Smart Phone Sensor Data: Comparative Analysis of Various Classification Methods for Task of Human Activity Recognition

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***Abstract*—Human Activity Recognition has a long history of research and requires further exploration to produce useful and optimal outcomes. Areas such as medicine, daily routine, and security are some benefits that smartphone enables via embedded sensors. Our work has chosen sensor data of six activities such as standing, walking, laying from pre-recorded dataset gathered via smartphone to evaluate the performance of various supervised machine learning algorithms. The results suggest that logistic regression has been an optimal choice based on experiments. Whereas, the Support Vector Machine (SVM) has shown to perform well with ninety-five percentage accuracy.**

Keywords—HAR, Classification, RNN, Ensemble, SVM, Machine, Learning, Activity Recognition

I. Introduction

Smartphones now come equipped with a wide range of sensors capable of detecting and recognizing human activity at a reasonable price, thus making it easier for the digital world to recognize human activities. Several ways to recognize various human activities have been explored by researchers [1]. The most common embedded sensors in smartphones are an accelerometer, a gyroscope and magnetometer that the researcher used to perform Human Activity Recognition (HAR). According to statistics, about 3.5 billion users use smartphones globally, and it published lot of its sensor data as a standard dataset at UCI Machine Learning Repository [2]. It employs these standard datasets to evaluate the performance of various designed algorithms in recognizing human activities.

We can see the importance of recognizing human activities. It enables users to track their activities. For instance, statistics about how much training a user does per day and the type of activity they perform. Additionally, it has helped diabetic and cardiac patients to maintain fitness. In this work, we have analyzed the effectiveness of HAR using different algorithms that are categorized as linear, non-linear, ensemble, and artificial neural networks. While each classifier performs well on a dataset, results suggest the SVM performed with about 95% accuracy followed by ensemble learning methods such as the extra tree and gradient boosting. Linear and non-linear models and recurrent neural networks are not as effective. However, their testing accuracy out of training is incredible.

The paper organization is as follows. Section II describes related work followed by extensive experimental work to analyse various classification techniques. Later, results and their comparison with report algorithms are discussed in section IV. The paper concludes and future work in the section VI.

II. Related Work

HAR is a combination of signal processing and classification techniques [3]. It has been categorized into physical activities and video-based recognition of activities. Further, physical activities are classified into wearable and object-based recognition [4].

Various approaches built on a particular data characteristic have appeared [4], [5], [6]; however, algorithms used for classification do not support easy modification to the system, e.g., including more activities and a new paradigm directed toward improving the accuracy of recognition and systems effectiveness. To enhance the effectiveness of recognition, researchers described the categorization of action based on data patterns. The classification model builds on 10 volunteer datasets achieved around 90% accuracy using 11 activities [7]. However, the different classification model has required for each group.

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In [5], the authors use five accelerometer sensors on different parts of the body achieved accuracy up to 84%, assuming it can improve the accuracy with an increase in number of sensors. In comparison, the authors in [8] showed that accuracy improved by increasing data samples. In [9], the authors describe a model to add different activities into the system; however, it increased the system's complexity. Proposed model [10] suggests, it can improve the accuracy to some extent if uses the adaptive time window method. Authors [11] improve the accuracy with the help of proper orientation and location of a smartphone. Whereas [12] suggests that more sensors may be the reason for an excellent performance. [13] suggests SVM has strong stability.

Surveys conducted in [10], [11], [12], [13] that HAR using wearable sensors show various concerns. A classification paradigm becomes more complex, less accurate, and inefficient as it relies on the running procedure of a machine learning algorithms. It requires sufficient power to monitor routine activity and complex classifiers are the reason for high power consumption [14]. Real-time data collection from smartphone and feature selection described [1], [15].

A study in [6] concludes that certain statistical features give an insight into the activity's data pattern, as data pattern analysis helps to divide the exercises into various groups, which are later used to build different classification models for each group to reduce the complexity and increase efficiency.

III. Experimental Work

To evaluate the performance of detecting and classifying human activities, we chose a standard data set from UCI Machine Learning Repository [2]. This repository is freely available and widely used as a benchmark. The dataset is named “Human Activity Recognition using Smartphone Dataset Version 1.0”.

