HUMAN ACTIVITY RECOGNITION USING SMARTPHONE

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "**Human Activity Recognition using Smartphone**", submitted by Ashraful Alam, ID No: 171-15-9363, Anik Das, ID No: 171-15-9378, Md. Shahriar Tasjid ID No: 171-15-9384 and Singnuching Marma, ID No: 171-15-9366 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 31 January 2021.

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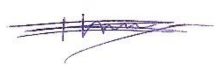

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Mr. Ahmed Al Marouf, Lecturer, Department of CSE,** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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Finally, with due respect we acknowledge the constant support and patience of our parents.

ABSTRACT

Smart devices like smartphone, smart watches have made this world smarter than any other time at every scale. A lot of facilities can be taken from these devices. Proper use of built in sensors such as accelerometer, gyroscope, GPS are few of them. In everyday life people do a lot of physical activities which can be important for analysis like health state prediction, how much exercise they do etc. by using those sensors based on Artificial Intelligence. In this paper we have implemented both machine learning and deep learning to detect and recognize eight activities with maximum 99.3% accuracy. Of those activities few are similar in physical movements and actions like sitting in a chair at home, standing and sitting in a car. These are almost similar and difficult to distinguish. Going upstairs and downstairs are also almost similar to separate. So we showed that, with more number of sensors and data collection points a wide range of activities can be recognized and the accuracies can be increased. We proved our point through comparing the results of using less sensors and again using data of only one positions of either pocket or wrist. Then finally we showed that putting all the sensors and data of pocket, wrist together, we can recognize those activities accurately and in this way, a wide ranges of activities can be recognized with precision.

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CHAPTER 1 INTRODUCTION

1.1 INTRODUCTION

We are living in the age of technological advancement. In this era, the field of humancentric computing research is an emerging field of research in which we can understand the behavior of human behavior, etc.

Human activity recognition is a type of work where all we have to do is predict human movement, their personality and psychological state by studying and analyzing human computer interaction (HCI), video surveillance, wearable devices or sensors. However the challenging part here is to detect, predict these things with accuracy. In our research work we tried to recognize human activity by using phone sensors. Sensors gave numerous data in seconds with the physical movement of different parts of the body. Thus it is a challenging task to predict the human activities from a wide range of sensors data precisely.

We have placed one smartphone with an accelerometer and gyroscope in wrist and one in pocket to capture data of different activities. Several machine learning algorithms e.g. KNN, CNN, Bi-directional LSTM, SVM etc. have been applied.

1.2 MOTIVATION

In this digitalized era, our lifestyle has been changed over time. Now we hardly go outside for outdoor activities. Rather we prefer using social media or watching movies on our gadgets. We are now being home centric. Many psychological disorders are originating from abstaining from outdoor activities. Most of the time, people are using their cellphone when they are home. By studying the data from the sensors of the phone we can make suggestions about healthier life. Our motivation is to develop and train a model that can precisely recognize human activity.

Moreover if human activities can be recognized precisely, we can use them in a healthcare environment to observe patients' activities for their safety. Some patients are asked not to stay at certain kinds of postures. If they do so, it can affect their postoperative condition or worsen their lifestyle.

1.3 RATIONALE OF THE STUDY

Our main focus is on developing a model that can precisely detect human activities and prove that using more data collecting points from different parts of the body we can increase the accuracy and wide ranges of activities with similarities in bodily movements can be recognized accurately.

1.4 RESEARCH QUESTION

- **What is the topic?**

  Human Activity Analysis.

- **What is the main purpose?**

  In past decades many attempts were made to recognize human activity. In our work we claimed that we can recognize more activities that are complex and similar in action if we increase the data collecting points from the human body.

- **A lot of work has been done before. Why do we do this work again?**

  A lot of work has been done before. But our claim is, more the data collecting point for example hand, pocket, legs, neck etc. and more sensors, the accurate it is to detect all kinds of activities whether they are complex or similar in action. We used Wrist and Pocket for our data collecting point and used accelerometer and gyroscope data in both the devices to collect data. And we showed similar activities can be detected very precisely.

1.5 EXPECTED OUTPUT

In this research project our expected outcome is a model with better accuracy though some of them are very similar in action and movement of body. That means the model can predict different activities precisely. We have proved our claim with eight activities. By accelerometer and gyroscope sensor data of a smartphone our model can accurately detect those eight activities.

1.6 PROJECT MANAGEMENT AND FINANCE

Table 1: Project Management and Timeline

Activities	Timeline
Planning and Knowledge Gathering	4 months
Data Collection	1 Months
Data Preprocessing	1 Months
Implementation	1 Months
Report Generation	15 Days
Total	7 Months 15 Days

This project is financed by all the team members of this project.

1.7 REPORT LAYOUT

There are Six Chapters in our report. First chapter consists of Introduction, Motivation, Objectives, Expected Outcome, & Report Layout. Then the next chapter contains Terminologies, Related Works, Comparative Analysis and Summary, Scope of the Problem and Challenges. The Third chapter contains Research Subject and Instrument, Data Collection Procedure, Statistical Analysis, Proposed Methodology and Implementation Requirements. Fourth Chapter contains Experimental Setup, Experimental Results and Analysis, Discussion. Fifth Chapter Consists of Society Impact, Environmental impact, Ethical Aspects, Sustainability Plan, and the last chapter includes Summary of the Study, Conclusions and Implication for Further Study.

CHAPTER 2 BACKGROUND

2.1 TERMINOLOGIES

Human Activity Recognition (HAR):

In everyday life we perform a wide range of tasks. For example walking, sitting, standing, eating, watching television, jogging, driving a car, riding a bicycle etc. HAR is a field of study where researchers try to identify what type of task is a person doing from data. The data can be images, videos within an observed space or the data can be collected from sensors like accelerometer, gyroscope, gps etc. These data are trained in different models and then these models are evaluated. These types of research are known as HAR in short.

Accelerometer:

Accelerometer sensors can be either biaxial (2 axis) or triaxial (3 axis). Almost all of the modern devices use triaxial accelerometers. So, from 3 axis the sensor can detect accelerations in all the directions. All the axes can measure from -5g to +5g. Here g stands for Gravity. With the combination of the three axes, an accelerometer can even measure the angle of tilt a device has relative to the earth.

Gyroscope:

Gyroscope works as a helping wrist for an accelerometer. Accelerometers main job is to measure the changes of displacement in each axis. Though they can measure tilt, these are not accurate. To increase the accuracy of angular rotational velocity, gyroscopes are used along with accelerometers. This way with the combination of accelerometer and gyroscope, almost all kinds of displacement can be measured quite accurately.

PCA:

Principal component analysis of a data matrix extracts the dominant patterns in the matrix in terms of a complementary set of score and loading plots [6]. So this is a well-known dimensionality reduction technique. This method projects the original data which have many dimensions to lower dimensions without any significant data loss. So this technique increases interpretability of the dataset. Too many features means too many dimensions.

This problem is known as ‘Curse of dimensionality’. To solve this sparsity of data with lots of dimensions, PCA is applied. This helps to improve the statistical analysis where statistical significance is needed to measure and analyze.

ML:

Machine learning is a field of study combined with Computer Science and Statistics, where a model learns from observing some data and then predicts the results on unobserved data. More the data is given the better the machine learns in most of the cases. In other words, Machine learning is some set of algorithms which improves statistical analysis using iteration through data over and over again.

HMM:

Abbreviation of HMM is the Hidden Markov Model. This algorithm is used in Machine Learning as a probabilistic analysis. When there is a scenario where unobservable states are present, HMM works very well there. The algorithm assumes that there will be some unobservable states and thus it operates. So for time series analysis this algorithm is very useful. A lot of researchers took help from HMM when they worked on HAR.

ANN:

ANN stands short for Artificial Neural Network. The working procedure of ANN tries to mimic the human brain. Human brain has billions of neurons connected to each other. One neuron passes information to another and keeps learning from experience. ANN works almost the same way. There are multiple units connected to each other in a neural network. The network learns patterns from the dataset after lots of iterations. Each iteration has two phases or propagations. In forward propagation, when data is fed with the ground truths, the network tries to predict the labels. After each forward iteration there is a loss function which evaluates how well the prediction is. This way with enough data, the network learns about the unobserved data.

CNN:

CNN stands for Convolutional Neural Networks. This network comprises single or multiple layers of Convolutions which extracts features from image or any kinds of big matrix. So, it is capable of finding the area of interest from a sparse matrix or a matrix that has information we do not need. What makes this algorithm so popular is that finding features from a huge matrix is fully automated.

