

Design of LSTM-RNN on a Sensor Based HAR using Android Phones

K. Arthishwari, M. Anand

Abstract: Activity Recognition (AR) is monitoring the liveliness of a person by using smart phone. Smart phones are used in a wider manner and it becomes one of the ways to identify the human's environmental changes by using the sensors in smart mobiles. Smart phones are equipped in detecting sensors like compass sensor, gyroscope, GPS sensor and accelerometer. Human Activity Recognition (HAR) framework collects the raw data from sensors and observes the human movement using different classification methods. This paper focuses for Activity Recognition (AR) based on smart phone by analyzing the performance of various Deep Learning (DL) approach using in-built gyroscope and accelerometers. In this work, HAR dataset can be utilized from UCI based Machine Learning repository. The sensors such as gyroscope and accelerator are used to record the signals and performs various activities namely walking-downstairs, walking-upstairs, jogging, standing, walking and sitting while a user wearing the smartphone in a pocket. The performance metrics has analyzed to recognize user's activities using DL approach namely Recurrent Neural Network with Long-Short Term Memory (RNN-LSTM) were applied. The result provides 96% better accuracy for RNN-LSTM with minimum Mean Absolute Percentage Error (MAPE) when compare to other machine learning classifier.

Keywords: Accelerometers, Gyroscope, Human Activity Recognition (HAR), Smartphone.

I. INTRODUCTION

Smartphones have become increasingly popular in human's daily life nowadays. Many users used it to check news, play games, watch videos and navigate social networks, but on smartphones there were a lot of useful research. The portable working framework with computing ability and interconnectivity, Application Programming Interfaces (API) for executing outsiders' tools and applications, mobile phones have highlights such as cameras, GPS, web browsers so on., and implanted sensors such as accelerometers, gyroscope and magnetometer which permits the improvement of applications in view of client's specific area, movement and context. To develop resourceful smart phone application, it is imperative to utilize context recognition and situational attention of the gadget's client [1]. AR is one of the most significant innovations many based on device apps namely health monitoring, context-aware mobile apps, fall detection, human study framework, home robotics, etc. Active research area is the smartphone-based AR system because it can lead to

Revised Manuscript Received on January 24, 2020.

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mobile applications as new types. The system of HAR takes the input from mobile devices as raw sensor reading and predicts human movement behavior through exploiting smartphones with different sensors like light sensors, accelerometers, GPS, gyroscopes, compass sensors, barometers, etc. Smart phones for HAR are becoming the main platform due to their unassertive, none or low costs of installation and ease of use. A model is being built that fits into a phone to interpret different activities using information gathered under the real-world conditions through a single triaxial accelerometer [2][3]. A triaxial accelerometer that produces a gauge of acceleration from which it is possible to determine speed and displacement along the axes x, y and z. AR interests to perceive the moves accomplished by an individual given a fixed of perceptions itself and encompassing environments. Recognition might be executed as an instance through exploiting the data recovered from inertial sensors. In some smart devices, the sensors are inserted with the aid of default and to define a set of physical events such as standing, kneeling, walking, lying, upstairs scrolling and downstairs scrolling by means of handling inertial frame markers for hardware with confined resources. Total classifier execution with monitored training certainties despite the minimal memory available on the smart devices. Accumulating the training records and it tends to be directly utilized for category steps, which diminishes the weight at the clients. The contraption is demonstrated to examine the state of an individual. HAR framework collects the raw data from sensors and observes the human movement using different deep learning approach. This paper has been written as follows: Section II explains related work, and Section III defines the proposed system on working flow of designed model. Section IV describes the evaluation based on machine learning model and Section V describes experimental results based on performance metrics and the conclusion is finally described in section VI.

II. LITERATURE REVIEW

Min et al. [4] described as two models based on the addition to accelerating sensor data, which has only data from the acceleration sensor and another form the location information. Before feature extraction, the acceleration sensor data is divided into time segments which is said to be temporal segmentation. In order to handle streaming of data, sliding window technique is used. Qingzhong et al [5] proposes a method for activity recognition in two steps.