The dataset is divided into two parts for training and testing [16], [17]. Seventy percent (70%) of which is used for training and the rest 30% is used for testing. There are 10299 instances and 561 attributes in total; however, the dataset is already preprocessed, having 30 subjects, ranging in age from 19 to 48. The accelerometer and gyroscope sensors on the Samsung Galaxy S II were used to collect this data.

Fig. 1 shows the distribution of features used by different sensors such as accelerometers, gyroscopes, and others. In Fig. 1, the y-axis represents the number of features, and the x-axis represents the motion sensors.

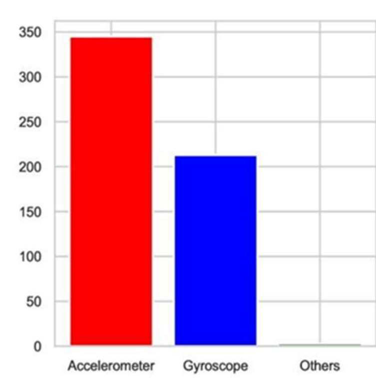

Fig. 1. Motion Sensors and Body Movement Features

TABLE I. ASSIGNED LABELS TO ACTIVITIES NAME

Activities Name	Activities Labeled
Laying	LY
Sitting	STG
Standing	STD
Walking	WLK
Walking Downstairs	WLK DS
Walking Upstairs	WLK US

The dataset of six human activities distributed into training and testing shown in TABLE II. Dataset is evenly distributed in each activity ratio. Each action should be balanced to avoid over-fitting and under-fitting issues. The described activities have been given labels in TABLE I. TABLE II shows the training and the testing ratio of activities.

TABLE II. DISTRIBUTION OF DATASET BY ACTIVITIES

Activities Label	Training Datasets	Testing Datasets
LY	19.14%	18.22%
STG	18.69%	18.05%
STD	17.49%	16.83%
WLK	16.68%	16.66%
WLK DS	14.59%	15.98%
WLK US	13.41%	14.25%

The activities are laying, sitting, standing, and walking. Laying means sleeping in a horizontal position on the bed, whereas walking is being categorized into walking on the smooth surface, walking upstairs, and walking downstairs. The activity standing means a person is standing on a straight horizontal floor and the activity sitting means the person is sitting on a chair.

To get better insight, Fig. 2 and Fig. 3 represent partitioned datasets by subjects using a pie chart. The colors show the distributed dataset with the numbers on the outer layer representing the subject’s unique identity. Twenty-one subjects with unique IDs have performed the training.

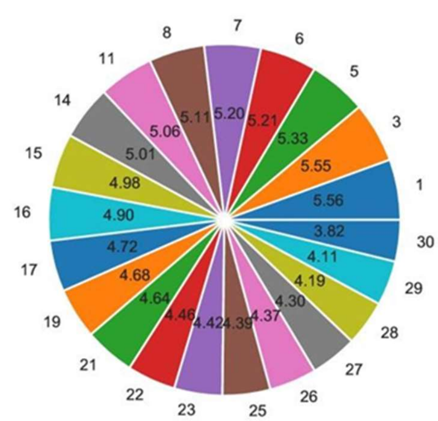

Fig. 2. Distribution of Training Dataset by Subjects

The remaining nine have performed testing. Each subject have performed six activities to avoid unfairness.

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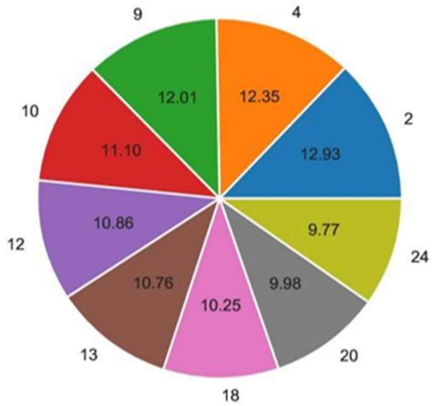

