Journal of Engineering Science and Technology
Vol. 13, No. 8 (2018) 2549 - 2568

ONE-AGAINST-ALL BINARIZATION CLASSIFICATION STRATEGY TO RECOGNIZE INTERCLASS SIMILARITIES ACTIVITIES FROM SEVERAL SENSOR POSITIONS

M. N. SHAH ZAINUDIN*, MD. NASIR SULAIMAN,
NORWATI MUSTAPHA, THINAGARAN PERUMAL

Faculty of Computer Science and Information Technology, Universiti Putra Malaysia,UPM Serdang, 43400, Serdang, Selangor, Malaysia
Faculty of Electronic and Computer Engineering, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia
*Corresponding Author: noorazlan@utem.edu.my

Abstract

Prior knowledge in pervasive computing recently has garnered a great deal of attention due to the high demand in most applications in order to fulfil the human needs. Human Activity Recognition (HAR) has considered every bit unitary of the applications that are widely explored to provide the valuable information to the human. Small in size within the various smartphones, accelerometer sensor has utilized to undergo the HAR research. Current HAR is not only covered the simple daily activities but also, broadly covered the complex activities. Nevertheless, the existence of high interclass similarities activities tends to increase the level of incorrectly classified instances. Hence, this study demonstrates the binarization classification strategy to tackle the above-mentioned issue for the activities with a high degree of similarities. Acceleration signal in the time domain is transformed into frequency terms for separating the signals between gravitational and body acceleration. Two different groups of features; statistical, and frequency analysis are extracted in order to increase the diversity in differentiating between stationary and locomotion activities. The problem complexity is simplified using the binarization strategy before the extracted subset is evaluated. One-Against-All (OAA) classification strategy is introduced to tackle the challenge in improving the accuracy for very similar activity. The proposed work significantly resulted with high accuracy performance, particularly in differentiating between the various high interclass similarities activities using two physical activity datasets; WISDM and PSRG.

Keywords: Accelerometer, Binarization, HAR, Interclass similarities, One-against-all, WISDM.

1. Introduction

The advancement of pervasive computing has become an emerging discipline in the area of intelligent computing. Human Activity Recognition has one of the most ubiquitous intelligent application that has been aggressively explored. Activity recognition is seen as an important discipline in the smart environmental applications, but likewise to provide contextual knowledge for human-computer interaction applications. In a smart environmental application such as smart homes, the residents able to monitor and control their home appliances when they are away from their homes [1]. In addition, this application also talented to observe the regular resident activities in a certain period. For instance, the residents will receive a reminder through their smartphone to perform their regular task such as taking medicine or feeding their pets and also to engage the door when they are off from their homes. In the healthcare perspective, the activity recognition is capable to monitor and track the daily physical exercise particularly for those who need the intensive care to raise the degree of their physical activities such as elderly or stroke patient [2, 3]. It is unmanageable to manually record the regular practice sessions everyday chores since it wastes a great deal of time to do so [4]. Therefore, the automatic self-recorded system becomes a solution. These opportunities are not only yielding benefits to the mentioned group but also tend to ameliorate the human lifestyle by promoting people to execute a simple regular physical exercise.

Numerous types of sensing technologies appeared in HAR such as an environmentally-based sensor, vision-based sensor and wearable-based sensor [5]. The environmental-based sensor is designed to observe the interaction between the user and the environment by monitoring and recognizing the type of activity performed. This kind of sensing technologies has not required any user intervention to manage the system. Nevertheless, the monetary value of the system implementation is commonly high and considered impractical to be implemented since it requires an abundant number of sensors to be installed. The camera, motion, temperature, humidity are the typical sensors need to be bound in a certain area at homes including the home appliances, furnitures, doors and windows [6]. The vision-based sensor might take place when the monitoring of the human behaviour is seen as crucial and desires [7] especially when it is involved disabled or aged people. The video camera will record the daily human chores including the daily routines or the uncommon routines. In certain cases, the system is able to predict what are the next incoming activity will be directed based on the previous pre-recorded activity. Unfortunately, the lighting condition and the activities complexity turn out to be this technology is unable to perform well to acknowledge the activity [8]. Moreover, this system might unpractical to be carried out due to it will reveal the resident identity that will reduce the level of human satisfaction [9, 10]. Thus, the wearable-based sensor is considered as a favourable in activity recognition system and gained popularity to provide more comprehensive intelligent physical activity application. Small in sizes and less in cost, the wearable sensor granted an outstanding deal to perform the HAR applications [11].

The accessibility of the onward motion in the Micro-Machined Electromechanical Sensor System (MEMs) such as an accelerometer sensor has provided an opportunity to undergo the HAR applications. Practically designed, an accelerometer sensor is easy to attach to any part of the human body to sense the human action. Furthermore, this sensor also has been equipped with the various smartphones and smartwatches without requiring any additional devices. Many works that have been done in HAR utilized numerous sensors such as accelerometer, gyroscope and magnetometer attached to different parts of the human bodies [12, 13]. Even though the accuracy obtained is considerably high, it might burden the carrier to hold a bunch of sensors and increase the uncomfortable feeling to practice their bit. Furthermore, the sensor placements also play important roles in defining the activity. Different sensor placements would produce different accuracy performance since the sensor placement is highly correlated with the signal characteristics [14]. In fact, even though the same activity performed by the same user, it might produce a different signal pattern due to several influences [15]. Hectic, emotional mood and the environment setting are considered as unitary of the facets that contribute to the generated signal. In addition, the signal pattern from the same activity might produce the different characters from the different users. This occurred due to the energy expenditure influenced by the human ages and the gait of each human might differ. An adult might produce a different signal pattern with elderly people even if they perform the same activity like jogging, running or walking.

Furthermore, the existence of the high similarities between the activity categories is treated as a dominant crucial issue in HAR [16]. Moreover, the issue of handling the abundant number of features also plays important matters particularly in machine learning applications [17]. Generally, the interclass similarities could appear when the characteristics of the classes are fundamentally different, but present very similar characteristics in the signal pattern. The high amount of activity with interclass similarities yield to decrease the accuracy of performance. This occurs due to the signal between two or more activities are very similar and always confounding on each other. For representative, two walking activities with a different surface like ascending or descending stairs has always mystifying each other or with walking, even if the upshot of the gravity force makes the signal production differently. Previous work reported that those two kinds of activities are very difficult to discriminate and usually tends to increase the falsely with other walking activities. Hence, these works provide several contributions to tackle the issues that have been brought up. These fusions of the statistical with frequency analysis features is able to show a good performance in recognizing the stationary and locomotion activities. Binarization classification strategy using One-Against-All (OAA) [18] is proposed to increase the diversity of differentiating between high interclass similarities activities such as walking upstairs and walking downstairs with high accuracy performance. The high accuracy performance also gathered using the proposed method even if various numbers of sensor placements are utilized. The proposed methods have also been evaluated with various types of machine learning classifiers in order to evaluate the effectiveness of this classification strategy.

