Human Activity Recognition for Healthcare using Smartphones

Godwin Ogbuabor
School of Computer Science
University of Lincoln, United Kingdom
gogbuabor@lincoln.ac.uk

Robert La
School of Computer Science
University of Lincoln, United Kingdom
rlabs@lincoln.ac.uk

ABSTRACT

The healthcare benefits associated with regular physical activity monitoring and recognition has been considered in several research studies. Solid evidence shows that regular monitoring and recognition of physical activity can potentially assist to manage and reduce the risk of many diseases such as obesity, cardiovascular and diabetes. A few studies have been carried out in order to develop effective human activity recognition system using smartphone. However, understanding the role of each sensor embedded in the smartphone for activity recognition is essential and need to be investigated. Due to the recent outstanding performance of artificial neural networks in human activity recognition, this work aims to investigate the role of gyroscope and accelerometer sensors and its combination for automatic human activity detection, analysis and recognition using artificial neural networks. The experimental result on the publicly available dataset indicates that each of the sensors can be used for human activity recognition separately. However, accelerometer sensor data performed better than gyroscope sensor data with classification accuracy of 92%. Combining accelerometer and gyroscope performed better than when used individually with an accuracy of 95%.

CCS Concepts

Computing methodologies → Machine learning approaches

Keywords

Healthcare, Artificial Neural Networks, Smartphone, Accelerometer sensor, Gyroscope sensor.

1. INTRODUCTION

Human activity recognition plays vital role in the mental and physical wellbeing of the population. Chronic diseases such as obesity, diabetes and cardiovascular could potentially managed by automatic recognition and monitoring of patients daily activities by their physicians [11]. These patients are usually required to follow a definite active exercise routine such as walking, jogging and running as part of their treatment [19]. Providing activity recognition system will assist patients manage their lifestyle and empower their physicians to properly monitor them, hence, offer appropriate recommendations. Continuous activity monitoring of patients will definitely reduce the hospital stay, improve reliability of diagnosis and equally enhances patients' quality of life [2].

The manufacturers of mobile devices such as smartphones recently incorporated many powerful sensors which include accelerometer, GPS, Gyroscope, temperature and blood pressure sensors [16]. Their high computational power, low cost, and small size make it possible for people to carry it always [19]. The availability of these sensors in recent smartphones has made human activity recognition using machine learning technique an exciting research area; providing an avenue for data scientist to make massive use of the sensed data for analysis, which developers can take advantage in developing mobile and web based applications.

Report from World Health Organization (WHO) shows that the major cause of overweight and obesity is lack of physical exercise to balance energy between consumed calories and expended calories [4]. Physical inactivity, which can result to obesity and overweight will not only affect the quality of life, but equally bring financial burden to the government and individuals. Machine learning tools and techniques have contributed immensely in human activity recognition. It provides computational methods and learning mechanisms that will help us to induce knowledge from sensor data. Due to the recent outstanding performance of artificial neural networks in human activity recognition, this work aims to investigate the role of gyroscope and accelerometer sensors and its combination for automatic human activity detection, analysis and recognition using artificial neural networks. These sensors are chosen for the analysis, because they are mostly used by researchers.

2. MOTIVATION

The healthcare benefits associated with regular physical activity monitoring and recognition has been considered in several research studies. Solid evidence shows that regular monitoring and recognition of physical activity can potentially assist to manage and reduce the risk of many diseases such as obesity, cardiovascular and diabetes. Alford [1], in his paper, argued that *"apart from not smoking, being physically active is the most powerful lifestyle choice an individual can make for improved health outcomes".* Participating in physical activity is necessary for people of all ages. It positions individual in a state of fitness, thereby, enhancing the quality of peoples' life. Physical inactivity which can result to obesity and overweight will not only affect the quality of life, but equally bring financial burden to the government and individuals. I believe that effective monitoring and recognition of physical activities using smartphone is timely and can create a substantial encouraging impact in our society.

3. RELATED WORK

Human activity recognition using smartphone sensor is an important research area full of challenges and opportunities. This is due to the wide range of human activities, along with the

ICMLC 2018, February 26–28, 2018, Macau, China

ACM ISBN 978-1-4503-6353-2/18/02…$15.00
DOI: https://doi.org/10.1145/3195106.3195157

variation in how a particular activity is to be performed [33]. Most of the studies on human activity recognition focus mainly on accuracy, real-time ability and robustness.