Fig. 3. Distribution of Testing Dataset by Subjects

A. Preprocessing

ML strategies that recognize human activity rely on two fundamental preprocessing methodologies [18], [19], before the learning task, one depends on the subordinate boundaries of elements, and the other deals with crude information. The first requires the segmentation of data and extraction of inferred highlights. On these data generally decision tree-based classification is used. Second one, is the profound learning technique, which learns automatically required features from the raw data using deep learning models [20]. The Preprocessing has been done, where data from the sensor (accelerometer and gyroscope) has gone through noise filters that the sample with a fixed width sliding window of 2.56 seconds. The sensor acceleration signal, which has body motion and the gravitational component, has been separated by using a low pass Butterworth filter. For instance, the gravitational frequency component is being filtered using a 0.3 Hz cut-off frequency. It gets later a vector of features from each window after applying calculation in time and frequency domain.

B. Classifiers

Machine learning is an emerging field of research [21] [15], [22], algorithms by their ability of learning done tasks easy. In this case, the dataset was supervised in nature. Therefore, available supervised algorithms have been used to measure the performance.

However, we are still unable any or only one classifier can satisfy all dataset's unique properties, so that each classifier should get effective and improved results. We have used different algorithms; it categorizes those as Linear Algorithms, Non-Linear Algorithms, Ensemble Algorithms, and Artificial Neural Networks.

IV. Results

The results are listed with classification reports and confusion matrices.

A. Logistic Regression

Logistic Regression (LR) is a supervised machine learning linear classification algorithm. Logistic function (1) was imported via the Sklearn library, and searching was performed using the GridSearchCV method with cross-validation (CV) of 3-fold.

TABLE III. Classification report of Logistic Regression

ACTIVITIES	Precision	Recall	F1-Score	Support
LY	1.000	1.000	1.000	537
STG	0.966	0.874	0.918	491
STD	0.897	0.972	0.933	532
WLK	0.948	0.992	0.968	496
WLK DS	0.990	0.960	0.975	420
WLK US	0.963	0.945	0.954	471
Accuracy	------	------	0.958	2947
Macro Avg	0.960	0.957	0.958	2947
Weighted Avg	0.959	0.958	0.958	2947

$$f(x) = \frac{L}{1+e^{-k(x-x_1)}} \quad (1)$$

The model solver "lbfgs" used with the random state value "42" after training the model, provided the testing dataset to predict using the logistic function. Table III describes the classification report and Table IV contains the confusion matrix of logistic regression.

TABLE IV. Confusion matrix of Logistic Regression

ACTIVITIES	*LY*	*STG*	*STD*	*WLK*	*WLK DS*	*WLK US*
LY	537	0	0	0	0	0
STG	0	429	59	0	0	3
STD	0	15	517	0	0	0
WLK	0	0	0	492	3	1
WLK DS	0	0	0	4	403	13
WLK US	0	0	0	25	1	445

Accuracy has been calculated by adding the True Positive (TP) and True Negative (TN) values then divided by the sum of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values as shown in (2).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+F} \quad (2)$$

Support describes the number; each number represents the sample value of the respective row. The accuracy row shows support value 2947, which is the total number of samples of the testing dataset shown in Table III.

B. Support Vector Machines

Support Vector Machine (SVM) is a supervised learning model [23], with associated learning algorithms that analyze data for classification and regression [24], [25].

TABLE V. Classification report of support vector machine

ACTIVITIES	Precision	Recall	F1-Score	Support
LY	1.000	1.000	1.000	537
STG	0.938	0.894	0.914	491
STD	0.908	0.945	0.926	532
WLK	0.942	0.984	0.963	496
WLK DS	0.992	0.914	0.952	420
WLK US	0.932	0.958	0.945	471
Accuracy	------	------	0.950	2947
Macro Avg	0.952	0.949	0.958	2947
Weighted Avg	0.951	0.950	0.958	2947

These six activities have predicted in terms of their classes on the testing dataset using 3-fold cross-validation with a kernel of "RBF" and random value of "42", this model has achieved good prediction results as shown in Table V and confusion matrix in Table VI.

