Mobile Sensor Behaviour for Human Activity Recognition using Deep Convolution Neural Network

*Neeraj Varshney[1], Brijesh Bakariya[2], Alok Kumar Singh Kushwaha[3]
[1]*Research Scholar, I K Gujral Punjab Technical University, Kapurthala*
[2]*I K Gujral Punjab Technical University, Hoshiarpur Campus, Hoshiarpur*
[3]*Guru Ghasidas Vishwavidyalaya, Bilaspur*
Email: [1]neeraj.varshney@gla.ac.in, [2]dr.brijeshbakariya@ptu.ac.in, alokkumarsingh.jk@gmail.com*

***Abstract*—Human activity recognition using sensor data is catching the eyes of the researchers as no interference in the privacy of an individual while capturing data through the sensors. Different sensors behave differently because of their own function and orientation. This paper present the deep convolutional neural network based approach to identify the human activity recognition using tri-axis accelerometer and gyroscope data. Heterogeneity Dataset for Human Activity Recognition (HHAR) chosen for the experiment. The accuracy with accelerometer data is 95.42% whereas with the gyroscope data it is 88.47%. Activity recognized by the accelerometer is more accurate as compare to the gyroscope.**

Keywords: *Human Activity, Deep Learning, Sensor Data, ADL, Accelerometer*

I. Introduction

Human behavior and pattern among can be easily identified through activity perform by the user. The availability of sensors in mobile platforms has enabled the development of a variety of practical applications for several areas of knowledge [1] such as, identification of fall [2], monitoring the elderly people [3], individual activity monitoring solutions [5] etc. it is also useful to monitor the health of an individual [4], crowd behavior analysis [6], and tracking the objects [7]. Sensors are all around us and widely used by various devices used in our daily life. Internet on Things possible to capture and process the information generated by these sensors. In this paper deep learning model is applied individually to accelerometer and gyroscope data. Accelerometer data produce more accurate result compare to the gyroscope data [15].

II. Literature Survey

Many researchers share their wisdom for identification of human activity recognition using deep learning approaches. But still many issues are untouched and required huge scope of upgradation. Sensor based activity recognition does not harm the privacy of an individual but required strong mechanism to identify the activity in real time application.

