Micro Activity Recognition of Mobile Phone Users Using Inbuilt Sensors

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Abstract**—— Human Activity Recognition using smartphone sensors is an area of active research. Micro activities of locomotion are indicators of higher level activities and general wellbeing of a user. In this paper, an approach for detecting a set of most common micro activities has been proposed and implemented. Five micro activities of locomotion namely sitting, standing, running, staircase ascend and descend have been considered. A two level classification model has been implemented to recognize these activities from data of inbuilt sensors of smartphone held in any of the three common positions by the user. Recognition accuracy of proposed approach is better than results reported in literature for similar problem. For purpose of training and testing, datasets have been collected on three different users and an android app has been developed to recognize activities in real time.**

Keywords— Physical Activity Recognition, Mobile Apps, Sensors

I. INTRODUCTION

Smartphones have continuously expanded their reach in recent years. Phone hardware with modules like processors, memory, camera and sensors have also evolved making it a truly versatile device. These resources and associated data can be leveraged to provide additional user oriented services, specifically in health care. In this paper, an application of usage of phone sensors' data to provide micro physical activity information of user has been proposed. Interpreting the sensor data to predict other contexts of a user can be extrapolated to knowing his lifestyle patterns and any deviations from it. The deviations, in turn can be used to raise alerts to family, friends or care takers. This knowledge can be gathered over a period of time, say a week or even a month, to recognize trends or daily habits. Owing to the age of digitization where there is separation between the individuals, healthcare has turned out to be an essential emerging area of concern for the researchers. It is extremely important to recognize the activities of the individuals and monitor it irrespective of the distance over the IoT devices. For all such IoT models it's a prerequisite to identify the activities of the users to undergo training and recognition thereafter. Therefore this study is crucial for such applications and footprints of its implications are going to be evident in future researches.

An activity recognition system, in general, has some subtle requirements. First, it should identify activities in real-time. This demands that the features used for classification are simple, light-weight and computable in real-time to be able to run on resource constrained smartphones [2].

Many researchers have targeted this problem earlier using accelerometer sensor of phone. However, accuracy on specific activities like staircase has been limited. Moreover, most of the studies have assumed specific phone positions like being tied to a body part or held in certain manner. Few applications are available on App store too. Accuracy of detection by these apps was not found to be very good on usage. In other words, the models aren't generalized to work accurately without any training [3].

This study has been carried out owing to above mentioned concerns and ultimate goal of realization of the application in day to day life for tracking more abstract activities of interest. Inferences drawn could potentially serve as the learning model for future health care solutions.

In this paper, the drawbacks in activity recognition have been tried to address. A robust model that can do accurate classifications irrespective of the phone positions and also improves classification of hard to define activities has been proposed. Common micro level physical activities that a person typically does in a day like sitting, walking, running, staircase ascend and descend have been considered. We collected sensors data during these activities for three users with their own android mobile phones as supervised training set with physical activity labels. After removal of noise, the patterns of each activity were clearly visible during exploratory analysis of sensor data.

Most popular supervised machine learning algorithms have been used to train the classifier for activity detection. Initially results were not good as the classifier was getting confused between staircase and walking or running activities. This problem has been mentioned in earlier works too [4]. We solved this problem by designing a two level classifier. A lot better recognition results were then obtained in 10 fold cross validation with decision tree based classifier. This two level decision tree based model learnt from training data was then embedded in an android app to do real time activity detection. This app on testing was giving good detection results even across users with whom the app hasn't been trained.

The detailed work is provided in rest of the sections as follows: Section 2 reproduces some of the related work in this domain. Section 3 describes the data collection process for various activities by users and the preprocessing steps. Extraction of appropriate features and classifiers has been described in Section 4. Results obtained and their discussion is elaborated in Section 5. The paper has been concluded in Section 6.

II. Related Work

A. Literature Review

Some pioneer works on sensor based activity recognition studies made use of external wearable devices. In [5], Bao and Intille used accelerometer sensors worn by subjects at various body locations to recognize activities such as sitting, standing, walking or running. In [6], a low-power sensor board with small form factor to be tied to body was designed. A hybrid approach using feature selection and HMMs was used to effectively capture boundaries and temporal patterns of the activities. This work was further extended to a practical personal activity recognition system in [7].