2. Previous Work on HAR

The earlier work of HAR using wearable-based sensor has reported in the 90's where the author's utilized the accelerometer sensor in their work [19]. However, there are several unanswered questions that have been stated and still unsolved. The choice of attributes, the implementation of portable and inexpensive devices, the features that going to be used, either the data has been gathered in the real condition environment, the generalization of the training data and to minimize the energy and processing requirement of the data [20] are the several issues highlighted in recent

HAR. Due to these reasons, the more exploration using wearable sensing in HAR becomes prevalent. Bao and Intille [21], have done the pioneering work in HAR. A Decision Tree, decision table, Naïve Bayes, the nearest neighbour has utilized to classify accelerometer activities collected from five biaxial accelerometer sensors. These sensing elements are tied to various placements of the human bodies during the data collection. Mannini et al. [22] have proposed a work on a single accelerometer sensor and compared the effectiveness of the sensor placements to classify the physical activities in order to minimize the use of the sensor. Wrist and ankle placements have been utilized and compared in defining the most optimal performance to produce a decent performance. Later, they spread out their work in defining the best sensor placements from five different positions, ankle, thigh, hip, arm, and wrist [23].

Kwapisz et al. [24] have collected physical activity dataset for six different physical activities using a single accelerometer sensor equipped with a smartphone. The Android smartphone has attached to front pant user pocket. They assess their work using several machine learning classifier models to recognize the activity performed. They obtain an acceptable result, yet though the accuracy for walking downstairs and upstairs seems to produce the less accuracy performance less than 62%. Catal et al. [25] have extended a study to improve the recognition performance. In this study, the same pre-processed has been carried out as Kwapisz et al. [24]. However, they utilized several ensemble voting methods and compared the proposed method with several ordinal classifier models. Walse et al. [26, 27] have employed the same dataset to recognize the activities using several well-known classifier models. They claimed that the ensemble classifier model using Random Forest and rotation forest produced high accuracy performance on average. Nevertheless, the above work is unable to produce the high level of accuracy to portray the high interclass similarities activities. Easy and directly derived from the acceleration signal, most of the study reported in HAR has utilized the features from time domain analysis than the frequency domain. Arif and Kattan [4] and Arif et al. [28], have reported two articles in the HAR to recognize various stationary and locomotion activities in the free-living environment. Referable to the simplicity, they drew out several features from time domain features in their work and reported that these features are able to recognize perfectly for postural activities rather than locomotion activities.

As mentioned, most reported works are able to accomplish the high accuracy in average but neglected to differentiate between very similar activities involving the stairs activities [16]. Zhang and Sawchuk [29] have collected several stationary activities and additional locomotion activities from Motion Node sensing devices. In this work, five different types of walking activities are recorded. These walking activities are categorized into two categories; 2D (walk left, walk right, walk forward) and 3D (walk up, walk down). Zheng [13] has utilized that dataset and evaluated their work using five classifier models; Artificial Neural Network (ANN), Decision Tree, K-Nearest Neighbour (KNN), naïve Bayes and Least-Squared Support Vector Machine (LS-SVM). Average accuracy obtained considered high, but the accuracy for 2D and 3D walking activities considered were more depressed than other types of activities. Recently, deep learning neural network such as Convolutional Neural Network (CNN) has become a solution to resolve the problem of interclass similarities activities [16, 30]. Nevertheless, the model complexity and the high ambiguity of features are considered as several drawbacks of the CNN. Ronao et al. [16] found tha the recognition of high interclass similarities produced an acceptable performance, but the proposed model is incapable to recognize the stationary activity accurately. Furthermore, the implementation cost is definitely high since it involves a very high processing requirement to be implemented and it might impossible to be conducted in real-time applications. Binarization classification strategy has introduced to tackle this issue of the high interclass similarities. There are two types of learning methods in this classification strategy, that is One-Against-All (OAA) and One-Against-One (OAO) [18]. This learning method has been proven to produce good accuracy to recognize the types of food within the same image that considered consists of high interclass similarities and various of intra-class variations [31, 32]. He and Jin [33] carried out the work to recognize physical activity using OVO. However, the work only covered the limited number of activities such as walking, jumping, still and running. The author also excluded the stairs activities in their experiment.

3. Proposed Framework on HAR

In this section, a comprehensive work regarding on the proposed HAR framework is discussed. Analytical methods are depicted in detail on how the processes have been carried out. The step and process of the framework are visualized in Fig. 1.

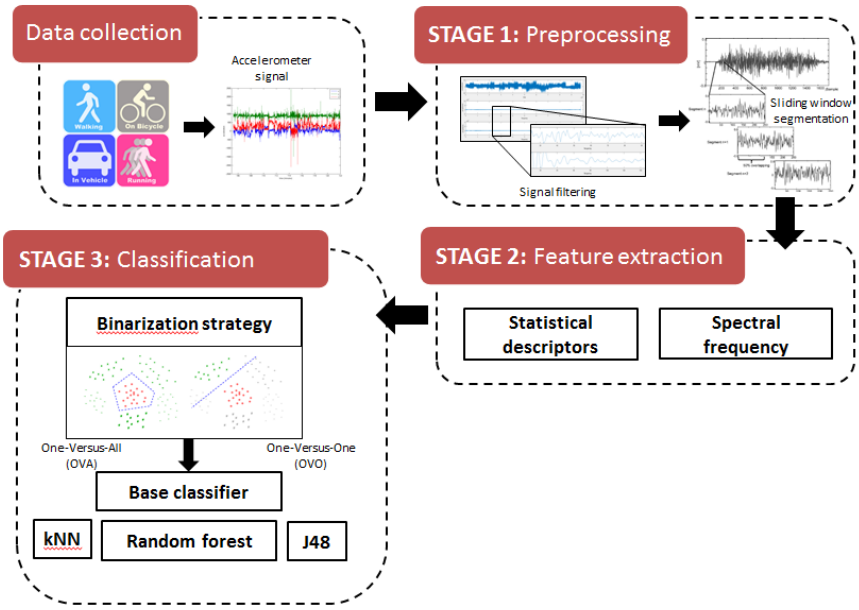

Fig. 1. The framework of the proposed HAR.

3.1. Physical activity dataset

In this study, two physical activity datasets are used to assess the performance of this work. Wireless Sensor Data Mining (WISDM) Laboratory has collected activity recognition dataset using the accelerometer sensor embedded in Android smartphone [24]. The device was placed in subject front pants leg pockets for thirty-six participants including male and female. The sampling frequency used is 20 Hz.

