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Human Activity Recognition using SVM, KNN & Logistic Regression

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***Abstract*— Nowadays, Human activity recognition (HAR) is a very active yet challenging and demanding area and it has most popular uses of machine learning algorithms. HAR has a very significant role in different fields such as health care, theft detection, work monitoring in an organization and detecting emergencies, sports, smart home-based, childcare, security or work safety, human computer interaction, video surveillance system, robotics, daily monitoring, wildlife observation, and other diverse areas.**

However, identifying human activities and actions is challenging from video sequences or still images is a challenging task due to the complexity of activities, speed of action, dynamic recording, background clutter, partial occlusion, changes in scale, viewpoint, lighting, and appearance and diverse application areas. Besides that, all the actions and activities are performed in distinct situations and backgrounds. Many applications, including video surveillance systems, human-computer interaction, and robotics for human behavior characterization, require a multiple activity recognition system.

There is a lot of work done in HAR; finding a suitable algorithm and sensors for a certain application area is still challenging. Here by using its embedded accelerometer or gyroscope in the classification model, SVM, KNN, and Logistic regression is implemented. The purpose of this paper is, to solve the HAR problem under wireless body area network to achieve the profitable HAR method.

***Index Terms*— Body Acceleration, Human Activity Recognition, K-Nearest Neighbor, Machine Learning, Postural Transitions, Support Vector Machine, Wireless Body Area Network.**

I. Introduction

Detecting human activity is also needed to automate systems to monitor ambient and detect suspicious activity while performing surveillance. Besides, providing appropriate information about individuals is a necessary task in pervasive computing[1].

Purpose For achieving the profitable HAR method aims to provide information on human physical activity and to detect simple or complex actions in a real-world setting. It allows computer systems to assist users with their tasks and to improve the quality of life in areas such as senior care, rehabilitation, daily life logging, personal fitness, and assistance for people with cognitive disorders. In the present scenario, it becomes important to model the active learning paradigms with the help of wearable sensors for analysing human activities. Wireless Body Area Network (WBAN) is a novel technology with the incorporation of numerous types of devices, which is also employed in health monitoring applications. Human activity recognition (HAR) receives more interest in recent times along with wearable sensors. HAR system provides information about a person's identity, personality, and psychological state. The main intent of this paper is to implement the WBAN-based HAR system using the improved deep learning model. Although various deep learning models and existing algorithms secure better outcomes through the sensor data analysis regarding HAR, the decision-making evaluation seems to be a complex one. this paper solves the HAR problem under WBAN using a developed ensemble learning approach[2].

Here a new smartphone-based online HAR system for classifying activities based on a multi-class support vector machine (SVM) that performs activity probability estimation for each activity is proposed to avoid reduction in performance, compared to other available activities because of low incidence and short duration most HAR methods ignore transitions between activities, thus to improve its performance combining the predictions from previous samples, these estimates are interpreted as activity probability signals, and eventually, they are heuristically filtered to improve classification accuracy during PT(Postural Transitions).

Due to the rapid development of smart gadgets and technologies, the value of ubiquitous systems has become a significant attraction for researchers, Here by using the records of the people as BA (Body Acceleration) and PT a HAR dataset is introducing for research purposes. Two main approaches for deployment of HAR systems are external and wearable sensors[3].

A. External Approach

In the external approach, the monitoring devices are set at fixed points, and users are expected to interact with them. The vision-based technique, for example, is one of the well-known external methods that have been extensively studied for human activity analysis. However, it faces many challenges in terms of coverage, accuracy, privacy, and cost. It requires infrastructure support, such as the installation of video cameras in surveillance areas, which is usually costly. Additionally, cameras cannot capture any data if the user performs out of their reach [4].

B. Wearable Approach

In the wearable approach, on-body sensors, such as accelerometers, gyroscopes, and magnetometers, are used to translate human motion into signal patterns for activity recognition. Recent advances in embedded sensor technology have made it feasible to monitor the user’s activity using smart devices. Several research studies have reported the use of smart watches and smart phones in human activity monitoring, and have presented a satisfactory performance. Although these devices provide a privacy-aware alternative solution that overcomes many disadvantages of the external approach, they still might not be able to address the requirements of a diverse range of applications[5].

II. HUMAN ACTIVITY RECOGNITION AND TYPES

Human activity recognition (HAR) can be referred to as the art of identifying and naming activities using Artificial Intelligence (AI) from the gathered activity raw data by utilizing various sources (so-called devices).

