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Human Activity Recognition Using Smartphone

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Abstract – *Human Activity Recognition is the study of human activity using sensors which predict human activity like walking, running, sitting etc. This HAR model has been studied and tested using inbuilt 3-dimensional sensors present inside the smartphone. They are Accelerometer and Gyroscope. The readings from this sensors is taken as input and estimates motion actions using deep learning technique. In this paper CNN (Convolutional Neural Network) is used along with LSTM (Long Term Short Memory) for the performance prediction. The entire proposed system is implemented on a Smartphone device (Android Application) as it is available for all to use.*

Key Words: Human Activity Recognition, Deep learning, Convolutional Neural Network (CNN), CNN-LSTM, Gyroscope, Accelerometer, Smartphone Sensors.

1. INTRODUCTION

In this emerging technological world, the smartphone has not only become omnipresent but also an integral part of the lifestyle that we live in. From day to day communication, entertainment and keeping yourself organized it can accomplish every task. It is almost like carrying a miniature version of a computer in your pocket. A recent survey from Statista shows that alone in the year 2020, approximately 1.5 billion smartphones were sold with an average increase of 23.72% yearly.

There are multiple aspects in which a smartphone can be used to bring about a change. One such domain that it can also cover is HAR (Human activity Recognition). HAR can be used for maintaining your lifestyle with regard to fitness and health. HAR is a technique of predicting what type of activity a person is doing based on the trace of their movement using sensors. Sensors which are used record the data in three dimensions (X axis, Y axis, Z axis).

With the system that we have proposed, the smartphone will be able to classify these activities performed by the user like running, jogging, walking, sitting along with features to count the number of steps and returning other features like distance traveled and calories burnt while doing so.

It will be able to do so by taking inputs from the inertials sensors of the smartphone namely the Accelerometer, Gyroscope and the Pedometer which are inbuilt in your smartphone and which adds to the high availability, feasibility and also making it cost efficient as the user won't have to rely on any type of external device.

In this project we have tried to implement a fitness based android application that will be able to recognise human activities in a smartphone by taking raw values and classifying it using the CNN-LSTM model capable of predicting activities.

1.1 LITERATURE REVIEW

The research around the field of Human Activity Recognition shows the rise in number of technologies that can be used to to achieve the desired output solution. Initially the approaches that were used for this problem task revolved around the different machine learning algorithms which can be used to solve such real world problems. However, due to recent advancements in the field of Artificial Intelligence, deep learning has started to gain the supremacy in terms of accuracy when trained with large amounts of data when it comes to prediction and classification using the older machine learning algorithms. This section talks through these few algorithms that can be implemented for the purpose of HAR.

In a research study [1], many supervised machine learning algorithms were used for the implementation of HAR. Algorithms such as J48, Support Vector Machine (SVM), Naive Bayes and Multilayer Perceptron to classify the output in three categories: walking , running and sitting . Which is done by monitoring the changes after every 20 instances and by using a fixed window length without overlapping in the feature extraction stage. The SVM algorithm was found to be the one giving the highest accuracy of more more than 90%.

A published[2] work reveals more information about HAR when implemented using ML and DL models. Models were created using algorithms like (Support Vector Machines)SVM, K-Nearest Neighbors (KNN) and Convolutional Neural Network (CNN). Where it found that the accuracy of SVM and CNN were very similar to each other even after adding dimension reduction.

So when further study is done, we find out that even though the accuracy rates of both ML and DL approaches are fluctuating . Studies[3] show why deep learning outperforms machine learning techniques. Unlike the ML tools, Deep learning techniques learn by creating a more abstract representation of data as the network grows deeper, as a result the model automatically extracts features and yields higher accuracy results. It loosely mimics the brain functions, multiple layers of neural networks stacked one after another like the classical brain model.

Another research paper[4] which focuses mainly on the detailed deep learning part for HAR implementation using a one-dimensional (1D) Convolutional Neural Network (CNN).