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TABLE VI. CONFUSION MATRIX OF SUPPORT VECTOR MACHINE

ACTIVITIES	*LY*	*STG*	*STD*	*WLK*	*WLK DS*	*WLK US*
LY	537	0	0	0	0	0
STG	0	438	51	0	0	2
STD	0	29	503	0	0	0
WLK	0	0	0	488	3	5
WLK DS	0	0	0	10	384	26
WLK US	0	0	0	20	0	451

C. *K-Nearest Neighbors*

K-Nearest Neighbors (KNN) is a non-linear classification algorithm, whereas the non-parametric method has used for classification and regression. TABLE VII describes the classification report of KNN.

TABLE VII. CLASSIFICATION REPORT OF K-NEAREST NEIGHBORS

ACTIVITIES	Precision	Recall	F1-Score	Support
LY	0.998	0.987	0.993	537
STG	0.994	0.823	0.879	491
STD	0.857	0.966	0.908	532
WLK	0.864	0.986	0.921	496
WLK DS	0.985	0.767	0.862	420
WLK US	0.879	0.924	0.901	471
Accuracy	------	------	0.950	2947
Macro Avg	0.921	0.909	0.911	2947
Weighted Avg	0.920	0.914	0.913	2947

K-Nearest Neighbor algorithm is imported from a Sklearn library to classify six activities. We have trained the model using a training dataset by 3-fold cross-validation, the algorithm has been used “brute force” and for model metric Minkowski distance formula (3). Finally, it has provided a testing dataset to determine the accuracy. A confusion matrix of KNN is shown in the TABLE VIII.

$$D(X,Y) = \left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{1/p} \tag{3}$$

TABLE VIII. CONFUSION MATRIX OF K-NEAREST NEIGHBORS

ACTIVITIES	*LY*	*STG*	*STD*	*WLK*	*WLK DS*	*WLK US*
LY	530	6	1	0	0	0
STG	1	404	85	0	0	1
STD	0	18	514	0	0	0
WLK	0	0	0	489	4	3
WLK DS	0	0	0	42	322	56
WLK US	0	0	0	35	1	435

D. *Decision Tree*

Decision Tree (DT) builds classification and regression models in the tree's form structure. It separates a dataset into increasingly small subsets, while a related decision tree is evolved. The result is a tree with decision trees and leaf nodes.

TABLE IX. CLASSIFICATION REPORT OF DECISION TREE

ACTIVITIES	Precision	Recall	F1-Score	Support
LY	1.000	1.000	1.000	537
STG	0.966	0.874	0.918	491
STD	0.897	0.972	0.933	532
WLK	0.948	0.992	0.968	496
WLK DS	0.990	0.960	0.975	420
WLK US	0.963	0.945	0.954	471
Accuracy	------	------	0.958	2947
Macro Avg	0.960	0.957	0.958	2947
Weighted Avg	0.959	0.958	0.958	2947

TABLE X. CONFUSION MATRIX OF DECISION TREE

ACTIVITIES	*LY*	*STG*	*STD*	*WLK*	*WLK DS*	*WLK US*
LY	537	0	0	0	0	0
STG	0	370	121	0	0	0
STD	0	59	473	0	0	0
WLK	0	0	0	470	17	9
WLK DS	0	0	0	11	352	57
WLK US	0	0	0	75	31	365

The classification report has been shown in a TABLE IX and the confusion matrix of Decision Tree described in TABLE X. The decision tree model was built using Sklearn, where Gini (4) was a model criterion and 42 was the random state value. It is supervised machine learning, mostly it is used in classification, and it has tree structure performs rule-based decision.

$$Gini_{(i=1)} = 1 - \sum_{i=1}^{n} [(pi)]^2 \tag{4}$$

E. *Extra Tree*

Extra Tree (ET) stands for an extremely randomized tree and is a type of ensemble which combines the results of various de-correlated decision trees. We use the same criterion for measuring their accuracy on the HAR dataset as we did when measuring their accuracy on the decision tree. The performance of classifiers on static activities reaches high, such as laying, standing, except for sitting, as shown in TABLE XI. The value of precision, recall, and f1-score in TABLE XI is explained. Walking activity performs well in dynamic activities.

