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RECOGNIZING ACTIVITY BY USING LONG SHORT-TERM MEMORY

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ABSTRACT

Utilizing raw sensor information to demonstrate and prepare networks for Movement recognizing can be utilized in various applications, from wellness following to security observing applications. These models can be effectively stretched out to be prepared with various information hotspots for expanded exactness's or an expansion of orders for various expectation classes. A precision of above 65% and a deficiency of under 40% has been reached in the initial 55 epochs.

Keywords: TensorFlow, keras, deep learning, neural networks, AI

I. INTRODUCTION

The ongoing innovation propels in cell phones like PDAs, numerous sensors, a piece of these gadgets, have additionally improved significantly in the course of recent years. These incorporate movement sensors, light sensors, GPS, picture sensors (camera/s), sound sensors (receiver), and so on with the registering execution expansions in these gadgets, the capacity to perform assignments, that would have been considered too handling escalated continuously a couple of years back, have been made conceivable, without requiring the information to be communicated to a worker for preparing. Because of these progressions, there are energizing new spaces of advancement that are opened up, which can aid numerous spaces of our day by day lives. The major purpose of the project is to inspect and assemble an answer for distinguish the exercises by utilizing an open-source dataset, delivered by the (WISDM) Lab. The dataset incorporates marks for every one of the six exercises, each including the x, y and z hub esteems for the tri-pivotal accelerometer during the named exercises. The exercises accessible in the dataset incorporates standing, sitting, strolling, running, rising and slipping steps.

AI can be performed with this information utilizing different strategies; this paper will break down LSTM cells. LSTM has input associations, giving it the capacity to register all that a Turing machine can perform. It can likewise handle both single information focuses, like pictures, and successions of information, like discourse, video, human action, and so forth LSTM units each comprise of a cell, and three controllers/entryways, specifically an info and yield door, and a neglect door. Every cell recollects upsides of discretionary time-stretches, while the entryways direct the data stream both from and to the cells. These organizations are ideal for characterization, preparing and foreseeing time-arrangement based information. LSTMs is demonstrated to dominate in getting the hang of, handling and ordering such kinds of information.

II. MODEL TRAINING

2.1 Raw Data Activity analysis

This study consists of about six total actions, namely jog, sit, stand, walk, upstairs movement and downstairs movement. These actions are accessible in raw dataset, provided by WISDM lab, and is perfect to use as a base for the research. Most of these actions also involves monotonous gesture making it very easy to train it and recognize them. The actions have been logged using a tri-axial accelerometer sensor. The x-axis characterizes the horizontal signal, which is towards the left-side and right-side of the smart-phone. This is used to know the horizontal nature of the leg. The y-axis senses the vertical nature which is the direction to the topside and bottom of the phone, while the z-axis represents the motion into and out of the screen, which can be used to capture the leg's backward movement and forward motion.

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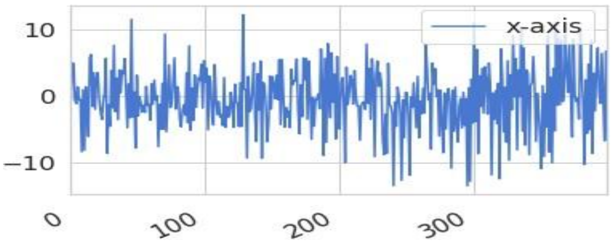