Typically, HAR consists of four stages shown in Figure:1 including

- Capturing of signal activity
- Data pre-processing
- AI-based activity recognition
- User interface for the management of HAR.

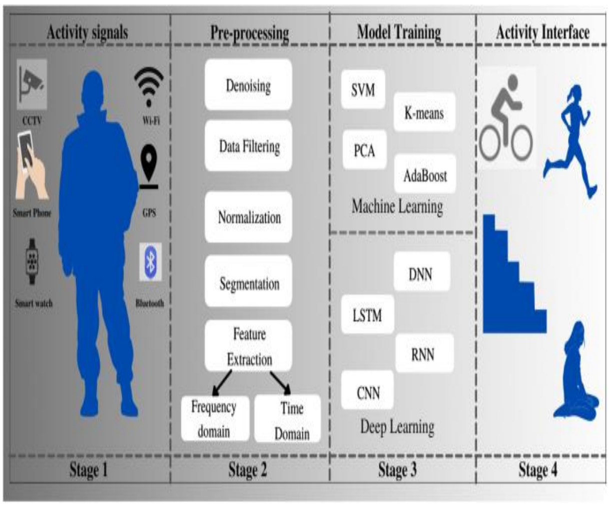


Figure:1 HAR Stages

Each stage can be implemented using several techniques bringing the HAR system to have multiple choices. Thus, the choice of the application domain, the type of data acquisition device, and the processing of artificial intelligence (AI) algorithms for activity detection makes the choices even more challenging[6]. Types of Human activity recognition are as:

A. Sensor-based, single-user activity recognition

Sensor-based activity recognition is a challenging task due to the inherent noisy nature of the input. Thus, statistical modeling has been the main thrust in this direction in layers, where the recognition at several intermediate levels is conducted and connected. At the lowest level where the sensor data are collected, statistical learning concerns how to find the detailed locations of agents from the received signal data. In sensor-based activity recognition

Empowering ubiquitous computers and sensors to monitor the behavior of a subject. This Sensor-based activity recognition integrates the emerging area of sensor networks with novel data mining and machine learning techniques to model a wide range of human activities. Today's smart phones provide sufficient sensor data and calculation power to enable physical activity recognition to provide an estimation of the energy consumption during everyday life[7].

B. Sensor- based, multi-user activity recognition

The fundamental problem of recognizing activities for multiple users from sensor readings in a home environment, and propose a novel pattern mining approach to recognize both single-user and multi-user activities in a unified solution. acceleration sensors were used for identifying group activity patterns during office scenarios, Whereas for multiple users by using on-body sensors first appeared in the work by ORL using active badge systems[8].

C. Sensor-based group activity recognition

Group behavior is emergent in nature, meaning that the properties of the behavior of the group are fundamentally different than the properties of the behavior of the individuals within it, or any sum of that behavior. Group activity recognition has applications for crowd management and response in emergency situations, as well as for social networking and quantified self applications.

The main challenges are in modeling the behavior of the individual group members, as well as the roles of the individual within the group dynamic. Challenges which must still be addressed include quantification of the behavior and roles of individuals who join the group, integration of explicit models for role description into inference algorithms, and scalability evaluations for very large groups and crowds[9].

D. Vision-Based Activity Recognition

In vision-based activity recognition, the machine method is usually divided into four steps, precisely human recognition, human pursuit, activity recognition, and high-level activity analysis. This visually based activity recognition work usually appears to be the ICCV (IEEE Computer Society Conference) and CVPR (Computer Vision and Pattern Recognition) scientific conferences[10].

With the recent emergency of deep learning, RGB video based activity recognition has seen rapid development. It uses videos captured by RGB cameras as input and perform several tasks, including: video classification, detection of activity start and end in videos, and spatial-temporal localization of activity and the people performing the activity[11].

III. SVM, KNN AND LOGISTIC REGRESSION

Generally, activities are recognized from a series of actions performed by the human through vision-based sensors or non vision based sensors. Due to the articulated nature of human motion, it is not trivial to detect human activity with high accuracy for all applications[12]. For performance analysis in Human Activity Recognition system following steps need to be executing as mentioned in below Figure 2.

