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HUMAN ACTIVITY RECOGNITION USING DEEPLEARNING

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ABSTRACT

Human Activity Recognition is a new field of research with many innovations and applications. Digitalization, mobile development, and technological advances that conquer humanity have made smartphones an integral part of our lives. Living without a mobile phone is almost impossible because we rely so much on science and its innovations. As technology advances, we have a responsibility to supply humanity with efficient, traditional and sustainable resources. Implementation of the idea"Technology at your fingertips" is what our project aims. We evaluate the solution against two datasets (one using only accelerometer data and the other using only gyroscope data) with great effect. We've also implemented predictive models using Deep Learning approaches LSTM (Long Short-Term Memory) ,RNN (Recurrent Neural Networks) and GRU(Gated Recurrent Unit). The predicted results show decent accuracy for recognizing all six activities, with especially good and accurate results obtained for walking, running, sitting, and standing.

Keywords: *Deep Learning , LSTM ,RNN,GRN, Accelerometer , Gyroscope.*

1. INTRODUCTION

Nowadays smartphones became more and more popular in human daily life. Most of the people used it for searching news, watching videos, playing games and accessing social network but there were many useful studies on smartphones. Activity recognition is one of the most important technologies behind many applications on smartphone such as health monitoring, fall detection, context-aware mobile applications, human survey system and home automation etc., Smartphone-based activity recognition system is an active area of research because they can lead to new types of mobile applications.

Technology, definitely has its own pros and cons but taking the utmost advantage of it, can be beneficial to mankind. One such field where smartphones play an important role and is a budding area of research and development, is the Human Activity Recognition (HAR).

In the world, the human activities recognition, which use sensors to recognize human actions, have been studied for a long time to produce the simpler system with high precision. Smartphones, nowadays have become an essential gadget in human's life. These smartphones have embedded sensors like Gyroscope, GPS, Accelerometer, Compass sensor etc. These sensors can be used to predict the state of the user. Human activity recognition is an important yet challenging research area with many applications in healthcare, smart environments, and homeland security. Computer vision-based techniques have widely been used for human activity tracking, but they mostly require infrastructure support, for example, installation of video cameras in the monitoring areas. Alternatively, a more efficient approach is to process the data from inertial measurement unit sensors worn on a user's body or built in a user's smartphone to track his or her motion.

The HAR system is executed by taking input from smartphones, whereby exploiting data recovered from inertial sensors and observing the human movement using various approaches. Though smartphones today are loaded with a whole lot of sensors like light sensors, motion sensors, compass sensors, this study specifically aims at using two motion sensors available in every smartphone. The reason being its availability and feasibility, making it available to all and cost effective so that its usability increases. AR (Activity Recognition) is one of the most significant innovations in the sector of Health monitoring, mobile health applications and user's activity tracking. Utilizing this important feature of smartphones and their sensors, the study of HAR is developing and evolving over time.

2. LITERATURE SURVEY

On the Personalization of Classification Models for Human Activity Recognition was presented by Anna Ferrai In this paper they have experimented several personalization methods on three public datasets in order to make the results reproducible and thus allowing future research on this topic. The personalization methods experimented are based on the concept of similarity between users. This means that users may have similar physical characteristics or have similar accelerometer signals and that, such a similarity can be employed to weight training data in a way that data belonging to more similar subjects to the subject under test count more than data of less similar subjects.[6]

Human Activity Recognition:A Survey by Charmi Jobanputra in this survey, they have carried out the comprehensive study of various tools and techniques which can be used in human activity recognition which included different machine learningalgorithms and neural network techniques.[7]

Real Time Human Activity Recognition presented by Teena Varma [8] In this paper they have explained Hybrid Models.The idea of Hybrid Models, is an advantage to the implementation of Deep Learning Approach. Though they have implemented a CNN-LSTM model and got a accuracy rate less than a simple LSTM, They can implement with more hybrid models.

3. PROPOSED SYSTEM

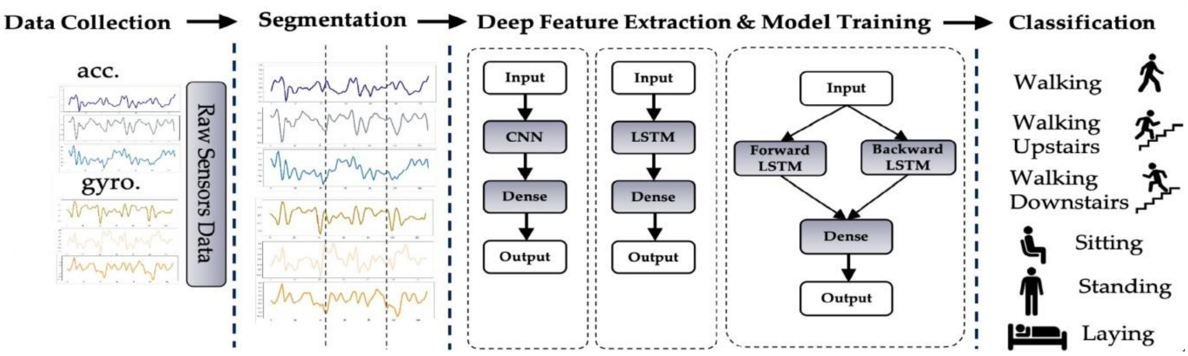


Figure 1: Overview of Human Activity recognition

The proposed system for detection of Human Activity Recognition is elaborated below.