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In step 1, accelerometer provides unrefined sensor data which recognizes the actions and the course of mobile phones indicating the gyroscope senses rotational movements which are large to detect by people. In step 2, feature extraction method is performed for the sensed data. Machine learning models worked for action recognition, at that point the profound learning model dependent on convolutional neural system. Erhan et al. [6] suggests numerous supervised machine learning algorithms namely KNN, decision trees, SVM and classification methods namely Boosting, Stacking and Bagging for ensemble. For classification, binary decision tree is used in which 53.1% of accuracy. Kumar polu [7] In the long run, this sensor detects the alteration by 3D x, y and z axis which rotate estimation of the increasing speed of the device concerning free fall. George and kizhalckethottam[8] described to evaluate the quality and course of alluring fields. The sensor enables the gadget to select with high accuracy its orientation by breaking down Earth's magnetic field. Kumar and bhavani [9] Gradient boosting is an AI method for relapse and order issues, which creates an expectation model as a group of powerless forecast models, normally choice trees. The goal of any directed learning algorithm is to characterize a misfortune work and limit it. Pavel Dohnalek [10] Classification and Regression Tree algorithm characterizes a sample as indicated by gatherings of different examples with comparative properties. During training, the training information is constantly isolated into smaller subsets. At the point when the divisions are done, the examples are grouped together as per their properties. Voicu et.al [11] propose a system for the identification of human physical AR system based on data obtained from mobile sensors. The result shows especially for recognizing good statistics for all the 6 events namely sitting, walking, standing and running. Mo et.al [12] this can be achieved by utilizing different senses, close to those that humans have. Many approaches have been based on computer vision whereas other research were centered on audio processing methods [13] (slightly a supplement to current approaches) or RFIDs [14–16]. Kose et.al [17] paper

uses the built-in accelerometers to evaluate the efficiency of various online AR classification methods on smart phones. AR is one of many mobile technology sub-domains which has developed rapidly over the previous few years [18]. These fields of use include smart homes [19], fitness tracking, healthcare observing system [20], protection and security applications [21], tele-immersion applications [22], etc.

III. PROPOSED SYSTEM

The proposed system of HAR has been composed of two representation namely RNN with LSTM. HAR dataset is originally obtained from the repository of UCI machine learning. In our research work dataset has been composed of 1,087,316 rows and 6 columns which has no more missing values. There are 6 activities can try to recognize: Walking, Jogging, Upstairs, Downstairs, Sitting, Standing. Let's have a closer look at the data. Use of the integrated accelerometer and gyroscope to monitor 3-axial linear and 3-hub acceleration precise speed at a steady rate of 50Hz. The attained dataset consists of 70% have been chosen for training the volunteers as preparing information and 30% have been used for testing. The dataset is loaded primarily which contains 3 main types namely body acceleration, total acceleration and gyroscope. Then develop the model of RNN is applied with LSTM which supports the several sequence of activities to make the predictions.

A. Working Flow of Designed Model

1) Walking

Walking creates a periodic pattern which offers a large number of information for each of the sensors to the learning algorithm therefore classifier have easier to differentiate from the other activities can be illustrated in figure.1. The below signal specifies the one possible pattern based on the characteristics namely gender, age, height etc. Here, interval or range of values which moves only fewer important metrics but the movement based on pattern and shape has been almost same.

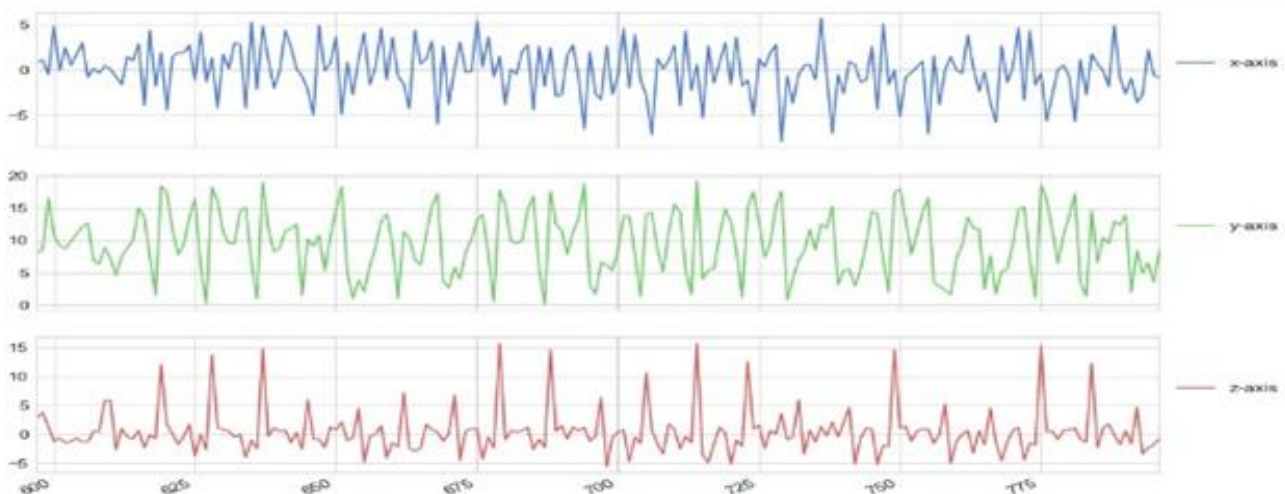


Fig. 1. Representation of graphical data from accelerometer sensor during walking

2) Jogging

Jogging denotes a movement comparable to walking but more quickly faster. In figure.2, illustrate a periodic pattern

for this action, with a smaller timing difference between running periods than walking periods.