TABLE XI. CLASSIFICATION REPORT OF EXTRA TREE

ACTIVITIES	Precision	Recall	F1-Score	Support
LY	1.000	1.000	1.000	537
STG	0.964	0.878	0.919	491
STD	0.897	0.970	0.932	532
WLK	0.921	0.958	0.939	496
WLK DS	0.950	0.852	0.898	420
WLK US	0.893	0.938	0.915	471
Accuracy	------	------	0.936	2947
Macro Avg	0.937	0.933	0.934	2947
Weighted Avg	0.938	0.936	0.936	2947

Confusion matrix defines the sample value of six activities; how many samples are correctly or wrongly predicted as shown in the TABLE XII. Laying activity pattern is smooth and clear so that the result of classification remains excellent.

TABLE XII. CONFUSION MATRIX OF EXTRA TREE

ACTIVITIES	*LY*	*STG*	*STD*	*WLK*	*WLK DS*	*WLK US*
LY	537	0	0	0	0	0
STG	0	439	51	0	0	1
STD	0	14	518	0	0	0
WLK	0	0	0	484	6	6
WLK DS	0	0	0	24	351	45
WLK US	0	0	0	24	4	443

F. *Gradient Boosting*

Gradient Boosting (GB) is an ensemble classifier, and GB classifiers are a group of machine learning algorithms that combine many weak learning models to create a strong predictive model. A classification report and confusion matrix are tabularized in the TABLE XIII and TABLE XIV.

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TABLE XIII. CLASSIFICATION REPORT OF GRADIENT BOOSTING

ACTIVITIES	Precision	Recall	F1-Score	Support
LY	1.000	1.000	1.000	537
STG	0.923	0.855	0.888	491
STD	0.880	0.936	0.907	532
WLK	0.936	0.980	0.958	496
WLK DS	0.972	0.921	0.946	420
WLK US	0.928	0.930	0.929	471
Accuracy	------	------	0.939	2947
Macro Avg	0.940	0.937	0.938	2947
Weighted Avg	0.939	0.939	0.938	2947

In this problem to construct new base learners, which can be optimally correlated with a negative gradient of the loss function relevant to the entire ensemble.

TABLE XIV. CONFUSION MATRIX OF GRADIENT BOOSTING

ACTIVITIES	*LY*	*STG*	*STD*	*WLK*	*WLK DS*	*WLK US*
LY	537	0	0	0	0	0
STG	0	420	68	0	0	3
STD	0	34	498	0	0	0
WLK	0	0	0	486	5	5
WLK DS	0	0	0	7	387	26
WLK US	0	1	0	26	6	438

G. Random Forest

Random Forest (RF) is an ensemble learning method for classification, regression, and other tasks that work by building several decision trees at training time and outputting the class that is the model of the classes or mean prediction of the individual trees for searching, it has used "Gini" as a model criterion and imported "RandomizedSearchingCV" with a CV value of 3. You can find the classification report in TABLE XV. The classification report describes the evaluated result of a classifier.

TABLE XV. CLASSIFICATION REPORT OF RANDOM FOREST

ACTIVITIES	Precision	Recall	F1-Score	Support
LY	1.000	1.000	1.000	537
STG	0.902	0.884	0.893	491
STD	0.895	0.912	0.903	532
WLK	0.893	0.974	0.932	496
WLK DS	0.968	0.855	0.908	420
WLK US	0.895	0.902	0.899	471
Accuracy	------	------	0.924	2947
Macro Avg	0.925	0.921	0.922	2947
Weighted Avg	0.925	0.924	0.924	2947

It is shown in TABLE XVI, walking downstairs activity predicated better than the walking upstairs; however, both activities are of the same nature, but the pattern of activities may vary, and the classifier evaluates on a pattern.

TABLE XVI. CONFUSION MATRIX OF RANDOM FOREST

ACTIVITIES	*LY*	*STG*	*STD*	*WLK*	*WLK DS*	*WLK US*
LY	537	0	0	0	0	0
STG	0	434	57	0	0	3
STD	0	47	485	0	0	0
WLK	0	0	0	483	6	7
WLK DS	0	0	0	18	359	43
WLK US	0	0	0	40	6	425

H. Bagging Classifier

The evaluated result of Bagging Classifier (BC) on testing dataset has been displayed in the TABLE XVII and TABLE XVIII. Bagging Classifiers are very natural to use for classification. It is an ensemble meta-estimator, having two approaches, which are majority vote and average estimated probabilities.