The subjects were required to perform six different types of activities such as sitting, standing, jogging, walking, ascending stairs and descending stairs. All the activities were conducted in a laboratory environment condition and were guided by one of their team members. The second dataset was downloaded from the Pervasive System Research Group (PSRD) activity dataset [34]. Similarly, WISDM, six physical activities such as walking down, walking up, walking, running, sitting and standing were collected from four male participants. Four Samsung Galaxy S2 smartphones are utilized and attached to four different sensor placements; dominant arm, belt, pocket and right wrist. The sampling rate used in this dataset is 50 Hz and the data entered at the same time for each of the actions. Each of the participants required to perform the activity in duration 3 to 5 minutes. Walking and running were performed in the department corridor, office space used for sitting activity and standing activity was carried out during the coffee break. For ascending and descending activities, 5-floor stairs were used.

3.2. Butterworth bandpass filter

The accelerometer signal consists of noise, which, leads to degrading the accuracy performance. Since the accelerometer sensor is highly sensitive to the device placement, hence the noise is existed due to the effect of the gravitational forces. Filtering process needs to be applied to pre-process the raw signal stream before any further calculation is performed. Referable to the effect of the gravity forces, accelerometer sensor produces the signal in two different acceleration signals; gravitational acceleration and body acceleration. The high-frequency components of the gravitational acceleration are not used to specify the action performed. While the low-frequency component represented by body acceleration signal is needed to portray the activity. The bandpass filter could be employed to discriminate between both of these frequency components. The raw signal in the time domain will be transformed into a frequency domain by using a Fast Fourier Transform (FFT). In this work, 5^{th} order Butterworth low pass filter has been employed to separate acceleration signal into gravitational and body acceleration [35]. In this filter, the selection of cut-off frequency might be crucial. If the chosen cut-off is too high, it is potential to wipe out the meaningful information from the signal. Hence, 0.3 Hz [35-39] is considered sufficient to split the signal by removing the unnecessary information of the acceleration signals.

3.3. Proposed feature extraction

It any classifier model, it is difficult to learn the class pattern by using a very minimum number of characteristics. Moreover, the diversity of different activities highly associated with the signal variations, which, leads to the recognition accuracy. Hence, the chosen features tend to help the classifier model to be able to learn the signal characteristic. Some of the features are able to describe the stationary activity, but might incapable to describe the locomotion activity. In order to address this matter, several features from two different groups are brought out. The signal for each dimension (*x*-axis, *y*-axis and *z*-axis) is segmented by using the well-known segmentation method namely sliding window. The size of the window segment needs to be determined before the signal is divided into an equal size of window segment. In this work, sliding window sizes of 64 samples with 50% overlapping between two consecutive window segments are applied. Subsequently, several features from two groups of features (statistical and frequency analysis) are extracted.

3.3.1. Statistical features

The simple statistical features as shown in Table 1 are used to recognize the stationary or postural activities [35] such as sitting, standing and laying down due to the signal representation of stationary activity not diverges. Besides the benefit of having a capability to recognize stationary activities, these features also require less computational complexity and directly derive from each window segment.

3.3.2. Frequency analysis features

Nevertheless, the statistical features seem to be unable to recognize the locomotion activity perfectly due to the signal of locomotion activity, which, extremely depends on the activity complexity. Moreover, the activity such as walking and jogging require the involvement of more actions from different types of human body, which, results to the different signal variations from each dimension. In addition, these frequency analysis features are considered as less susceptible to signal quality variations and correlate to the periodic nature of the specific activity. These features also used to specify a periodic action that produces different statistical measures such as walking and jogging since it requires correlated acceleration patterns in different ways. The names of the features extracted from frequency analysis are listed in Table 1.

Table 1. Features extracted from both groups of features.

	Features group
Minimum	Statistical features
Maximum	
Mean	
Variance	
Standard deviation	
Skewness	
Kurtosis	
Harmonic mean	
Power bandwidth	Frequency features
Band power	
Occupied bandwidth	

3.4. Binarization strategy classification learning method

The choosing of the classifier model is crucial in order to evaluate the extracted feature subsets. This stage is necessary to estimate the feature subsets by measuring the ability level of the classifier model to portray the activity class. The effectiveness of any classifier model is measured by evaluating the training model in recognizing the unseen data to the particular class. In some cases, some classifier models are able to solve the two-class classification problems, but simply unable to manage the multi-class classification problems accurately. It is difficult for any classifier model to produce the accurate prediction when the data is sparser. Also, most of the classifier models are able to produce a perfect recognition in separating the data into two different classes by minimizing the selection class probabilities. In order to tackle this matter, the original multi-class problems need to be transformed into a series of two-class problems. Therefore, it will increase the probability of the classifier model to learn and recognize the class pattern within the two-class classification problems.

The binarization strategy is applied by converting the multi-class problems into a series of two-class problems [18]. There are two strategies could be enforced, One-Against-All (OAA) and One-Against-One (OAO). In OAA, one binary class (two-class) will be created for each of the classes where the selected class belongs to the positive class whereby the negative class belongs to the union of all other classes. In this approach, the number of classifier model constructed is n-1 where n represents the number of classes. Alternatively, OAO is done by transforming the multi-class into a series of class problems where n (n-1)/2. This approach also being called as a round-robin classification. All the training instances need to be trained for all created models. In order to obtain the final prediction, the prediction results from each model needs are combined. The class who received the most majority vote is classified as the final class. However, the time consuming for OVO is extremely longer than OAA due to the expansion of the training model. In this study, several base classifier models such as Random Forest (RF), K-Nearest Neighbour (KNN) and Decision Tree (J48) are utilized.

3.4.1. Random Forest ensemble classifier

Two types of ensemble learning methods are widely applied in solving various applications including activity recognition problem; bagging and boosting [40]. In boosting, the incorrectly predicted points are received an extra weight from successive trees on the early predictors. Later, the weighted vote is taken to classify the final predictions. Unlike boosting, bagging does not depend on the earliest trees and each tree is independently generated by using a bootstrap sample of the dataset. Breiman [41] has proposed new ensemble classifier models called Random Forest, which, utilized additional randomness layer in bagging. The tree in the forests is changed by using different bootstrap of sample information. Each node is split using the best among subset predictors, which is randomly chosen from the generated node. These decision trees based algorithm utilized the same parameter setting to specify the final prediction class using majority voting. Moreover, this method has also been proven likened with several classifiers like SVM and ANN by minimizing the potential of overfitting.

3.4.2. K-Nearest Neighbour

K-Nearest Neighbour is required high computational space since all the data is stored and needed during the testing process [42]. K nearest instances search for the query instances and assigned to the common class among k neighbour in the vector space. The initial population is selected from all instances and each of them corresponds to the particular activity. Afterwards, the neighbour is identified and the nearest instances with the test instances are selected. The majority K-Nearest Neighbour corresponds to the activity is determined as final prediction. The advantage of this method is, the training time could be minimized due to this classifier model does not require to do any generalization.