With the increase in the number of the sensors in the mobile phones, phone based human activity recognition has drawn research attention in the recent years.

Sefen et al [8] used sensor data of smartphones and smart watches for activities like Being idle, Walking, Jogging, Stairs, Climbing Rope, Jumping, Pushups, Crunches, Squats. Only one orientation was however considered where the participants wore the watch on the left hand and placed the phone in the front right pocket of the pants while performing diverse activities. A total of 16 participants (8 males and 8 females) performed the complete set of the selected activities. Muhammad Shoaib et al [9] used seven activities including walking, jogging, walking upstairs, walking downstairs, running, sitting and standing.

Taking cues from these works, we also selected day to day activities performed by an individual in his normal routine. These activities were sitting, walking. Staircase ascend, staircase descend and running.

Sampling frequency of data collection has been ranging from 20 – Hz to 100 Hz in previous works [10-11]. However, we collected data from the mobile application at the sampling rate of 10 Hz, so that details can be captured even after compression during preprocessing. A window of 10 samples corresponding to 1 seconds of accelerometer data for feature extraction from each of the time series was chosen because it can sufficiently capture cycles in activities such as walking , running , sitting with 90% overlap between the consecutive windows.

In the preprocessing and feature selection, Figo et al [12] listed time domain and frequency domain features that can be extracted from sensors. The time domain features, which were found to be less computationally complex such as moving average, standard deviation, minimum, maximum and range variance, were considered for implementation. Some more features such as kurtosis along the axes, difference to y, Sum of range of X and Z gravity components, Gravity range difference, Sum of range of linear acceleration, Simple moving average of sum of range of linear acceleration have been suggested in [13].

Range of results was obtained in all the above mentioned works showing that there is no clear winner algorithm for activity recognition purpose. However, Naive Bayes outperformed other classifiers in both the classification accuracy and efficiency in many [5-11]. It can be said that the proposed approaches were able to well recognize various human activities. However, staircase activities were among least well identified ones due to confusions between walking and using the stairs activities.

Authors in [11] had addressed similar problems but proposed an online classification model on data collected on their own for activities like walking, running, driving, sitting, standing and biking. Average, minimum, maximum, and standard deviation over sampling frequency of 50 Hz has been used as feature set. Here, we have tried to provide an offline solution so that it can be used by people who do not have stable and prolonged Internet access.

Jeffrey W. Lockhart and Gary M. Weiss [10] demonstrated through their study that hybrid personalized models perform better than actual ones. We aim to use the hybrid models for the cross user validation.

For the study being done here, results obtained by [14 – 15] have been considered as benchmarks. In [14], a well cited work in this area; authors have considered walking, jogging, upstairs, downstairs, sitting and standing activities. We also take the same set of activities except jogging that has been replaced by running. Accuracy of staircase activities is reported to be up to 60% by them. A recent work proposed in [15] by Mandal et al. using cell phone accelerometer based datasets reported an improved 71 to 77% accuracy in these activities. The main reason behind lowered accuracy for these two activities is confusion between walking and upstairs activity. With respect to these two works, we aim to address following :- (1) distinguish walking and staircase activities more accurately (2) Make recognition as unobtrusive as possible by doing recognition while user holds the device in his own way (3) Classifier learnt on test set of persons can be used by any other person too.

III. Data Collection and Preprocessing

Five classes of micro physical activities of a normal day to day routine were decided to be logged. These were Staircase Ascend (C1), Staircase Descend (C2), Walking (C3), Running (C4) and Sitting (C5). In order to make the recognition phone- position independent, it was allowed to hold the phone in any of the three most common positions namely – in hand, in trouser pocket and in shirt pocket.

The first stage is to collect multivariate time series labeled data from the smartphone's sensors. The sensors were sampled with a frequency of 10 Hz. An android based mobile app was developed to collect data for training purposes. The interface of this app is shown in Fig 1.