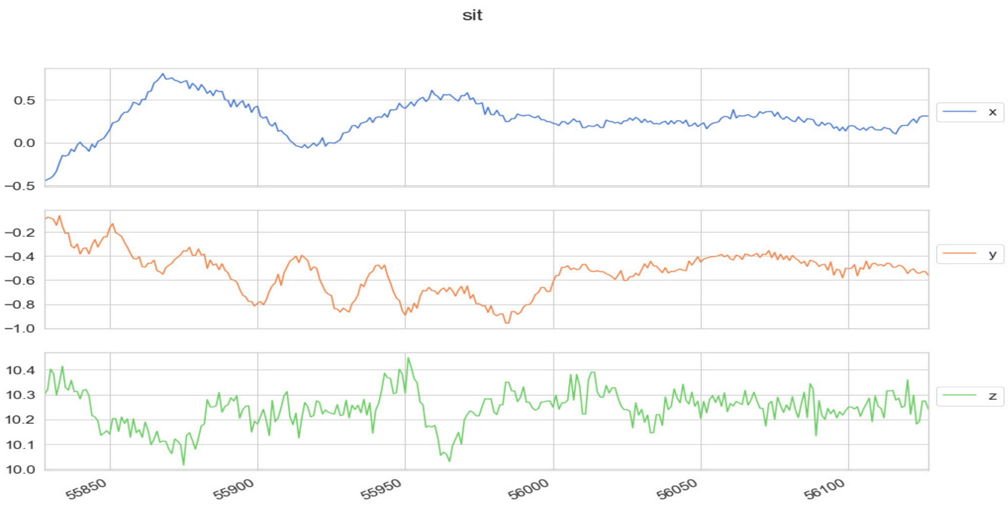

Fig 1: Signal Representation of Accelerometer Data

ISBN: 978-93-91355-11-1

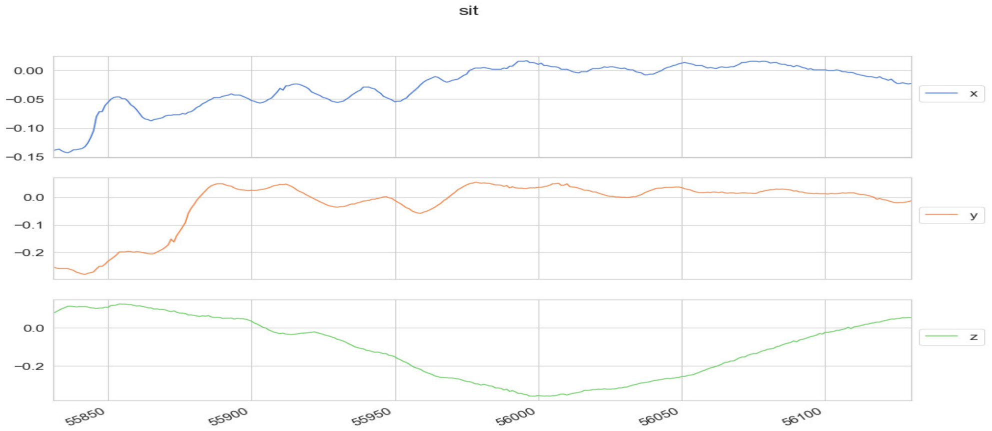

Fig 2: Signal Representation of Gyroscope Data

Shoaib *et al*. [8] proposed a solution for the sensors like accelerometer, magnetometer and gyroscope placed on various location of the human body. Three different scenarios were considered for the experiment purpose. In the first, sensor based smart phone, for the second one placed on some other place on human body and also evaluate classification model for the data generated by the same users.

Khan *et al*. [9] proposed fusion of different modality sensors to identify the human activity. They experimented on the data generated through the pressure sensor, microphone and accelerometer placed at the different location on human body. Data generated from the various sensors were pre-processed and fused and apply LDA, PCA and KDA. Author addressed that the combination of KDA with RBF kernel produced the better result as compare to the others.

Lee *et al*. [10] proposed CNN model with different combinations which required additional computational power. They used variable size of the kernel for identifying the temporal features. Deepkia et al. [11] proposed a LSTM model and choose three different datasets for the experiment purpose. A one dimensional CNN model was proposed by Heeryon et al. [12]. They offer a two stage learning mechanism and experimented on two publically available dataset named UCI-HAR dataset and opportunity dataset.Nidhi et al [16] proposed a deep learning model including CNN and GRU for end to end training.

III. Proposed Model

The data received from the sensors are preprocessed first and then partitioned into the same size time-series segments as the window frame. Chosen the size of the window play an important role to achieve the accuracy so it is very necessary to choose the window size carefully [13].

Our idea is to keep the model light so three convolutional layers of 2x2 kernel are chosen with Relu activation function. Relu activation function is much faster and also Relu reduce the problem of vanishing gradient also Relu show better convergence compare to other activation functions, also to reduce the dimensions of the feature map. pooling reduce the number of parameter to be learn so as to reduce the computation as well. At the end softmax function used for the classification of the multiclass activity.

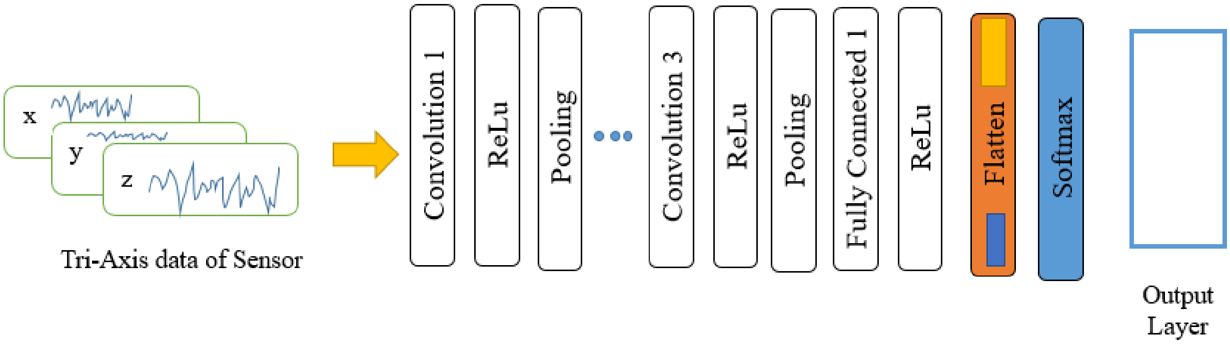

Fig 3: Proposed Model

IV. Dataset

The Heterogeneity Dataset for Human Activity Recognition from Smartphone and Smartwatches is chosen for the experiment [14]. The dataset contains the time-series record of two most common sensors found in smart-phones. The dataset includes 4 different files maintain the record of accelerometer data and gyroscope data of mobile phone and smart watch. Activities included in the dataset are 'Biking', 'Sitting', 'Standing', 'Walking', 'Stair Up' and 'Stair down'.