LSTM:

The abbreviation of LSTM is Long short-term memory. This is a Recurrent neural network algorithm. The specialty of this algorithm is, it has feedback loops. So, it does not only analyze a single data point, it can store memory from the feedback of an entire dataset no matter how big it is. The model learns itself which memories to keep or which to forget. This way it can work well with almost any kind of time series data. Here we used slightly modified version Bidirectional LSTM[16].

2.2 RELATED WORKS

There has been intense research going on the past 2 decades. Several attempts have been made to detect Human Activity from different body points attached to the bodies. Here [1] accelerometer and microphone data was used to recognize activities in a certain environment. Their attempt was to get good accuracy even if the device's location in the body changes. Another attempt here [2] used only a triaxial accelerometer of a phone to detect activities. They performed their experiment keeping the phone both in wrist and pocket. Then both models accuracy was compared. They used both individual and combinations of classifiers. They both showed promising results. Vinh [7] used the data of the accelerometer from both hip and waist. Their attempt was to detect recognition using low power and low cost devices. Bao [9] used biaxial accelerometer data retrieved from wrist, ankle, thigh, elbow and hip. While collecting data they did not ask the user where they should put the device while doing the activities. So the data came up from those five different body locations. After testing with several algorithms and comparing them, they proved that only thing and waist data combined, can perform close to the five data points combined. Decision tree was the best classifier in their experiment. Jatoba [10] and his team's work has been done for monitoring activities of patients. So, they analyzed the data of micro accelerometers placed on the patient's chest. With K-NN and CART they were able to get decent accuracy.

Most of the work has been done on the accelerometer data taken from either waist or wrist. But Zhu [8] used accelerometer data from foot and waist. And their best performed algorithm was HMM. They reduced the complexity of the dataset by fusion of the data collected from foot and waist. This way they overcame the problem of the need for strong displacement of sensors for the HMM model to work well. Some of the attempts were made in the discriminative way too [5]. The closest work to us is the work of San-SegundoHernández [4] and E. Bulbul [3]. In [4], they used accelerometer data from wrist and pocket. They claimed accelerometer data provided better results compared to that of gyroscope. What we have done is that, instead of analyzing the data of the accelerometer and gyroscope separately, we treated both sensors as features and trained our model from that data. This way a wide range of activities can be measured accurately as the model gets more features to work on. Bulbul [3] in their work, used both the sensors together to build the model. He achieved very good results too. But they used pocket data. But our work includes both the sensors from two different devices placed on the pocket and wrist. This way the model can be trained to successfully distinguish among wide ranges of different activities even if they are quite similar like sitting in a moving car or a chair in a stationary place.

2.3 COMPARATIVE ANALYSIS AND SUMMARY

There are wide ranges of approaches made to detect human activity. Experiments used different algorithms, sensors, sensors location in body varied and different accuracy was

Table 2: Comparative Analysis and Summary of different approaches made to detect human activity.

Paper	**Sensors**	**Sensor placed**	**Best Algorithms**	**Best accuracy obtained**

L. Vinh [7]	Accelerometer	Waist, hip	SMCRF	88.38%
L. Bao [9]	Accelerometer	Wrist, ankle, thigh, elbow, hip	KNN, NB	84%
L. C. Jatoba [10]	Accelerometer, SPI	Chest	KNN, CART	95%
C. Zhu [8]	Accelerometer	Foot, waist	HMM	90%
Z. He [11]	Accelerometer	Pocket	SVM	97.51%
A. Khan [12]	Accelerometer	Chest	ANN	97.9%
Lester [1]	Accelerometer, Microphone	Waist, wrist, shoulder	HHM	90%
Akram Bayat [2]	Accelerometer	Either wrist or waist	SVM, LMT, Random Forest	91.15%
E. Bulbul [3]	Accelerometer, Gyroscope	Pocket	SVM, k-NN, Bagging, Stacking	99.4%
San-Segundo-Hernández [4]	Accelerometer	Pocket, wrist	CNN-LSTM, HMM	99.4%

obtained from them. So here [Table 2] is an analysis between those.

There have been several researches going on recognizing human activities. Different experiments used different sensors placed on single or multiple places of body locations. There are lots of algorithms that are implemented, but few of them perform well. For example: SVM, ANN, HMM, CNN-LSTM etc. It is evident from the comparison above that when different sensors are combined together or the same type of sensors placed in multiple places, the performance and accuracy is achieved much better.

2.4 SCOPE OF THE PROBLEM

Human Activity Recognition is a very challenging task as people are spontaneous in their works. Often we perform multiple tasks at the same time. For example we might be watching TV while we are eating. From a single data point like waist or just wrist it is very difficult to identify the activity a person is doing. So we took two data points: wrist and waist. To make the data more meaningful to our model, we added gyroscope data to the accelerometer. This way the models have more features to work on and recognize the tasks. As each sensor has three dimensions and there are 2 devices, total twelve dimensions are featured in our dataset. We have come to a conclusion from the previous works that adding gyroscope data to the accelerometer increases the accuracy of models that are built from the data collected from the waist. And when another device is added in wrist and adding its data together with the data of waist, the model can detect a wide range of activities because the machine learning models get more features that interpret the activities very well. Our work proves this too, when gyroscope data is added, the models work better than the accelerometer data alone. We have achieved 99.3% accuracy in our work.

2.5 CHALLENGES

Human activity comprises complex movements of the parts of the whole body. Often these movements are quite similar in different activities. For example sitting in a car and sitting in a chair uses the same posture, but activity the person doing is totally different in those cases. Another problem is, people do not perform a single activity very often. Activities often overlap which is very difficult to distinguish. This is still a huge challenge for the researchers.

We faced lots of difficulties when annotating the data as the sampling rate of the sensors are very fast, and we had to label the data without any errors. We had to be careful when we joined the data of wrist and waist matching the same rows as they are featured to specific tasks like cycling or riding a car. The accelerometer and gyroscope data are almost identical and very difficult to interpret. Moreover a single sample cannot be identified as an activity. Because to label an activity we need a window which contains a certain number of samples for which the model can analyze and learn what an activity looks like and how the values change in the different axes of the accelerometer and gyroscope. So we divided the data into windows of 4 seconds each had almost 200 data points.

Each window was treated like a single sample and it was given a labeled accordingly. And these data were trained in Bi directional LSTM and 2 dimensional Convolutional Neural Networks. But for traditional Machine Learning algorithms like SVM, K-NN, Random Forest etc, windows of data cannot be fed directly. So, we flattened the three dimensional dataset. So each window was flattened to a single sample.

Time series data has lots of noises when recorded. We had to remove the noises carefully so that no important information gets lost. Another challenge was to match the frequency rate of the two devices placed in the waist and wrist. Because, different phones provide different samples per second even if we select 50Hz sample rate because of their different model and specifications. This was very problematic for us. So, we had to find devices that provide recorded data in the same frequencies.

CHAPTER 3 RESEARCH METHODOLOGY

3.1 RESEARCH SUBJECT AND INSTRUMENT

Now-a-days, every person has at least one smartphone in their pocket. Along with that, people have been starting to wear wrist bends instead of analog watches. These gadgets have different kinds of sensors built in, especially accelerometers and gyroscopes which are common. There are a lot of usages of these two sensors.

In our paper, we are focusing on human activities detection and recognition by using accelerometer and gyroscope sensors data. Here we have detected eight activities and these are walking, standing, sitting, upstairs, downstairs, jogging, cycling and sitting in the car. We have collected time series data by using three android operating system based smartphones. These were Samsung Galaxy S10 Plus, Redmi Note 7s and Huawei Y9. We have used a paid application called “Sensor Data” to collect our required data.

3.2 DATA COLLECTION PROCEDURE

As we had to collect time series data it was challenging to collect data properly. At first, we managed 17 volunteers to perform different activities for a specific time period. The android application which we used to collect data was set up at 50Hz sampling rate. So, the application counted 50 samples per second. We used two smartphones at a time. One was in the pocket and the other was tied to the wrist.

The device tied to the wrist can get the similar data to a wrist bend. Then after performing those activities we got two types of data (wrist and pocket) for each of the activities. Each of them has both accelerometer and gyroscope sensor data with three data points known as axes (x, y, z). Finally we have stored each distinct type of data such as ‘Activity_Hand_accelerometer’, ‘Activity_Hand_gyroscope’,‘Activity_Pocket_accelerometer’,‘Activity_Pocket_gyroscope’ into the text files. That is the procedure of our time series data collection. After finishing the data collection phase, we have preprocessed the raw data to make a suitable dataset where we can implement different algorithms.