Figure 1: jog given in x-axis

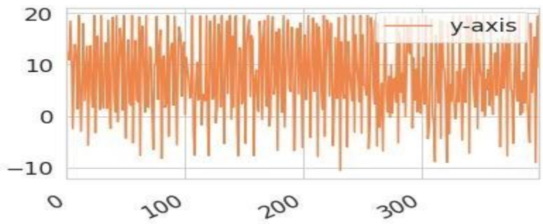

Figure 2: jog given in y-axis

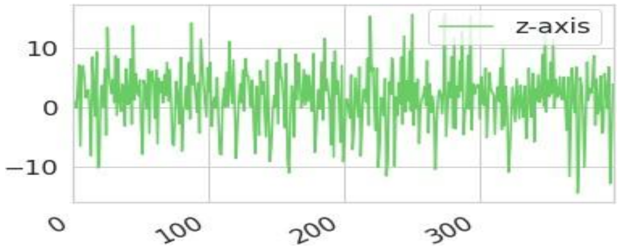

Figure 3: Jog given in z-axis

2.2 Data Processing

From the dataset, it is important to part the information into preparing, testing and approval sets for demonstrating purposes. A contending concern is that, with a more modest preparing set, the boundary gauges have more difference. Nonetheless, with a more modest test set, the exhibition measurements will have a more prominent fluctuation. It is significant that neither of the changes are excessively high. With huge datasets, regardless of whether it is a 70:3, this doesn't impact, since the two parts oughts to have the option to give good fluctuations in the assessments. The justification having approval information is to help assess the nature of the model, to keep away from over-and under-fitting, and to help with choosing the model that would play out the best on concealed information. The means needed for information partition are subsequently:

• split the given data set into 80:20, training: testing, for example

• split the leftover into 80:20, training: validation

III. MODELING

The LSTM network has been developed in the year 1997 and has been widely accepted and been followed from then. It is improved structured then RNN (recurrent neural network). The LSTM have been created to avoid long term memory loss problem. So, these have very high remembering attribute for long time as well. The cell state given is a kind of like a conveyer belt. It runs straight down the complete chain, with only some negligeable linear interactions. It's very easy for information flow along it remains unchanged. The LSTM does have the ability and agility to remove its info or add information to the present cell state, carefully controlled by strong structures called gates. These are a method to optionally let info pass through it. They are composed out of a sigmoid or tanh neural net layer and a pointwise multiplication operation.

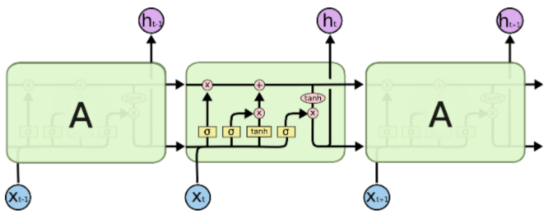

Figure 4: The repeating module in an LSTM contains four interacting layers

IV. RESULTS AND DISCUSSION

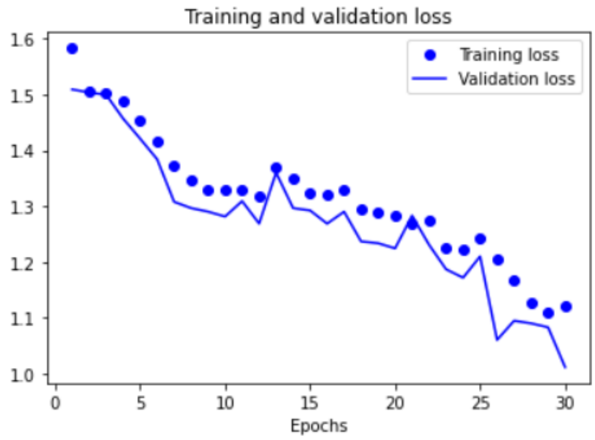

Figure 5: Training and validation loss

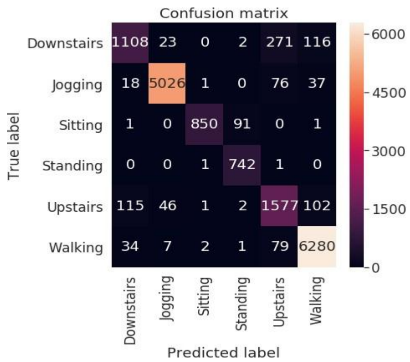

Figure 6: Confusion Matrix

From figure 5 shows the trained model's prediction performance in the form of a graph. And from the confusion matrix we can get to know about the greatest confusion lies in the prediction of upstairs and downstairs that is confusion with walking. The interpretation of up and downstairs as walking may not be necessarily incorrect, but it is a misclassification considering the available classes. There is also some confusion between sitting and standing, although the prediction is surprisingly good.