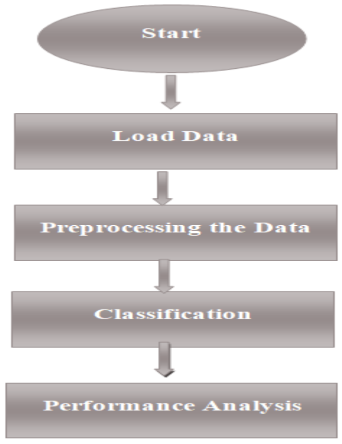


Figure 2: Flow Diagram for Performance Analysis

Here for input data, dataset of Human Activity Recognition (HAR) is utilizing. Whereas all the predicted data using K-means algorithm. To evaluate performance of human activity recognition system, using classification methods in the classification algorithm including SVM, KNN, and Logistic Regression. After getting experimental results from SVM (Support Vector Machine), KNN (K-Nearest Neighbor), and Logistic Regression, analyzing accuracy of each algorithm and display the visualization graph here shown in Figure 3.

The Modules for Human Activity Recognition system is as:

- Data Selection and Loading
- Data Preprocessing
- Splitting Dataset into Train and Test Data
- Classification
- Prediction
- Result Generation

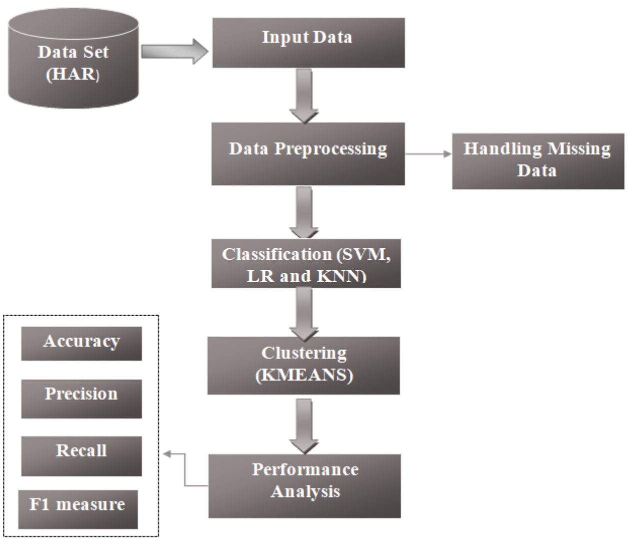
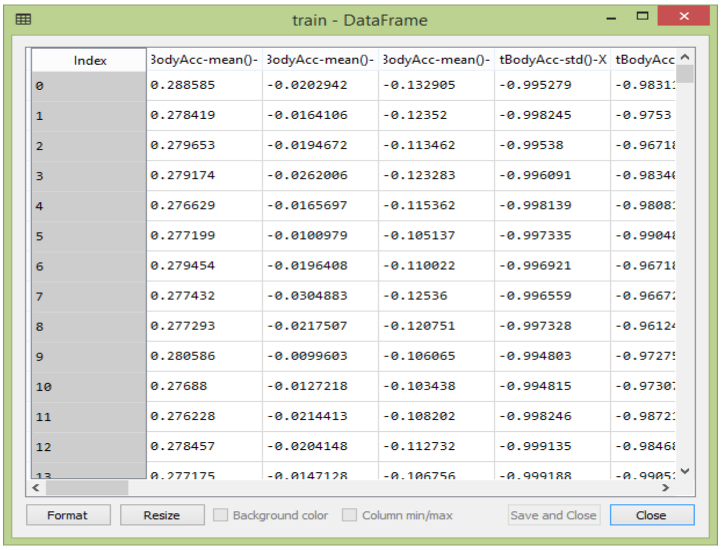


Figure 3: Flow Diagram

A. Data Selection and Loading

From the inertial sensor the input data of different actions as Sitting Down, Standing up, Walking Upstairs, Walking Downstairs, Normal Walking and Laying are collected by utilizing 30 different subject Smartphone's. Here for "X" the train and test dataframe are shown in Figure 4(a),(b) Data frame of Train and Test Dataset.