3.4.3. Decision tree (J48)

A Decision Tree is proposed based on the theory of technology in generating the knowledge-based system by inductive reference from the examples [43]. Due to the limitation of an early version of the Decision Tree, namely Iterative DiChaudomiser (ID3), the enhancement of the newest version of the tree is introduced to undertake the problem in order to manage very large numbers of values. This enhanced version is called as *C*4.5, which, work by recursively partitioning the training data set according to the test for the potential feature values in the separating the class. Easy to be implemented, this new tree is able to cater to the problem of incomplete data, continuous data and having the advantage to generate the pruned tree after the tree has been made. J48 comes when the Decision Tree integrates with the Java platform.

4. Results and Discussion

The experimental comprises two different environments from two different datasets. Unlike WISDM, PSRG has utilized four sensor placements (arm, belt, pocket and wrist) to decide, which position produce an optimum result to distinguish several types of actions. In this entire work, there are two independent experiments have been conducted. Firstly, the experiment on WISDM is conducted based on one sensor placement to evaluate the strength of the proposed method and the solution obtained is compared with various related works. The second experiment is conducted to determine the best sensor placement to recognize several types of actions.

4.1. Experiment on WISDM physical activity dataset

In this section, we visualize the acceleration signal in Fig. 2 for two high interclass similarities activities, which are downstairs and upstairs. This signal is represented in the time domain analysis, which, the signal represented in amplitude against time. To translate the signal into frequency response, Fourier analysis would be applied by using FFT where the signal is presented to identify how much the energy propagates in the range of frequencies. These processes need to be repeated for each of the signal dimensions (x-axis, y-axis and z-axis).

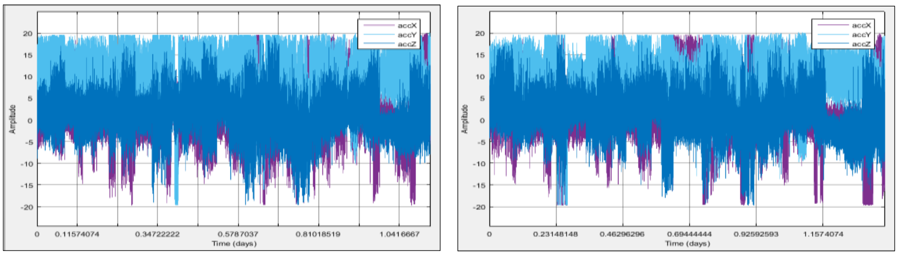

Fig. 2. Raw signal in time domain analysis for downstairs (left) and upstairs (right) activities.

It is clearly being seen that the recorded signal in stairs activities is extremely comparable. Furthermore, the unwanted information has also been clearly noticed due to the representative of the high peak of signal amplitude. This unnecessary information (high-frequency component) needs to be removed before further calculation conducted. Since the only body acceleration signal used to govern the natural action, gravitational acceleration signal needs to be removed. Hence, we apply 5th order Butterworth low pass to separate the signal between gravitational and body acceleration. Figure 3 shows the unfiltered signal and the signal after the filtering process is applied.

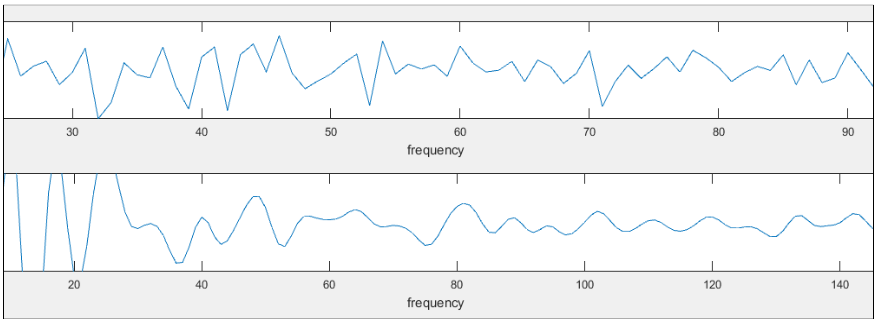

Fig. 3. Unfiltered signal (top) and filtered signal using 5th order Butterworth low pass filter (bottom).

Referring to the Fig. 3, it is clearly can be shown that the filtered signal (bottom) represents in a proper sinusoidal wave in comparison with the unfiltered signal (top). This process is to ensure that the unwanted information (represented by a rough sinusoid wave) is excluded. Hence, the smooth sinusoid wave is gathered as shown in Fig. 3 (bottom) to show that the noise is being cleared. We choose 0.3 Hz cut-off frequency to produce the smooth sine wave. However, it seems to the likelihood of reducing the meaningful information if the chosen cut-off is too high. We choose several numbers of the cut-off parameter as shown in Table 2 to evaluate the signal before any further calculation takes place.

Table 2. Accuracy using several numbers of the cut-off frequency.

Cut-off	Accuracy	Precision
0.3 Hz	0.998	0.998
0.5 Hz	0.994	0.994
0.7 Hz	0.993	0.993
0.9 Hz	0.987	0.987

Afterwards, we segmented the filtered signal into a number of pre-determined sizes of window segments. Thus, 64 samples were generated by 50% of two consecutive segments was overlapped. In each segment, we extracted several features (as described in section 3.3) to evaluate the performance of the proposed features. In this experiment, we conduct two different experimental conditions, which is evaluating the features individually and in combining between both feature groups. In each evaluation, the 10-fold cross-validation testing strategy is applied for validation purposes. Two measurement indicators such as average accuracy and precision are used to evaluate the classification performance. Tables 3 to 5 show the classification accuracy for WISDM with different categories feature subsets; statistical, frequency analysis, and both categories respectively.

Table 3. Classification result using statistical features.

	RF-OAA		KNN-OAA		J48-OAA	
	Accuracy	**Precision**	**Accuracy**	**Precision**	**Accuracy**	**Precision**
Downstairs	0.988	0.997	0.768	0.721	0.926	0.934
Upstairs	0.991	0.999	0.720	0.846	0.956	0.956
Walking	1.000	0.996	0.948	0.904	0.986	0.986
Jogging	0.999	1.000	0.946	0.918	0.993	0.992
Sitting	1.000	1.000	0.855	0.970	0.995	0.998
Standing	1.000	0.999	0.692	0.940	0.979	0.965
Average	0.998	0.998	0.889	0.890	0.979	0.979

Table 4. Classification result using frequency analysis features.

	RF-OAA		KNN-OAA		J48-OAA	
	Accuracy	**Precision**	**Accuracy**	**Precision**	**Accuracy**	**Precision**
Downstairs	0.802	0.950	0.401	0.294	0.798	0.809
Upstairs	0.848	0.948	0.453	0.448	0.841	0.848
Walking	0.975	0.927	0.747	0.700	0.942	0.932
Jogging	0.979	0.957	0.660	0.740	0.949	0.950
Sitting	0.997	0.997	0.703	0.905	0.980	0.982
Standing	0.973	0.991	0.475	0.767	0.917	0.945
Average	0.947	0.947	0.641	0.660	0.920	0.920

Table 5. Classification result using combinational of statistical with frequency analysis features.

