International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-3, September 2019

Classification of Activities of Daily living using Smart Phones

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***Abstract**: Smart phones have become an integral part of everyday human life. These phones are packed with various sensors for different purposes. Most of them are used for understanding the environment in which the user uses the phone so that the device could respond rapidly. Indirectly the phone extracts context information of the users like the activity performed using accelerometer and gyroscope sensors. This information can be used for a variety of applications like home automation, smart environment, etc to perform automatic changes to the environment without direct input from the user. This paper deals with the classification of activities of daily living like walking, jogging, sitting, standing, upstairs and downstairs using the data collected from accelerometer sensor within the smart phone. A comparative analysis has been performed on different machine learning techniques for activity classification.*

***Keywords** : Activities of daily living classification, smart phone, sensors, accelerometer, multilayer perceptron, support vector machine and decision tree.*

I. INTRODUCTION

Smart phones have become an essential part of daily living. Globally the smart phone user count is estimated to reach 2.87 billion by the year 2020 [1]. Modern smart phones are more powerful in terms of processing, communication and data acquisition from built-in sensors [2], thus making it an integral part of pervasive computing. Applications such as health care assistance, health monitoring, M-commerce, home automation, smart environments, human machine interaction and so on are focused on the effective utilization of smart phone sensor data. Sensors such as accelerometer, gyroscope, GPS, compass are widely used to monitor the phone user. Such monitoring activity would enable mobile applications to adapt their behavior according the user's need without their manual intervention leading to context-aware assistance [3]. This automatic adaption requires determination of user's behavioral pattern from the sensor data which involves computations on the acquired data. Gait analysis is one of the methods to determine user's behavior through walking pattern. Analysis on user's Gait could provide valuable information of the activity performed by the user. This analysis can be utilized for a wide variety of health care applications. This enables patients under observation to move freely without carrying heavy recording equipment along with them always. Identification of user through the recorded Gait can also be used as bio metric to access the mobile phone without manual bio-metric input. This improves the response time of the device while it is being accessed. The accelerometer sensor data is the primary input for Gait analysis since the sensor is capable of determining the orientation of the device with reference to earth's gravity. The main applications of the sensor are to enable automatic screen rotation and 3D motion based games according to device orientation. Hence the sensor can be used for determining the device orientation when the user carries while performing various activities and thus indirectly recording Gait. This paper discusses about classification of Activities of Daily Living (ADL) using a smart phone based on machine learning techniques. The MotionSense data set is used for the classification of ADL [4]. The data set consists of accelerometer time series recorded for different activities using iPhone 6. Various machine learning techniques are used for classification and their performance is compared using metrics like accuracy, precision and F-measure. The rest of this paper is organized as follows: related works describes about the recent research occurred in the field of human activity recognition; methodology explains about the various steps involved in data acquisition, feature extraction and classification; results explains about the various performance metrics of different classifiers in activity classification and finally conclusion summarizes about the work in this paper and lists the possible applications of activity recognition in real time applications.

Manuscript published on 30 September 2019
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II. RELATED WORKS

Human Activity Recognition (HAR) has its applications in surveillance systems, health care systems and human machine interaction. Human activities can be classified into gestures, interactions, actions and group activities. Gestures are composed of simple movement of body parts like head, hands and legs. Interaction involves gestures between two or more people or people and machines. Actions involve performing activities like walking and jogging. Finally group activities involve activities performed by group of people and/or objects [5].

In [6], authors have explored the use of smart phone in the ADL classification. The smart phone enables the acquisition of contextual information from the user when he/she is performing different activities.

The authors have utilized the accelerometer and gyroscope sensors to evaluate their technique of feature fusion using publicly available dataset. In [7], smart phone accelerometer is used to record user's walking pattern. With the recorded pattern, multi-class classifier has been employed for user identification. The authors have extracted 27 features from the recorded pattern for training and validation. Decision table has been found to be more accurate in user identification. In [8], authors have considered six activities of daily living for classification. The activities include walking, walking upstairs, walking downstairs, sitting, standing and lying. Ensemble methods have been applied on base learning techniques like support vector machine and random forest for activity classification. The classification is based on the time series data acquired from smart phone accelerometer sensor. In order to improve the classification accuracy, authors [9] have implemented voting based technique. Two classifiers are fed with same feature data for classification. Final output is based on average of probabilities. With these techniques, accuracy of 93.35% and 90.15% has been achieved for the activities walking and walking downstairs respectively. Six different activities of daily living were considered in [10]. Using multiclass support vector machine (SVM) activity classification has been performed. This has resulted in the best possible accuracy for classifying static activity like lying relative to dynamic activities like walking and climbing stairs. This static activity recognition could be used for fall detection activity which is identical to laying. Fall detection is an important research topic in the field of medicine to aid the elderly people.