First of all, we have removed unnecessary strings from the text files. Because the mobile application generated some irrelevant strings at the beginning of the text file. Then we have converted each text file into comma-separated values (csv) file. Here, we have 12 input columns for each of the activities and 1 output column where we have labeled the activity name. And for each of the activities we have taken 44,000 samples. After that we have merged all the csv files into one to get our complete dataset. In our dataset we have got a total 3, 52,000 samples.

After that we had done feature engineering where we removed null values by using mean and median methods. There were noises in the dataset which are not expected. So, we have done filtering by using the butterfly method to remove the noises from the dataset and make the dataset smooth. Then we have done label encoding. As our output label was categorical data, we had to convert that into numerical data by using label encoding function. Furthermore we have split our dataset into input and output columns. Along with this we also split our dataset into a train set and test set at the ratio of 4:1.

After splitting the dataset we have implemented feature scaling on our dataset to bring all the data points into a specific range. We used Robust Scalar and Standard Scalar to scale the dataset. We have implemented both scalar fitting and transformation on train dataset but only implemented transformation on test dataset. By doing this we were able to keep our test dataset intake for getting the actual accuracy.

As we have time series data, we had to make a window which is also known as filter size from the dataset to implement deep learning algorithms. That is why we have made windows of different sizes based on our algorithms. We also have defined the hop size which is known as stride size. Hop size was actually used to reduce the overlapping. It ensures the diversity of samples in the windows.

After determining the window size and hop size, we have got 3D data. But there were some problems with 3D data while implementing the scalers for scaling the data. So, we have also made an alternative option to reshape the whole train dataset. For doing that we had to go through all the frames and then reshape all the samples of a specific window.

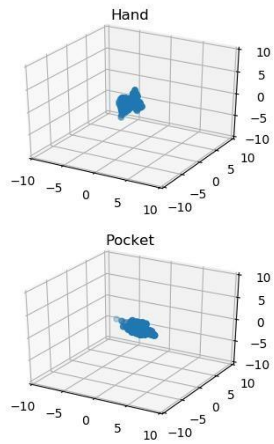
This is the complete procedure of our data collection, data storing, data cleaning and data preprocessing.

3.3 STATISTICAL ANALYSIS

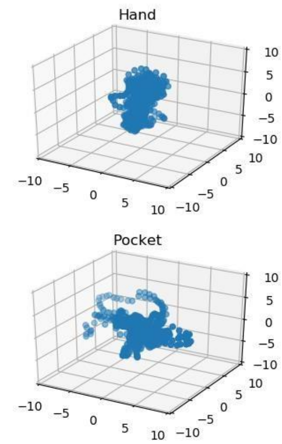
While performing any kind of activity, the orientation of phone and smartwatch is expected to differ in different kinds of activities. And in most of the cases this difference occurs. But often two or more activities can provide similar kinds of data. This can be seen from the Fig 1 visualization of the data.

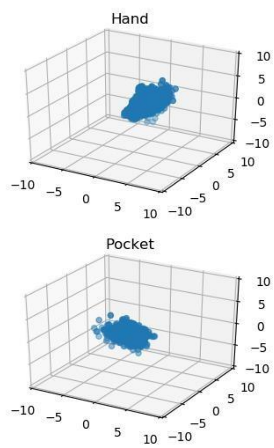
Looking at the accelerometer data of pocket, downstairs and upstairs data have similar kinds of dispersion, range and orientation. So, Machine learning algorithms will struggle to distinguish between those activities most of the time. In cases like these wrist data helps more. Looking at the wrist data of the accelerometer, data defers in dispersion and orientation in upstairs and downstairs activities. Adding the gyroscope to that, we will be able to add a lot more information that can very easily be distinguished. From the visualization of gyroscope data we can see that both upstairs and downstairs data differs a lot. So, with these 4 sensors (2 in wrist and 2 in waist) the margin of error is very low for any activity that provides almost similar kind of data.

Accelerometer **Gyroscope**

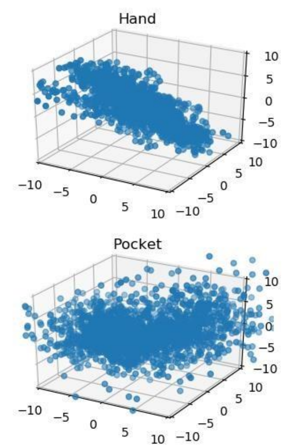


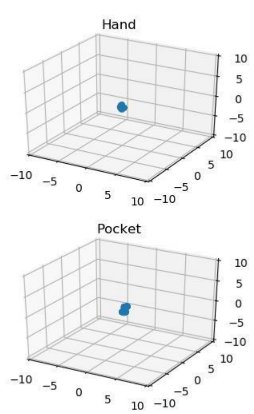
Walking



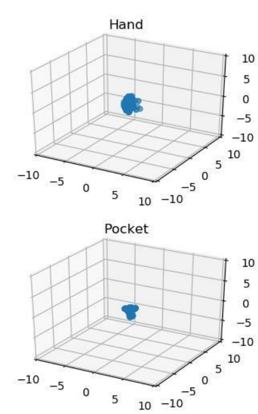


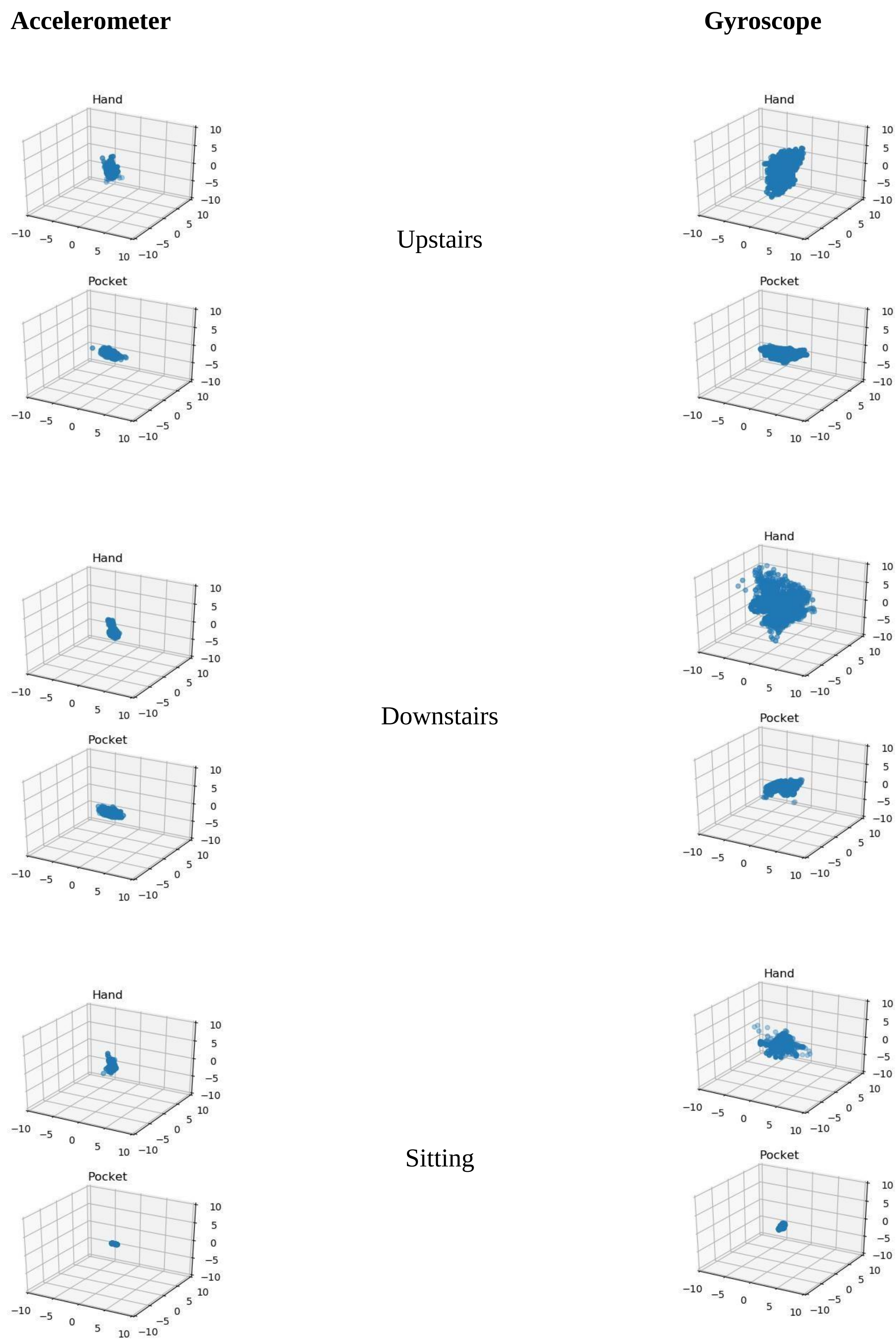
Jogging





Standing




Accelerometer
Gyroscope
Hand
Pocket
Upstairs
Hand
Pocket
Downstairs
Hand
Pocket
Sitting