The app allows the user to record labeled data by selecting one of the activities in the drop-down list (C1-C5) and the position in which the Smartphone was kept (shirt pocket, trouser pocket, hand). The shirt-pocket, trouser-pocket and hand were the respective positions where smartphone was kept while recording the data. While collecting the data the lags were clearly eliminated while recording by actually delaying the recording sessions by a reasonable time to allow smartphones to be placed at site. Apart from this the read-write discrepancy was also addressed while recording the activities so that owing to the variations in changes across different sensors the number of tuples does not vary for each activity and position. Once the user is ready, he starts logging by pressing on required button. The captured sensor data is recorded in a CSV file on pressing "write to file button". Each user is asked to prepare such files multiple times for each activity. These files are later used for training classifiers and building models based on them that can be later loaded to another android app for activity prediction using pre-built model.

(a)

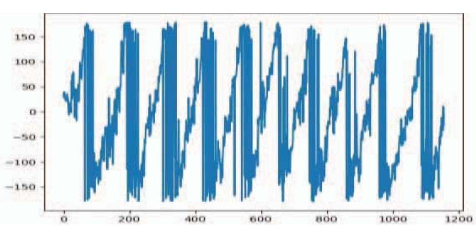
(b)

Fig. 1. (a) App interface to select configuration and log data (b) Live readings shown in tap interface

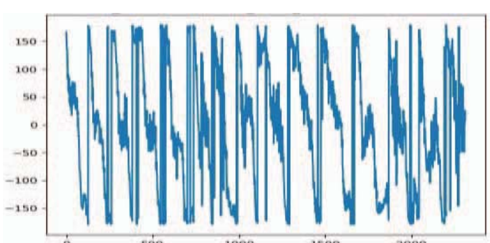
Mobile phone was kept in any of the three different positions representative of the usual way in which a user carries phone. These were trouser, upper pocket and holding in hand.

A. *Observations*

Exploratory data analysis was done on collected sensor data to establish that it can well characterize the activities. It was found that sensor data shows periodic patterns on different activities and hence can be used for prediction of same.



(a)



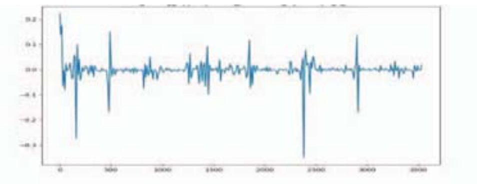
(b)

Fig.2. (a) Staircase descend (b) Staircase ascend movement patterns in Azimuth sensor

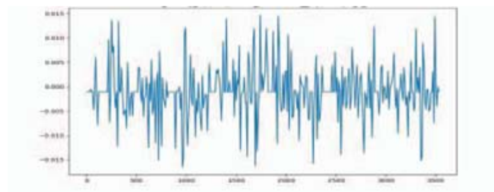
Plots of Orientation (azimuth) sensor while doing staircase descend and ascend activities are shown in figures 2(a) and 2(b) respectively. The symmetric movement patterns are clearly visible in the data. Similar patterns were observed in other activities too.

B. *Preprocessing*

The raw dataset collected from mobile application using in-built sensors was very noisy. When long term plots of the activities were observed, abnormal spikes (outliers) were noticed in the continuous time series plots. Median filter was applied on raw data to remove these outliers. This improved the quality of data by reducing most of the noise due to erratic movements. The outcome of outlier removal for Gyroscope sensor has been shown in figures 3(a) and 3(b).



(a)



(b)

Fig. 3. (a) Sensor data with outliers (b) Sensor data without outliers (Median Filtered)

After detecting and eliminating outliers, all numerical sensor data values were normalized to a uniform scale. The normalized data was then used in a sliding window of 10 samples for feature calculation required in the next step. There was an overlapping of 90% samples in two adjacent windows.

IV. Implementation

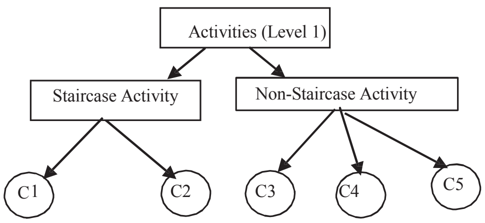
A. *Feature Extraction*

Several time-domain features were extracted from preprocessed data to obtain relevant information that can distinguish various activities. Researchers have proposed frequency domain features also, but these have been ignored due to their computational complexity and hence infeasibility of calculations in real time with limited resources of a phone [12]. The list of sensors used in activity recognition, their significance or role in achieving correct recognition and features used has been listed in Table I.