train - DataFrame

Index	3odyAcc-mean()-	3odyAcc-mean()-	3odyAcc-mean()-	tBodyAcc-std()-X	tBodyAcc
0	0.288585	-0.0202942	-0.132905	-0.995279	-0.9831
1	0.278419	-0.0164106	-0.12352	-0.998245	-0.9753
2	0.279653	-0.0194672	-0.113462	-0.99538	-0.9671
3	0.279174	-0.0262006	-0.123283	-0.996091	-0.9834
4	0.276629	-0.0165697	-0.115362	-0.998139	-0.9808
5	0.277199	-0.0100979	-0.105137	-0.997335	-0.9904
6	0.279454	-0.0196408	-0.110022	-0.996921	-0.9671
7	0.277432	-0.0304883	-0.12536	-0.996559	-0.9667
8	0.277293	-0.0217507	-0.120751	-0.997328	-0.9612
9	0.280586	-0.0099603	-0.106065	-0.994803	-0.9727
10	0.27688	-0.0127218	-0.103438	-0.994815	-0.9730
11	0.276228	-0.0214413	-0.108202	-0.998246	-0.9872
12	0.278457	-0.0204148	-0.112732	-0.999135	-0.9846
13	0.277175	-0.0147128	-0.106756	-0.999188	-0.9905

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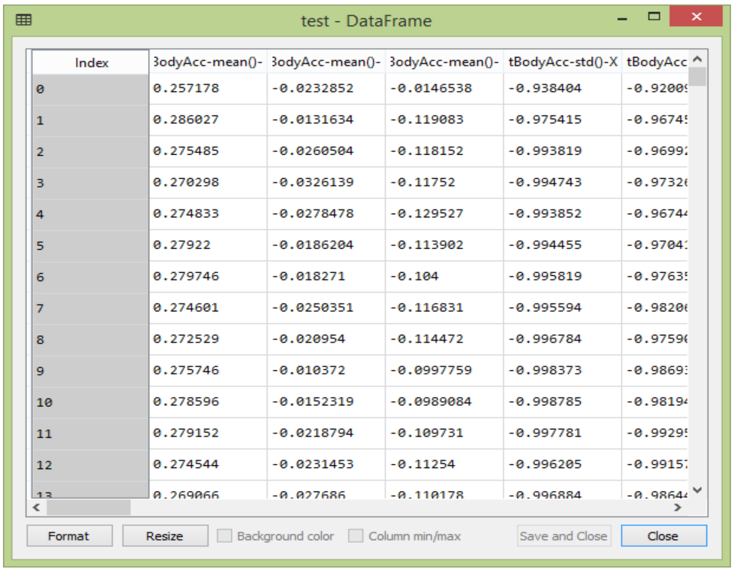
Figure 4(a): Train Dataset.



test - DataFrame

Index	3odyAcc-mean()-	3odyAcc-mean()-	3odyAcc-mean()-	tBodyAcc-std()-X	tBodyAcc
0	0.257178	-0.0232852	-0.0146538	-0.938404	-0.9200
1	0.286027	-0.0131634	-0.119083	-0.975415	-0.9674
2	0.275485	-0.0260504	-0.118152	-0.993819	-0.9699
3	0.270298	-0.0326139	-0.11752	-0.994743	-0.9732
4	0.274833	-0.0278478	-0.129527	-0.993852	-0.9674
5	0.27922	-0.0186204	-0.113902	-0.994455	-0.9704
6	0.279746	-0.018271	-0.104	-0.995819	-0.9763
7	0.274601	-0.0250351	-0.116831	-0.995594	-0.9820
8	0.272529	-0.020954	-0.114472	-0.996784	-0.9759
9	0.275746	-0.010372	-0.0997759	-0.998373	-0.9869
10	0.278596	-0.0152319	-0.0989084	-0.998785	-0.9819
11	0.279152	-0.0218794	-0.109731	-0.997781	-0.9929
12	0.274544	-0.0231453	-0.11254	-0.996205	-0.9915
13	0.269066	-0.027686	-0.110178	-0.996884	-0.9864

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Figure 4(b): Test Dataset.

B. Data Preprocessing

Here machine learning algorithms require input and output variables in numerical format only, so to erase not required data from input dataset, this pre-processing is needful. Numeric number "0" is replaced in such cases like appeared null values, missing or blank values. As well to remove unwanted data from the input dataset this data pre-processing process is needful[13].