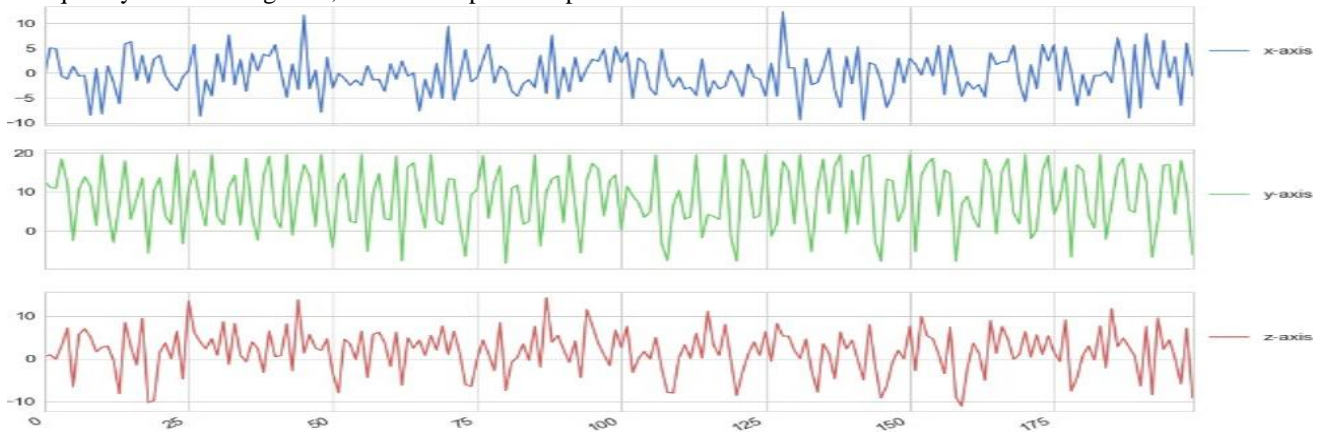


Fig. 2. Representation of graphical data from accelerometer sensor during jogging

3) Upstairs

Upstairs walking is a task that can be accomplished in many respects in comparison to the previous ones. It's not that everyone moves or runs the same way, but they create more or

less similar with a few variations. In figure.3 illustrates as far as going upstairs is concerned, people do it two steps at a time, step by step, sluggish, others even three, quick, or hopping, so it's not very easy to recognize.

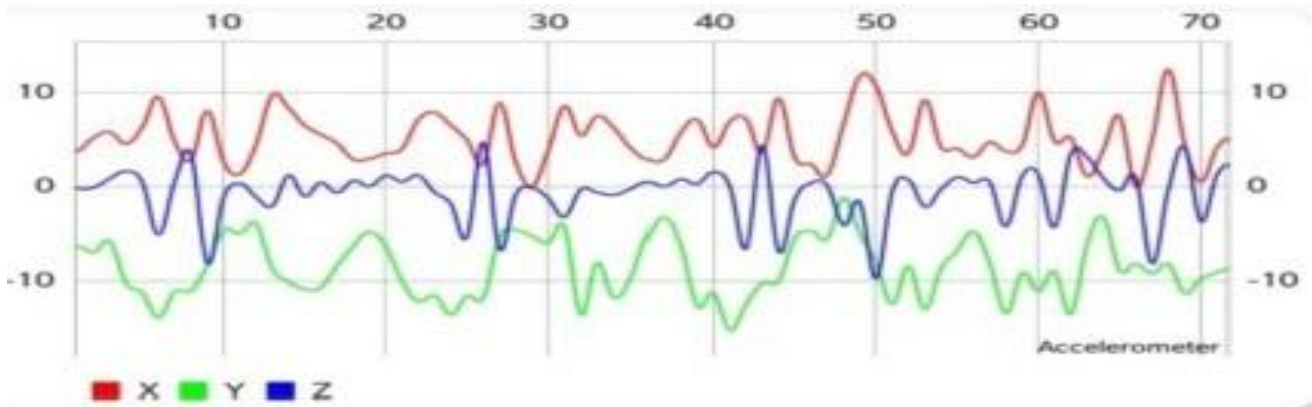


Fig. 3. Representation of graphical data from accelerometer sensor during Upstairs

4) Walking Downstairs

While trying to differentiate it from other tasks, downstairs is more difficult to detect. The signal patterns are going down the stairs which tend to differ similarly to going upstairs. The

going upstairs is quickly confused this practice with walking. The major difficulty, though, in identifying both going upstairs and downstairs is the reality which they are almost the same, which can be clearly seen by figure.4, which indicates that the AR struggled to find out which one was really done.