Chawla and Wgner[5], compared the accuracy of four classifiers (K-Nearest Neighbour, Support Vector Machine, Artificial Neural Network, and Decision Tree) and argued that due to the high performance of the algorithms, they can be used for real-time human activity recognition. Artificial Neural Network gave highest accuracy of 96.77%. However, the quantity of data collected is relatively small by using only 8 participants. "Collecting data from a small number of people might be insufficient to provide flexible recognition of activities on new users" [19]. Also, the data were collected in studio with participant trained to perform the activity. This might result to similarities of data obtained from different users. A comprehensive study should collect data from different populations of different gender, height, age, weight and conditions, in order to properly determine the accuracy of the algorithms.

In order to enhance the accuracy of activity detection, Daghistani and Alshammari [8] used ensemble method by combining AdaBoost with other classifiers (Decision Tree, Logistic Regression, Multi-Layer Perceptron). Their result shows that combining AdaBoost with Decision Tree gave highest accuracy of 94.03%, similarly, Walse et al [25] studied the effect of adaptive boosting on performance of classifiers for activity recognition. Adaptive boosting (AdaBoost) is a boosting method used to develop a compound classifier by sequentially training classifiers, thereby putting more emphasis on particular patterns [23]. They claimed that using AdaBoost.M1 with Random Forest enhances the classification accuracy. Some authors such as [21], [31], [28], and [15] used Hidden Markov Model in order to improve classification accuracy. This model is a probability model that has ability to handle sequential data [13]; it is efficient and easy to implement [6].

Bayat et al [3] compared three classifiers (Multi-Layer Perceptron, Support Vector Machine, Random Forest) using two different datasets collected from smartphone in different positions (phone in-hand and phone in pocket). Their accuracy was almost the same using Multi-layer Perceptron and quite different using Support Vector Machine and Random Forest. Due to the nature of accelerometer embedded in smartphones, the raw data generated from the sensor seriously depends on the sensor's orientation and position of the phone on the wearer's body [22]. For instant, reading data from the smartphone is quite different when the wearer is running with the phone in his/her pocket compares to when the phone is in his/her hand [22]. To address this issue, some authors proposed different methods. Zhu et al [34], applied the concept of similarity in order to bridge the gap between different positions. They extracted and got the average features of different activities and locations, and compute its similarity with the average features before applying classification algorithms. Similarly, Fan et al [10], collected data from different positions of the smartphone. To model position-independent recognition, they mixed all the collected data and studied three different kinds of modelling methods- vector (activity, position) based modelling, activity based modelling and position based modelling. Khan et al [14], collected sensor data from five different body positions. They applied kernel discriminate approach in order to extract important non-linear discriminating features and reduce the within-class variance and increase between class variance. Classification was carried out using artificial neural network and obtained about 96% accuracy.

Ustev et al [24], used multiple sensors (Accelerometer, Gyroscope and Magnetic field sensor). Magnetic field sensor was introduced in order to remove the effect gravity on the accelerometer readings and obtain absolute orientation independent by converting accelerometer readings to earth coordinate system. However, using multiple sensors can create serious challenge due to mobile phone battery limitations- low battery capacity [20]. Activity recognition needs continuous sensing from the mobile phone [22]. To minimize the battery challenge, Liang et al [20] proposed energy-efficient method (hierarchical recognition scheme) of activity recognition using single tri-axial accelerometer sensor in smartphone. They developed the algorithm with a lower sampling frequency and argued that their method extends the battery time for activity recognition. Furthermore, an Adaptive Accelerometer-Based Activity Recognition (A3R) strategy was introduced by [29]. This strategy adaptively makes choice on the accelerometer sampling frequency and the classification features. They claimed that their strategy achieved 50% energy savings under normal conditions.