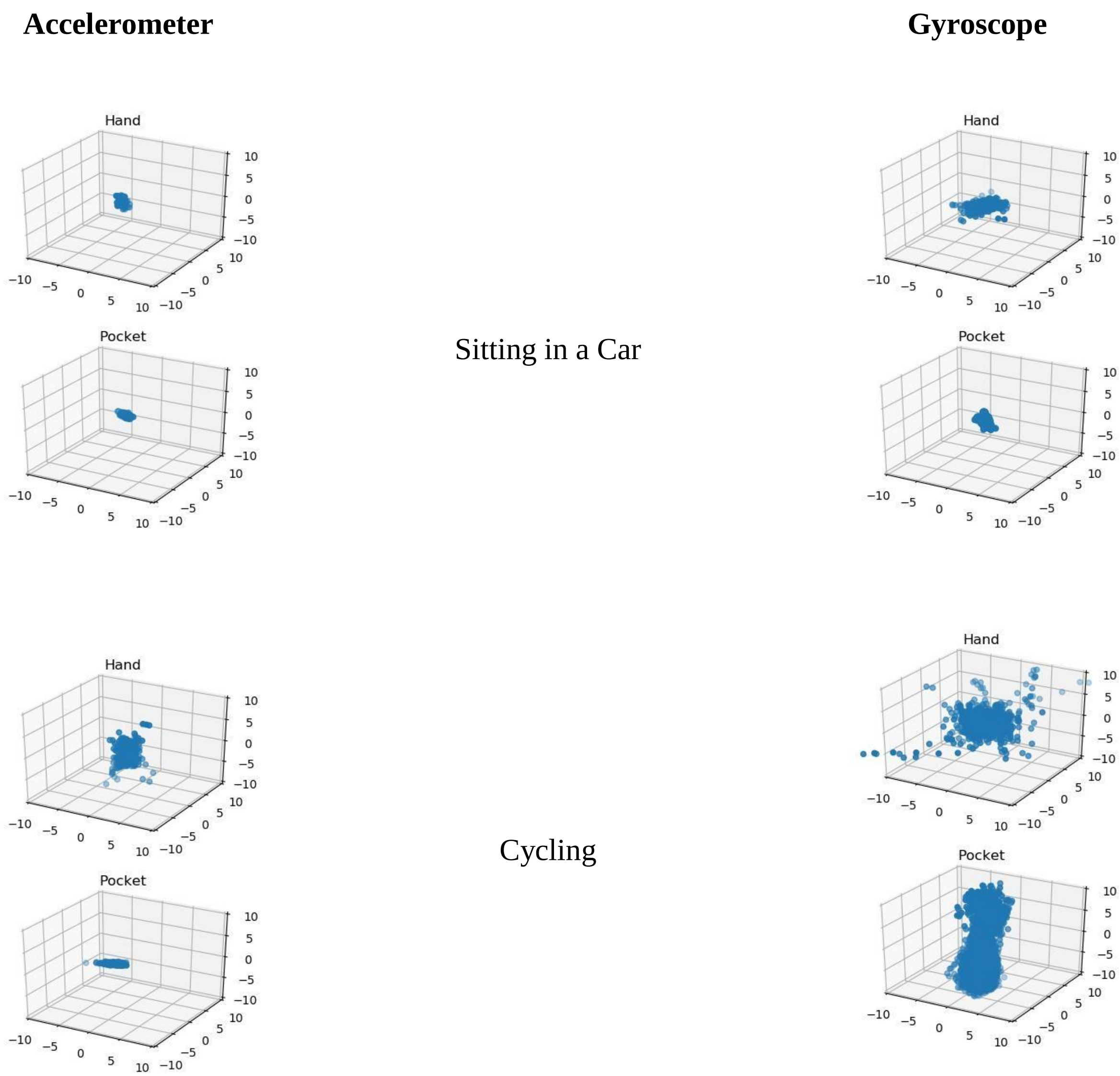


Figure 1: Comparative visualization of Accelerometer and Gyroscope data points in different activities

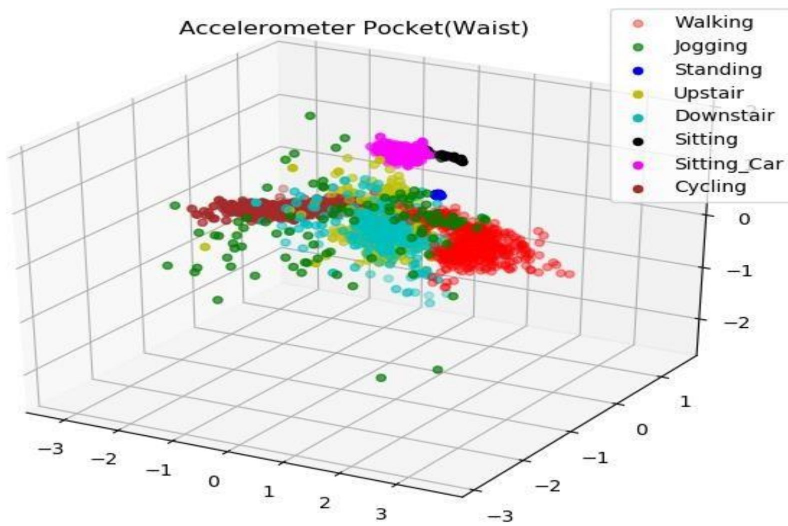
Sitting in a car and sitting home in a chair is almost similar activity in action and hard to distinguish between those. From the Fig 1 visualization we can see that accelerometer data of those 2 activities is hard to differentiate between. Data points have almost the same dispersion and orientation. So any Machine learning algorithms will have lots of errors when trying to predict if someone is sitting in a car or in a chair at home. In this scenario too, the gyroscope data adds lots of information that can easily differentiate between those two activities.

From the above two scenarios we can see that, when data are analyzed together from waist accelerometer, gyroscope and wrist accelerometer, gyroscope we can predict the very accurately even if the activities are very similar in action.

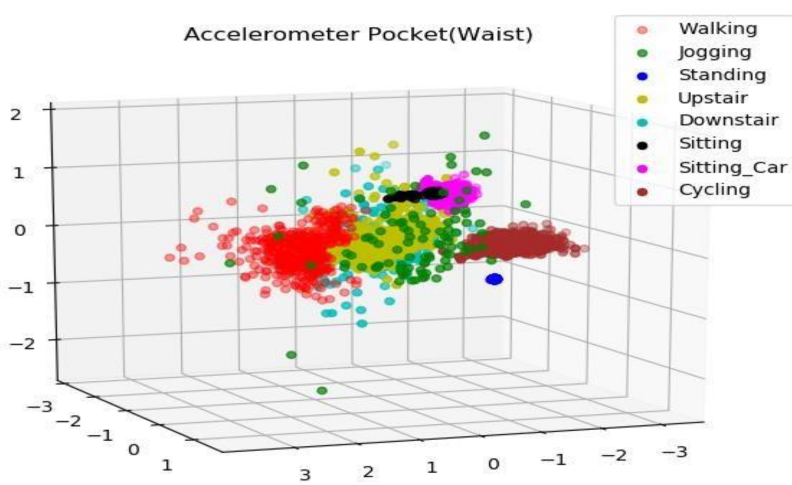
When all the activities are put together in a single graph, we can further illustrate why it is better to use two devices each having 2 sensors.

All the data plotted in these 4 figures (Figure 2, Figure 3, Figure 4, and Figure 5), these are the data of the same instance. In other words these are data for specific 10 seconds from the entire dataset so that we can compare how the data points change for different activities.

So we can clearly see that upstairs and downstairs are overlapping in Figure 1, Figure 2 and Figure 3 which are Yellow and Cyan respectively. So even from those 3 sensors we might often not be able to distinguish between Upstairs and Downstairs. Some errors will come up. But from Figure 4, we can easily distinguish between Cyan and Yellow. So these activities will be separated quite accurately. Same way others activities that are almost similar will be differentiated with those 4 activities even if they are almost similar in action. That is the reason why we are able to achieve accuracy of 99.3% even though some of the activities are very similar to each other.