	RF-OAO		KNN-OAA		J48-OAA	
	Accuracy	**Precision**	**Accuracy**	**Precision**	**Accuracy**	**Precision**
Downstairs	0.986	0.998	0.724	0.646	0.931	0.922
Upstairs	0.992	0.998	0.689	0.791	0.952	0.960
Walking	1.000	0.995	0.921	0.888	0.985	0.986
Jogging	1.000	1.000	0.919	0.888	0.993	0.991
Sitting	1.000	1.000	0.803	0.952	0.993	0.997
Standing	1.000	1.000	0.622	0.923	0.978	0.968
Average	0.998	0.998	0.857	0.859	0.979	0.979

The classification result by using a different feature subset is tabulated in Tables 3 to 5. Table 3 shows the classification result using statistical features with three different base classifier models; RF, KNN, and J48. On average, RF recorded the decent achievement compared to other two base classifier models; KNN and J48. Average accuracy and precision obtained are above 99%, which is considered as the virtuous performance. All the instances from stationary activities sitting and standing are correctly classified as its classes. Furthermore, a walking also recorded 100% of accuracy and 99.6% of precision. In fact, jogging outperformed other activities where almost 100% accuracy was obtained using RF. Also, the most difficult activity, which is reported very challenging to be classified such as downstairs and upstairs were recorded very encouraging result. Above 99% precision is recorded for both of these activities respectively. The lowest accuracy and precision is obtained from KNN where the average result recorded 89%. Standing recorded the lowest accuracy 69% using KNN. Two high interclass similarities activities downstairs and upstairs recorded 76% and 72%, respectively considered as an unsatisfied achievement. However, J48 recorded the second highest position since the accuracy and precision were recorded above 97%.

Downstairs and upstairs reported acceptable performance above 92% for accuracy and 95% for precision.

Nevertheless, the result recorded is drastically declined when the feature subset from a frequency analysis is employed. Average accuracy and precision reported slightly lower using RF about 94% as indicated in Table 4. Two activities considered the most problematic to be differentiated have also recorded a decrease in their performance where it is below than 90% for both of them. 80% and 84% accuracy obtained on downstairs and upstairs activities, but precision recorded slightly more depressed than other stationary activities. Above 92% and 97% of accuracy and precision obtained from other types of activities. The worst result obtained by KNN where accuracy average and precision obtained 64% and 66% respectively. Stairs activities and standing recorded the lowest among others and this could be concluded that the accuracy was drastically dropped when features from frequency analysis were applied. To measure the functioning of our proposed features, both of the features are fused into one subset and the carrying out of the result as tabulated in Table 5. Even though the average accuracy obtained similar to Table 3, but the accuracy for two locomotion activities (walking and jogging) and stationary activities (sitting and standing) recorded significantly increase to 100%. Upstairs also recorded second highest (99.2%) followed by downstairs (98.6%). Unlike RF and J48, KNN recorded slightly decline the performance of the result about 3% - 4%when both of the features were combined. There is no radically different for J48 when the same feature subsets are used.

3.5. Experiment on PSRG physical activity dataset

In this section, two different experimental environments are utilized. Firstly, we conducted the experiment to find the most optimal sensor placements portray the various activity types. Secondly, we fused the sensor placement from a different position to compare with the former environment. Since the previous experiment showed good performance by using combinational of features from both statistical with frequency analysis, thus this experiment will discard the previous steps to measure the performance by using a single group of features. Tables 6 to 9 show the classification accuracy for PSRG dataset based on different sensor placements respectively.

Table 6. Classification result using combinational of statistical with frequency analysis features (arm position).

	RF-OAA		KNN-OAA		J48-OAA	
	Accuracy	**Precision**	**Accuracy**	**Precision**	**Accuracy**	**Precision**
Downstairs	0.978	0.981	0.815	0.734	0.929	0.917
Upstairs	0.949	0.987	0.666	0.769	0.901	0.920
Walking	1.000	0.973	0.854	0.799	0.957	0.963
Running	0.998	0.998	0.984	0.980	0.994	0.985
Sitting	0.997	0.996	0.890	0.857	0.982	0.988
Standing	0.996	0.996	0.791	0.875	0.975	0.986
Average	0.992	0.992	0.884	0.885	0.971	0.971

Table 7. Classification result using combinational of statistical with frequency analysis features (belt position).

	RF-OAA		KNN-OAA		J48-OAA	
	Accuracy	**Precision**	**Accuracy**	**Precision**	**Accuracy**	**Precision**
Downstairs	0.955	0.973	0.816	0.731	0.881	0.894
Upstairs	0.980	0.966	0.762	0.822	0.905	0.923
Walking	0.997	1.000	0.856	0.837	0.965	0.963
Running	0.996	0.993	0.908	0.912	0.957	0.947
Sitting	0.999	0.998	0.938	0.947	0.991	0.974
Standing	1.000	1.000	0.947	0.977	0.988	0.994
Average	0.991	0.991	0.880	0.883	0.955	0.954

Table 8. Classification result using combinational of statistical with frequency analysis features (pocket position).

	RF-OAA		KNN-OAA		J48-OAA	
	Accuracy	**Precision**	**Accuracy**	**Precision**	**Accuracy**	**Precision**
Downstairs	0.967	0.990	0.761	0.686	0.909	0.900
Upstairs	0.982	0.990	0.702	0.806	0.904	0.906
Walking	1.000	0.983	0.888	0.803	0.938	0.928
Running	0.996	0.994	0.860	0.866	0.935	0.940
Sitting	1.000	1.000	0.941	0.959	0.994	0.997
Standing	1.000	0.999	0.901	0.956	0.989	0.996
Average	0.993	0.993	0.854	0.858	0.949	0.949

Table 9. Classification result using combinational of statistical with frequency analysis features (wrist position).

	RF-OAA		KNN-OAA		J48-OAA	
	Accuracy	**Precision**	**Accuracy**	**Precision**	**Accuracy**	**Precision**
Downstairs	0.978	0.983	0.806	0.727	0.906	0.876
Upstairs	0.957	0.988	0.735	0.778	0.890	0.882
Walking	0.998	0.974	0.873	0.785	0.951	0.948
Running	1.000	1.000	0.935	0.890	0.945	0.962
Sitting	1.000	0.999	0.842	0.872	0.991	0.991
Standing	0.999	1.000	0.781	0.925	0.968	0.980
Average	0.991	0.991	0.834	0.839	0.947	0.947

The classification result of the proposed method for each sensor placement; arm, belt, pocket, and wrist as tabulated in Tables 6 to 9 respectively. It is clearly can be ascertained that the accuracy and precision of each sensor position recorded above 99.1% using the proposed binarization classification OAA with ensemble RF base classifier model. As shown in Table 6, arm showed the highest performance to describe the walking. Running and two stationary activities, sitting and standing achieved above 99%. Downstairs and upstairs recorded acceptable performances where the accuracy obtained was 97.8% and 94.9%, respectively, which are higher than KNN and J48. J48 produced the second highest accuracy, followed by KNN where 97.1% and 84.4% respectively. In contrast, stationary activities recorded the uppermost when the sensor placed on a subject belt as referred to Table 7. Walking and running also recorded above 99.6% using RF and range from 95% to 99% obtained using J48. Contradictory to Table 6, the accuracy for upstairs recorded slightly upper than downstairs when the sensor is placed on the belt. This figure also recorded similar achievement when the sensor changes to a pocket position. In this instance, there was little improvement in accuracy when the pocket is used to collect the signal where a 1.2% increase for downstairs and 0.2% incline for upstairs as evidenced from the Table 8.