V. CONCLUSION

In this project, an activity recognizing design has been proposed using an LSTM neural architecture. The network is able to learn all six classes successfully and efficiently with only a few hundred epochs, reaching high accuracies. The work can be further extended with different data sources as well as different classes. Further we have developed an application and are currently undergoing the testing of the application as-well. The android application has been built around the TFlite version of TensorFlow for android.

VI. REFERENCES

[1] WISDM Lab: Dataset." [Online]. Available: http://www.cis.fordham.edu/wisdm/dataset.php#actitracker. [Accessed: 05-Apr-2019].

[2] A. Graves, G. Wayne, and I. Danihelka, "Neural Turing Machines," pp. 1–26, 2014.

[3] D. Britz, "Recurrent Neural Networks Tutorial, Part 3 – Backpropagation Through Time and Vanishing Gradients – WildML," 2015. [Online]. Available: http://www.wildml.com/2015/10/recurrent-neural-networks- tutorial-part-3-backpropagation-through-time-and-vanishing-gradients/.

[4] "A Gentle Introduction to Exploding Gradients in Neural Networks." [Online]. Available: https://machinelearningmastery.com/exploding- gradients-in-neural-networks/. [Accessed: 07-Apr-2019].

[5] "The Vanishing Gradient Problem – Towards Data Science." [Online]. Available: https://towardsdatascience.com/the-vanishing-gradient- problem-69bf08b15484. [Accessed: 07-Apr-2019].

[6] D. N. T. How, K. S. M. Sahari, H. Yuhuang, and L. C. Kiong, “Multiple sequence behavior recognition on humanoid robot using long short-term memory (LSTM),” 2014 IEEE Int. Symp. Robot. Manuf. Autom. IEEE- ROMA2014, no. November, pp. 109–114, 2015.

[7] “Create Segments and Labels.” [Online]. Available: https://gist.github.com/ni79ls/6701d610b031c6e31e0fd43be1eafe4f.

[8] G. Hoffman, “GarrettHoffman/lstm-oreilly: How to build a Multilayered LSTM Network to infer Stock Market sentiment from social conversation using TensorFlow.” [Online]. https://github.com/GarrettHoffman/lstm- oreilly.[Accessed:20-Apr-2019].

[9] “Tensorflow Placeholders - Databricks.com.” [Online]. Available: https://databricks.com/tensorflow/placeholders. [Accessed: Apr-2019].

[10] D. P. Kingma and J. Ba, “Adam: A Method for Stochastic Optimization,” pp. 1–15, 2014.

[11] “Differences between L1 and L2 as Loss Function and Regularization,” 2013. [Online]. Available: http://www.chioka.in/differences-between-l1- and-l2-as-loss-function-and-regularization/. [Accessed: 07-Apr-2019].

[12] S. Sharma, “Epoch vs Batch Size vs Iterations – Towards Data Science,” 2017. [Online]. Available: https://towardsdatascience.com/epoch-vs- iterations-vs-batch-size-4dfb9c7ce9c9. [Accessed: 14-Apr-2019].

[13] Pranesh Vallabh, et.al., "Fall detection monitoring systems: a comprehensive review", Journal of Ambient Intelligence and Humanized Computing, Vol.9, no.6, pp.1809-1833, 2019.

[14] Babedi Betty Letswamotse, et.al., "Software Defined Wireless Sensor Networks (SDWSN): A Review on Efficient Resources, Applications and Technologies", Journal of Interent Technology, Vol.19, no.5, pp.1303-1313, 2018.

[15] Babedi Betty Letswamotse, et.al., "Software defined wireless sensor networks and efficient congestion control", IET Networks, vol.7, no.6, pp.460-464, 2018.

[16] Johan Wannenburg, et. al., "Wireless Capacitive-Based ECG Sensing for Feature Extraction and Mobile Health Monitoring", IEEE Sensors Journal, Vol. 18, no.14, pp.6023-6032, 2018.

[17] Arun C. Jose, "Improving Home Automation Security; Integrating Device Fingerprinting into Smart Home", IEEE Access, Vol. 4, pp.5776- 5787, 2016.

[18] Zhong-qin Wang, et. al. "Measuring the similarity of PML documents with RFID-based sensors", International Journal of Ad Hoc and Ubiquitous Computing, Vol.17, no.2, pp.174-185, 2014.