Step 1: Data Collection – We have used the UCI and WISDM dataset . A total of 1,098,209 examples are present in the dataset. A total of 36 participants participated in the experiment. To collect data for this experiment, every participant was required to carry a smartphone running on the Android operating system during the performance of each of the six activities. The subjects were required to carry their Android phones in a pocket situated in the front portion of their pants. Furthermore, they were advised to sit, walk, stand, jog, climb upstairs and go downstairs for specific durations of time. An Android application, running on the smartphone, controlled the data collection from the accelerometer during activity performance by the subjects. The application used in the experiment comprised a graphical user interface, which permitted the experiment supervisor to record the subject’s name and label the activity that the subject performed. Furthermore, the application also provided a feature to start and stop collecting data. In addition, the application enabled the supervisor to control the type of data from different sensors (e.g., gyroscope, accelerometer) and to set the frequency of data collection. Overall, the data from the accelerometer were collected every 50 milliseconds at the rate of 20 samples per second.

Step 2: Data Filtering – The collected data may contain noise and the data so it is processed to eliminate the noise by applying noise filters and low-pass filter technique. Time-domain and frequency-domain features have been extensively used to filter relevant information within acceleration and rotation signals. In this paper, we used four features : MIN, MAX, MEAN and Standard deviation. Bythese statistical operations features were calculated.

Step 3: Data Segmentation – Data segmentation is a crucial stage in the activity recognition process; normally sliding window approach is used for segmentation but no clear consent exists on which window size should be preferably employed. Intuitively, decreasing the window size allows faster activity detection, as well as reduced resources and energy needs. On the contrary, large windows are usuallyconsidered for the recognition of complex activities. The filtered sensor data is divided into small segments for feature extraction using windowing approaches.

Step 4: Feature Extraction – This step aims to extract the most significative portion of information from the data to be given to the classification algorithm while reducing data dimension.

Step 5 : Classification – This step aims training and testing the algorithm. That is, the parameters of the classification model are estimated during the training procedure. Thereinafter, the classification performances of the model are tested in the testing procedure.

4. MODEL EVALUATION

After the training is finished, it is necessary to gauge our model so that we can be sure that it can predict human activities well enough. For this purpose, two learning curves were plotted, which are presented in this paper.

1. **LSTM**

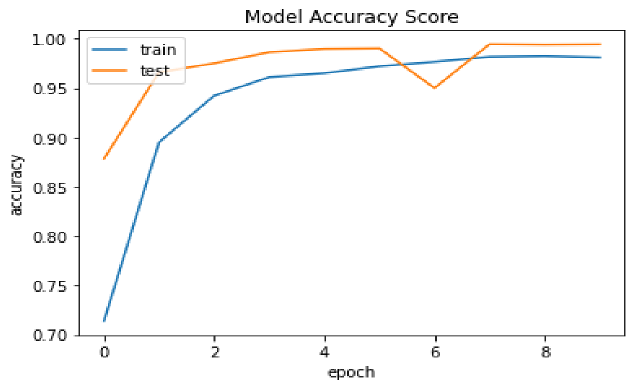


Figure 2 shows the plot of training and validation accuracy values for all the ten epochs. Next,

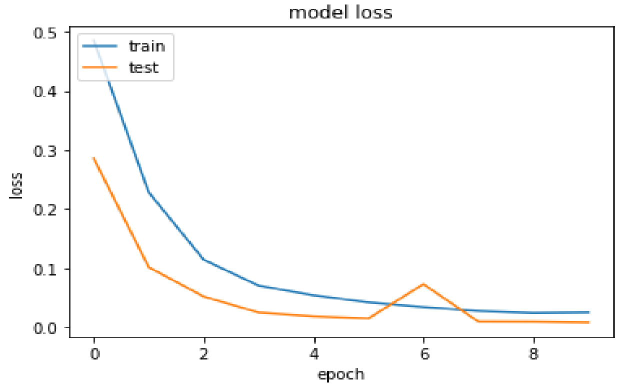


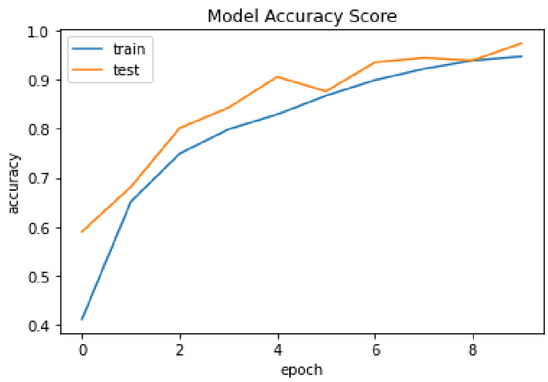
Figure 3 shows the plot of training and validation loss values for all the ten epochs.