Precision for both of these activities also recorded 99%, which is considered the eminent among the other positions. Three activities such as walking, sitting and standing recorded with 100% accuracy. This could be proven that the pocket position is the best sensor placement to determine the stationary activities. According to Table 9, running and sitting recorded 100% correctly classified instances for wrist placement. Two other activities like walking and standing recorded above 99% accuracy, followed by downstairs 97.8% and upstairs 95.7%. This figure indicates that the hand sensor position gives the best accuracy for incline walking and body position placement produce better achievement for decline walking. The average accuracy and precision range from 83% to 88% obtained by KNN and from 94% to 97% by the J48 classifier. The next experiment has been done by combinational of all the acceleration from all sensor placements. The principle of this experiment is to evaluate if any improvement of accuracy when utilizing more than one sensor. The features extracted from all four sensor placements are incorporated and assessed using the proposed method as shown in Table 10.

Table 10. Classification result of all sensor positions.

	RF-OAA		KNN-OAA		J48-OAA	
	Accuracy	**Precision**	**Accuracy**	**Precision**	**Accuracy**	**Precision**
Downstairs	0.990	1.000	0.932	0.863	0.886	0.865
Upstairs	0.996	0.993	0.868	0.957	0.885	0.913
Walking	1.000	0.996	0.968	0.933	0.961	0.967
Running	1.000	1.000	0.990	0.987	0.974	0.969
Sitting	1.000	1.000	0.990	1.000	0.991	0.985
Standing	1.000	1.000	0.986	0.999	0.989	0.987
Average	0.998	0.998	0.962	0.963	0.955	0.955

Average accuracy and precision of all the activities significantly achieved 98% using RF. The KNN is fractionally better than J48 particularly in recognizing the stairs activities. Accuracy for downstairs and upstairs significantly increased to 99% and 99.6%, respectively, when all sensor positions were used. Precision for downstairs recorded 100%, which is considered the greatest achievement. Other four activities recorded almost 100% for both accuracy and precision. The accuracy and precision for both of stairs activities have also been increased by using KNN. Unfortunately, the accuracy in classifying the stairs activities was slight drops by using J48. Nevertheless, it is distinctly established that there is improvement obtained when all the data from all the sensor positions were merged. Our result also indicates that the binarization strategy classification learning OAA produced good results for making out the stairs activities, which, reported one of the cases leads to the decreasing of the recognition accuracy.

3.6. Comparison classification with benchmark studies

In order to evaluate the performance of our proposed method, we compared our work with previous studies. In order to make the fairer comparison, the experiment is conducted according to their procedure. Figure 4 shows the comparison result for WISDM with three previously reported work.

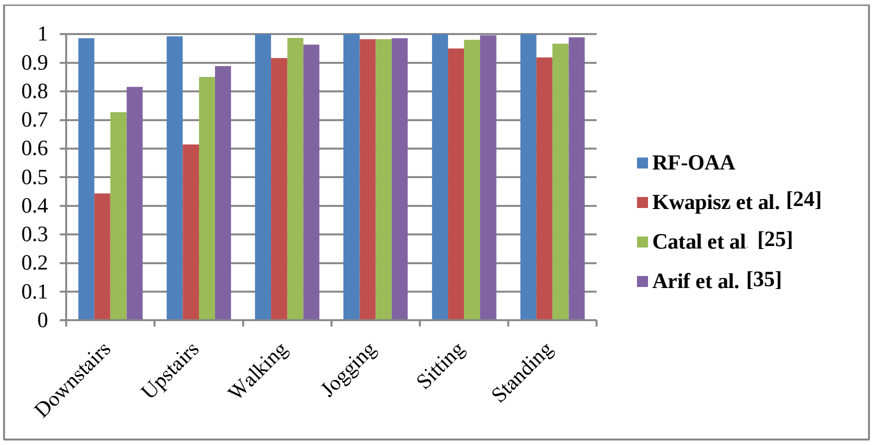

Fig. 4. Comparison result with previous work for WISDM.

It is distinctly demonstrated that the performance of our work outperforms the previous works [24, 25, 35]. Virtually all activities achieved a high level of accuracy, especially for jogging and walking. The most difficult activities reported with high interclass similarities activities (downstairs and upstairs) significantly outperform the work has been done by Arif et al. [35], who carried out the experiment by pruning the number of instances to reduce the space complexity of the KNN. Unfortunately, the accuracy of stairs activity recorded the lowest than others, even if the high percentage number of instances are pruned. In addition, it might possible insufficient instances remained to portray the activity. Catal et al. [25] also reported that the lowest accuracy contributed to stairs activities, but their result slightly improves the result obtained by Kwapisz et al. [24]. However, below than 85% of accuracy received when the authors combined the three classifier models (J48, logistic regression and multilayer perceptron) and predict the final prediction result using ensemble voting strategy. It might be concluded that the ensemble voting strategy able to improve the accuracy on average, but incapable to portray the high accuracy for the very similar class pattern. Even though the authors [24] has combined both stairs activities into one types of class, the recognition of those activities recorded lower than 78%. Figure 5 shows the comparison result with those obtained by Shoaib et al. [34] using the PSRG dataset.

In this comparison, it is obviously highlighted that the accuracy of our proposed method outperforms the work reported by Shoaib et al. [34]. Each of the activity obtained above 99% accuracy, which is decidedly higher than their work. Even though the belt position recorded a bit more depressed than their work, but we were able to produce the promising result for the other three placements (arm, pocket and wrist). Shoaib et al. [34] claimed that the pocket position gives an optimal recognition performance in recognizing various activities. However, the accuracy of stairs activities recorded somewhat below than 90% on average. Hence, it could be summarized by applying our proposed features from both categories (statistical and frequency analysis features) significant upsurge in the performance in differentiating between stationary and locomotion activities. Furthermore, the most difficult activity to be recognized involving the stairs activities also able to contribute to the virtuous performance of various sensor placements. The introducing of binarization strategy able to simplify the original multi-class classification problems into a series of two-class classification problems. Hence, this particular simplifies problem provides more probabilities to define the respected class by learning from the example within the two-class problems. As a result, the high interclass similarities activities (walking, downstairs and upstairs walking) are able to produce the high accuracy performance while minimizing the class selection probabilities. In comparison with previous work, the author has utilized the ordinal classifier model in their evaluation. It might happen some of the classifier models such as multilayer perceptron, logistic regression and KNN are unable to give a higher performance in differentiating the activity, which, involving very similar acceleration signal.

