Dynamic Classifier for Human Activity Recognition using Sensor Data and the Impact of Data Quality

Abstract—In today’s world of big data, data is collected from various sources in ample amount of quantity. One such example is that of sensors, as it continuously collects data round the clock. The abundance of data collected from sensors can be of great use for analysis provided it is of good quality. So how good can be the quality of this data, such that it can be used confidently for analysis i.e. Veracity of data. Also, in today’s fast paced world, real time application with efficient outcome becomes an integral part of day to day life. Human Activity Recognition is one such example which is also one of the greatest research field in today’s world, it can be used in a vast variety of application such as smart homes, health care systems etc.

In this paper, I have presented a dynamic classifier using recurrent neural networks for predicting the human activity in a real time environment. I have showed that why a dynamic classifier is the best choice for human activity recognition in real time systems as compared to the static classifiers which have a fixed set of training and testing data, by comparing its results on different types of data sets. A major emphasis has been given to the time factor in predicting human activity and thus evaluating the efficiency of recurrent neural network in this time series domain.

Index Terms—Human Activity Recognition, Recurrent Neural Network, Time Series, Sensor Data.

I. INTRODUCTION

Human activity recognition is one of the biggest research field in today’s world. One of the vital reason for this, is its rich set of application. In this modern world of technology people are focusing majorly on automation by making most of the systems to run on it’s own and with no or very less need of humans. This increase in automation has been because of the vast development of Artificial Intelligence.

The process of activity recognition can be done on a single user, multi user as well as on a group of users. Applications of activity recognition include but are not limited to the field of home automation, Internet of things, medical systems, home based medications, security based application. In the field of home automation, the systems can be modeled in such a way that the electronic application will only be used when someone in need of it is in the surrounding, in this way we can save the electricity from its unwanted wastage. Similarly, in medical systems, there are many patients for whom a 24 hour monitoring is required because of medical reasons. Alloting human resource for each individual will not make this much needed medical help expensive but, can also result in unwanted wastage of human resources. Using activity recognition, one can collate multiple activity recognition monitoring systems which are running simultaneously into one, So that one resource can track multiple systems and hence reducing the total number of human resource required.

Another great application of activity recognition is that of health monitoring system. A fitness device keeps track of what all activities a person has done throughout the day. With this device, one can actively monitor his physical activities in process of keeping himself fit. In this type of systems, devices with sensors are mounted on a human body via some other devices like mobile phone, fitness tracker device etc. The sensors in this device continuously logs the data, this sensors can be of different types i.e. accelerometer, which records acceleration of device in different tri-axial directions while gyroscope records angular velocity. Other sensors being pressure, light, magnetometer etc. The data recorded by the this sensors are then used for activity recognition. We can clearly see how important is the quality of sensors data here and what role does it play. Not all sensor data are good and can provide good efficiency, because of which, it becomes increasingly important to select appropriate sensor for this purpose. Hence, making it compulsory to consider the veracity of data, to get good results for activity recognition. In this case, veracity of sensor data.

Apart from quality of the data, another important aspect of activity recognition is the technique/method used to classify human activity. Lots and lots of methods have been discovered over the time but, to keep pace with this fast world we need to consider a method which can be handy for some real time applications. Static classifiers, which includes traditional classifying techniques such as decision tree, naive bayes, k nearest neighbor etc uses fixed training data sets which means they are trained on fixed static data set and then tested against new incoming data set. This approach might fail if the nature of data changes suddenly which is a real probability. Another reason this method can fail in this domain is that of human gait. The gait of humans differ from person to person and it becomes difficult to find some static pattern in data collected from humans with vast differences in their gait. So, a new method needs to be looked after which can dynamically and continuously adapts to the changing nature of data sets and can give god accuracy in all scenarios. Recurrent Neural Network is one such method which considers previous inputs in predicting current scenario, Hence, it takes in to consideration recent input unlike static classifying techniques which uses a fixed set of data.

In this paper, we proposed a dynamic classifier for human activity recognition in time series domain and see how it fares in front of static classifiers like decision trees, naive bayes etc. To create this classifier, we have used recurrent neural network which will take into consideration the time aspect of this
data. We have also compared the accuracy of classifier when different sensors are used, so that, we can readily find which sensor would work best for this work. Also, we tried, and combined data from different sensors and saw if that would give us enhance accuracy like ensemble classifier. Finally, we train our network with a data collected form one human and test it with data collected form different human having completely different gait, telling us how good recurrent neural network can be for recognizing human activity in time series domain.