Based on exploratory experiments, we deduced that simple statistical features like mean and standard deviation over sliding windows would be sufficient to differentiate the chosen set of activities. In [16], authors have mapped the problem of identification of fine grained activities of daily living as being done in specific positions of either standing, sitting and lying. They have also proposed a set of seven customized features to characterize the transitions between these positions. Enhanced accuracy with a set of new logical features extracted from accelerometer and gravity sensors has been reported. The use of these features was well elaborated in the previous research [16]. The differentiation of mobile and immobile states was captured through the simple moving average of sum of range of linear acceleration and moving average of sum of variances of gravity. When distinguishing the large staircase movements difference to y gravity and maximum slope of simple moving average of sum of variances. Thus, in this paper we have evaluated these features on our more elaborate sensor dataset. Details of this evaluation are described in results section.

TABLE I. LIST OF SENSORS USED, THEIR PURPOSE AND FEATURES EXTRACTED FROM EACH

Sensors	Purpose in AR	Features Extracted
Accelerometer	To distinguish between immobile and mobile states	• Mean • Standard deviation • Difference to Y • Sum of range of linear acceleration • Sum of range of X and Z components, • Kurtosis x, y and z axis • Gravity Range Difference • Maximum slope of simple moving average of sum of variances of gravity • Z score – X, Y, Z axis
Gyroscope	Measures rotations around all three axis – Specifically useful in "Sitting" Activities	
Magnetometer	Direction of device to differentiate between phone positions	
Orientation	Physical orientation of person , differentiating sitting from standing activities	
Gravity	Measures tilt, useful in staircase activities	



Level 1: Staircase vs non staircase activities classifier
C1: Staircase Ascend
C2: Staircase Descend
C3: Walking
C4: Running
C5: Sitting

Fig 4: Two level classifier

B. *Classification*

User wise labeled features collected as per previous section were collectively used to train classifiers. The combined set of activities in a single classifier was not giving good accuracy for staircase activities which were being confused with other motion activities. The spillover was closely inspected to be distributed across the staircase and non-staircase activities. To improve the recognition capacity of the model it was necessary to differentiate staircase or non-staircase activities accurately. Thus, a two level classifier as shown in figure 4 was designed. Level one of the classifier was used to differentiate staircase activities from non-staircase activities. On the level two, classifier was applied to detect individual activity of detected category.

Representative models of supervised classifiers namely J48, SMO, Logistic Regression and Naïve Bayesian classifiers were implemented. However, as J48 gave best results in terms of accuracy with least computation time; all results have been presented using this classifier only. J48 takes into account the variable interactions and since the data collected had multiple sensor logs, this classification technique was highly suitable to eradicate the redundancy. A 10 fold cross validation has been applied to test the robustness of classifiers.

V. RESULTS AND DISCUSSION

A. *Metrics and Tools Used*

Confusion Matrix and Accuracy that are standard metrics for performance of classifiers have been used to assess the correctness of model. Confusion matrix is a matrix of size "n X n" where in our case n is the number of types of activities being classified. The matrix depicts exact number of instances in which an activity has been classified as itself or other activities. It gives an idea of which activity has been difficult to be identified by learnt model.

Accuracy of activity detection has been taken as the metric to assess the performance of detection model. Accuracy has been defined as the percentage of correctly classified instances of sensor data during testing.

Weka Toolkit has been used for classification on learning the initial model from training and test data. Accuracy computation and plotting of graphs has been done in Python. Android toolkit for developers has been used for implementation of mobile apps for data collection and prediction.

B. *Results with 2 level classifier*

First of all, the classifier was learnt and tested for all activities together. Approximately 93% activities were correctly classified in this classification. The confusion matrix for one of the run of same is given in Table II. It can be seen that there are about 20% spillovers of staircase-ascend and descend activities. The walking activity was confused with staircase descend that is demonstrated in the confusion matrix Table II.