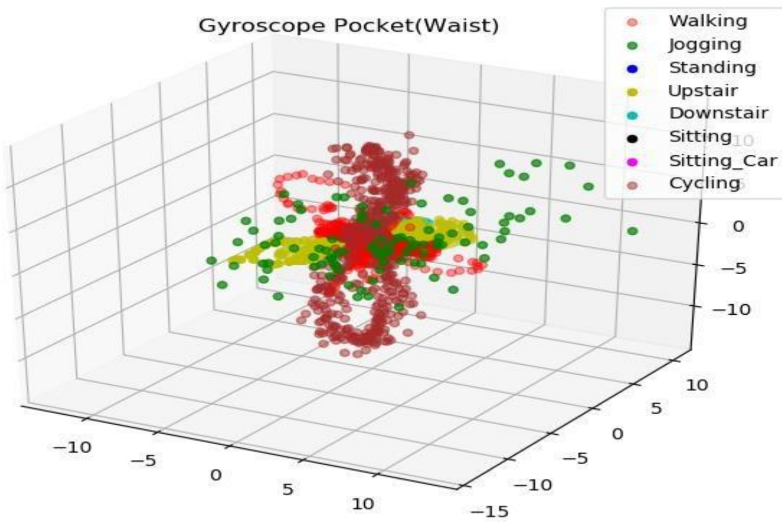


View: 1

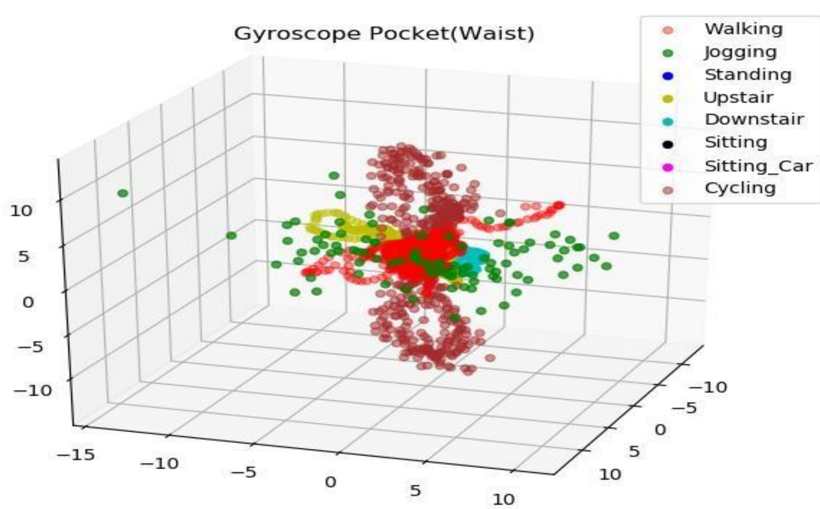


View: 2

Figure 2: Views from different angles of Accelerometer data recorded from the waist (pocket) of 8 activities together.

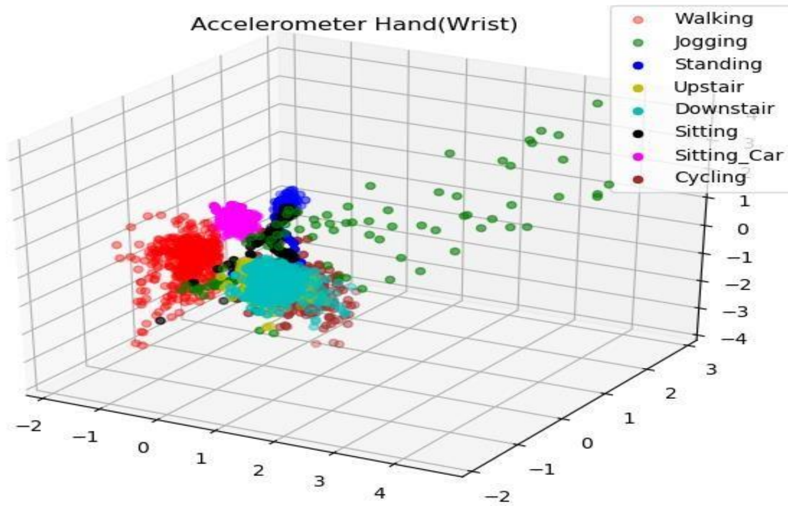


View: 1

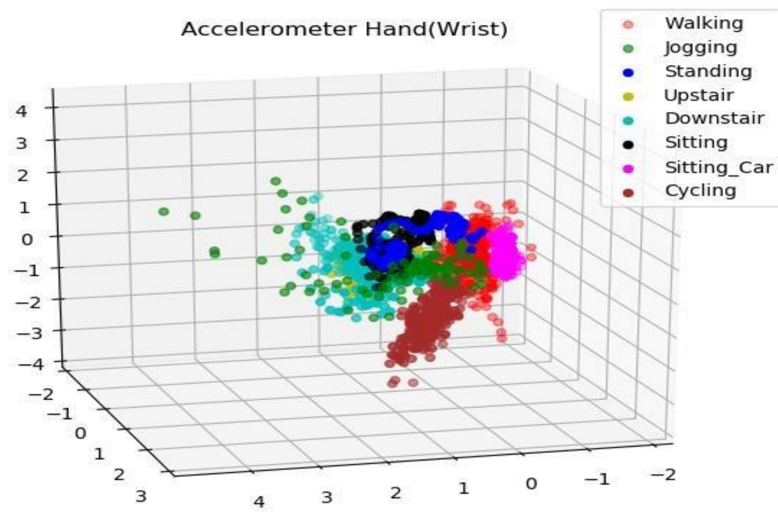


View: 2

Figure 3: Views from different angles of Gyroscope data recorded from waist (pocket) of 8 activities together.

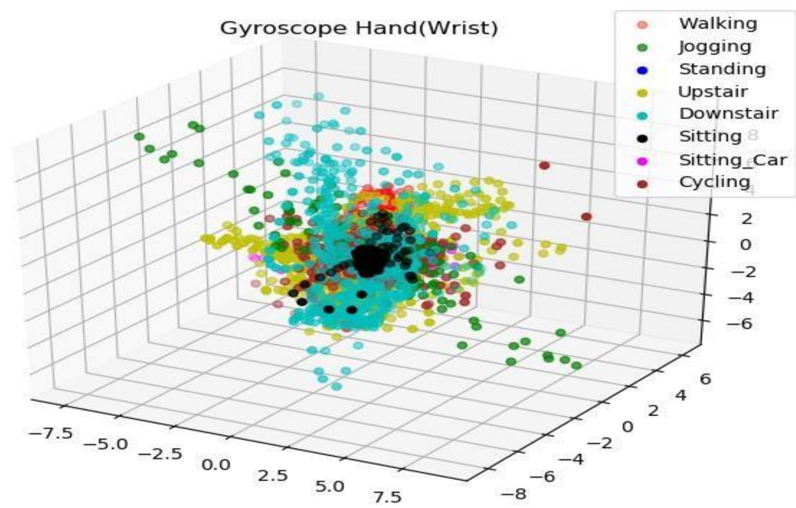


View: 1

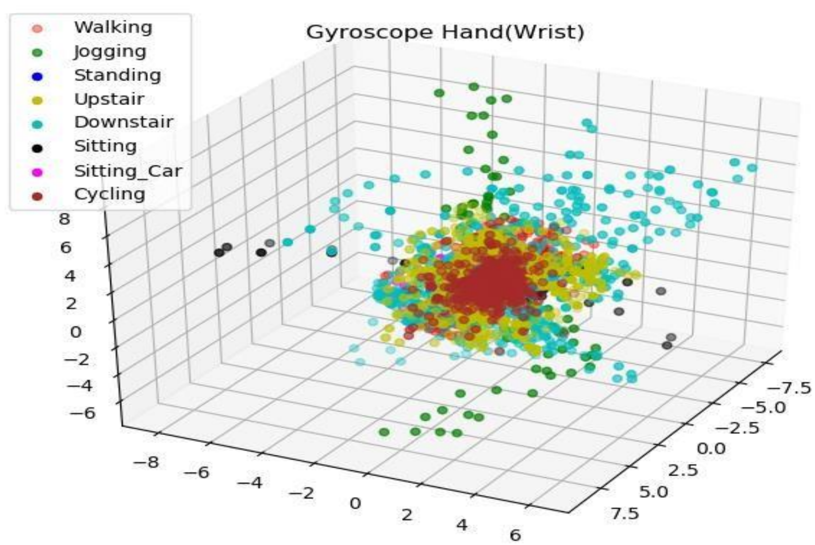


View: 2

Figure 4: Views from different angles of Accelerometer data recorded from wrist (hand) of 8 activities together.