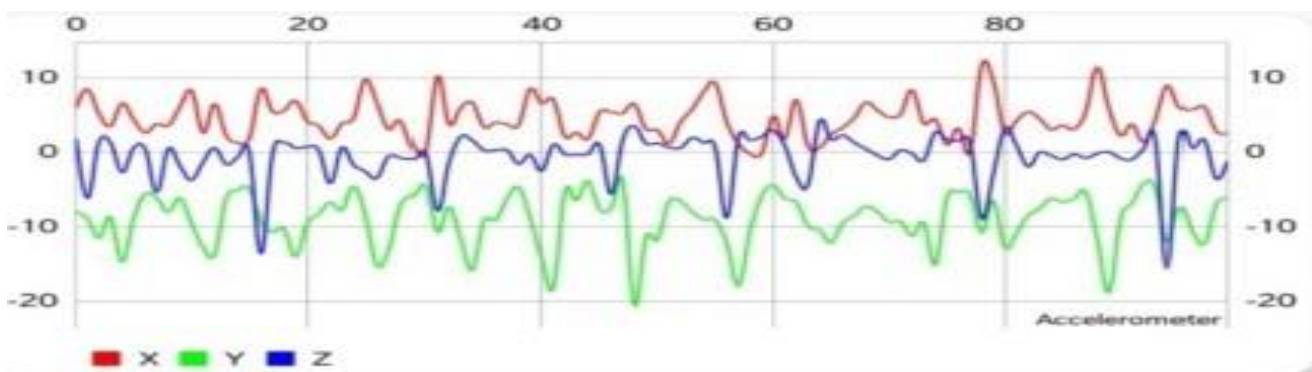


Fig. 4. Representation of graphical data from accelerometer sensor during Downstairs

5) Sitting

Sitting is a motionless event unlike the earlier two events if it can be measured an action at all. In figure.5 describe the values of each of the 3 axes in which the accelerometer

sensors display no difference. Even though the sensors display much less variation than running and walking, thereby creating it very easy to distinguish sitting activity from them.