Table II. CONFUSION MATRIX OF ACTIVITY RECOGNITION WITH J48 CLASSFIER

	C1	**C2**	**C3**	**C4**	**C5**
C1	28406	1970	1127	97	90
C2	2075	26447	1116	154	89
C3	1013	962	37790	82	40
C4	99	183	116	6143	10
C5	103	77	65	16	30343

Hence, a 2 level classifier was designed for first differentiating staircase with non-staircase activities in the set since this was essential to the core idea of detecting the activities accurately in real-time for the live streaming data collected through the appropriate mobile application so that then each activity in a particular category is differentiated appropriately without any confusion. As shown in Fig. 5, this classification model designed was able to differentiate between two categories about 96% of times. However, it was 91% and 98% respectively in each class. Thus from equation (1), overall accuracy was about 90.7%. The results are clearer through confusion matrices of both categories of activities as shown in Table III and IV. In Table III, it can be seen that spillovers for staircase activity reduced to about 10% as compared to Table II. Table IV shows that for non-staircase activities too, inter-activity confusion has either refused or at least remained same. Thus, two-level classification has not negatively impacted these activities.

$$\text{Overall Accuracy} = \Sigma\,(M*N)/2 \qquad (1)$$

$$0.907 = (0.96*0.98+0.96*0.91)/2$$

M - Accuracy of detecting staircase and non-staircase activities
N - Accuracy of detecting the sub activities within the detected category

As seen in Fig. 7, with two-level classifier accuracy has improved for all activities.

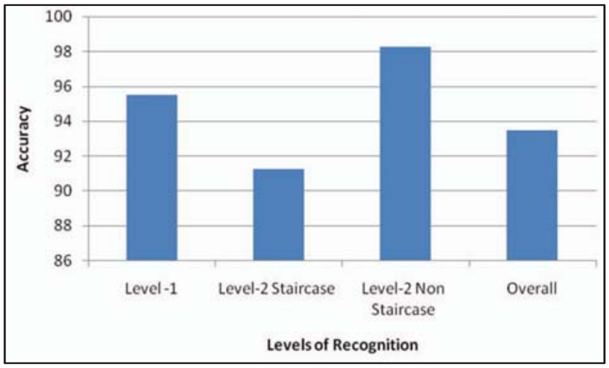


Fig 5: Level Wise and Overall Accuracy of Category Detection

TABLE III. CONFUSION MATRIX FOR STAIRCASE ACTIVITIES

	Walking	Running	Sitting
Walking	14725	137	51
Running	158	4030	6
Sitting	46	14	4382

TABLE IV. CONFUSION MATRIX FOR NON STAIRCASE ACTIVITIES

	Staircase-Ascend	Staircase-descend
Staircase-Ascend	8384	881
Staircase-descend	873	9957