V. Result

This section discussed the result of the proposed model. We choose HHAR dataset for the experiment. Proposed model achieve 95.42% accuracy with the tri-axis data of accelerometer. Figure 5 shows the accuracy of the model per epoch for the accelerometer data and shown remarkable training and validation accuracy. Model achieve 88.47% with the gyroscope data and figure 6 show the accuracy of gyroscope data.

It is observed from figure 7 that model had batter perform and achieve 100% accuracy for sitting, and 99% accuracy for the stair-up data of the accelerometer and approx. similar accuracy for the walk, bike and stair-down activity. Likewise, confusion matrix in the figure 8 show that, for gyroscope data model achieve remarkable accuracy for walk and stair-down data

Table 1: Accuracy of Model on Accelerometer and Gyroscope Data

Model accuracy with Accelerometer data	95.42%
Model accuracy with Gyroscope data	88.47

Fig 4: Activity Type in HHAR Dataset

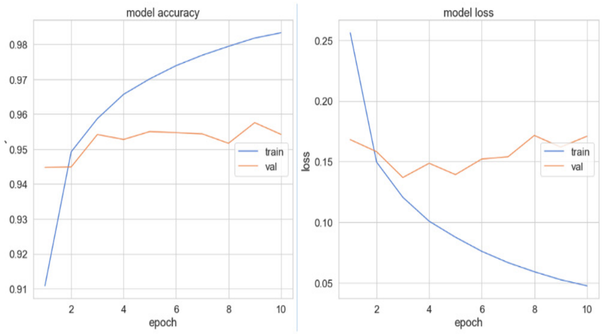

Fig 5: Accuracy and Loss for Accelerometer Data

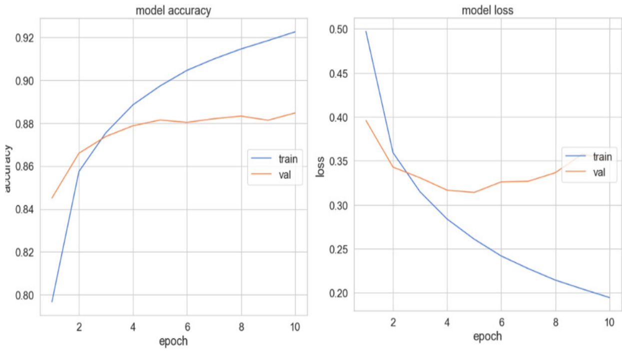

Fig 6: Accuracy and Loss for Gyroscope Data

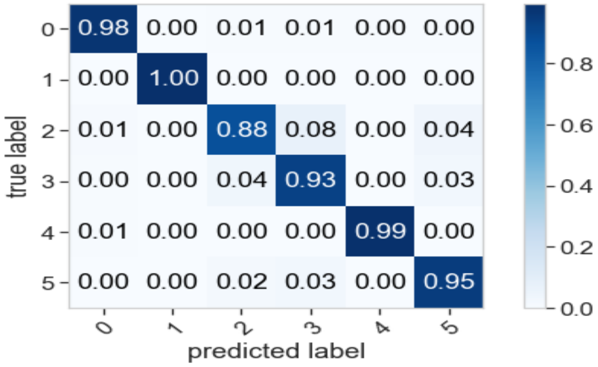

Fig 7: Confusion Matrix for the Accelerometer Data

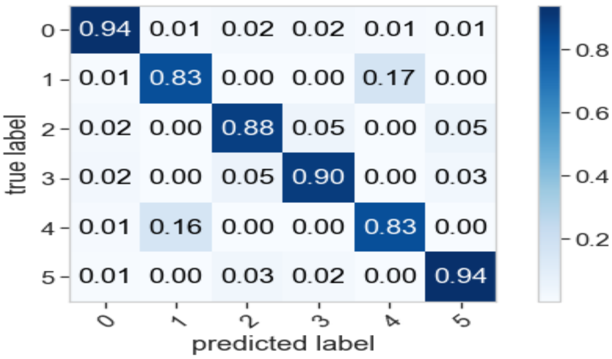

Fig 8: Confusion Matrix for the Accelerometer Data

ISBN: 978-93-91355-11-1

VI. Conclusion

This paper presents a deep learning model for human activity recognition. The article consider the data generated through the accelerometer and gyroscope sensor of the mobile phone available in the HHAR dataset. Result of accelerometer data and gyroscope data analyse and identified that data generated through the accelerometer perform batter result compare to the gyroscope. In future we are planning to combine the data of both the sensors and also try to combine the data generated through different devices like mobile phone and smart watch also planning to analyse the axis based combination of different devices.