C. Splitting Dataset into Train and Test Data

In Data splitting, for re-examine purpose the observed data splitting into two portion, the main data portion is utilizing for training and to develop a predictive model thus known as education set or training set, and remaining or smaller data portion is used for validate purposes thus known as testing set[14]. Here for “X” the processed train and test data set are shown in Figure 5(a),(b) respectively.

x_train - DataFrame

Index	3odyAcc-mean()-	3odyAcc-mean()-	3odyAcc-mean()-	tBodyAcc-std()-X	tBodyAcc
0	0.288585	-0.0202942	-0.132905	-0.995279	-0.9831
1	0.278419	-0.0164106	-0.12352	-0.998245	-0.9753
2	0.279653	-0.0194672	-0.113462	-0.99538	-0.9671
3	0.279174	-0.0262006	-0.123283	-0.996091	-0.9834
4	0.276629	-0.0165697	-0.115362	-0.998139	-0.9808
5	0.277199	-0.0100979	-0.105137	-0.997335	-0.9904
6	0.279454	-0.0196408	-0.110022	-0.996921	-0.9671
7	0.277432	-0.0304883	-0.12536	-0.996559	-0.9667
8	0.277293	-0.0217507	-0.120751	-0.997328	-0.9612
9	0.280586	-0.0099603	-0.106065	-0.994803	-0.9727
10	0.27688	-0.0127218	-0.103438	-0.994815	-0.9730
11	0.276228	-0.0214413	-0.108202	-0.998246	-0.9872
12	0.278457	-0.0204148	-0.112732	-0.999135	-0.9846
13	0.277175	-0.0147128	-0.106756	-0.999188	-0.9905

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Figure 5(a): Dataframe of Train Dataset_X

x_test - DataFrame

Index	3odyAcc-mean()-	3odyAcc-mean()-	3odyAcc-mean()-	tBodyAcc-std()-X	tBodyAcc
0	0.257178	-0.0232852	-0.0146538	-0.938404	-0.9200
1	0.286027	-0.0131634	-0.119083	-0.975415	-0.9674
2	0.275485	-0.0260504	-0.118152	-0.993819	-0.9699
3	0.270298	-0.0326139	-0.11752	-0.994743	-0.9732
4	0.274833	-0.0278478	-0.129527	-0.993852	-0.9674
5	0.27922	-0.0186204	-0.113902	-0.994455	-0.9704
6	0.279746	-0.018271	-0.104	-0.995819	-0.9763
7	0.274601	-0.0250351	-0.116831	-0.995594	-0.9820
8	0.272529	-0.020954	-0.114472	-0.996784	-0.9759
9	0.275746	-0.010372	-0.0997759	-0.998373	-0.9869
10	0.278596	-0.0152319	-0.0989084	-0.998785	-0.9819
11	0.279152	-0.0218794	-0.109731	-0.997781	-0.9929
12	0.274544	-0.0231453	-0.11254	-0.996205	-0.9915
13	0.269066	-0.027686	-0.110178	-0.996884	-0.9864

Format Resize Background color Column min/max Save and Close Close

Figure 5(b): Dataframe of Test Dataset_X

D. Classification

- **Support Vector Machine (SVM):** For classification and Regression problems this Supervised learning algorithm is used, However, primarily, SVM utilizing for classification challenges appear in ML. This algorithm also useful for face detection, image classification, text categorization, etc. The goal of the SVM algorithm is to create the best line or decision boundary (known as Hyper-Plane) that can

```
Logistic Regression accuracy: 95.86019681031559%
---Classification Report---
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00       537
         1.0       0.87      0.96      0.92       445
         2.0       0.97      0.90      0.93       575
         3.0       0.99      0.94      0.97       522
         4.0       0.96      0.99      0.98       408
         5.0       0.94      0.97      0.96       460

    accuracy                           0.96      2947
   macro avg       0.96      0.96      0.96      2947
weighted avg       0.96      0.96      0.96      2947
```

segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. The SVM accurate values are mentioned here. SVM can be of two types one as Linear SVM and another is Non-linear SVM[15].

- **K-Nearest Neighbor (KNN):** The k-nearest neighbors algorithm, also known as KNN or k-NN, is a non- parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point. While it can be used for either regression or classification problems, it is typically used as a classification algorithm, working off the assumption that similar points can be found near one another [16]. The k-nearest neighbors classifier values are:

```
K Nearest Neighbors Classifier accuracy: 90.02375296912113%
---Classification Report---
              precision    recall  f1-score   support

         0.0       0.99      1.00      1.00       534
         1.0       0.79      0.91      0.85       428
         2.0       0.93      0.83      0.88       596
         3.0       0.98      0.85      0.91       570
         4.0       0.79      0.94      0.86       353
         5.0       0.89      0.90      0.89       466

    accuracy                           0.90      2947
   macro avg       0.90      0.90      0.90      2947
weighted avg       0.91      0.90      0.90      2947
```