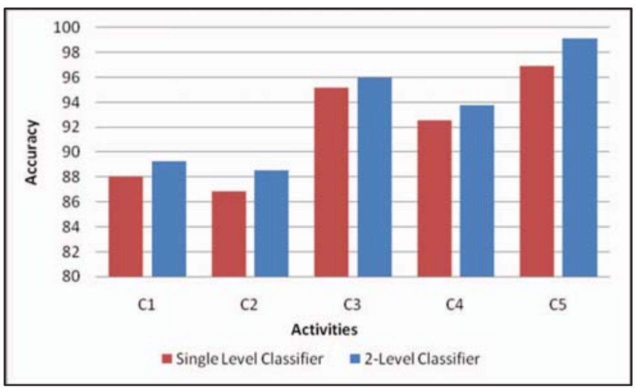


Fig.6. Accuracy of Recognition of Each Activity in 2- Level Classifier

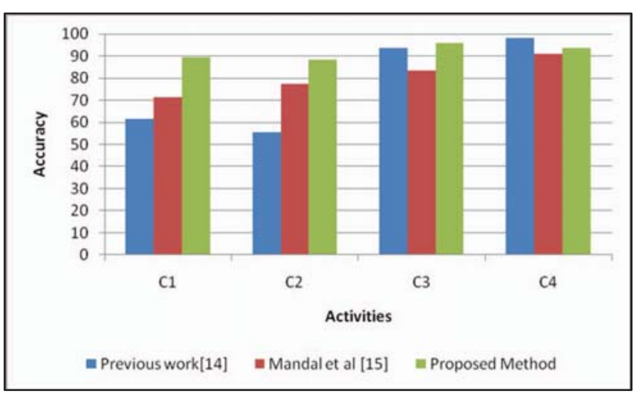


Fig.7. Comparison of results obtained by our method with existing work

Results obtained by our classifier were compared with those available in literature. In Fig. 8, comparison of accuracy with respect to two previous works [14-15] has been shown. Comparison of their results with ours is presented in Fig. 8. One exception can be seen for activity C4 (Running), for which [14] has reported better accuracy. This is due to the fact that they have considered jogging activity; while we have taken running whose corresponding sensor data is noisier due to more rapid movements. This might have caused the 4% difference in accuracy. While our approach is only 3% better at recognition of "Walking" activity, the difference is about 20% in staircase ascend activity with [15] and 30% with [14]. Thus, a significant gain in accuracy has been obtained by our two- level classifier approach for difficult to recognize activities.

C. Choice of Sensors:

Many previous studies make use of accelerometer data only, assuming that the motion can be captured by the only sensor. But studies on our data (output shown in Fig. 9) shows that recognition can be improved, if other inbuilt sensors of smartphones like gyroscope and magnetometers are utilized too. Proximity and orientation sensors made the activity recognition, phone position and handling independent.

D. Effect of Choice of Attributes

Attribute selection was applied on the dataset by exhaustively testing subsets of attributes and their classification results. It was inferred that Moving Average and Standard Deviation of all sensors gave almost similar accuracy to the subset of eight features described in section IV. This leads to a smaller dataset and hence lesser model build- time as compared to using all the features as shown in Fig. 10.

E. Implementation of App for Real Time Prediction and Cross User Accuracy

The two-level classifier model was built and embedded in mobile application (app). Real time activity predictions were done by the app in an unobtrusive fashion. The user interface of the app and instances of two different activity predictions are shown in Fig. 11.

Only few earlier works of this domain have addressed cross user accuracy. The training models created from the dataset generated by the data collection app, was thereafter incorporated as a classification model in the offline application for real time activity prediction. This helped in prediction of the activities of the unknown users. This activity prediction app was used on various users without any pre training. An average accuracy of 75.5% on staircase activities and about 90% for non-staircase activities were obtained for the tested users. A trade-off between the training time and accuracy was observed, as the pre-trained model was used to recognize a cross-user activity. This can be further improved by including more users and more instances of each activity data in training of basic classifier.

Fig. 8. Comparison of Accuracy with accelerometer with enhanced set

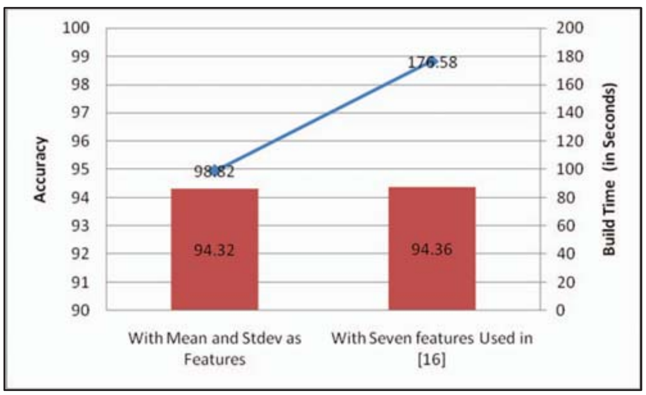
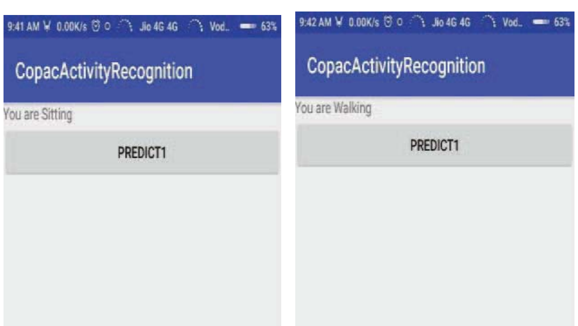


Fig. 9. Accuracy and Build Time of Model with and without Specific Features



(a) (b)

Fig. 10. App developed to predict activity being performed by user (a) predicted result was sitting (b) predicted result was walking

VI. Conclusion

In this paper, owing to the application in the real-time activity recognition of various activities using inbuilt sensors of the smart-phones, a two level approach to physical activity recognition using smartphone sensors has been proposed. The research addressed the problem of activity recognition using low-computational cost features along with enhanced data-set comprising of data from sensors along with accelerometer in recognizing the activities. Another aspect to this research has been centric to accuracy of classifying the activities for which judiciously, J48 classifier has been used to predict the activities in real time. Accuracy of prediction results ranges from 88% to 99% for personalized activity recognition irrespective of the way phone is being carried. Real time usage of app based on proposed classification has also found to be good giving accuracy ranging from 75.5% to 89.5%. Current study is based on training datasets of limited users. Recognition results may further improve if data of more people is included in the training set to provide the desired versatility.