In section 2, have talked about the previous work that has been done in this field and its result. Section 3 presents the data collection and preprocessing work including feature extraction and selection. Section 4, talks about the different kind of experiments we conducted and its result, alongside comparison with the static classifier. We conclude with our contribution and the scope for future work in section 5.

Figure 1 describes how this system works.

II. BACKGROUND

A lot of work has been done previously in the field of human activity recognition, people have tried many different methods to accurately predict activity based on the sensor data. Methods such as 1-D convolution neural network, 2-D convolution neural network, recurrent neural network are amongst the few which has been tried earlier and are favorites amongst researchers.

Mi Lee and Sang Min Yoon [1] showed that activity recognition can be done using 1 dimensional convolution neural network. They have designed a model using 3 hidden layers in their convolution network. The data logged for 3 axis by mobile sensors are provided as input in the form of a vector to the one dimensional convolution neural network model. The hidden layers are used to create more features and then filter out the ones which are of least importance. As per their result, convolution neural network provides improved accuracy as compared to the static classifier, random forest approach.

Akira, Tomoki and Kayuza [2] created an activity recognition model for elderly people using deep neural network (RNN). The authors used Long Short Term Memory (LSTM) and compared their result with the studies and experiment on feed forward neural network (FF-NN) and project layer for the sole purpose of how well it can adapt a subject. Their result proves that, LSTM - RNN is much more effective in two conditions; when there is sparse data to train the model and in comparison to the feed forward neural network.

Igor, Justine and Bhaskar [3] mainly addressed the quality of data produced by the sensors attached to a monitoring device. They say that gait of humans differs from person to person and hence, it is a challenging task to create an activity classifier for all-in-one. Also, the quality of the data logged by the sensors, depends highly on the mounting position of device. Considering the above mentioned situations, the authors have suggested a novel mechanism through which one can improve on creating an activity recognition system which would fetch good accuracy considering the quality of data logged by the sensor and its mounting position.

Rohit Bhaskar [4] has showed that how mounting position and human gait plays an important role in the process of activity recognition. The author has used the traditional static classifier methods like J48, Naive Bayes and Random forest for activity recognition techniques. Author has mainly demonstrated that, difference in human gait will be the main reason for low accuracy of static classifying techniques. They trained the model with data logged from device mounted on one position say head and then tested the same model against data collected from device mounted at different position say arm, waist, thigh etc. The results show that a maximum accuracy of around 50 percent can be achieved when the model is trained and tested against different mounting positions. If the model is trained and tested against the same mounting position, then the maximum accuracy shoots to 90 percent which is expected.

In another paper by Shashank[5], he has focused on the analysis of different kind of features for the classification of human activity. Once the features has been extracted, it becomes important to select appropriate features which could give us maximum classification possible. The author here shows that, how one should select appropriate sensors for their system and even though the quality of sensor data is good, the work is still not done as feature selection is an integral part of the activity classification systems. The maximum accuracy of around 85 percent can be achieved by appropriately selecting features from the processed data. Although, the achieved result is less than those provided in [4] but it is still a significant number in terms of accuracy achieved for activity classification.

Multiple methods and systems has been proposed by the people earlier but no significant method has been provided by anyone considering the time series aspect and dynamic nature of data for the activity classification process.

III. DATA COLLECTION, PREPROCESSING AND FEATURE EXTRACTION

In this paper, I am trying to implement a dynamic classifier for human activity recognition and compare its result with
static classifier as done in [4] [5]. To make comparison more sensible, I have used the same data as that used in [4] [5].

A. Data Collection

As per [4] [5] data was collected using smart phones which has sensors in it and can log data which can be used later on. The data was collected from people with different gait i.e. people with different height, different body postures etc. For all these people, devices were mounted at different body parts which include:

- Waist
- Head
- Ankle
- Thigh
- Upper Arm
- Wrist

Different mobile phones were used to log data from different sensors and the sensor with the best data was used for activity recognition. The best of data can be defined as one which shows huge variations for different activities performed. Different position of mounting with various gait completely mixes up the data and provides us the exact kind of data for our experiment. The activities were classified into following classes[5]:

- Standing
- Walking
- Running
- Cycling
- Sitting
- Walking Up
- Walking Down

For logging the data, the subject was selected to perform the activity and then device was mounted on various parts of the body and activities were performed in a particular order with each activity spanning twenty seconds and two seconds was selected as the transition time between activities. As per [5] order in which the activities were performed was Sitting, Standing, Walking, Cycling, Cycling, Running, Walking Down, Walking Up, Walking, Cycling, Standing, Running, Sitting, Walking Down, Walking Up, Sitting, Walking, Standing, Running, Walking Down, Walking Up.