- **Logistic Regression:** It is one of the most popular ML algorithms, which comes under the Supervised Learning technique. It is used for predicting the categorical dependent variable using a given set of independent variables. It predicts the output of a categorical dependent variable according to input values[17]. Therefore the outcome must be a categorical or discrete value, which is the requirement of Activity Recognition system. It can be either Yes or No, 0 or 1, true or False, etc. but instead of giving the exact value as 0 and 1, it gives the probabilistic values which lie between 0 and 1. The logistic regression accurate values are

```
Training Data :(7352, 563)
null values in train_data :False
Testing Data :(2947, 563)
null values in test_data :False
```


```
Logistic Regression accuracy: 95.86019681031559%
---Classification Report---
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00       537
         1.0       0.87      0.96      0.92       445
         2.0       0.97      0.90      0.93       575
         3.0       0.99      0.94      0.97       522
         4.0       0.96      0.99      0.98       408
         5.0       0.94      0.97      0.96       460

    accuracy                           0.96      2947
   macro avg       0.96      0.96      0.96      2947
weighted avg       0.96      0.96      0.96      2947
```

- **Prediction:** Predictive analytics algorithms try to achieve the lowest error possible by either using "boosting" (a technique which adjusts the weight of an observation based on the last classification) or "bagging" (which creates subsets of data from training samples, chosen randomly with replacement)[18].

IV. PERFORMANCE ANALYSIS

Here to analyse the human activity recognition like walking, sitting, standing and lying, three different techniques as SVM, KNN and Logistic regression is used and by the observed experimental results the Accuracy of each algorithm and display the visualization graph is shown below in Figure 6.

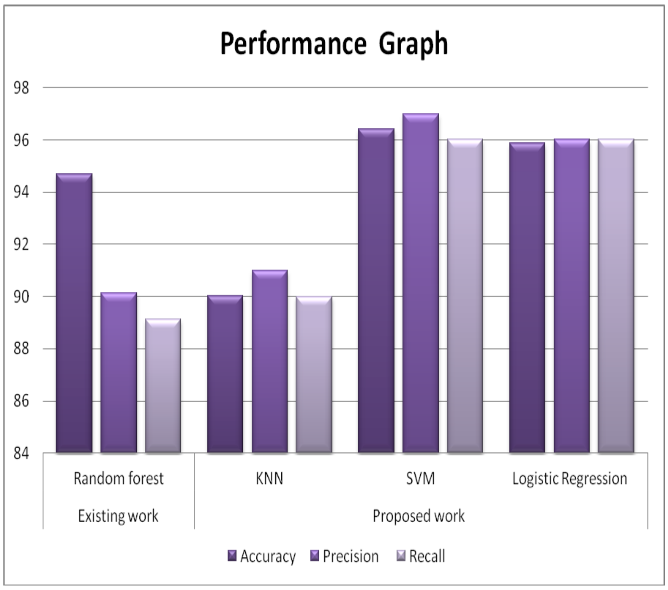

Figure 6: SVM, KNN and LR Performance Graph

V. CONCLUSION

The simulation has performed on python software. After analysis the human activity recognition like walking, sitting, standing and laying the observed classification accuracy among three machine learning classifiers is as shown in Figure 7.

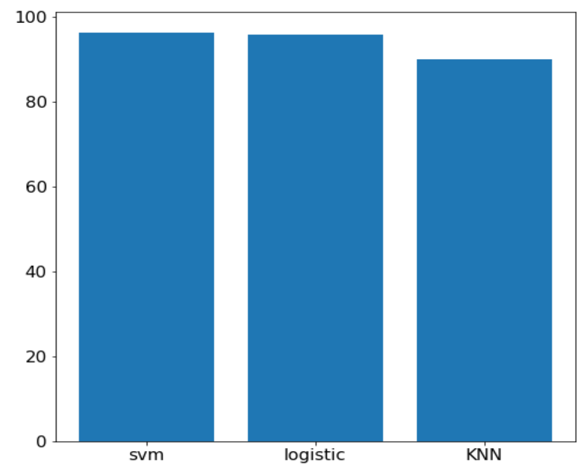

Figure 7: Classification Accuracy

By this comparative study among SVM, KNN and Logistic regression techniques it is observed that SVM classification shows better performance in comparison to Logistic Regression and KNN.

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