Most of the aforementioned systems are developed with pre-defined data sources and supervised machine learning techniques, which result in static model. However, initial data source might be replaced with new data source. It is expected that a robust system be able to adapt to this dynamism by automatically incorporate the available data source [27]. To address this problem, Wen and Wand [27] developed a model using ensemble classifiers that can automatically adapt and refine the recognition system at run-time. They argued that ensemble classifiers, particularly Adaboost, can automatically discover and adapt to the differences between the original dataset and new the dataset.

To train classifiers from sensor data, labels are required and obtaining them can be tedious, costly and painstaking and equally require expertise. Unsupervised learning was applied by [18], [26], [7] and [30] to address this issue. Unsupervised learning is a machine learning method that does not require ground truth (class label), but aims at modelling the distribution in the data in order to learn more about the data and discover hidden patterns. Another challenge is a situation where majority of the sensor data are not labelled (semi-supervised). Guan et al [12] proposed a semi-supervised algorithm called 'En-Co-training' in order to utilize the unlabelled sample of the sensor data.

4. METHOD

4.1 Description of Dataset

We used publicly available human activity recognition datasets from the UCI repository. The dataset were generated from 30 different volunteers from accelerometer and gyroscope sensors using smartphone. Each volunteer worn the smartphone on the waist and performed six different activities- (Walking, Sitting, Laying, Walking Downstairs, Walking upstairs and Standing). The dataset is partitioned into two sets, 70% percent of the participants was selected for generating the training data while 30% is for testing data. But for our analysis, we combined the training and testing data.

4.2 Data Preprocessing and Feature Extraction

Classifiers, in most cases do not perform well in a raw dataset from accelerometer and gyroscope sensors. Therefore, it is important to pre-process the data to extract necessary features from the sensor data. The raw sensor data from accelerometer and gyroscope were pre-processed and presented in Kaggle website. Noise filters were applied and then sampled in fixed-width sliding windows of 2.56Sec and 50% overlap (128 reading/window). Time domain and frequency domain features of each window were calculated making it a total of 561 feature vector. For the purpose of this work, we separated the accelerometer and gyroscope sensor data in different files to investigate the role of each sensor. Table1, Table 2 and Table 3 below shows the time and frequency domain features extracted from accelerometer, gyroscope and its combination.

Table 1. Accelerometer sensor features

Time Domain	tBodyAcc-XYZ, tGravityAcc-XYZ, tBodyAccJerk-XYZ, tBodyAccMag tGravityAccMag, tBodyAccJerkMag
Frequency Domain	fBodyAcc-XYZ,fBodyAccJerk-XYZ,fBodyAccMag, fBodyAccJerkMag

Table 2. Gyroscope sensor features

Time Domain	tBodyGyro-XYZ, tBodyGyroJerk-XYZ, tBodyGyroMag, tBodyGyroJerkMag
Frequency Domain	fBodyGyro-XYZ, fBodyGyroMag, fBodyGyroJerkMag

Table 3. Combination of accelerometer and gyroscope sensor features

Time Domain	tBodyAcc-XYZ,tGravityAcc-YZ, tBodyAccJerk-XYZ, tBodyAccMag, tGravityAccMag, tBodyAccJerkMag, tBodyGyro-XYZ,tBodyGyroJerk-XYZ, tBodyGyroMag, tBodyGyroJerkMag
Frequency Domain	fBodyAcc-XYZ, fBodyAccJerkXYZ, fBodyAccMag, fBodyAccJerkMag, fBodyGyro-XYZ, fBodyGyroMag, fBodyGyroJerkMag, angle(X,gravityMean), angle(Y,gravityMean), angle(Z,gravityMean)

5. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) is one of the classification models which aims to mimic the neurological functions of the human brain [32]. It is specifically designed to imitate the operation of the actual neural networks in our brain, for image processing, pattern recognition and classification of data into different sets. One major advantage of ANN is the ability to handle noisy data [32]. Multi-Layer Perceptron (MLP) is the most widely used ANN which is considered to be a great model for classification and prediction task. MLP is made up of three layers, namely, input layer, hidden layer and the output layer. The input layer represents the number of features in a given dataset, output layer is the representatives classes involve in the given dataset while hidden layer makes use of different neuron and activation function in order to give the required output. Figure 1 below shows MLP architecture with five neurons in the input layer, three neurons in the hidden layer and two in the output layer.