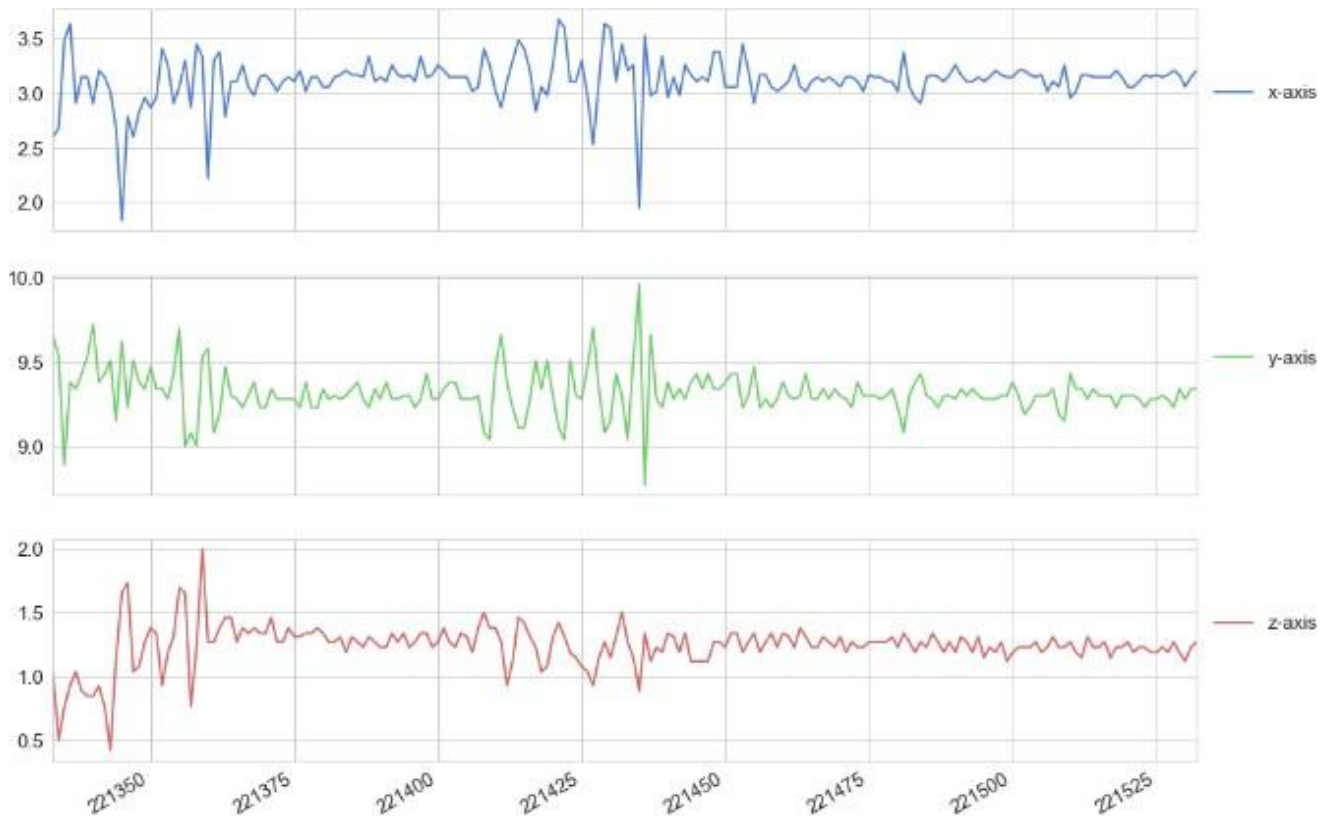


Fig. 5. Representation of graphical data from accelerometer sensor during sitting

6) Standing

The activity of standing in figure.6 denotes few differences can be seen in accelerometer sensors but the direction in axes of the graph shows the main indicator when trying to

differentiate the two events. An overlap of axes Y and Z can be found by transitioning from one movement to another. Though these two behaviors are somewhat unfamiliar, they can be recognized quite quickly.

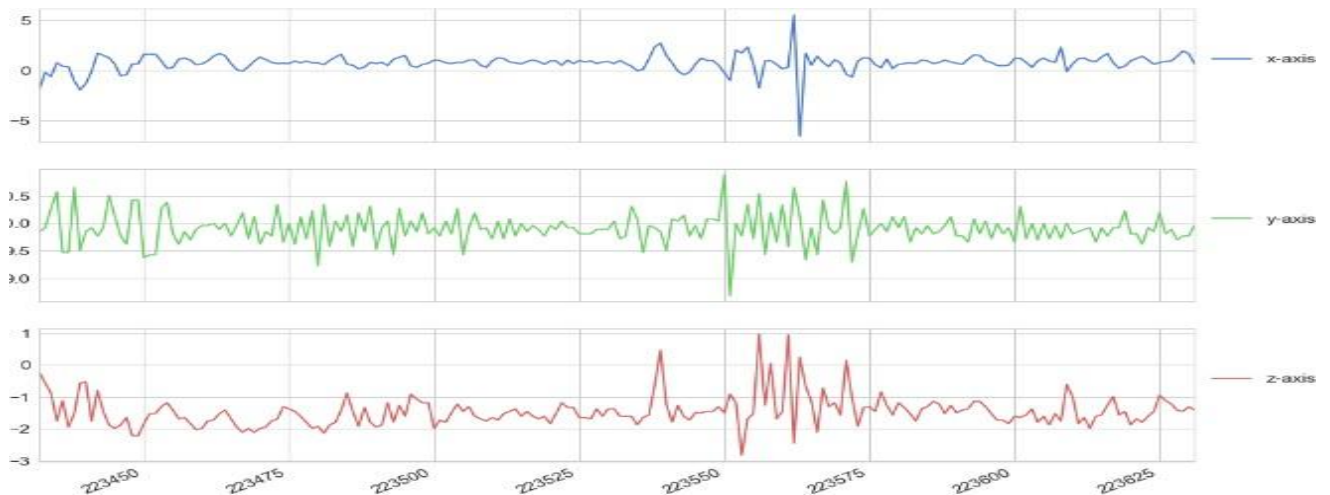


Fig. 6. Representation of graphical data from accelerometer sensor during sitting

The data set was analyzed to test the equilibrium between the observations of the behavior produced by the 30 subjects. While for all the operations, the distribution of data is not identical, which they are strongly matched. In figure.7 illustrates that the maximum number of observations based on

walking activity and minimum number of observations based on standing activity whereas it can be shown in training dataset also.