This paper discusses about classifying ADLs like walking, jogging, sitting, standing, climbing and descending stairs using different machine learning techniques and analyze the performance of their classification.

III. METHODOLOGY

Classification of activities of daily living involves data collection from the sensors, signal conditioning on the acquired data, feature extraction from the data, training of machine learning algorithm and validation of classification.

1. Data Collection and Signal Conditioning

Smart phone with inbuilt accelerometer sensor is used for data acquisition. Figure 1 shows the coordinates of acceleration in a smart phone. X-axis corresponds to roll movement, Y and Z axes correspond to pitch and yaw respectively. In this paper, MotionSense dataset [4] is used. The data has been collected using iPhone 6s. The volunteers carried the phone in the front pocket while performing different ADL.

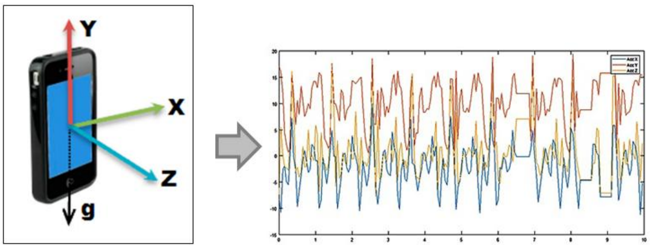

Fig 1. Mobile phone Acceleration Coordinates and Accelerometer Sample Data

The accelerometer data is then logged with corresponding activity tags for further research. ADL considered in this paper are walking, jogging, sitting, standing, upstairs and downstairs. The dataset contains the accelerometer and gyroscope time series recorded from 24 subjects of different age in the range 18-46 years. Table-1 summarizes details of the dataset.

Table 1. Dataset details

Activity	Number of samples	Contribution to dataset (%)
Walking	19,750	15.2
Jogging	20,150	15.51
Upstairs	19,625	15.12
Downstairs	21,609	16.63
Sitting	20,107	15.48
Standing	28,647	22.05
Total number of samples		1,29,888

The accelerometer sensor data is sampled at a frequency of 50 Hz [11]. The time series recorded per person ranges from 30 seconds to 3 minutes. A subset of the dataset has been considered for classification. The subset contains on an average of 20,000 samples for each activity.

The sensor data is a combination of several components such as acceleration about an axis, earth's gravity and noise. The gravitational component occupies the frequency of 0-0.8Hz and the maximum frequency within which the activities occupy is 5Hz [12]. So an IIR elliptic band pass filter as shown in Figure 2 with pass band of 0.8Hz and stop band of 23Hz has been used for filtering the time series data.

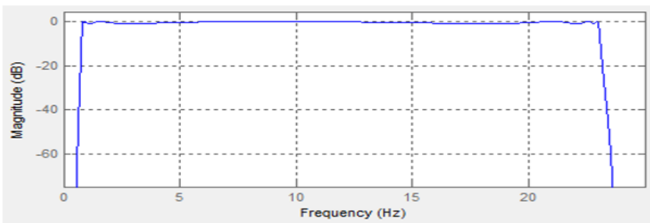

Fig 2. Frequency Response of Band Pass Filter

2. Feature Extraction

Raw time series data contains large number of data samples. In order for training the machine learning model, features must be extracted from the raw data [13].

Features represent the characteristics of the data. For better accuracy in classification, more number of features is required from each activity.

So the dataset is divided into segments with 200 data samples. Each segment contains the data for 4 seconds. Seventeen features have been generated from each segment; however they are variants of the following basic five features,

- Average [13]
- Standard Deviation [13]
- Average Resultant Acceleration – Average of square root over the sum of squared acceleration about each axis [13]
- Average Absolute Difference – Average of difference between the data samples and mean for each axis [13]
- Time between peaks – Time interval between the consecutive peaks for each axis [13]

In total, eleven thousand features were generated from the raw time series containing 3,90,000 data samples covering the six ADLs.

3. Classification

Six ADL considered for classification are walking, jogging, sitting, standing, walking upstairs and walking downstairs. The algorithms considered for classification are Multi-Layer Perceptron, Support Vector Machines, Bagging, J48 and Random forest. Weka data mining suite [14] has been used for analyzing the performance of the classifiers using MotionSense dataset.