Where x, y, and z acceleration data are converted into vector magnitude data which can later be used as the input for learning the 1D CNN. Which achieved the accuracy of 92.71 % outperforming that of random forest approach that gives an accuracy of 89.10%.

1.2 METHODOLOGY

Human activity recognition has become one of the important subjects to study these days due to more and more availability of the sensors. As a result one can see every small accessory like a watch provides HAR features. To increase the usage of HAR in real time can be achieved by making it available on a device like a smartphone.

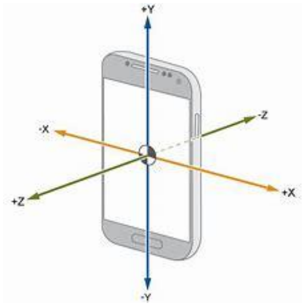
However implementation of HAR features in a device like a smartphone is a tedious task. It is a challenging problem when it comes to the observations which are produced every second, nature of these observations and lack of pre defined way to relate these sensor data to known movements.

Some classical approaches to this problem definition is by creating features from the time series data based on fixed window size and training machine learning models which often requires deep expertise in the field. However, using deep neural networks like CNN or recurrent neural networks like LSTM has shown more effectiveness on HAR tasks with less data feature engineering. The LSTM (long short term memory) is a type of recurrent neural network capable of predicting sequences of data.

Just like how there are multiple ways to accomplish the task of classification there are also multiple sensors present inside the smartphone that will initially provide the raw data sensor reading upon which the model will work. The accelerometer is the sensor mainly responsible for this sensor based HAR. Another sensor that can be used is a gyroscope. In the scope of the project we have used an additional sensor pedometer for the purpose of step counting of the user.

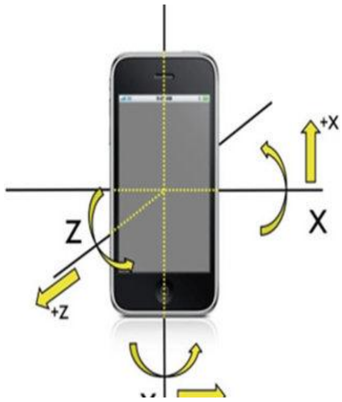
1.2.1 Sensors based: Accelerometer

Accelerometer is an Inbuilt smartphone sensor that is used to measure acceleration. It is 3-dimensional which means it can measure acceleration on 1st,2nd and 3rd axis(As it is 3dimensional).The readings measured can be of static or dynamic objects. Now a days this sensors are available in every smartphones so use it can be cost effective and reliable.



1.2.2 Sensors based: Gyroscope

Angular velocity and orientation of a static or dynamic object can be found or maintained by using Gyroscopic Sensors.This Sensor is also found in smartphones in the form of microchip-packed known as gyrometer.This sensor helps to maintain stability in readings of various human movements like walking,standing,sitting etc



1.2.3 Sensor based: Pedometer

Pedometer is a device used to count steps of the person by detecting its motion as the person walks.

People who love fitness, nowadays use pedometer regularly for fitness purpose. As most of smartphones nowadays are enhanced with an integrated accelerometer, with the help of these pedometer functionality can be used in smartphones which is the thing we have used in this project .Purpose of this pedometer in our project was to cut the cost of fitbit devices for which we pay about 5k-6k.

2. HAR Dataset

The dataset [5] that has been used is taken from the University of Twente and has also been researched on.
It consists of data values of smartphone sensors Accelerometer and Gyroscope for six different physical activities. The data has been collected from four participants. Additionally every participant was provided with 4 more smartphones on four different body positions(right and left jeans pocket, arm, wrist, belt) to read values when the phone is held at different positions. The activities have been labeled as walking, running, standing, sitting, walking upstairs and walking downstairs. Data from sensors has been collected at a rate of 50 samples per second.

However in our system we have only used data values from the right jeans pocket and left jeans pocket only.