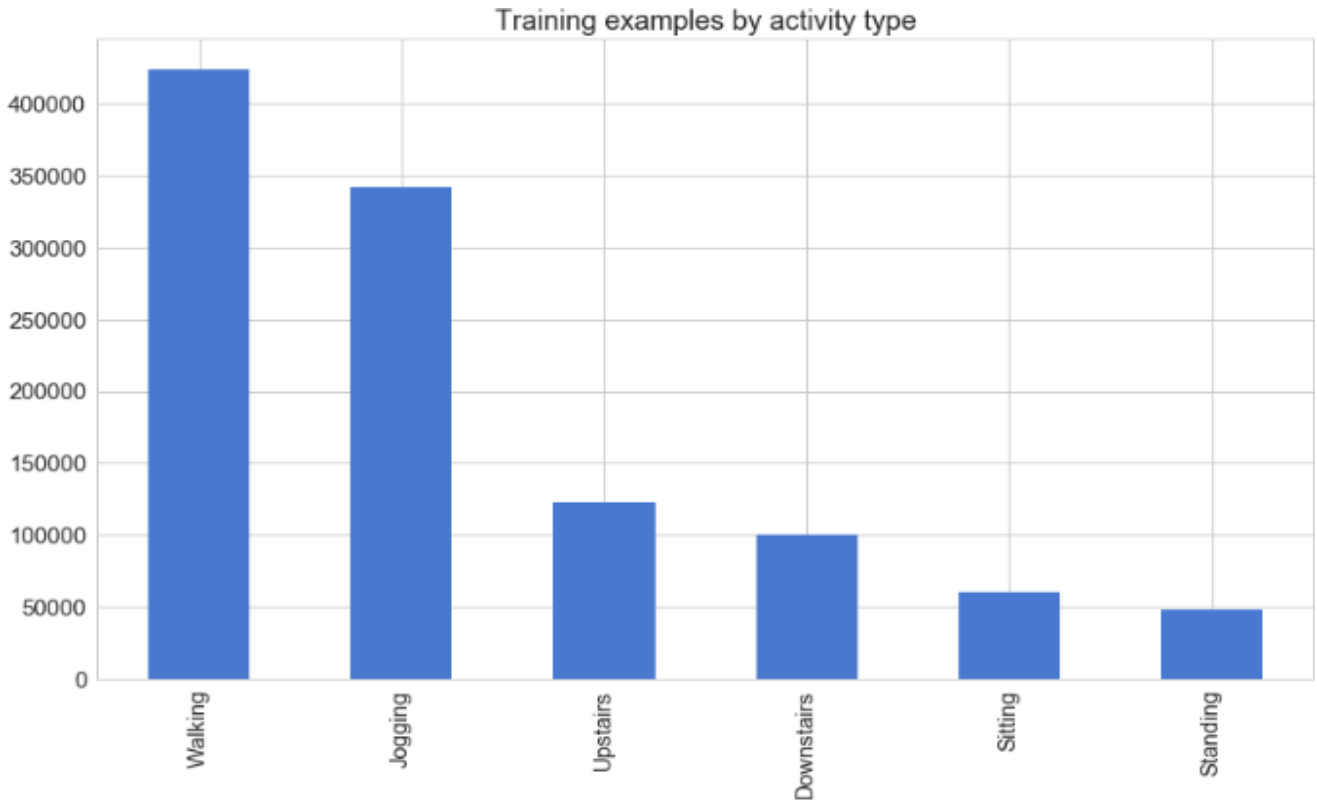


Fig. 7. Training dataset based on activity

IV. EVALUATION

These approach needs the training and testing of the classifier datasets. The operation makes of both training and testing which has been recorded in a database and the strategy is tested for consistency. Then recorded values of the accelerometer sensors and the corresponding index of time.

The accelerometer has been designed due to phone movements and vibrations to identify alterations. The phone's orientation and rotation has been measured using the accelerometer sensors. Each data set assessment ended after 600 attempts, with each operation are being done 100 times. These researches were carried out only with new collected data in figure.8 illustrates the model reaches the accuracy of 97% of training progress.