IV. RESULTS

Each classifier is subjected to ten-fold cross validation. The results of the classification are compared with the metrics namely precision, recall, true positive rate, false positive rate and overall accuracy. Confusion matrix for each classifier is essential for determination of matrix. Tables 2 to 8 show the confusion matrix of the different classifiers. Table 2 shows the confusion matrix for the probabilistic classifier, Naïve Bayes. Though the ADLs are independent from each other, the speed at which the activity is performed differs for different users. So this leads to the error in classification.

Table 2: Naïve Bayes – Confusion Matrix

Classified as	Walking	Jogging	Upstairs	Downstairs	Sitting	Standing
Walking	107	0	0	0	1	0
Jogging	1	99	0	0	0	0
Upstairs	1	0	89	10	0	0
Downstairs	0	0	10	131	2	0
Sitting	0	0	0	0	89	9
Standing	0	0	0	0	4	94

Table 3: Multilayer Perceptron – Confusion matrix

Classified as	Walking	Jogging	Upstairs	Downstairs	Sitting	Standing
Walking	108	0	0	0	0	0
Jogging	1	99	0	0	0	0
Upstairs	0	0	99	1	0	0
Downstairs	0	0	2	141	0	0
Sitting	0	0	0	0	98	0
Standing	0	0	0	0	2	96

Table 4: SVM (Polynomial Kernel) – Confusion matrix

Classified as	Walking	Jogging	Upstairs	Downstairs	Sitting	Standing
Walking	108	0	0	0	0	0
Jogging	1	99	0	0	0	0
Upstairs	0	0	97	3	0	0
Downstairs	0	0	4	139	0	0
Sitting	0	0	0	0	95	3
Standing	0	0	0	0	3	95

Table 5: SVM (RBF Kernel) – Confusion matrix

Classified as	Walking	Jogging	Upstairs	Downstairs	Sitting	Standing
Walking	108	0	0	0	0	0
Jogging	1	99	0	0	0	0
Upstairs	0	0	97	3	0	0
Downstairs	0	0	4	139	0	0
Sitting	0	0	0	0	95	3
Standing	0	0	0	0	3	95

Table 6: Bagging – Confusion matrix

Classified as	Walking	Jogging	Upstairs	Downstairs	Sitting	Standing
Walking	108	0	0	0	0	0
Jogging	0	99	1	0	0	0

Upstairs	0	0	99	1	0	0
Downstairs	0	0	0	142	1	0
Sitting	0	0	0	0	97	1
Standing	0	0	0	0	0	98

Table 7: J48 – Confusion matrix

Classified as	Walking	Jogging	Upstairs	Downstairs	Sitting	Standing
Walking	107	0	1	0	0	0
Jogging	0	100	0	0	0	0
Upstairs	0	0	99	1	0	0
Downstairs	0	0	0	142	1	0
Sitting	0	0	0	0	96	2
Standing	0	0	0	0	0	98

Table 8: Random Forest – Confusion matrix

Classified as	Walking	Jogging	Upstairs	Downstairs	Sitting	Standing
Walking	108	0	0	0	0	0
Jogging	1	99	0	0	0	0
Upstairs	0	0	99	1	0	0
Downstairs	0	0	0	143	0	0
Sitting	0	0	0	0	98	0
Standing	0	0	0	0	3	95

Whereas neural network based classifier; multi-layer perceptron is able to classify the activities better than Naïve Bayes by considering the dependencies during the process of training. The confusion matrix is shown in Table 3. Table 4 and Table 5 shows the confusion matrix of support vector machine, its classification is similar to multilayer perceptron. Tree based techniques like bagging, J48 and random forest are able to classify the activities with less false classifications since the training process in these techniques happen activity wise. Table 6, 7 and 8 shows the confusion matrix of tree based techniques.