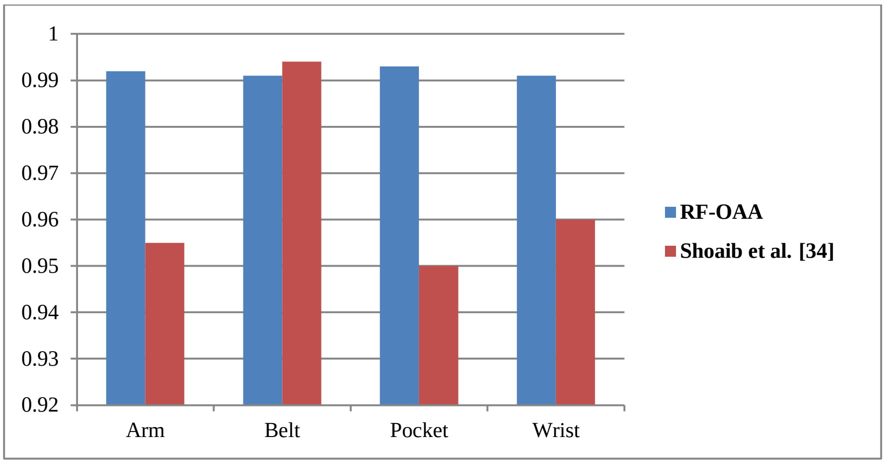

Fig. 5. Comparison result with previous work for PSRG.

5. Conclusions

This paper investigates the work in HAR using single accelerometer sensors placed in different sensor placements. Two physical activity datasets, WISDM and PSRG are utilized in which, the activity is collected by using the accelerometer sensor embedded in smartphones. Several contributions are highlighted in this work. In order to improve the performance of differentiating between stationary and locomotion activities, features from statistical descriptors and frequency analysis are introduced. The combinational from both of these features shown significantly upsurge the classification performance on average. The frequency features are able to describe the activity, particularly involving the high diversity motions from different signal dimensions. Secondly, we prove that the performance of the activity, which is involving the very similar signal pattern, is able to produce the high accuracy by simplifying the multi-class problems into several two-class problems. Binarization strategy, using OAA is introduced by transforming the multi-class problems into a series of coupling problems, which, the selected class is defined as a positive class while the rest of the class is defined as a negative class. Hence, it will give the classifier model more chances to learn and define the respected class for the example by minimizing the class selection probability.

Therefore, we are able to produce the high level of accuracy, particularly in differentiating between high similarities activities, which are involving the walking and stairs walking. In addition, the OAA binarization strategy has also proven the effectiveness with the integration with the Decision Tree classifier and with ensemble classifier models such as a Random Forest. Lastly, we also compare the effectiveness of the proposed work by using several sensor placements. The high accuracy performance is obtained even if various sensor positions are utilized. For projection work, we plan to carry out the experiment by minimizing the number of features, which, leads to the highest level of accuracy. Thus, it could minimize the classifier model complexity by utilizing the minimal number of features. The proposed OAA also could evaluate using other domain areas such as in Bioinformatics, text mining and medical image.

Abbreviations

ANN	Artificial Neural Network
CNN	Convolutional Neural Network
FFT	Fast Fourier Transform
HAR	Human Activity Recognition
J48	Decision Tree
KNN	K-Nearest Neighbour
LS-SVM	Least-Squared Support Vector Machine
MEMs	Micro-Machine Electromechanical Sensor System
OAA	One-Against-All
OAO	One-Against-One
PSRG	Pervasive System Research Group
RF	Random Forest
WISDM	Wireless Sensor Data Mining

References

1. Alam, M.R.; Ibne Reaz, M.; and Mohd Ali, M.A. (2012). A review of smart homes-past, present, and future. *IEEE Transactions System Man and Cybernetics Part C (Applications and Reviews)*, 42(6), 1190-1203.
2. Suryadevara, N.K.; Mukhopadhyay, S.C.; Wang, R.; and Rayudu, R.K. (2013). Forecasting the behavior of an elderly using wireless sensors data in a smart home. *Engineering Applications of Artificial Intelligence*, 26(10), 2641-2652.
3. Zainudin, M.N.S.; Sulaiman, M.N.; Mustapha, N.; and Perumal, T. (2015). Activity recognition based on accelerometer sensor using combinational classifiers. *Proceedings of the IEEE International Conference on Open System.* Bandar Melaka, Malaysia, 68-73.
4. Arif, M.; and Kattan, A. (2015). Physical activities monitoring using wearable acceleration sensors attached to the body. *PLoS One*, 10(7), 1-16.
5. Chen, L.; Hoey, J.; Nugent, C.D.; Cook, D.J.; and Yu, Z. (2012). Sensor-based activity recognition. *IEEE Transactions on Systems, Man, Cybernetics, Part C Applications and Review*, 42(6), 790-808.

6. Noury, N.; and Hadidi, T. (2012). Computer simulation of the activity of the elderly person living independently in a health smart home. *Computer Methods and Programs in Biomedicine*, 108(3), 1216-1228.
7. Zainudin, M.N.S.; Radi, H.R.; Abdullah, S.M.; Rahim, R.A.; Ismail, M.M.; Idris, M.I.; Sulaiman, H.A.; and Jaafar, A. (2012). Face recognition using principal component analysis (PCA) and linear discriminant analysis (LDA). *International Journal of Electrical and Computer Sciences*, 12(5), 50-55.
8. Fang, H.; He, L.; Si, H.; Liu, P.; and Xie, X. (2014). Human activity recognition based on feature selection in smart home using back-propagation algorithm. *ISA Transactions*, 53(5), 1629-1638.
9. Brezovan, M.; and Badica, C. (2013). A review on vision surveillance techniques in smart home environments. *Proceedings of the 19th International Conference Control System and Computer Science*. Bucharest, Romania, 471-478.
10. Zainudin, M.N.S.; Sulaiman, M.N.; Mustapha, N.; Perumal, T.; and Ahmad Nazri, A.S. (2018). Hybrid relief-f differential evolution feature selection for accelerometer actions. *Advanced Science Letters*, 24(2), 1168-1171.
11. Lara, O.D.; and Labrador, M.A. (2013). A survey on human activity recognition using wearable sensors. *IEEE Communications Survey and Tutorials*, 15(3), 1192-1209.
12. Maurer, U.; Smailagic, A.; Siewiorek, D.P.; and Deisher, M. (2006). Activity recognition and monitoring using multiple sensors on different body positions. *Proceedings of the International Workshop on Wearable and Implantable Body Sensor Networks.* Cambridge, Massachusetts, USA, 4 pages.
13. Zheng, Y. (2015). Human activity recognition based on the hierarchical feature selection and classification framework. *Journal of Electrical and Computer Engineering*, Article ID 140820, 9 pages.
14. Awan, M.A.; Guangbin, Z.; Kim, C.G.; and Kim, S.D. (2014). Human activity recognition in WSN: A comparative study. *International Journal of Networked and Distributed Computing*, 2(4), 221-230.
15. Capela, N.A.; Lemaire, E.D.; Baddour, N.; Rudolf, M.; Goljar, N.; and Burger, H. (2016). Evaluation of a smartphone human activity recognition application with able-bodied and stroke participants. *Journal of Neuroengineering and Rehabilitation*, 13, 1-10.
16. Ronao, C.A.; and Cho, S.-B. (2016). Human activity recognition with smartphone sensors using deep learning neural networks. *Expert Systems with Applications*, 59, 235-244.
17. Zainudin, M.N.S.; Sulaiman, M.N.; Mustapha, N.; Perumal, T.; Nazri, A.S.A.; Mohamed, R.; and Manaf, S.A. (2017). Feature selection optimization using hybrid relief-f with self-adaptive differential evolution. *International Journal of Intelligent Engineering & Systems*, 10(2), 21-29.
18. Park, S.-H; and Furnkranz, J. (2007). Efficient pairwise classification. *Proceedings of the 18th European Conference on Machine Learning.* Warsaw, Poland, 658-665.
19. Foerster, F.; Smeja, M.; and Fahrenberg, J. (1999). Detection of posture and motion by accelerometry: A validation study in ambulatory monitoring. *Computers in Human Behaviour*, 15(5), 571-583.

