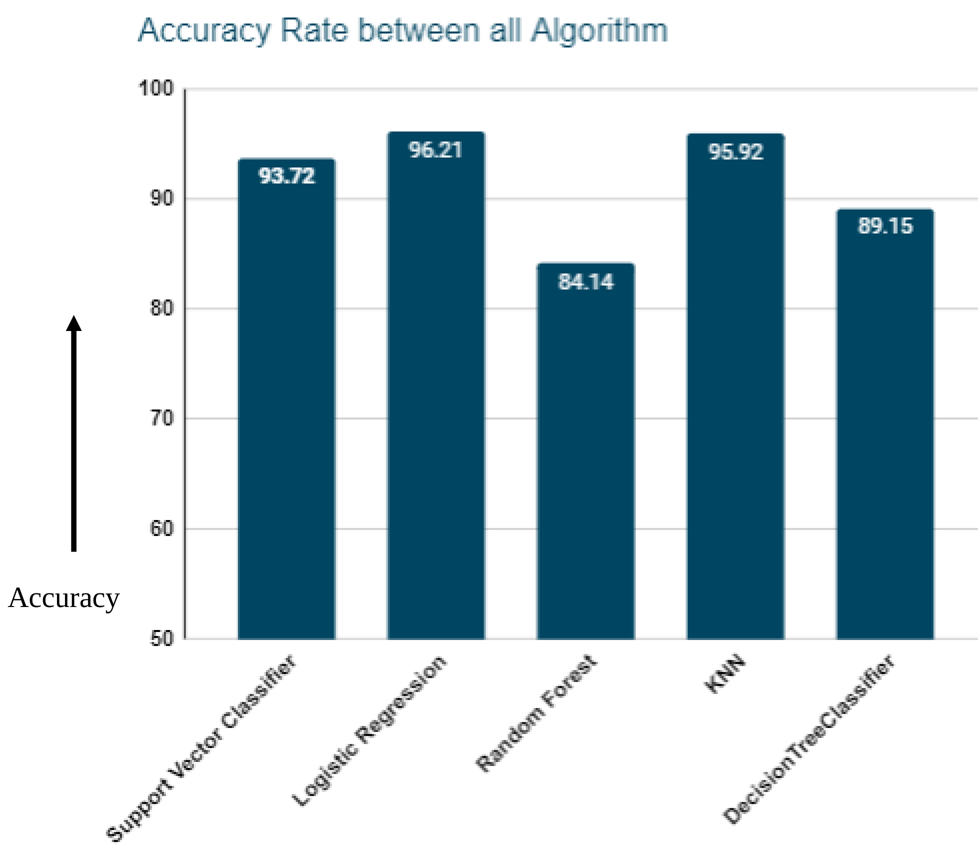

Figure 5 Comparison Between the Classifiers.

In this study, classifiers were used to predict human activities. Figure 5 compares the accuracy rates of the classifiers used in this study. The same condensed dataset is used for all classifier experiments in this study in order to maximize classifier performance. The logistic regression performs the classifiers with the best performance. The classification of techniques results in the best accuracy rate, which is 96.21%.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

Based on a publicly accessible UCI-human activity recognition dataset, this work provides a method for daily human activity recognition (HAR). These datasets used accelerometers and gyroscope sensors, already found in smartphones, smartwatches, and other wearable gadgets that enable you to monitor your body's actions throughout the day. Due to the accelerometer sensor's three-dimensional operation, the reduction of dimensions approach is performed. to minimize the number of features to minimize overfitting and increase model generalization. To choose the features with the best variance, we used SelectKBest. We passed two parameters: the scoring metric, f classif, and the value of K, which represents the number of features we want in the final dataset by reducing the dimensionality of the original data and also identifying the key characteristics for classifying human activities.

In this study, we verified a number of classification strategies to evaluate a variety of human actions, such as standing, sitting, lying down, walking, and walking both upstairs and downstairs. Pre-processing mode was used to complete the computation using Python, the Sci-Kit Learn packages, and other tools. Feature engineering was used Univariate Feature selection. To choose the features with the best variance, we used SelectKBest. In the training and testing experiments, many classifiers were employed. We also used hyper-tuning for improve model accuracy. In the training and testing experiments, many classifiers were employed. Unlike other machine learning classifier algorithms, logistic regression performs at its highest level and with the most significant degree of reliability. 96.21% is the highest accuracy rate obtained using logistic regression. Compared to other machine learning classifiers like K-Nearest Neighbors at 95.92%, the SVC model at 93.72%, and the Decision Tree Classifier at 89.15%, the random-Forest model also performs well, with an accuracy rate of 84.14%.

6.2 Future Work

In later research, the accuracy rate of this machine learning classifier methodology might be contrasted with that of other activity identification techniques, such the probabilistic approach. Additionally, we want to expand the scope of our work in activity recognition. First of all, a variety of activities can be classified as human activities, including context-based activities like typing, sleeping, using the toilet, shaving, brushing one's teeth, hand waving, hand clapping, boxing, and cooking. Then, from a different user with a variety of ages, we will get further data. Caretakers can utilize this study to help them monitor the health of older folks. The last phase involves analyzing performance in more difficult activity prediction, such as identifying bicycle falls.

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