TABLE XVII. CLASSIFICATION REPORT OF BAGGING CLASSIFIER

ACTIVITIES	Precision	Recall	F1-Score	Support
LY	1.000	1.000	1.000	537
STG	0.872	0.802	0.836	491
STD	0.830	0.891	0.859	532
WLK	0.877	0.962	0.917	496
WLK DS	0.938	0.867	0.901	420
WLK US	0.884	0.854	0.868	471
Accuracy	------	------	0.899	2947
Macro Avg	0.900	0.896	0.897	2947
Weighted Avg	0.900	0.899	0.898	2947

Such a meta-estimator can typically diminish the fluctuation of a black-box estimator by bringing randomization into the development system and afterward making an ensemble out of it. The required parameters have been imported from “Sklearn” library to evaluate the classifier’s performance on this dataset. Finally, a classification report and confusion matrix have been generated.

TABLE XVIII. CONFUSION MATRIX OF BAGGING CLASSIFIER

ACTIVITIES	*LY*	*STG*	*STD*	*WLK*	*WLK DS*	*WLK US*
LY	537	0	0	0	0	0
STG	0	392	99	0	0	0
STD	0	58	474	0	0	0
WLK	0	0	0	477	14	5
WLK DS	0	0	0	9	369	42
WLK US	0	0	0	59	11	401

I. Recurrent Neural Networks

Recurrent Neural Networks (RNN) is a modern approach that solves feed-forward networks [25], [22]. It is composed of different layers and works on the structure and function of the human brain. LSTMs are a special kind of RNN capable of learning long-term dependencies and storing information for a long period of time. TensorFlow has opened the doors to research in many fields of science and technology. This framework is powerful and useful for improving results and making discoveries. A confusion matrix of RNN has been shown in the TABLE XIX. We have imported LSTM, sequential, dense, and dropout, trained the machine using different values for epoch, batch size, and a hidden layer to improve accuracy.

TABLE XIX. CONFUSION MATRIX OF RECURRENT NEURAL NETWORKS

ACTIVITIES	*LY*	*STG*	*STD*	*WLK*	*WLK DS*	*WLK US*
LY	510	0	1	0	0	26
STG	0	428	62	1	0	0
STD	0	120	411	1	0	0
WLK	0	0	0	473	1	22
WLK DS	0	0	0	9	404	7
WLK US	0	0	1	18	0	452

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While dropout has been set at a constant rate of 0.5 and providing different parameters to optimizer and activation function. Finally, we have proved in our experiment that using SoftMax as an activation function, and Adam for optimizer with 100 epochs, set batch size as 200, and hidden layers 150, we have got up to 93% accuracy as shown in Fig. 4, whereas model loss is shown in Fig. 5.