20. Kim, E.; Helal, S.; and Cook, D. (2010). Human activity recognition and pattern discovery. *IEEE Pervasive Computing*, 9(1), 48-53.
21. Bao, L.; and Intille, S.S. (2004). Activity recognition from user-annotated acceleration data. *Proceedings of the Second International Conference, PERVASIVE 2004, Linz/Vienna, Austria, Pervasive Computing*, 1-17.
22. Mannini, A.; Intille, S.S.; Rosenberger, M.; Sabatini, A.M.; and Haskell, W. (2013). Activity recognition using a single accelerometer placed at the wrist or ankle. *Medicine and Science in Sports and Exercise*, 45(11), 2193-2203.
23. Mannini, A.; Sabatini, A.M.; and Intille, S.S. (2015). Accelerometry-based recognition of the placement sites of a wearable sensor. *Pervasive and Mobile Computing*, 21, 62-74.
24. Kwapisz, J.R.; Weiss, G.M.; and Moore, S.A. (2011). Activity recognition using cell phone accelerometers. *ACM SIGKDD Explorations Newsletter*, 12(2), 74-82.
25. Catal, C.; Tufekci, S.; Pirmit, E.; and Kocabag, G. (2015). On the use of ensemble of classifiers for accelerometer-based activity recognition. *Applied Soft Computing*, 37(C), 1018-1022.
26. Walse, K.H.; Dharaskar, R.V.; and Thakare, V.M. (2016). A study of human activity recognition using adaboost classifiers on wisdm dataset. *IIOAB Journal*, 7(2), 68-76.
27. Walse, K.H.; Dharaskar, R.V; and Thakare, V.M. (2016). Performance evaluation of classifiers on activity recognition for disasters. *Proceedings of the Second International Conference on Information and Communication Technology for Competitive Strategies*. Udaipur, Article No. 26.
28. Arif, M.; Kattan, A.; and Ahamed, S.I. (2015). Classification of physical activities using wearable sensors. *Intelligent Automatic and Soft Computing*, 23(1), 21-30.
29. Zhang, M.; and Sawchuk, A.A. (2012). USC-HAD: A daily activity dataset for ubiquitous activity recognition using wearable sensors. *Proceedings of the 14th International Conference on Ubiquitous Computing*. Pittsburgh, Pennsylvania, United States of America, 1036-1043.
30. Ravi, D.; Wong, C.; Lo, B.; and Yang, G.Z. (2016). A deep learning approach to on-node sensor data analytics for mobile or wearable devices. *IEEE Journal of Biomedical and Health Informatics*, 21(1), 56-64.
31. Kawano, Y.; and Yanai, K. (2015). FoodCam: A real-time food recognition system on a smartphone. *Multimedia Tools and Application*, 74(14), 5263-5287.
32. Kong, F.; He, H.; Raynor, H.A; and Tan, J. (2015). DietCam: Multi-view regular shape food recognition with a camera phone. *Pervasive Mobile Computing*, 19, 108-121.
33. He, Z.; and Jin, L. (2009). Activity recognition from acceleration data based on discrete consine transform and SVM. *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics*. San Antonio, Texas, United States of America, 5041-5044.
34. Shoaib, M.; Scholten, H.; and Havinga, P.J.M. (2013). Towards physical activity recognition using smartphone sensors. *Proceedings of the IEEE 10th International. Conference on Ubiquitous Intelligence and Computing.* Vietri sul Mere, Italy, 80-87.

35. Arif, M.; Bilal, M.; Kattan, A.; and Ahamed, S.I. (2014). Better physical activity classification using a smartphone acceleration sensor. *Journal of Medical Systems*, 38(9), 1-10.
36. Machado, I.P.; Gomes, A.L.; Gamboa, H.; Paixao, V.; and Costa, R.M. (2015). Human activity data discovery from triaxial accelerometer sensor: Non-supervised learning sensitivity to feature extraction parametrization. *Information Processing and Management*, 51(2), 201-214.
37. Acharjee, D.; Mukherjee, A.; Mandal, J.K.; and Mukherjee, N. (2016). Activity recognition system using inbuilt sensors of smart mobile phone and minimizing feature vectors. *Microsystem Technologies*, 22(11), 2715-2722.
38. Hoseini-Tabatabaei, S.A.; Gluhak, A.; and Tafazolli, R. (2013). A survey on smartphone-based systems for opportunistic user. *ACM Computer Surveys*, 45(3), 1-51.
39. Anguita, D.; Ghio, A.; Oneto, L.; Parra, X.; and Reyes-Ortiz, J.L. (2013). A public domain dataset for human activity recognition using smartphones. *Proceedings of the European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning.* Bruges, Belgium, 437-442.
40. Wu, W.; Dasgupta, S.; Ramirez, E.E.; Peterson, C.; and Norman, G.J. (2012). Classification accuracies of physical activities using smartphone motion sensors. *Journal of Medical Internet Research*, 14(5), 1-9.
41. Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5-32.
42. Mitchell, T. (1997). *Machine learning*. New York: McGraw Hill Science/Engineering/Maths.
43. Quinlan, J.R. (1986). *Machine learning*. Induction of decision trees. The Netherlands: Kluwer Academic Publishers.