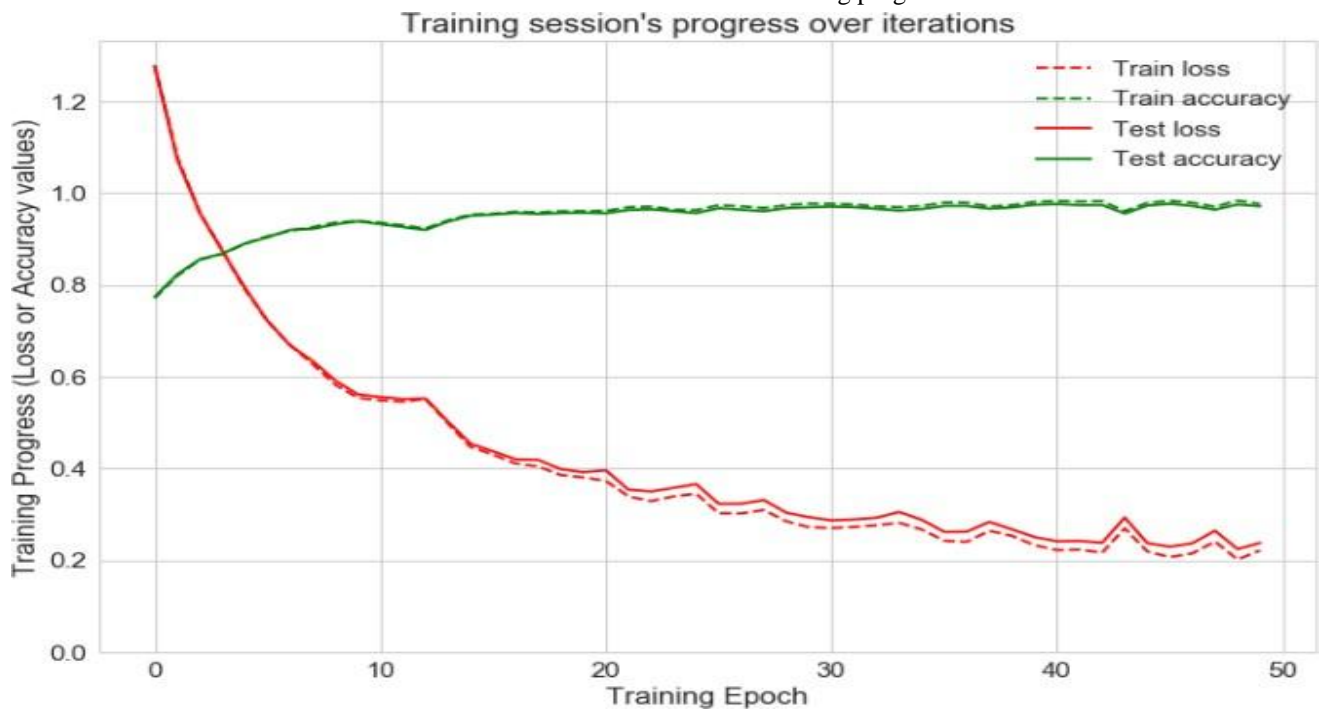


Fig. 8. Model reaches the accuracy of 97% of training progress and loss balanced at around 0.2 values

A. Machine Learning Model

1) Gradient Boosting

Gradient boosting is an AI method for relapse and order issues, which creates an expectation model as a group of powerless forecast models, normally choice trees. The goal of any directed learning algorithm is to characterize a misfortune work and limit it [20]. Gradient boosting machines are in light of an ensemble of choice trees where numerous weak learner trees are utilized in mix as a group to give preferred forecasts over singular trees. Boost has unrivalled regularization and better treatment of missing qualities and also much improved proficiency.

2) CNN with LSTM

The CNN LSTM Network design includes utilizing CNN layers on input information for feature extraction joined with LSTMs to help arrangement prediction. CNN LSTMs has been created for forecast issues by visual time arrangement and the utilization of producing literary depictions from successions of images. It has been characterizing into two sub-models namely the highlight extraction of CNN Model and the highlights deciphering of LSTM Model for the crosswise over time steps. A 2D convolutional system as contained Conv2D and Max Pooling 2D layers. Then apply the CNN model to each information and then permit on the yield of each information as a solitary time step to the LSTM. Wrapping the whole input CNN model i.e. one layer or more in a Time Distributed layer. This layer accomplishes the ideal result of relating a similar layer on different occasions. These models have demonstrated extremely powerful on recognizing and automatically portraying the content.

3) RNN with LSTM

Instead of using feature optimized input, a model of LSTM network is built to distinguish human activity from the raw

inertial signals. This experiment was conducted to check the network ability of time series data from a sequence to learn features and verify if the features it learns to identify the human activities. The actual inertial signals consist of 3 primary signals namely cumulative acceleration, gyroscope of the body and acceleration of the body with every component measuring data over the three axes such as x, y and z. Then 9 variables are registered for a period of 2.56 seconds or 128-time steps to provide a total of 1152 elements which means $9 * 128$ for every data row. RNN-LSTM's are appropriate for data from time series data which have the capability to learn and evoke over long data categorizations. The software ' Android HAR' is a good fit for an LSTM network as it is designed to be used with data strings, up to 400-time steps. Instead of physically scheming the functionality, the RNN-LSTM absorbs directly from the time series signals which can able to attain the comparable results with models based on function of optimized data.

V. RESULT AND DISCUSSION

In this experiment, the human activity is recognized based on their movements is initiated with preprocessing. The Gradient Boosting, Conv-LSTM and RNNLSTM are used as classifiers. The accelerometer data for all the six activities are displayed. The performance of the model is validated based on Accuracy, Mean Absolute Error (MAE), and MAPE.

A. Performance metrics

MAE is the normal over amassed dataset tests. It offers total variety between forecast and genuine perception. MAE esteem ought to be not exactly or equivalent to RMSE. MAPE is utilized to quantify the exactness of expectation technique. Regularly, the littler these qualities with the better expectation. The Table.1 and figure.9 and figure.10 demonstrates the performances of the various designed models based on accuracy, MAE and MAPE.