References

[1] Lane, Nicholas D., et al. "Bewell: A smartphone application to monitor, model and promote wellbeing." *5th international ICST conference on pervasive computing technologies for healthcare*. 2011.

[2] Kim, Eunju, Sumi Helal, and Diane Cook. "Human activity recognition pattern discovery." *IEEE Pervasive Computing 9.1* (2010).

[3] Kwon, Yongjin, Kyuchang Kang, and Changseok Bae. "Unsupervised learning for human activity recognition using smartphone sensors." *Expert Systems with Applications* 41.14 (2014): 6067-6074.

[4] Aggarwal, Jake K., and Michael S. Ryoo. "Human activity analysis: A review." *ACM Computing Surveys (CSUR)* 43.3 (2011): 16

[5] Bao, Ling, and Stephen S. Intille. "Activity recognition from user-annotated acceleration data." In *International Conference on Pervasive Computing*, pp. 1-17. Springer Berlin Heidelberg, 2004..

[6] J. Lester, T. Choudhury, N. Kern, G. Borriello, and B. Hannaford. " A hybrid discriminative/generative approach for modeling human activities". *In Proc. of the International Joint Conference on Artificial Intelligence (IJCAI)*, pages 766–772, 2005

[7] J. Lester, T. Choudhury, and G. Borriello. "A practical approach to recognizing physical activities". *Lecture Notes in Computer Science : Pervasive Computing*, pages 1–16, 2006.

[8] Bishoy Sefen, Sebastian Baumbach, Andreas Dengeland Slim Abdennadher. "Human Activity Recognition - Using Sensor Data of Smartphones and Smartwatches ", In Proceedings of the 8th International Conference on Agents and Artificial Intelligence - Volume 2: ICAART, 488-493, 2016, Rome, Italy

[9] Shoaib, Muhammad, Stephan Bosch, Ozlem Durmaz Incel, Hans Scholten, and Paul JM Havinga. "Complex human activity recognition using smartphone and wrist-worn motion sensors." Sensors 16, no. 4 (2016): 426.

[10] Weiss, Gary M., and Jeffrey W. Lockhart. "The impact of personalization on smartphone-based activity recognition." In AAAI Workshop on Activity Context Representation: Techniques and Languages, pp. 98- 104. 2012.

[11] Ustev, Yunus Emre, Ozlem Durmaz Incel, and Cem Ersoy. "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, 2013.

[12] Figo, Davide, Pedro C. Diniz, Diogo R. Ferreira, and Joao MP Cardoso. "Preprocessing techniques for context recognition from accelerometer data." Personal and Ubiquitous Computing 14, no. 7 (2010): 645-662..

[13] Capela, Nicole A., Edward D. Lemaire, and Natalie Baddour. "Feature selection for wearable smartphone-based human activity recognition with able bodied, elderly, and stroke patients." PloS one 10, no. 4 (2015): e0124414.

[14] Kwapisz, Jennifer R., Gary M. Weiss, and Samuel A. Moore. "Activity recognition using cell phone accelerometers." ACM SigKDD Explorations Newsletter 12, no. 2 (2011): 74-82.

[15] Mandal, Itishree, S. L. Happy, Dipti Prakash Behera, and Aurobinda Routray. "A framework for human activity recognition based on accelerometer data." In Confluence The Next Generation Information Technology Summit (Confluence), 2014 5th International Conference-, pp. 600-603. IEEE, 2014.

[16] Capela, Nicole A., Edward D. Lemaire, and Natalie Baddour. "Improving classification of sit, stand, and lie in a smartphone human activity recognition system." In Medical Measurements and Applications (MeMeA), 2015 IEEE International Symposium on, pp. 473-478. IEEE, 2015.