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A Critical Review and Analysis of a wearable sensor-based activity prediction system to facilitate edge computing in the smart healthcare system

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ABSTRACT

With increase in IOT's influence in healthcare systems, to handle big data is a very tedious way and still a big challenge to handle big data obtained through the cloud IOT systems. That is why this paper has put forward Edge-of-Things (EoT) computing. The proposed system focuses on processing sensor data and activity prediction on devices such as laptop, GPU in a smart home.

Keywords: *Healthcare systems, Wearables, Internet of Things, Edge-Computing, RNN*

1. INTRODUCTION

This paper focuses on the transformation of healthcare systems with the help of Edge computing in IOT. There are various applications based on IOT in our lives now. Here the application primarily indulges in the Health Monitoring using wearable devices. The proposed system is used in monitoring the real-time human behavior. The prediction system of the model proposed uses Recurrent Neural Network (RNN) on edge devices. The parameters that are being taken in as inputs through the sensors are Electro-Cardiography (ECG), magnometer, accelerometer and gyroscope sensors. The paper is trying to put up a new approach which it tries to outperform the existing traditional approach followed in general.

2. SENSOR DATA COLLECTION AND PROCESSING

The paper uses the MHEALTH public dataset which is being used for the prediction, analysis and monitoring. The sensors in the system are based on motion based and the magnetic field orientation dynamics. The signals of the sensor are collected and recorded at the rate of 50Hz. All the data that the sensor collects are based on a 3-parameter system except for the ECG data which just needs lead 1 and lead 2 alone.

3. RECURRENT NEURAL NETWORK FOR SEQUENCE MODELING

ML models are capable of encoding time-sequential information is apt in terms to these which is one of the major reasons the author has suggested using RNN in this paper as it has hidden units. Each LSTM block contains a cell state and has three gates: input, forget, and the output gate. The input gate is determined as following

$$It = \beta\ (WPIPt + WHIHt-1 + bI)$$

Where W is weight matrix, b bias vectors, and β logistic sigmoid function.

The forget gate F can be expressed as

$$Ft = \beta\ (WPF\ Pt + WHF\ Ht-1 + bF)$$

The long-term memory stored in a cell state vector S as expressed

$$St = FtSt-1 + It\ \tanh(WPSPt + WHSHt-1 + bS\ )$$

The output gate O determines what is going to be an output as expressed a

$$s\ Ot = \beta(WPOPt + WHOHt-1 + bO)$$

The hidden state H is expressed as Ht = Ot tanh(St).

Finally, the output U can be determined as

$$U = softmax(WUHl + bU\ )$$

Here l is indicating the last LSTM number if RNN and shows the algorithms for training and prediction of activities through Recurrent Neural Network.

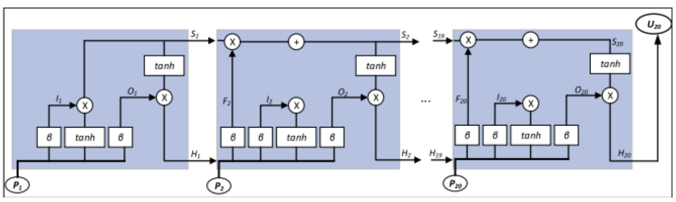

Fig 1. Architectural Structure of RNN

The dataset that was used in this RNN has vital signs and body motion data for volunteers of different people. The sensors were tested during the data collection performing various activities such as walking, running, jogging etc. The proposed RNN approach for this model achieved a mean prediction performance of 99.52%. The accuracy of the model is extremely precise and is very satisfactory relative to the traditional approach generally followed like the HMM, DBN experiments. Both have them have a prediction rate of 89.98% and 92.01%, showing how RNN has the upper hand to these approaches.

Algorithm1: Activity_Training (Training_Signals)
1. **Begin**
2. Assign N= Number of Training Signals
3. **For** i:= 1 to N do
4. Obtain a i^{th} signal, L_i = Training Signals(Training_Signals).
5. Obtain Z-score features from L_i, Z_i=Zscore(L_i)
6. **End for**
7..Assign activity label of i^{th} signal to U_i
*8.***End for**
*9.*Obtain all training features, Z and activity labels, U
*10.*Train a RNN, R based on K and U
*11.***End**

Fig 2 - Algorithm for training with RNN

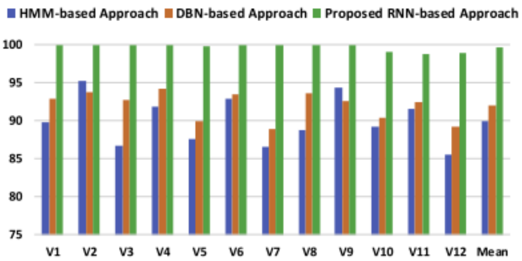

Fig 3 - Performance Analysis

The experiment was performed with confusion matrix which was proposed for RNN with subject as 1% to 10% and the Mean difference in each case was very minimal showing how precise the methods is been. It doesn't just have only the experimental data to have this edge but the system has been investigated on various wearable systems for healthcare and the deep learning method is been very successful and accurate. It has been trained intensively and practically with real life testing instead of just relying on the dataset that was used. The hybrid of IOT, EOT, COT and Edge computing has been very productive.

5. CONCLUSION

The author by proposing the system has been able to manage quite a significant improvement in the pre-existing systems used in health monitoring systems especially in wearables. The use of sensors by training the model using RNN has proved in the result analysis that it stands out relative to traditional approach. Although there can be further advancements in this model by proposing many other sensors which can help in detection of alcohol content, Accident prevention and so on which will help the monitor be more powerful in real life. The paper although trains with dataset and also live experiment data. The use of collection of data manually from beginning would've provided more novelty to the paper.

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