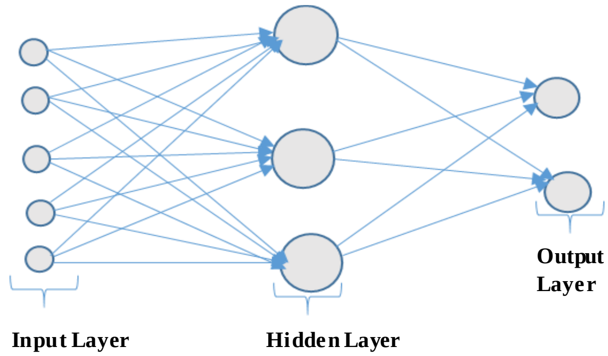

Figure 1. Multi-layer Perceptron Architecture

6. SMARTPHONE SENSORS FOR ACTIVITY RECOGNITION

Recent smartphones are becoming more useful due to different sensors such as accelerometer, GPS, Barometer, Step Detector Sensor, Step Counter Sensor, gyroscope, Temperature and Blood Pressure sensors embedded in them. These sensors can be used to carry out different tasks such as activity recognition, step counting, measuring temperature and heart rate. Accelerometer and gyroscope are the most widely used smartphone sensors for human activity recognition.

Accelerometer is a sensor embedded in smartphone that measures the acceleration of object, which is the change in velocity of the object. It provides the 3-axis (X, Y, and Z) accelerometer which can be extracted from the sensor. The accelerometer values can be utilized to determine the acceleration of the user, however, classifiers should be developed to accurately infer activities such as walking, running and sitting from the raw accelerometer data. The x-axis shows lateral movement of the phone, the y-axis describes vertical movement of the phone while the z-axis describes movement in and out of the plane defined by the x and y axes. The gyroscope sensor is used to measure the phone's orientation rate by detecting the roll, pitch and the yaw motions of the smartphone along the x, y, and z axis respectively. Figure 2 and figure 3 below show accelerometer and gyroscope axes on smartphone.

Figure 2. Accelerometer axes on smartphone

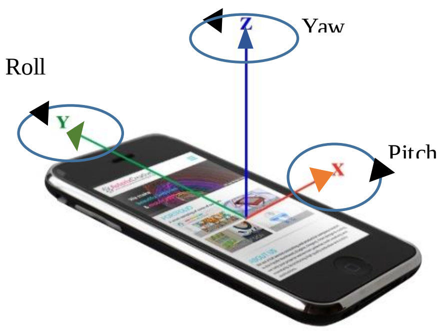

Figure 3. Gyroscope axes on smartphone

7. EXPERIMENTAL RESULTS AND DISCUSSION

After separating accelerometer and gyroscope sensor data from the dataset, we evaluate the performance of each sensor data individually and when they are combined using classification accuracy and confusion matrix. Multi-layer perceptron was used as classifier due to its performance in other work by Chawla and Wgner[5]. We used 10-ford cross validation for the experiment while the default SKlearn parameters in python were used for the training of the algorithm.

7.1 Classification Accuracy

The accelerometer sensor data is about 345 features which comprise of the time and frequency domain features of the sensor dataset. Using MLP as the classification model, the model recorded performance accuracy of 92%.

The gyroscope sensor data is made up of 213 features which involves the time and frequency domain features of the gyroscope sensor dataset. Using MLP as the classification model, the model recorded performance accuracy of 80%.

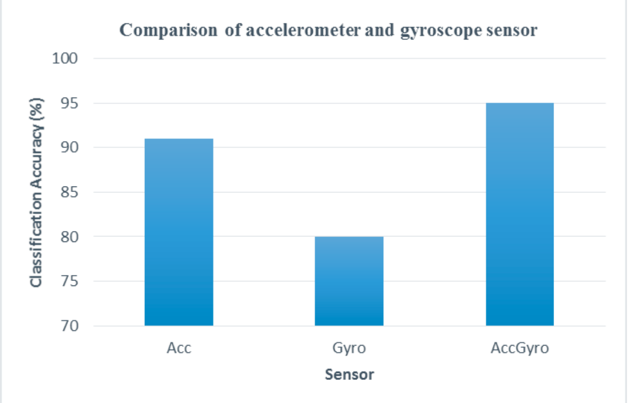

Figure 4. Comparison of Accelerometer (Acc), Gyroscope (Gyro) sensors and their combination (AccGyro)