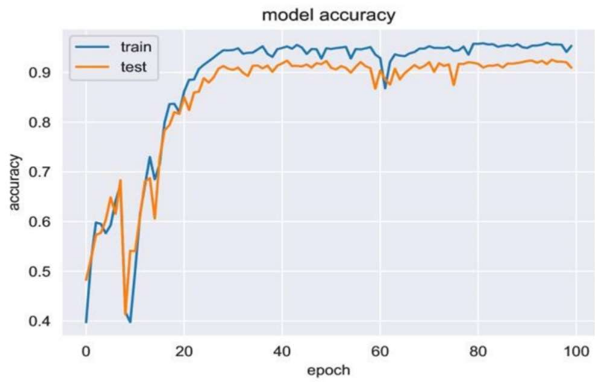

Fig. 4. Model Accuracy of Recurrent Neural Networks

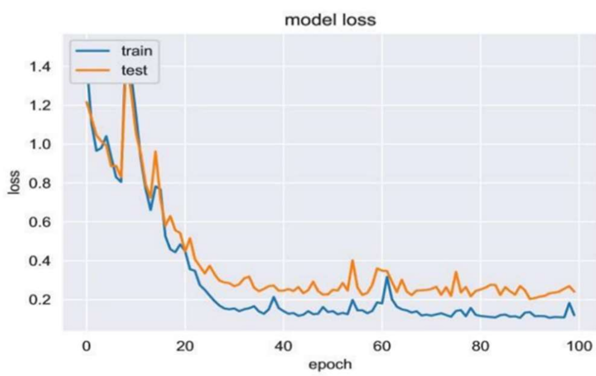

Fig. 5. Model Loss of Recurrent Neural Networks

V. COMPARISON

Fig. 6 shows the accuracy results of various ML algorithms for training and testing sets.

On certain training and testing datasets, the overall accuracy of each classifier was evaluated and compared. Fig. 6 shows a bar chart. The column represents accuracy values from 0 to 1, where 0 represents no accuracy (0%), and 1 represents 100% accuracy (100%). The bar chart indicates the performance of the classifiers right to left in descending order. The green shaded bars represent training accuracy. The first bar shows the training performance of KNN. KNN ranked seventh in the bottom testing data bar chart. Random Forest ranks second in the training accuracy chart, while in the testing accuracy chart Random Forest is ranked sixth. In the bar chart, we show the performance of the remaining classifiers on the training and testing datasets.

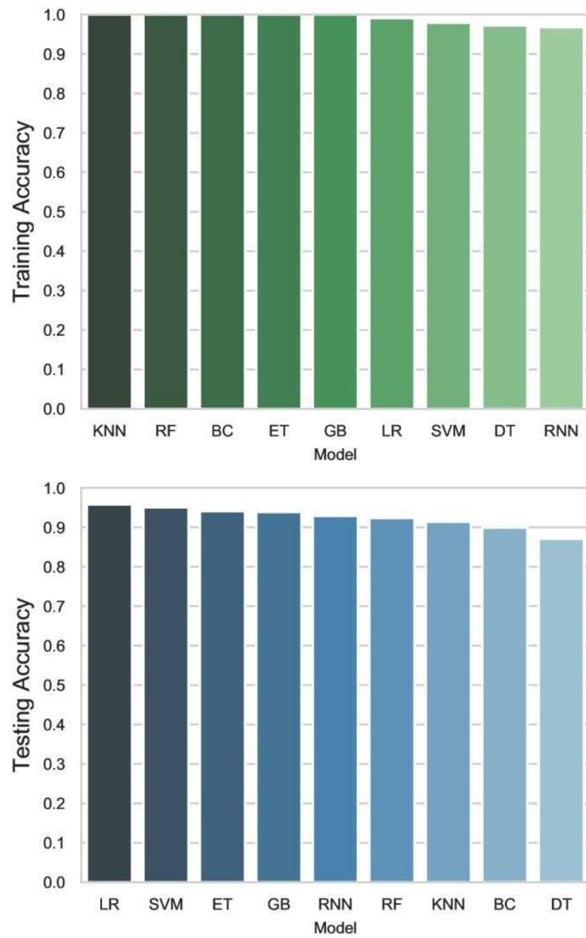

Fig. 6. Comparison of Accuracy of Various Machine Learning Classifiers

VI. CONCLUSION

Several algorithms were tested against the HAR dataset. In the training dataset, five algorithms, namely KNN, RF, BC, ET, and GB, reached approximately 100% accuracy. However, the outcome shows that 100% training accuracy does not mean that the algorithm would perform best. For instance, the LR and SVM algorithms perform best in correctly classifying HAR, even though their training accuracy is not 100%. We believed RNN would perform better; however, the performance depends on the dataset's characteristics as observed via the sub-optimal training accuracy of RNN. However, even with sub-optimal training, RNN outperformed algorithms that had approximately 100% accuracy, such as Random Forest, KNN, and Decision Tree.

For Fair comparison, we did not tweak the training dataset, i.e., filter outliers. For example, use essential middle 80% percentile values. Other parameters such as activation function, the number of Feed-forward layers, Input-Hidden-Output layer, neurons, training algorithm experimented. However, because of dataset characteristics training accuracy of RNN could not be improved.

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