View: 1



View: 2

Figure 5: Views from different angles of Gyroscope data recorded from wrist (hand) of 8 activities together.

3.4 PROPOSED METHODOLOGY

Both machine learning and deep learning algorithms are used to recognize activities from the dataset. We have trained our training dataset by implementing those algorithms. Then we have achieved different accuracy for different algorithms on the testing dataset. These algorithms we have implemented are following:

- Logistic Regression
- K-Nearest Neighbors (KNN)
- Random Forest Tree
- Support Vector Machine (SVM)
- Gradient Boosting Classifier
- 2D Convolutional Neural Networks (CNN)
- Bi-Directional Long Short-Term Memory (Bi-LSTM)

a) Logistic Regression: Logistic Regression is a supervised machine learning algorithm which is used for classification problems. Logistic regression is a linear regression algorithm but it has a complex cost function. It classifies through predictive analysis which is based on the concept of probability. The cost function of logistic regression is known as 'Sigmoid Function'. The hypothesis behind this cost function is to map the real values of the dataset into a range of 0 to 1. This Sigmoid function can be represented by given formula:

$$1 / (1 + e^{-value})$$

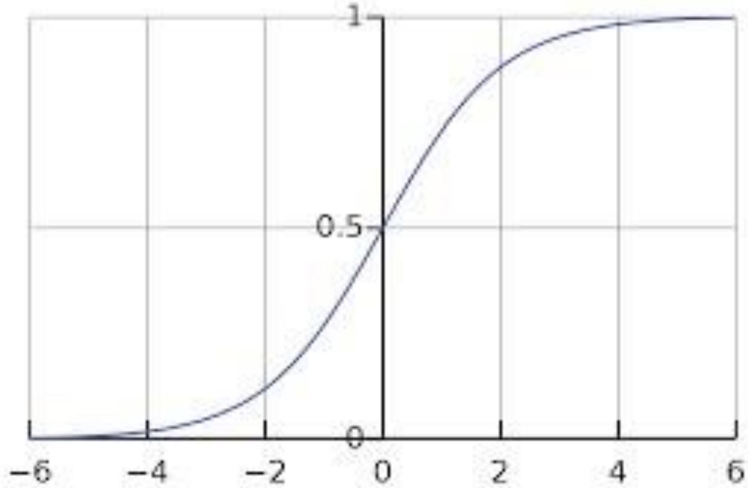


Figure 6: Sigmoid Function

We have implemented multi-class logistic regression where it gives us different labels (1, 2, 3 or 4) as output instead of giving numeric values. This algorithm has combined all the input values linearly by using coefficient values to predict the output values. The equation of logistic regression is given below:

y = e^(a0 + a1*X) / (1 + e^(a0 + a1*X)) [15]

Where,

X = Input value Y

= Output value a0

= Bias

a1 = coefficient of input value

By using this algorithm we have trained our training dataset where the coefficient associated with input value has been learned from the training data. Then the trained model was implemented on the test data to get the accuracy. Logistic regression has given us 84.2% accuracy on the test data. As logistic regression analyses are based on linearly predictive procedure and our dataset is a complex one so it was unable to predict with high accuracy. We can measure the performance of our implemented logistic regression algorithm from the confusion matrix. It is also known as error matrix which is given below:

Index	pred:Walking	pred:Jogging	pred:Standing	pred:Upstair	pred:Downstair	pred:Sitting	pred:Sitting_Car	pred:Cycling
true:Walking	271	0	2	0	1	0	0	0
true:Jogging	0	219	0	0	0	4	29	23
true:Standing	0	2	271	0	0	0	2	0
true:Upstair	0	0	0	275	0	0	0	0
true:Downsta…	0	0	0	4	271	0	0	0
true:Sitting	0	5	5	0	0	202	1	62
true:Sitting…	0	20	0	0	0	5	243	7
true:Cycling	0	64	0	3	0	46	61	101

Figure 7: Confusion matrix of Logistic Regression

b) K-Nearest Neighbors (KNN): Our second implemented algorithm is K-Nearest Neighbors (KNN) which is also a supervised machine learning algorithm used for both regression and classification problems. This algorithm learns from the training data based on distance metrics to classify labels on testing data. KNN algorithm works through major three steps. These are following:

1. Determining the optimal value of K.
2. Calculating the Euclidean distance between test point and center point.
3. Then getting the nearest neighbors.
4. Finally, making the prediction.

As there is no predefined statistical way to determine the value of K, we had to go through the random initialization or a conventional method where we would take the square root value of our total number of classes in the dataset. So, we have chosen the second way where,

$$\text{Number of classes, } n = 8$$
$$K = \text{sqrt}(n)$$
$$K = \text{sqrt}(8)$$
$$K = 2.83 \sim 3$$

So, at the beginning of computation we have the value of K = 3.

After that we have calculated the Euclidean distance between the test point and our K trained nearest neighbor. Euclidean distance is the straight line distance between two vectors. The formula is given below:

Euclidean Distance = sqrt(sum i to n (a1_i – a2_i)^2)

Then we have calculated the distance for all the data points and selected the closest instance based on the minimum distance. That indicates the similarity between the data point and a specific group. After doing the same process multiple times with the updated value of k and the distances, we have finally got the group or cluster of activities. In a specific cluster, the characteristics of each data point is quite similar among themselves. That is how we have trained our KNN model where the main motivation is to gather all the similar entities in a specific group. Then we have implemented our model on the testing dataset to classify the labels. And, we have achieved 90.7% accuracy on our testing dataset by using this KNN algorithm. We have also got our confusion matrix where we can measure the performance of our KNN model. The confusion matrix is given below:

Index	pred:Walking	pred:Jogging	pred:Standing	pred:Upstair	pred:Downstair	pred:Sitting	pred:Sitting_Car	pred:Cycling
true:Walking	273	0	0	0	1	0	0	0
true:Jogging	0	185	0	2	0	66	3	19
true:Standing	0	1	274	0	0	0	0	0
true:Upstair	0	0	0	275	0	0	0	0
true:Downsta...	0	0	0	2	273	0	0	0
true:Sitting	0	0	0	0	0	275	0	0
true:Sitting...	0	31	0	2	2	9	209	22
true:Cycling	0	15	0	0	0	26	2	232

Figure 8: Confusion matrix of KNN

This KNN algorithm has performed better than our previous Logistic Regression. Because, the data points for a specific activity are quite similar. So, our KNN model has easily learned from the training data and made the group of similar data points. And this KNN algorithm is also designed for this kind of labels classification.

Along with these, there is no need to tune several parameters or count additional assumptions. Selecting the optimal number of K is another reason to get the better accuracy as our main target is to classify among multiple classes. But the KNN algorithm is not efficient in some cases. It is known as a lazy learning method. Because it holds the entire training dataset and there is no work done until any prediction is required.

c) Random Forest Tree: Our third implemented method is Random Forest Tree. It is also a supervised machine learning algorithm for classification problems. Random Forest Tree algorithm is the special form of Decision Tree algorithm. It is the combination of a large number of individual decision trees which works as an ensemble. All the individual decision trees perform a class prediction and the class with maximum votes becomes the model's prediction. The process what we have followed to implement Random Forest algorithm is given below:

- At first, we selected the number of decision trees in our random forest. We have taken 500 decision trees which is also known as an estimator.
- Then our ensemble learning algorithm has constructed decision trees based on the estimator. These decision trees have predicted the class labels individually.
- After that, there was a vote counting among all the individual predictions.
- Finally, the prediction with maximum votes has been our final prediction on the testing dataset.

After finishing the ensemble learning from the training dataset, we have implemented our Random Forest Tree model on the testing dataset where we have achieved 95.8% accuracy. Here, we have the confusion matrix to measure the performance of our trained model on the testing dataset. The confusion matrix is given below:

Index	pred:Walking	pred:Jogging	pred:Standing	pred:Upstair	pred:Downstair	pred:Sitting	pred:Sitting_Car	pred:Cycling
true:Walking	272	0	1	0	0	0	1	0
true:Jogging	0	251	0	0	0	1	11	12
true:Standing	0	0	275	0	0	0	0	0
true:Upstair	0	1	0	274	0	0	0	0
true:Downsta…	0	0	0	3	271	0	0	1
true:Sitting	0	0	0	0	0	275	0	0
true:Sitting…	0	13	0	0	0	0	258	4
true:Cycling	0	19	2	0	0	0	23	231

Figure 9: Confusion matrix of Random Forest Tree

d) Support Vector Machine (SVM): This supervised machine learning algorithm we have implemented also to recognize activities. The concept of hyperplane is directly related to this Support Vector Machine algorithm. This algorithm finds hyperplanes in multidimensional space. Here, the dimension depends on the number of input features. By using this algorithm we have found different possible hyperplanes with different margins among data points. Then we have maximized the margin between the support vector and hyperplane to get a maximum plane. Then our final hyperplane which works as a decision boundary has classified the activities on the dataset. Support Vector Machine has given us 96.7% accuracy on testing the dataset. This is the highest accuracy we have got among supervised machine learning algorithms. The confusion matrix is given below which measures the performance of this model.