The sensors logged data in tri-axial directions i.e. x axis, y axis and z axis for the entire process. Along with the axial data, device logged time and the type of sensor that is collecting the data. Various different sensors were used for logging the data out of which, I have used the data logged by following sensors as it had the largest variation for various activities and the same has been used by [4] [5].

- Accelerometer
- Gyroscope

The huge variations caused in accelerometer and gyroscope for various activities can be seen in figure 2 and figure 3.

B. Data Preprocessing

Devices used for logging data gave raw data which cannot be used directly for experiment and needed some kind of processing. Once the recording was started, the device was securely mounted on a subject and at the end it was securely unmounted from the subject and then the recording was stopped. This activity of mounting and dismounting would consume significant time so, data recorded during that time would be of no use and if kept into consideration would only act as noise in the data. So, first one minute and last minute was taken of from the data.

The devices used for logging data, recorded timestamps along with other data which was not required for our experiment. So, it was straight away eliminated from the data. Data was then segregated into categories of sensors from which it was collected and into different CSV files for different peoples. So, we had 6 files of processed data each for Gyroscope and Accelerometer. Each files had 3 columns recording axial data for x, y and z axis and 4th column classifies which activity is being performed at that particular moment. As we had numeric data for consideration, the target class was also classified into numbers with different activities given different numbers in the actual data. Target class to number classification is as per figure 4.

C. Feature Extraction

Now, the raw data has been processed and segregated into different files for different sensors and different gait along with target labels. Can we use this data directly for our purpose? No. The sensors, for example accelerometer, logs the acceleration in 3 different axis. Now, assume that the device that logs the data is kept in pocket loosely instead of mounting tightly to a particular body part. So, now data logged by x axis of the accelerometer is the front and back
of the device. If the device tilts inside the pocket, the x axis would then remain constant as device is now facing upside down and x axis data will now be recorded with respect to ground. Even if the device is mounted to a particular body part, this problem can occur if, human bends his body part on which the device is mounted. Because of these reasons, the data logged and processed cannot be directly used for our experiment. Out of curiosity, I tried experimenting with this data and the best accuracy that was achieved was restricted to approx. 50 percent.

It now becomes compulsory to extract some important features from this data which would be most useful for our process. As per [5] a mean tilt was derived from the available data which is the square root of summation of squares of individual values. The formula used to calculate mean tilt as per [5] is:

$$\sqrt{x^2 + y^2 + z^2}$$

From this mean tilt, various different features are extracted such as Standard Deviation, Variance, Average. For each and every feature a window size of 10 was selected with an overlapping of 5 that means one feature value is derived from 1st data point to 10th data point, 2nd feature value is derived from 6th data point to 15th data point and so on. For the target labels every 5th target value was selected. In this way our data records of 4000 values will get reduced to 800.

IV. EXPERIMENTS AND RESULTS

We now had our data ready with features extracted and selected which we used for our experiments. In our various experiments, we will be testing recurrent neural network on accelerometer data initially. Then, we will take in to consideration both this data i.e. accelerometer and gyroscope data and see if we can get increased accuracy. At last, we experimented with different kind of accelerometer data sets wherein the model was trained and tested against different data sets representing different gaits.

For our experiments we have used recurrent neural network for time series application using closed loops, as recurrent neural network has proved to be a great deep neural network technique for time series application. We have used MATLAB’s neural network time series tool which provide the recurrent neural network for time series application.

Levenberg-Marquardt was selected as a sole algorithm for this experiments ahead of Bayesian Regularization and Scaled Conjugate Gradient as it uses validation data to avoid over fitting of model.

