HUMAN ACTIVITY RECOGNITION

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***Abstract*— This paper is based on comparing various ML models applied for human activity recognition. Then choosing the best model and making an android application and checking the accuracy on the app for the given model. Then drawing conclusion about what can be improved and related future work.**

INTRODUCTION

Human Activity Recognition or HAR in short deals with identifying the actions and activities of humans. Human Activity Recognition has wide range of applications in Health Care,Security & Surveillance, Human Computer Interaction, Navigation,Intelligent Environment etc. As a part of this report, we will look into the existing methods for HAR and also make comparative analysis among them.

EXISTING METHODOLOGY

Following are the conventional approaches that are followed while performing human activity recognition.

- Vision based :- This uses computer vision techniques to predict activity in an image. The image could be taken either through camera or scanner or it could be imported in jpg or png format.
- Wearable device based :- Wearable device consists of smart watch, smart belts or smart lens that have inbuilt sensors to recognize various human activities.
- Smartphone sensor based :- This uses smartphones in built sensors to detect various human activities.

OBJECTIVES

The main key objectives are to come up with the analysis of existing ML based approaches. This is verified by testing the models on the popular UCI - HAR dataset. Then drawing conclusion from it and improve accuracy further by hyperparameter tuning or modifying the DL architecture. And at last testing on Mobile Android app and drawing conclusion from it.

IV. DATASET USED

As a part of comparative analysis, UCI HAR Dataset is used. This data is obtained using the sensors of smartphone. The sensors used for extracting the data are accelerometer and gyroscope.3 signals from accelerometer in each dimension and 3 signals from gyroscope in each dimension. The sampling rate used is 50 Hz. The activities used in the dataset are walking, sitting, standing, lying, walking upstairs and walking downstairs. There are total of 561 features present

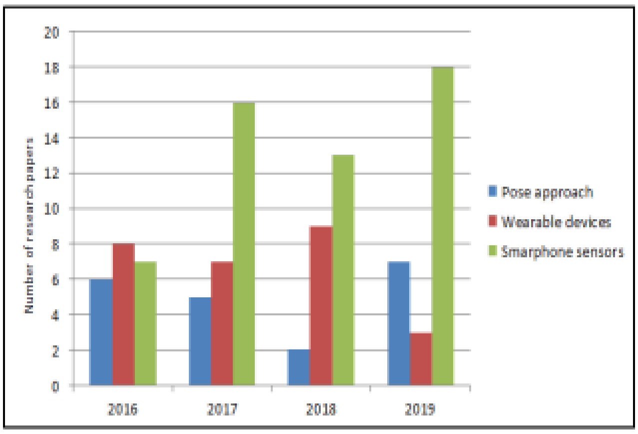
V. COMPARATIVE ANALYSIS

A total of 8 Machine Learning models viz. LSTM,Random Forest, Decision Tree, KNN, SVC, SVM, Logistic Regression and XGBoost are used for comparative analysis. All these ML models are trained on UCI HAR Dataset as mentioned above. The table below shows the accuracies of the models obtained on testing data.

TABLE

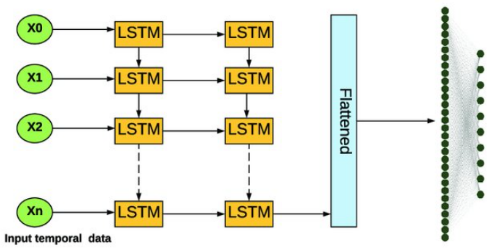
S.NO	Model	Accuracy
1	LSTM	92.8
2	Random Forest	93
3	Decision Tree	86.2
4	KNN	91.07
5	SVC	96.33
6	SVM	93.0
7	Logistic Regression	95.9
8	XGBoost	93.89

SVC outperformed among all the models used with an accuracy of 96.33 and Decision Tree least performed with an accuracy of 86.2. The performance of a decision tree lies in the number of leaf nodes it has. Less than 6 leaf nodes will result in poor accuracy as there are 6 activities involved.



The bar graph above shows the number of research papers published in the recent years in the areas of vision based, smartphone sensor based and wearable device based.Among the existing approaches for Human Activity Recognition, Smartphone sensor based method outperforms in terms of research going in that are and also in terms of it's usage. Vision based approach is the least used but can gain attention in the coming years. The main concern with vision based approach is privacy. Wearable device based approach is also gaining attention these days.