Index	pred:Walking	pred:Jogging	pred:Standing	pred:Upstair	pred:Downstair	pred:Sitting	pred:Sitting_Car	pred:Cycling
true:Walking	273	0	0	0	0	0	0	1
true:Jogging	0	246	2	0	0	3	5	19
true:Standing	0	0	275	0	0	0	0	0
true:Upstair	0	0	0	275	0	0	0	0
true:Downstair	0	0	0	2	273	0	0	0
true:Sitting	0	0	0	0	0	275	0	0
true:Sitting_Car	0	2	2	0	0	0	262	9
true:Cycling	0	18	0	0	0	1	9	247

Figure 10: Confusion matrix of SVM

e) Gradient Boosting Classifiers: This is the last supervised traditional machine learning algorithm we have implemented to recognize the activities. Combination of many learning models that are comparatively weak is used to build a strong model for prediction. Mainly decision trees are used to boosting gradient. We have set 100 as number of boosting stages to perform. Because the more boosting stages results better performance. Algorithm gives us accuracy of 95%. Which is third highest accuracy among traditional algorithm. The confusion matrix is given below which measures the performance of this model.

Index	pred:Walking	pred:Jogging	pred:Standing	pred:Upstair	pred:Downstair	pred:Sitting	pred:Sitting_Car	pred:Cycling
true:Walking	272	0	0	0	0	0	1	1
true:Jogging	0	252	0	0	0	0	8	15
true:Standing	0	0	275	0	0	0	0	0
true:Upstair	0	3	0	271	1	0	0	0
true:Downstair	0	0	0	2	272	0	0	1
true:Sitting	0	2	0	0	0	273	0	0
true:Sitting_Car	0	14	0	1	0	0	245	15
true:Cycling	0	26	0	0	0	1	17	231

Figure 11: Confusion matrix of Gradient Boosting Classifier

f) 2D Convolutional Neural Networks (CNN): After implementing four machine learning algorithms, we have gone through deep learning algorithms. We have used a deep neural network known as CNN. This algorithm works in a different way that our conventional machine learning algorithms cannot do. Deep learning algorithms memic the functionalities of the human brain. Human brain is a combination of millions of neurons. These neurons are connected to each other and create a complete network among themselves. This network is used for different purposes such as calculation, predictive analysis, decision making etc. Deep learning models are invented based on that concept. Here, the process is gone through multiple steps which is known as layers. Each layer is connected to its previous layer. There are a lot of nodes in a specific layer which are known as activation functions. This is the main point where all the calculations are performed. We have implemented 2D CNN to classify the activities. To perform this algorithm we have chosen a window size and a hop size. Because, the 2D CNN takes the input as a frame. So, our window size was 80 and hope size was 40 which is to reduce the overlapping of sample data. Then we have used the “Relu” activation function which finds a pattern and maps between input and output by using probability analysis. By implementing three hidden layers with this activation function we have got different probabilistic values for individual classes (activities). Then we have taken the highest value and made a single output by using the “Softmax” activation function.

We have trained our CNN model on training dataset and then implemented this model on testing dataset. This 2D CNN model has given us 98.2% accuracy on testing the dataset. The confusion matrix is given below to understand the performance of CNN model.

Index	pred:Walking	pred:Jogging	pred:Standing	pred:Upstair	pred:Downstair	pred:Sitting	pred:Sitting_Car	pred:Cycling
true:Walking	220	0	0	0	0	0	0	0
true:Jogging	0	206	0	0	0	0	9	5
true:Standing	0	0	220	0	0	0	0	0
true:Upstair	0	0	0	220	0	0	0	0
true:Downstair	0	0	0	1	219	0	0	0
true:Sitting	0	0	0	0	0	220	0	0
true:Sitting_Car	0	5	0	0	0	0	210	5
true:Cycling	0	2	0	0	0	0	5	213

Figure 12: Confusion matrix of 2D CNN

g) Bi-Directional Long Short-Term Memory (Bi-LSTM): We have implemented our last algorithm named Long Short-Term Memory which is a type of recurrent neural network. This algorithm is popular for sequence prediction problems. As we have sequential data, this algorithm has performed better than other algorithms we implemented.

We have used bi-directional LSTM where it has presented each training sequence forwards and backwards to two separate recurrent nets direction. And both are connected to the same output layer. It helps the algorithm to perform on the data point in a given sequence where the algorithm already knows the sequential information about other points before and after that given sequence.

By implementing bi-directional LSTM, we have achieved 99.3% accuracy on our testing dataset which is the highest accuracy among all our implemented algorithms. We can measure the performance of this algorithm from the confusion matrix which is given below.

Index	pred:Walking	pred:Jogging	pred:Standing	pred:Upstair	pred:Downstair	pred:Sitting	pred:Sitting_Car	pred:Cycling
true:Walking	274	0	0	0	0	0	0	0
true:Jogging	0	269	0	0	0	0	0	6
true:Standing	0	0	273	0	0	1	0	1
true:Upstair	0	0	0	271	4	0	0	0
true:Downstair	0	0	0	0	275	0	0	0
true:Sitting	0	0	0	0	0	275	0	0
true:Sitting_Car	0	1	0	0	0	0	273	1
true:Cycling	0	2	0	0	0	0	0	273

Figure 13: Confusion matrix of Bi-Directional LSTM

3.5 IMPLEMENTATION REQUIREMENTS

- Windows & Linux Operating System. ● Anaconda Navigator with Python 3.7.
- Spyder IDE (Integrated Development Environment).
- Libraries: Pandas, Numpy for data preprocessing.
- Libraries: Matplotlib for data visualization and graph plotting.
- ScikitLearn, Scipy, TensorFlow, Keras for implementing different algorithms.

CHAPTER 4 EXPERIMENTAL RESULTS AND DISCUSSION

4.1 EXPERIMENTAL SETUP

Our main purpose of this experiment was to recognize human's daily life activities with promising accuracy based on phone sensor data where our implemented algorithms can classify selected activities even those activities which have quite similar pattern or action.To get better results we included two devices at the data collection period. One device was in pocket and the other was tied in the wrist. And we collected accelerometer and gyroscope sensor data from both of the devices. The android application which we used to collect sensor data was set up with a 50Hz sampling rate. So, it was able to collect 50 samples per second which helped us to get less noisy data. And, there was a filter in our used application to reduce the unnecessary noises.Then the next part of the experiment was data preprocessing and model implementation. We have set up with Python 3.7 version and Spyder which is an integrated development environment (IDE). We installed a few frameworks such as scikit-learn, tensorflow, keras etc. for the model implementation purpose. Along with these we used some libraries such as pandas, numpy, scipy etc. for data preprocessing purposes. So, this is the complete experimental setup in which we performed different experiments to get the desired result.

4.2 EXPERIMENTAL RESULTS AND ANALYSIS

In the past two decades there have been many attempts to recognize human activities with precision. From our experiment we will show that, when we combine the accelerometer and gyroscope data from pocket and wrist in columns as features, it is possible to detect and recognize a wide variety of activities with precision. The dataset we built and experimented with gives us the result according to our hypothesis. Here is the in depth analysis of accuracies obtained from different combinations of sensors if not used all those together. It will be evident how the accuracy gets affected if we remove one or more sensors from our model.

Table 3: Data collected from wrist. Sensor: Accelerometer and Gyroscope

Algorithms	Lower Bound(f1-score)	Upper Bound(f1score)	accuracy
Logistic Regression	0.08	0.96	63%
Random Forest	0.76	0.98	90%
K-NN	0.63	1.00	85%
SVM	0.72	1.00	87%
Gradient Boosting Classifier	0.76	1.00	89%
CNN	0.77	0.99	90%

Bi-directional LSTM	0.66	0.99	84%

When we try to recognize human activities from accelerometer and gyroscope sensor data from the device placed on the wrist, the models do not perform very well. In Table 3, we can see that the best performing model here is CNN. It has predicted all the activities with 90% accuracy. But on individual activity level, we can see that the lowest f1-score is only 0.77. So it is evident that though some activity was detected quite accurately as the upper bound f1-score is 0.99, but to detect some activities CNN did struggle.