3.1 CNN

CNNs are deep neural network model which is widely used in computer vision. The architecture of a CNN imitates that of a visual cortex in the human brain. It is used for creating and processing structured arrays of data. CNN has three main types of layer:

- Convolutional Layer
- Pooling layer
- Fully connected layer

The convolutional layers are assembled on top of each other. These consist of the input layer, hidden layers and an output layer. Each layer connects to another and has a threshold limit. If the output of any individual layer crosses the threshold limit then the next layer is activated sending data to the next layer of the neural network and each layer returns an activation map. The data gets more defined after going through numbers of layers which is termed as max pooling. Which only returns the important features from the activation map which gets passed to the successive layer till you get the final layer. The final layer which is also the classification layer finally predicts the value based on the activation map.[]

3.2 LSTM

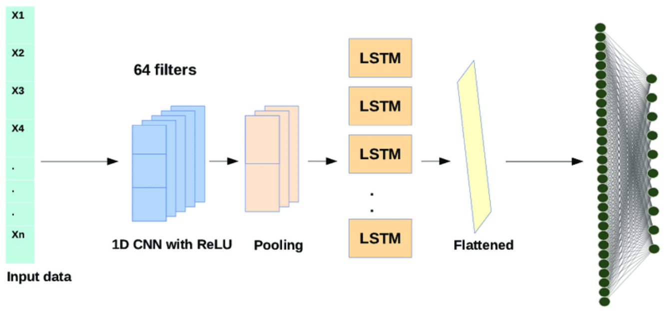
LSTMs are an extension of reccural neural network's, which give better results than standard RNNs when remembering dependencies for a long time. It does this by using long term memory into recurrent neural networks using a series of gates. These are stored into memory blocks which are connected through layers.

The three types of gates are:

- Input Gate: Scales input to cell (write)
- Output Gate: Scales output to cell (read)
- Forget Gate: Scales old cell value (reset)

3.3.1 CNN-LSTM

The CNN-LSTM model is a hybrid model that is a combination of Convolutional neural networks and Long short term memory. (LSTM)



3.1 Implementing CNN LSTM in Keras

A CNN LSTM model is usually trained jointly in Keras.
It can be defined as a stack of layers with CNN layers on the front end for feature extraction on input data followed by LSTM layers to support prediction sequence with a Dense layer on the output.

In Keras the CNN LSTM can be interpreted by wrapping it around the Time Distributed layer and later defining the LSTM and output layers.

There are two ways to define the model that are equivalent.
1. Defining the CNN model first, then adding it to the LSTM model by wrapping the entire sequence of CNN layers in a Time Distributed layer.
2. Another option is to wrap every layer in the CNN model in a Time Distributed layer while adding to the main model.

8. HAR Android Application: Real Time Activity Detection

The need for Activity Detection in Real Time will be a reality when the classification model is successfully deployed into an android application.

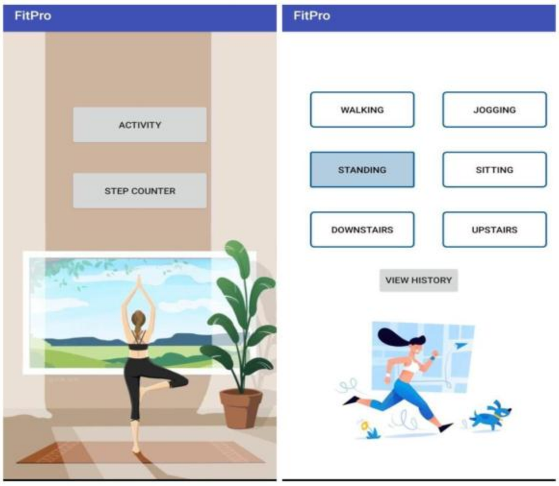
We have successfully implemented a system that predicts user activity, wherein we have used the CNN LSTM model to create a predictive model and then integrated it into our android application. This is done by converting the model into a protobuf format using tensorflow and then deploying it in the assets of the android application project. Which predicts activity efficiently and accurately.