Combining the accelerometer and gyroscope data, we have 561 features, which comprises of the time and frequency domain features of the sensor dataset. Using MLP as the classification model, the model recorded performance accuracy of 95%. Figure 4 below shows the classification accuracy of each sensor and their combination. It is obvious that combining the two sensors gave highest accuracy of 95%, followed by accelerometer sensor with accuracy of 92%, while gyroscope gave lowest classification accuracy of 80%. Based on the analysis, individual sensors can be used for the activity recognition alone, but accelerometer will be more effective by the result shown in figure 4. Combining both sensors increase the recognition accuracy but will affect the battery life of the smartphone since activity recognition is a continuous process.

7.2 Confusion matrix

Classification accuracy can be misleading in most case, especially if there is unequal number of observations in each class (class-imbalanced). Computing the confusion matrix provides a better picture of how the classification model performed with respect to each activity. It gives detail information about how each activity is classified by the model. The confusion matrixes of the MLP algorithm for the sensors are presented below. The diagonal entries in **bold** indicates the number of correctly classified instances. The classification accuracy for each activity is also indicated. table 4 represent the confusion matrix of accelerometer sensor data, table 5 shows confusion matrix of gyroscope sensor data while table 6 shows the confusion matrix for combination of accelerometer and gyroscope. From table 4 below, laying activity appears to be easier to identify with accuracy of 99% while sitting activity seems to be most difficult activity to identify with accuracy of 78%. The poor performance of sitting activity might be due to difficulty of the algorithm to differentiate between sitting and standing activities in some cases.

From table 5 below, walking upstairs and walking downstairs had reasonable identification accuracy with 91% and 86% classification accuracy respectively. While sitting activity, unlike accelerometer had the lowest identification accuracy of 72%. From table 6, laying had the highest classification accuracy of 99% followed by walking downstairs and walking upstairs with accuracy of 97%, while sitting had the lowest accuracy of 90%. It is obvious that combining both sensors performed better than using them individually in identifying each activity, however, using multiple sensors can impose a serious challenge to the user due to mobile phone battery limitations- low battery capacity [20], in the sense that activity recognition requires continuous sensing from the mobile phone. Accelerometer performed better than gyroscope in recognition of each activity.

8. CONCLUSION

In this work, we analyzed the role of accelerometer and gyroscope sensor in activity recognition using artificial neural networks. Based on the experiment, accelerometer and gyroscope sensors can be used to recognize human activities individual. Combining both sensors performed better than using them individually, however, using multiple sensors can create serious challenge due to mobile phone battery limitations- low battery capacity. Activity recognition needs continuous sensing from the mobile phone. In future, we will use accelerometer sensor data to implement real time human activity recognition using smartphone.

9. AKNOWLEDGEMENT

I would like to appreciate TETFUND Nigeria and Michael Okpara University of Agriculture, Umudike, for sponsoring the research degree when this research took place.

10. REFERENCES

[1] Alford, L. (2010). What men should know about the impact of physical activity on their health. *International journal of clinical practice*, 64(13), 1731-1734.

[2] Avci, A., Bosch, S., Marin-Perianu, M., Marin-Perianu, R., & Havinga, P. (2010, February). Activity recognition using inertial sensing for healthcare, wellbeing and sports

applications: A survey. In *Proceedings of 2010 23rd international conference on Architecture of computing systems* (ARCS). (pp. 1-10). VDE.

[3] Bayat, A., Pomplun, M., & Tran, D. A. (2014). A study on human activity recognition using accelerometer data from smartphones. *Procedia Computer Science*, 34, 450-457.

[4] Bielik, P., Tomlein, M., Krátky, P., Mitrík, Š., Barla, M., & Bielikov á, M. (2012, January). Move2Play: an innovative approach to encouraging people to be more physically active. In *Proceedings of the 2nd ACM SIGHIT international health informatics symposium* (pp. 61-70). ACM.

[5] Chawla, J., & Wagner, M. Using Machine Learning Techniques for User Specific Activity Recognition. In *Proceedings of the Eleventh International Network Conference* (INC 2016) (p. 25).