Table 4: Data collected from pocket. Sensors: Accelerometer and Gyroscope

Algorithms	Lower Bound(f1-score)	Upper Bound(f1-score)	Accuracy
Logistic Regression	0.47	1.00	83%
Random Forest	0.89	1.00	96%
K-NN	0.89	1.00	95%
SVM	0.90	1.00	96%
Gradient Boosting Classifier	0.85	1.00	94%
CNN	0.93	1.00	97%
Bi-directional LSTM	0.88	1.00	96%

Table 5: Using only accelerometer data. Device Location: Wrist and pocket

Algorithms	Lower Bound(f1-score)	Upper Bound(f1-score)	accuracy
Logistic Regression	0.46	1.00	79%
Random Forest	0.84	1.00	95%

K-NN	0.74	1.00	92%
SVM	0.64	1.00	86%
Gradient Boosting Classifier	0.78	1.00	93%
CNN	0.87	1.00	95%
Bi-directional LSTM	0.86	1.00	94%

When the accelerometer and gyroscope data is used from a device placed in the pocket we can see in Table 4, most of the algorithms perform well achieving 96% to 97% accuracy. But the Lower bound score still did not reach up to the expected point. Though it is better than the data used in Table 3. So to predict different activities accurately, data from only the pocket is not sufficient here.

If only accelerometer data is used (Table 5) from two devices placed in the pocket and wrist the models do not improve at all. Here best performed algorithms are CNN and Random Forest. Their Lower bound f1-scores are still very low. Some activities were recognized without any error though as the upper f1-score are perfect 1.00. But what we want is to detect all the activities with least margin of error.

Table 6: Using only gyroscope data. Device location: Wrist and pocket

Algorithms	Lower Bound(f1-score)	Upper Bound(f1-score)	Accuracy
Logistic Regression	0.23	0.61	41%
Random Forest	0.74	0.99	86%
K-NN	0.62	1.00	76%

SVM	0.03	0.99	72%
Gradient Boosting Classifier	0.71	1.00	86%
CNN	0.88	1.00	93%
Bi-directional LSTM	0.85	1.00	91%

In Table 6, the models are in no way any better than the previously analyzed situations. But what we can understand from these is, if we put all the data together they will add up additional information when the data overlap for two or more activities in one sensor or device. So the accuracy will improve as we claim in our hypothesis.

Finally the models are built using accelerometer and gyroscope data taken from pocket and wrist altogether as features. Looking at Table 7, it can be easily seen that all the models scaled up a lot. Our best performed model in Bi-directional LSTM. It has a lower bound f1-score of 0.99 which is very accurate and perfect for a model that can recognize human activities with very much precision. In our dataset we took data of activities that are very similar in action and hard to distinguish between. For example sitting in a chair at home, sitting in a can both are very similar in action. Sitting and standing are very stationary in action. But all those were recognized very accurately by Bi-directional LSTM.

Table 7: Using all the devices and sensors together. Device location: Wrist (Accelerometer and Gyroscope) and Pocket (Accelerometer and Gyroscope).

Algorithms	Lower Bound(f1-score)	Upper Bound(f1-score)	Accuracy
Logistic Regression	0.60	0.99	84.2%
Random Forest	0.89	1.00	95.8%

K-NN	0.74	1.00	90.7%
SVM	0.90	1.00	96.7%
Gradient Boosting Classifier	0.85	1.00	95%
CNN	0.94	1.00	98.2%
Bi-directional LSTM	0.99	1.00	99.3%

4.3 DISCUSSION

After completing every possible analysis we have realized that there can be various results depending on the way of collecting data, choosing sensors and implementing methods. It is proved that increasing the number of sensing devices can increase the possibility of getting better results. Along with that including both accelerometer and gyroscope sensors helped us to get high accuracy. On the other wrist, we have implemented both machine learning and deep learning models in our experiment. We have seen that deep learning models, specially, Bi-directional Long Short-Term Memory (LSTM) have the highest accuracy of 99.3%. Then the second highest accuracy is 98.2% which was given by 2D Convolutional Neural Networks (CNN).

But only Support Vector Machine (SVM) has given the best accuracy of 96.7% among all the machine learning algorithms. It is possible to improve the accuracy by including more sensing devices. We will further work on this to ensure the best possible accuracy.

CHAPTER 5 IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 IMPACT ON SOCIETY

This project will have its impact on the environment in different ways. If activity can be recognized accurately we can monitor patient’s activity and analyze their posture which will be a huge advantage in healthcare. Development of IoT, smart homes, has become a new technological trend. We can integrate this model with IoT based devices and be able to monitor toddlers too. Also it is possible to monitor the activity of members in a home and analyze their pattern of lifestyle. By that we can figure out a lot of useful information about their health and behavior. So, it will directly facilitate different aspects of daily life.

5.2 IMPACT ON ENVIRONMENT

As we are using 4 sensors simultaneously, devices will have high power consumptions. But as the technology improves, sensors are being more efficient in terms of power consumptions and smart devices having larger and efficient battery day by day. Batteries are evolving too in their architectures. So in future, we are hoping that this problem will be resolved and our project will have its impact at its full potential.

5.3 ETHICAL ASPECTS

We need personal information for our work. We have to be cautious about it. Without proper authorization, the personal data of an individual cannot be used. We need to let them know how much information and what kind of information we are gathering and what our reason is behind this. We have to strictly maintain people's privacy here.

5.4 SUSTAINABILITY PLAN

Human activity recognition is a very important task which has lots of important implications in the healthcare system and safety for elderly and toddlers. There is yet to be discovered how this is going to benefit us with the advancement of technology. Our goal is to detect a wide range of activities with the help of two data points which are wrist and pocket. Because these two devices are expected to exist in the future. From these two data collection points we can almost detect any activities which will benefit us in a great deal.

CHAPTER 6 SUMMARY, CONCLUSION, RECOMMENDATION, AND IMPLICATION FOR FUTURE RESEARCH

6.1 SUMMARY OF THE STUDY

Human activity recognition has been a popular research area concerned with identifying the specific movement or action of a person based on a variety of sensor data.[13] Sensor generated enormous data in seconds so recognizing activity from these data is quite a challenging task. The widespread usage of portable and wearable smart devices such as smartphones and smart watches has enabled the easy gathering of human activity data using various device-embedded sensors [14].

We have recorded activity from 17 subjects. We have seen that only an accelerometer or only gyroscope is not enough to identify all activity precisely. Accelerometer and gyroscope both used to identify activities. But a wide range of activity can’t be identified with precision with this method. So we have placed two smartphones with accelerometer and gyroscope, one in wrist and another one in pocket.

We have recorded activity from those two sources. This helps us to identify wide ranges of activity with precision. We worked on a total of eight activities. Various types of traditional machine learning algorithm and deep learning algorithm were implemented. Logistic regression, K-Nearest Neighbors, Random forest tree, Support vector machine (SVM), 2D Convolutional Neural Networks (CNN) and Bi-Directional Long Short-Term Memory (Bi-LSTM) were implemented on our dataset. We have seen that among them performance of Logistic Regression was not satisfactory. It gives us 84.2% accuracy. While all other algorithms give us accuracy of more than 90%. Bi-Directional LSTM performed quite well. We have achieved 99.3% of accuracy on our dataset using Bi-directional LSTM. Also It has an upper bound (f1 score) of 0.99 which is very accurate and perfect for the model that can recognize human activities. We have further plans with this project. Eight activities were recorded in this project. We will add more activities and also we will try to explore more deep learning algorithms or CNN architecture to increase the performance of our model.

6.2 CONCLUSION

Human Activity Can be recognized in different ways using different algorithms and sensors placing the devices in different places of a human body. But the aim is how accurately we can recognize an activity and most importantly if we can detect complex activities that might be similar in actions. Our Research project introduces an optimal way to recognize the activity by using accelerometer and gyroscope sensors from pocket and wrist. This helped us to accurately identify the eight activities where some of them are difficult to distinguish between for the similarities among them. Different traditional and Deep learning algorithms have been applied in our dataset. Among them Bi-directional LSTM gives optimal accuracy. Bidirectional LSTM gives us 99.3% of accuracy which is comparatively better.

In Our work we have collected data from two different sources. Data has been collected with the same frequency with the help of two smartphones. Smartphone with accelerometer and gyroscope sensor placed on pocket and wrist. Thus we can get data of an activity from two sources. This helps us to recognize those eight activities effectively.

6.3 IMPLICATION FOR FURTHER STUDY

We have further plans for this research project. For now eight activities are recognized in this project. We will add more activities in this project. We will try to explore different CNN architecture or deep learning algorithms to get better performance from our dataset.

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