Figure 2 : LSTM Model Accuracy Score

Figure 3 : LSTM Model loss

2. RNN

Figure 4 shows the plot of training and validation accuracy values for all the ten epochs. Next, Figure 5 shows the plot of training and validation loss values for all the ten epochs.



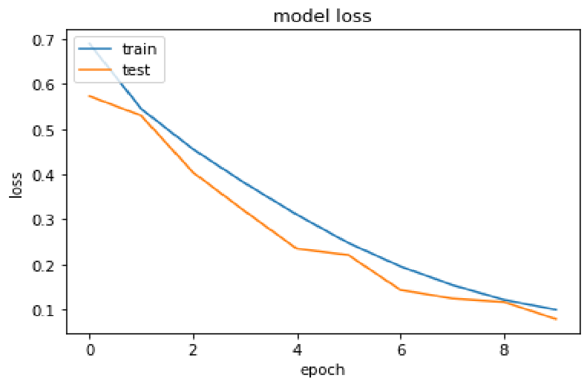


Figure 4 : RNN Model Accuracy Score

Figure 5 : RNN Model loss

3. GRU

Figure 6 shows the plot of training and validation accuracy values for all the ten epochs. Next, Figure 7 shows the plot of training and validation loss values for all the ten epochs.

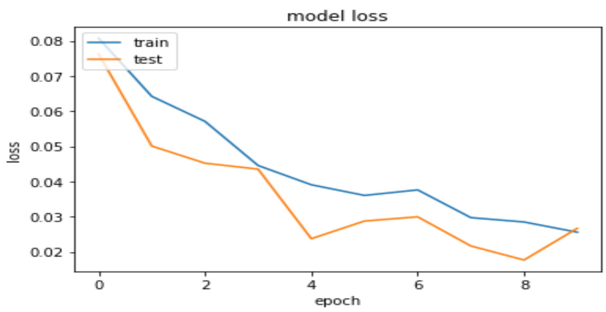


Figure 6 : GRU Model Accuracy Score

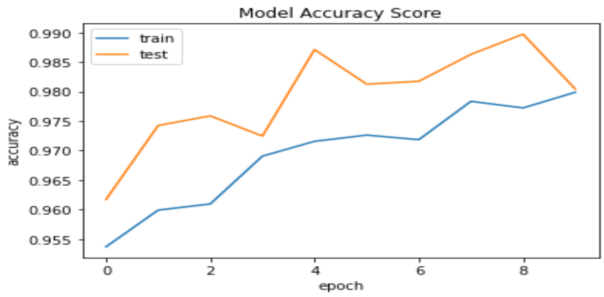


Figure 7 : GRU Model loss

5. IV.RESULTS

The experiments have been done on Python of version 3. The results for proposed model are shown in table . The result shows that Long Short Term Memory [LSTM] provides better accuracy of 99.37% .Recurrent Neural Network [RNN] have a accuracy of 97.29% .Gated Recurrent Unit [GRU] have a accuracy of 98.03%.

Accuracy Of All The Models Implemented			
Deep Learning Model	LSTM	RNN	GRU
Dataset			
UCI	99.37%	97.29%	98.03%
WISDM	97.07%	94.00%	95.00%

6. CONCLUSION AND FUTURE SCOPE

Taking into consideration our work of research, and the researches and studies reviewed for this paper, we come to a few conclusions:

1. Larger datasets do affect the accuracy of the models irrespective of the approach used.
2. The more the number of sensors, the more signals and increased data, this helps make Activity Recognition more accurate.

The main objective of this paper will be to design a prediction model and activity tracker for the humans; we assumed that a normal smartphone with minimal sensors would serve the purpose. And our model will perform the best from the rest. This theory may not be applicable to all sectors, but with improvement and advancement with technology comes the responsibility to cater to human needs.

Our future work can focus on working on newly developed datasets that are more aligned with real-life scenarios, consisting of a greater number of activities to predict and a bigger number of participants. Otherwise, an effort can also be made to collect data, per se, with a greater number of participants with different lifestyles, behaviour, ageing, etc. Another future work could include abnormal human behaviour prediction. With the help of a functional activity recognition system, one can supervise the dependent persons such as the elderly people in smart homes and evaluate their activity level for healthcare services. Moreover, for all the residents staying in smart buildings, human activity recognition can be utilized in checking their comfort level concerning factors such as temperature and humidity. Last but not least, 1D and 3D approaches towards building the CNN model could be tried out for predicting human activities in future.

The direction for future research in this field will be to evaluate whether additional features are necessary to improve classifier performance, without adding computational complexity to the algorithm and we will investigate the performance in more complex activities recognition such as bicycling, fall detection.

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