[6] Chen, L., Hoey, J., Nugent, C. D., Cook, D. J., & Yu, Z. (2012). Sensor-based activity recognition. *IEEE Transactions on Systems, Man, and Cybernetics, Part C* (Applications and Reviews), 42(6), 790-808.

[7] Chetty, G., White, M., & Akther, F. (2015). Smartphone based data mining for human activity recognition. *Procedia Computer Science*, 46, 1181-1187.

[8] Daghistani, T., & Alshammari, R. (2016). Improving Accelerometer-Based Activity Recognition by Using Ensemble of Classifiers. *International journal of advanced computer science and applications*, 7(5), 128-133.

[9] Dernbach, S., Das, B., Krishnan, N. C., Thomas, B. L., & Cook, D. J. (2012, June). Simple and complex activity recognition through smart phones. In *Intelligent Environments (IE), 2012 8th International Conference on* (pp. 214-221). IEEE.

[10] Fan, L., Wang, Z., & Wang, H. (2013, December). Human activity recognition model based on Decision tree. In 2013 *International Conference on Advanced Cloud and Big Data (CBD)*. (pp. 64- 68). IEEE.

[11] Gjoreski, M., Gjoreski, H., Luštrek, M., & Gams, M. (2016). How accurately can your wrist device recognize daily activities and detect falls?. Sensors, 16(6), 800.

[12] Guan, D., Yuan, W., Lee, Y. K., Gavrilov, A., & Lee, S. (2007, August). Activity recognition based on semi-supervised learning. *In Embedded and Real-Time Computing Systems and Applications, 2007. RTCSA 2007. 13th IEEE International Conference on* (pp. 469-475). IEEE.

[13] Inoue, M., Inoue, S., & Nishida, T. (2016). Deep Recurrent Neural Network for Mobile Human Activity Recognition with High Throughput. arXiv preprint arXiv:1611.03607.

[14] Khan, A. M., Lee, Y. K., Lee, S. Y., & Kim, T. S. (2010, May). Human activity recognition via an accelerometer-enabled-smartphone using kernel discriminant analysis. In *Future Information Technology (FutureTech), 2010 5th International Conference on* (pp. 1-6). IEEE.

[15] Kim, Y. J., Kang, B. N., & Kim, D. (2015, October). Hidden Markov Model Ensemble for Activity Recognition Using Tri-Axis Accelerometer. In *2015 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, (pp. 3036-3041). IEEE.

[16] Kwapisz, J. R., Weiss, G. M., & Moore, S. A. (2010). Activity Recognition using Cell Phone Accelerometers.

[17] Kwapisz, J. R., Weiss, G. M., & Moore, S. A. (2011). Activity recognition using cell phone accelerometers. *ACM SigKDD Explorations Newsletter*, 12(2), 74-82.

[18] Kwon, Y., Kang, K., & Bae, C. (2014). Unsupervised learning for human activity recognition using smartphone sensors. *Expert Systems with Applications*, 41(14), 6067-6074.

[19] Lara, Oscar D., and Miguel A. Labrador. 2013. A survey on human activity recognition using wearable sensors. IEEE *Communications Surveys and Tutorials* 15.3 (2013): 1192-1209.

[20] Liang, Y., Zhou, X., Yu, Z., & Guo, B. (2014). Energy-efficient motion related activity recognition on mobile devices for pervasive healthcare. *Mobile Networks and Applications*, 19(3), 303-317.

[21] San-Segundo, R., Montero, J. M., Moreno-Pimentel, J., & Pardo, J. M. (2016). HMM adaptation for improving a human activity recognition system. *Algorithms*, 9(3), 60.

[22] Su, X., Tong, H., & Ji, P. (2014). Activity recognition with smartphone sensors. *Tsinghua Science and Technology*, 19(3), 235-249.

[23] Schwenk, H., & Bengio, Y. (1998). Training methods for adaptive boosting of neural networks. *Advances in Neural Information Processing Systems*, 647-653.

[24] Ustev, Y. E., Durmaz Incel, O., & Ersoy, C. (2013, September). User, device and orientation independent human activity recognition on mobile phones: challenges and a proposal. In *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication* (pp. 1427-1436). ACM.