8.1 HAR android application:

The application created works in two phases.

1. **Activity Tracker :**

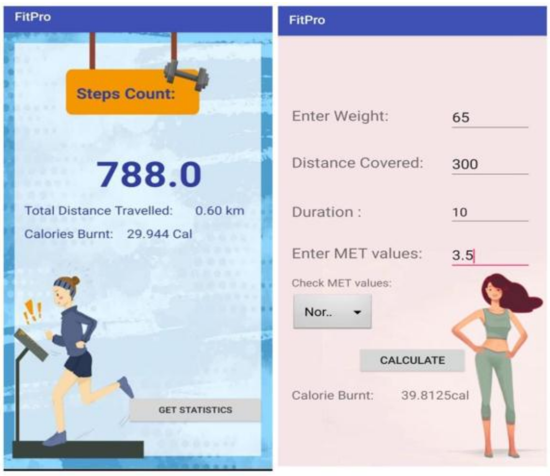
As depicted in the images below , our android application is capable of detecting the four basic activities which are walking, jogging, standing & sitting.



2. **Step Counter:**

Using the pedometer sensor, this part of the application can determine the number of steps the user has taken while walking and count distance traveled as well as estimate the amount of calories burnt while walking.

Upon further studies regarding the amount of calories burnt. We found that different types of physical activity lead to differences in the number of calories burnt. Other factors which affect calorie burn count are weight and duration and MET values(Metabolic Equivalent) which are different for different types of activities.



So we have added an additional feature that lets the user check how many calories a person has burnt depending on the different physical activities and their corresponding MET. []

3. CONCLUSIONS

Taking into consideration our thesis for this research, and few other researches and studies done for this paper, we conclude that:

1. For the purpose of achieving the best result it is better to go for a hybrid approach for model creation. Like the CNN-LSTM in our case.

2. For creating a stable application larger dataset is recommended as it surely affects the accuracy of the model.

One aspect that we would like to point out is that research in the field of Human activity recognition is limited to the use of two sensors the accelerometer and the gyroscope. The accuracy of classification can be increased by including data collected from additional sensors that are generally present inside the smartphone into the dataset as well. Like the proximity sensor, light sensor, pedometer, barometer. It would not only increase the overall accuracy but also categorize more of characteristic activities.

REFERENCES

[1] Yin, X., Shen, W., Samarabandu, J., & Wang, X. (2015, May). Human activity detection based on multiple smart phone sensors and machine learning algorithms. In 2015 IEEE 19th international conference on computer supported cooperative work in design (CSCWD) (pp. 582-587). IEEE.

[2] Shukla, P. K., Vijayvargiya, A., & Kumar, R. (2020, February). Human activity recognition using accelerometer and gyroscope data from smartphones. In 2020 International Conference on Emerging Trends in Communication, Control and Computing (ICONC3) (pp. 1-6). IEEE.

[3] Chauhan, N. K., & Singh, K. (2018, September). A review on conventional machine learning vs deep learning. In 2018 International conference on comp computing, power and communication technologies (GUCON) (pp. 347-352). IEEE.

[4] learning. In 2018 International conference on computing, power and communication technologies (GUCON) (pp. 347-352). IEEE.

[5] Lee, S. M., Yoon, S. M., & Cho, H. (2017, February). Human activity recognition from accelerometer data using Convolutional Neural Network. In 2017 ieee international conference on big data and smart computing (bigcomp) (pp. 131-134). IEEE.

[6] Shoaib, M., Scholten, H., & Havinga, P. J. (2013, December). Towards physical activity recognition using smartphone sensors. In 2013 IEEE 10th international conference on ubiquitous intelligence and computing and 2013 IEEE 10th international conference on autonomic and trusted computing (pp. 80-87). IEEE.