Table-I: Performance Metrics of the Classifier

Classifier	Accuracy (%)	MAE	MAPE (%)
Gradient Boosting	85.51	0.0124	5.65
Conv-LSTM	93.78	0.0005	4.31
RNN-LSTM	96.06	0.0003	3.48

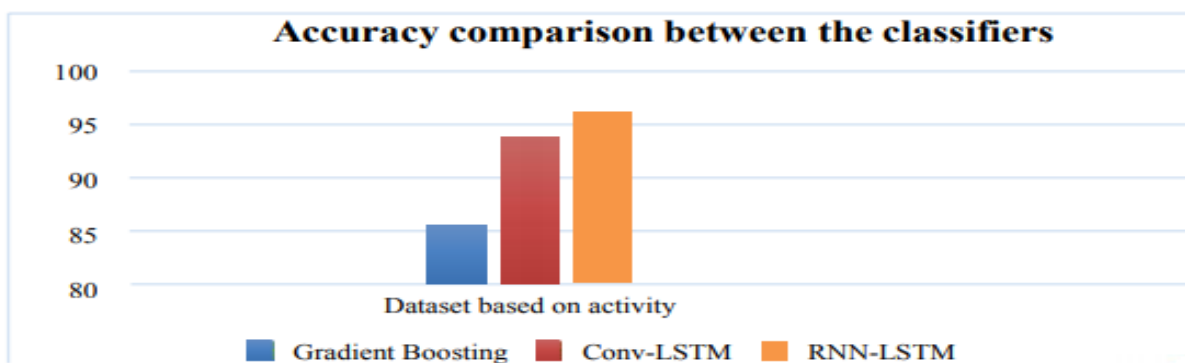


Fig. 9. Comparison of accuracy based on various DL models

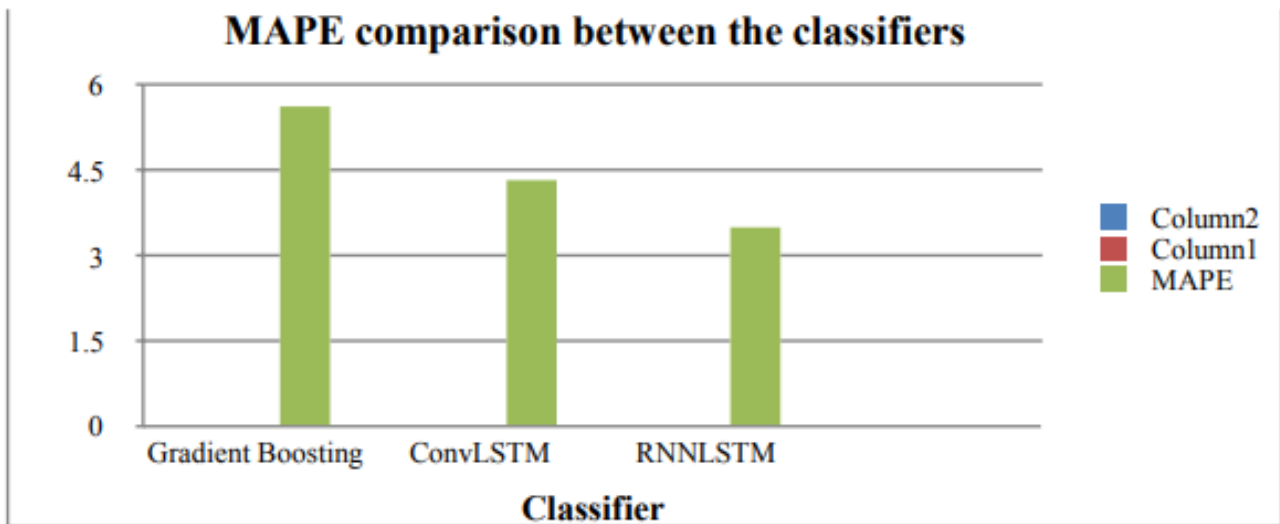


Fig. 10. Comparison of MAPE based on various DL models

The experiments have been done on Python of version 3. The result shows that RNN-LSTM provides the better accuracy with lower MAPE. RNN-LSTM have a better-balanced accuracy of 96.06%, MAE of 0.0003, and MAPE of 3.48%. Due to that, RNN-LSTM can be used to recognize the human activities in real world applications in order to reduce loss of lives.

VI. CONCLUSION

Smart phones are ubiquitous and becoming ever more common. This has shifted the scene of the day-to-day life of individuals and brought interesting knowledge processing tools. In this paper suggested an AR system that works on Android platforms that facilitates training and classification whereas using only the classification data for accelerometer. RNN-LSTM classifier performance efficiency has been evaluated. The RNN-LSTM model showed far better performance on mobile platforms with limited resources than the Conv-LSTM and Gradient Boosting in terms of accuracy. This research work built an RNN-LSTM model that can predict human activity from 200 time-step sequence with over 96% better balanced accuracy and 3.48% lower MAPE. The model was exported and used in an Android app.

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