[25] Walse, K. H., Dharaskar, R. V., & Thakare, V. M. (2017). A Study on the Effect of Adaptive Boosting on Performance of Classifiers for Human Activity Recognition. In *Proceedings of the International Conference on Data Engineering and Communication Technology* (pp. 419-429). Springer Singapore.

[26] Wawrzyniak, S., & Niemiro, W. (2015, September). Clustering approach to the problem of human activity recognition using motion data. In *2015 Federated Conference on Computer Science and Information Systems* (FedCSIS), (pp. 411-416). IEEE.

[27] Wen, J., & Wang, Z. (2016). Sensor-based adaptive activity recognition with dynamically available sensors. *Neurocomputing*, 218, 307-317.

[28] Xie, B., & Wu, Q. (2012, October). Hmm-based tri-training algorithm in human activity recognition with smartphone. In *2012 IEEE 2nd International Conference on Cloud Computing and Intelligent Systems (CCIS)*, (Vol. 1, pp. 109-113). IEEE.

[29] Yan, Z., Subbaraju, V., Chakraborty, D., Misra, A., & Aberer, K. (2012, June). Energy-efficient continuous activity recognition on mobile phones: An activity-adaptive approach. In *2012 16th International Symposium on Wearable Computers (ISWC)*, (pp. 17-24). Ieee.

[30] Yin, X., Shen, W., & Wang, X. (2016, May). Incremental clustering for human activity detection based on phone sensor data. In *2016 IEEE 20th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, (pp. 35-40). IEEE.

[31] Yiyan, L., Fang, Z., Wenhua, S., & Haiyong, L. (2016, November). An hidden Markov model based complex walking pattern recognition algorithm. In *2016 Fourth International Conference on Ubiquitous Positioning, Indoor Navigation and Location Based Services (UPINLBS)*,(pp. 223-229). IEEE.

[32] Yoo, I., Alafaireet, P., Marinov, M., Pena-Hernandez, K., Gopidi, R., Chang, J. F., & Hua, L. (2012). Data mining in healthcare and biomedicine: a survey of the literature. *Journal of medical systems*, 36(4), 2431-2448.

[33] Zhu, Y., Wang, C., Zhang, J., & Xu, J. (2014, December). Human activity recognition based on similarity. In *2014 IEEE 17th International Conference on Computational Science and Engineering (CSE)*, (pp. 1382-1387). IEEE.

Table 4. Confusion matrix of Multi-layer Perceptron using accelerometer sensor data

Activity	Sitting	Walking	Laying	Standing	Walking Downstairs	Walking Upstairs	Accuracy
Sitting	**1384**	0	15	375	0	3	78%
Walking	0	**1606**	0	0	34	82	93%
Laying	0	0	**1927**	15	2	0	99%
Standing	192	0	0	**1713**	1	0	89%
Walking Downstairs	0	30	0	0	**1327**	49	94%
Walking Upstairs	0	50	0	1	23	**1470**	95%

Table 5. Confusion matrix of Multi-layer Perceptron using Gyroscope Sensor Data

Activity	Sitting	Walking	Laying	Standing	Walking Downstairs	Walking Upstairs	Accuracy
Sitting	**1287**	0	331	154	0	5	72%
Walking	0	**1399**	0	0	205	118	81%
Laying	260	0	**1436**	241	3	4	73%
Standing	160	2	230	**1510**	3	1	79%
Walking Downstairs	0	124	1	0	**1208**	73	86%
Walking Upstairs	1	68	1	1	69	**1404**	91%

Table 6. Confusion matrix of Multi-layer Perceptron using Accelerometer and Gyroscope Sensor Data

Activity	Sitting	Walking	Laying	Standing	Walking Downstairs	Walking Upstairs	Accuracy
Sitting	**1608**	0	8	158	0	3	90%
Walking	0	**1639**	0	0	12	71	95%
Laying	1	0	**1922**	19	2	0	99%
Standing	161	1	0	**1744**	0	0	92%
Walking Downstairs	0	11	0	0	**1357**	38	97%
Walking Upstairs	0	27	0	0	23	**1494**	97%