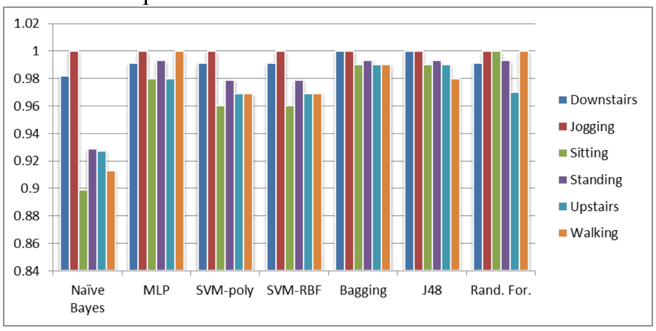

Fig 3: Classifier wise performance in terms of Precision

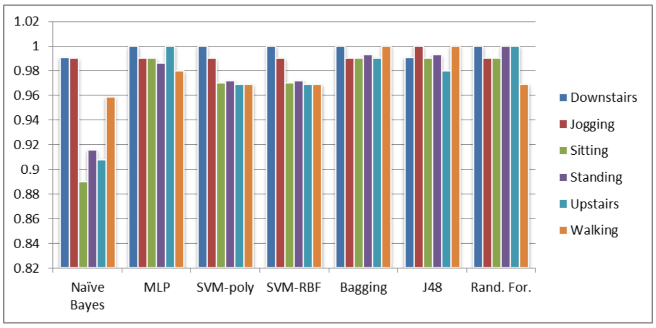

Fig 4: Classifier wise performance in terms of Recall

Precision and recall are measures of correctness in classification, while the F measure is the harmonic mean of precision and recall. Figure 3 to 5 depicts the performance of the classifiers in terms of precision, recall and F measure. Activities such as sitting and standing are poorly classified by Naïve Bayes when compared to other algorithms. These activities play a significant role in context aware fall detection systems. Though activity classification performances are relatively similar for other algorithms, bagging technique performs better in classifying the six ADLs.

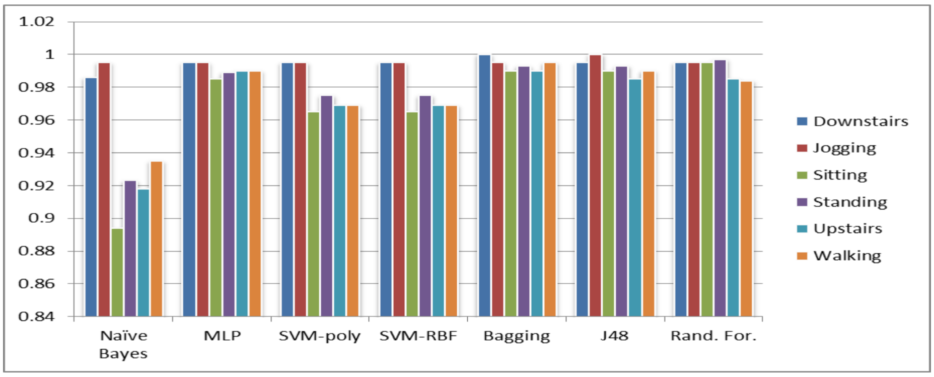

Fig 5: Classifier wise performance in terms of F-Measure

Table 9: Performance of classifiers and error in classification

	Naïve Bayes	SVM Poly	SVM RBF	MLP	Bagging	J48	Random Forest
Correctly Classified Instances (%)	94.1267	97.8362	97.8362	99.0726	99.3818	99.2272	99.2272
Incorrectly Classified Instances (%)	5.8733	2.1638	2.1638	0.9274	0.6182	0.7728	0.7728
Mean absolute error	0.0196	0.2227	0.2227	0.0075	0.004	0.0026	0.0155
Root mean squared error	0.1297	0.3111	0.3111	0.0535	0.0398	0.0508	0.0535

Table 9 lists the performance of classifiers in terms of number of instances classified and corresponding error in classification. Naïve Bayes classifier has maximum incorrectly classified instances. On the other hand, J48 and random forest has similar performance in classifying the activities. But in terms of error, J48 performs better than random forest. This is due to the presence of false negative instances in random forest as shown in Table 8.

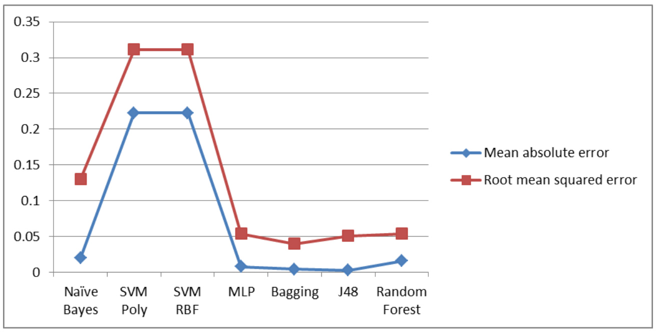

Fig 6: Classification Error plot

It is evident that bagging technique classifier has the maximum correctly classified instances when compared to other classifiers. Figure 6 shows the error plot in which bagging classifier has minimum error.