References

[01] Lockhart, J.W.; Pulickal, T.;Weiss, G.M. Applications of mobile activity recognition. In Proceedings of the 2012 ACM Conference on Ubiquitous Computing–UbiComp, Pitts-burgh, PA, USA, 5–8 September 2012.

[02] Dai, J.; Bai, X.; Yang, Z.; Shen, Z.; Xuan, D. PerFallD: A pervasive fall detection system using mobile phones. In Proceedings of the 8th IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOMWorkshops), Mannheim, Germa-ny, 29 March–2 April 2010; pp. 292–297.

[03] Fontecha, J.; Navarro, F.J.; Hervás, R.; Bravo, J. Elderly frailty detection by using accel-erometer-enabled smartphones and clinical information records. Pers. Ubiquitous Comput. 2013, 7, 1073–1083.

[04] Preuveneers, D.; Berbers, Y. Mobile phones assisting with health self-care: A diabetes case study. In Proceedings of the 10th International Conference on Human Computer Interaction with Mobile Devices and Services, Amsterdam, The Netherlands, 2–5 September 2008; pp. 177–186.

[05] Tapia, E.M.; Intille, S.S.; Larson, K. Activity recognition in the home using simple and ubiquitous sensors. In International Conference on Pervasive Computing; Springer: Ber-lin/Heidelberg, Gremany, 2004; pp. 158–175.

[06] Mehran, R.; Oyama, A.; Shah, M. Abnormal crowd behavior detection using social force model. In Proceedings of the 2009 IEEE Conference on Computer Vision and Pattern Recognition, Miami, FL, USA, 20–25 June 2009; pp. 935–994.

[07] Viola, P.; Jones, M. Rapid object detection using a boosted cascade of simple features. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), Kauai, HI, USA, 8–14 December 2001; pp. 511–518.

[08] Shoaib, Muhammad, Stephan Bosch, Ozlem Durmaz Incel, Hans Scholten, and Paul JM Havinga. "Fusion of smartphone motion sensors for physical activity recogni-tion." Sensors 14, no. 6 (2014): 10146-10176.

[09] Khan, Adil Mehmood, Ali Tufail, Asad Masood Khattak, and Teemu H. Laine. "Activity recognition on smartphones via sensor-fusion and kda-based svms." International Journal of Distributed Sensor Networks 10, no. 5 (2014): 503291.

[10] Lee, Song-Mi, Sang Min Yoon, and Heeryon Cho. "Human activity recognition from accel-erometer data using Convolutional Neural Network." In 2017 ieee international conference on big data and smart computing (bigcomp), pp. 131-134. IEEE, 2017.

[11] Singh, Deepika, Erinc Merdivan, Ismini Psychoula, Johannes Kropf, Sten Hanke, Matthieu Geist, and Andreas Holzinger. "Human activity recognition using recurrent neural net-works." In International cross-domain conference for machine learning and knowledge ex-traction, pp. 267-274. Springer, Cham, 2017.

[12] Cho, Heeryon, and Sang Min Yoon. "Divide and conquer-based 1D CNN human activity recognition using test data sharpening." Sensors 18, no. 4 (2018): 1055.

[13] Cao L, Wang Y, Zhang B, Jin Q, Vasilakos AV. GCHAR: An efficient Group-based Context—Aware human activity recognition on smartphone. Journal of Parallel and Distributed Computing. 2018 Aug 1;118:67-80.

[14] Stisen, A., Blunck, H., Bhattacharya, S., Prentow, T.S., Kjærgaard, M.B., Dey, A., Sonne, T. and Jensen, M.M., 2015, November. Smart devices are different: Assessing and mitigatingmobile sensing heterogeneities for activity recognition. In Proceedings of the 13th ACM conference on embedded networked sensor systems (pp. 127-140).

[15] Peppas, K., Tsolakis, A.C., Krinidis, S. and Tzovaras, D., 2020. Real-Time Physical Activity Recognition on Smart Mobile Devices Using Convolutional Neural Networks. Applied Sciences, 10(23), p.8482.

[16] Dua, N., Singh, S.N. & Semwal, V.B. Multi-input CNN-GRU based human activity recognition using wearable sensors. Computing 103, 1461–1478 (2021). https://doi.org/10.1007/s00607-021-00928-8