A. Experiment A

In this experiment, only the accelerometer data was taken into consideration. The data set that was collected from accelerometer was given as input to the neural network. The data set was then divided into 60 percent of training data, 20 percent of validation and 20 percent of testing data. In terms of hidden neurons and number of delayed input which is the historical input, keeping number of hidden layer as one, best accuracy was achieved for following configuration:

- Number of Hidden Neurons = 1
- Number of delayed(historical) inputs = 2

It was observed that as the number of delayed(historical) inputs were increased, the accuracy improved by only little margin. The accuracy achieved using dynamic classifier is clearly better that that of static classifier which can be seen in figure 5.

The reason for good accuracy of dynamic classifier is its fast learning rate. The spikes in figure 6 indicate how fast the model learns as it takes just single instance to learn the change in the activity.

B. Experiment B

In this experiment, we combined features extracted from accelerometer and that from gyroscope to see if there is any increase in accuracy if additional data is added. As per [5] 1 percent increase in accuracy was experienced in static classifiers.

Here, the three features namely standard deviation, variance, and average for accelerometer and gyroscope were combined
and a total of 6 columns of data points were given as inputs to the model where, first 3 belongs to accelerometer and next 3 belongs to gyroscope. The data was divided into the same configuration of 60 percent of training data and 20 percent of testing and 20 percent of validation data. Similar to experiment A, keeping number of hidden layer as one, best accuracy was achieved for following configuration:

- Number of Hidden Neurons = 1
- Number of delayed(historical) inputs = 2

We found from our results that there is same 1 percent increase in our accuracy as observed in static classifiers (J48) in [4] and the same can be seen in figure 7.

C. Experiment C

In our final experiment, which is the most important contribution of this paper, we train our model with one set of accelerometer data and test it against different set of accelerometer data which belongs to different human with unique gait.

As per [4], the maximum accuracy a static classifier can achieve when the model is trained and tested with different gait is 50 percent but, using dynamic classifier approx 90 percent of accuracy is achieved in all the scenarios. Even for this configuration the data was divided into 60 percent of training data, 20 percent of testing and 20 percent of validation data. The best results were again observed at the same configuration as above i.e.

- Number of Hidden Neurons = 1
- Number of delayed(historical) inputs = 2

Heat Map in figure 8 displays the accuracy obtained while training and testing against different set of accelerometer representing unique human gait. Row and column number represents the accelerometer data set.

V. CONCLUSION

Human activity recognition being one of the greatest field of research because of its rich set of application is a challenging task to design, because of its dynamic nature of data, quality of data and different gait contributing to vast variety of data.

As we have seen in [4], static classifiers fails when it comes to dynamic nature of data where, the model is trained and tested with different forms of data. In such scenarios the best accuracy achieved with static classifiers is 50 percent. Also, as per [5] the quality of data logged from sensors and the features extracted from that raw data significantly hampers the quality of accuracy achieved with static classifier model. Because of such reasons, it is not recommended to use this static classifier in a real life application where, the data changes frequently and data is logged in ample amount of quantity. Hence, we needed different classifiers which takes into consideration this dynamic nature of data and sensors quality.

In this paper, we tried to solve this issues by creating a dynamic classifier using recurrent neural network which is kind of feed back neural network and considers the time aspect of activity recognition data as data in this field changes with time. With this classifier we selected best features out of all available and trained our model with different configurations to find the best accurate model. Using this configuration, we got an accuracy of 93 percent using only single accelerometer which was limited to 85 percent in case of static classifier. We then combined our features extracted from accelerometer and gyroscope to observe that, combining sensor data does not increase the accuracy of a model to a greater extent and also takes more time for training as the amount of data increases.

Finally, we wanted to create a dynamic classifier which can be used for all kinds of data in this field i.e it should learn in a generic way so that, if it is trained on one kind of data set it should give accurate model when tested on all different kinds of data sets. We had 6 different kinds of accelerometer data sets collected by different subject(s) having unique gait and mounted at different parts of the body. The network was trained with each data set and tested against every other data set to see if this gives us a great classifier model. It indeed gave us an average accuracy of 90 percent using dynamic classifier which was restricted to mere 50 percent in static classifier. In this manner we proposed a novel dynamic classifier using recurrent neural network which can be used in a real world application as it gives good accurate model.

VI. FUTURE WORK

- It would be interesting to see if this system can be integrated into mobile operating system like android and test it on actual real life scenarios where, the speed does matter as different kind of disturbances occur in real world.
• It would be a good technique to analyze the time the system takes for the entire process and in any way, can we reduce this time by simultaneously maintain the accuracy.

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REFERENCES