V. Conclusion and Future Scope

This paper presents a comparative analysis of different classifiers in the process of classifying Activities of Daily Living using MotionSense dataset. Possession of mobile phone in front pocket has contributed in high classification accuracy among different classifiers. But in terms of maximum correctly classified activities and minimum error in classification, bagging technique is best suited for smartphone based human activity classification. This activity classification forms the vital part in context aware systems. Context awareness leads to minimum human machine interaction. Depending on the domain of deployment context aware system has got several interesting applications. In the case of context aware home automation systems, if the user has performed jogging for a long time, the system could adjust the preset room temperature setting automatically to increase the comfort of the user.

REFERENCES

1. Asad Butt, "We Compiled 101 Top Mobile Marketing Statistics for 2018 To Help You Plan Your Future Strategies in 2019 and Beyond", January 05, 2019. Accessed on: Jun. 20, 2019. [Online]. Available: https://quoracreative.com/article/mobile-marketing-statistics
2. Wesllen Sousa, Eduardo Souto, Jonatas Rodrigres, Pedro Sadarc, Roozbeh Jalali, and Khalil El-Khatib, " A Comparative Analysis of the Impact of Features on Human Activity Recognition with Smartphone Sensors", Proceedings of the 23rd Brazillian Symposium on Multimedia and the Web (WebMedia '17). ACM, New York, NY, USA, 397-404, 2017.
3. Amato G. et al., A Benchmark Dataset for Human Activity Recognition and Ambient Assisted Living. In: Lindgren H. et al. (eds) *Ambient Intelligence - Software and Applications – 7th International Symposium on Ambient Intelligence (ISAmI 2016). ISAmI 2016, Advances in Intelligent Systems and Computing*, vol 476. Springer, Cham, May 2016.
4. Mohammad Malekzadeh, "MotionSense Dataset : Smartphone Sensor Data", March 3, 2018. Accessed on: May 7, 2019. [Online]. Available: https://github.com/mmalekzadeh/motion-sense.
5. Aggarwal, J.K. and Ryoo, M.S., "Human activity analysis: A Review", ACM Computing Surveys (CSUR), v.43 n.3, p.1-43, 2011.
6. A. Jain and V. Kanhangad, "Human Activity Classification in Smartphones Using Accelerometer and Gyroscope Sensors," in IEEE Sensors Journal, vol. 18, no. 3, pp. 1169-1177, 1 Feb.1, 2018.
7. Akram Bayat, Amir Hossein Bayat and Amir Sina Ghasemi, "Classifying Human Walking Patterns using Accelerometer Data from Smartphone", International Journal of Computer Science and Mobile Computing, vol. 6, issue. 12, pg.78 – 83, Dec. 2017.
8. Ku Nurhanim Ku Abd. Rahim, I. Elamvazuthi, Lila Iznita Izhar and Genci Capi, "Classification of Human Daily Activities Using Ensemble Methods Based on Smartphone Inertial Sensors", Sensors for Gait, Posture, and Health Monitoring, vol. 18, issue 12, Dec. 2018.
9. Muhammad Sufyian Mohd Azmi and Md Nasir Sulaiman, "Accelerator-Based Human Activity Recognition Using Voting Technique with NBTree and MLP Classifiers", International Journal on Advanced Science Engineering Information Technology, vol. 7, issue 1, 2017.
10. Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra and Jorge L. Reyes-Ortiz, "Human Activity Recognition on Smartphones Using a Multiclass Hardware-Friendly Support Vector Machine", Ambient Assisted Living and Home Care. IWAAL 2012. Lecture Notes in Computer Science, vol 7657, 2012.
11. Mohammad Malekzadeh, Richard G. Clegg, Andrea Cavallaro and Hamed Haddadi. "Protecting Sensory Data against Sensitive Inferences", In Proceedings of the 1st Workshop on Privacy by Design in Distributed Systems (W-P2DS'18), ACM, Article 2, pp. 1-6, New York, USA.
12. Wan-Young Chung, A. Purwar and A. Sharma, "Frequency domain approach for activity classification using accelerometer," 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 1120-1123, Vancouver, BC, 2008.
13. J. R. Kwapisz, G. M. Weiss, and S. a. Moore, "Activity recognition using cell phone accelerometers," ACM SIGKDD Explor. Newsl., vol. 12, no. 2, p. 74, 2011.
14. Eibe Frank, Mark A. Hall, and Ian H. Witten. The WEKA Workbench. Online Appendix for "Data Mining: Practical Machine Learning Tools and Techniques", Morgan Kaufmann, Fourth Edition, 2016.

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