V. LSTM



We used LSTM model for further implementation even though LSTM did not showed highest accuracy. This is because of the following reasons:

- First of all accuracy of about 92.8 is also a decent accuracy.
- LSTM show good results when used over time- series dataset.
- Also LSTMs are able to distinguish between similar classes like Standing and Sitting.
- LSTMs are able to learn as well as remember over long sequences of input data.

VI. MODEL BUILDING

A. Dataset Collection

We have sensor activity dataset link of which is provided in the references. We will perform detection of activities such as Walking, Sitting, Standing, Jogging, Running , Walking Upstairs and Walking Downstairs. In this dataset each participant was equipped with 5 smartphones on 5 body positions:

1. One in their right jean's pocket.
2. One in their left jean's pocket.
3. One on belt position towards the right leg using a belt clipper.
4. One on the right upper arm.
5. One on the right wrist.

B. Sensors used

Sensors along with their uses is given below:

1. Gyroscope - Device used for measuring orientation and angular velocity.
2. Accelerometer - Device that measures the vibration, or acceleration of motion of a structure.
3. Linear Acceleration detector - Provides you with a 3D vector representing acceleration along each device axis, excluding gravity.
4. Magnetometer - Device for measuring the strength and direction of magnetic fields.

C. Training

Dataset data of 4 sensors along each axis. Split the dataset into train and test in ratio 4:1. Then apply LSTM model of Keras library. Number of classes are 7. Hidden units are 32 and learning rate to be 0.000001. Here is the model summary:

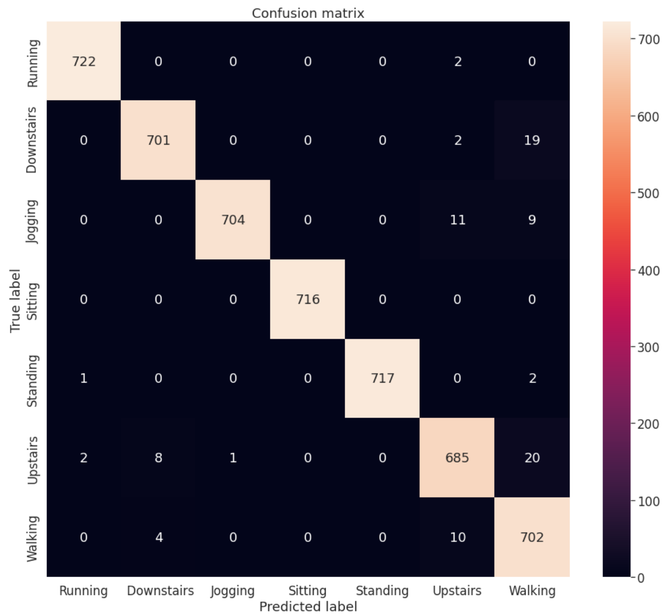
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 LSTM_1 (LSTM)               (None, 100, 32)           5760

 Flatten (Flatten)           (None, 3200)              0

 Dense_1 (Dense)             (None, 32)                102432

 Dense_2 (Dense)             (None, 7)                 231

=================================================================
Total params: 108,423
Trainable params: 108,423
Non-trainable params: 0
```

Now run the model over 40 epochs and see the accuracy.

VII. RESULTS

The developed android app for human activity recognition is quite successful in predicting high probabilities for the activities walking, jogging, sitting and standing. The LSTM model used gave an accuracy of 98.1

Picture below depicts the confusion matrix for the activities.



VIII. LIMITATIONS

The developed android app for human activity recognition is less accurate in predicting the activities running, walking upstairs and walking downstairs.

IX. CONCLUSIONS

As a part of the project, various ML models are compared and also existing methods on HAR are studied. An Android App is also successfully developed using the ML model built using LSTM.

FUTURE WORK

A relevant work that could be done in future includes to add more human activities that could be recognized and using appropriate sensors accordingly. Also to reduce latency that is appearing while detecting activities that have high motion changes which are running, walking upstairs and downstairs.

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