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# On the use of ensemble of classifiers for accelerometer-based activity recognition

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ABSTRACT

Activity recognition aims to detect the physical activities such as walking, sitting, and jogging performed by humans. With the widespread adoption and usage of mobile devices in daily life, several advanced applications of activity recognition were implemented and distributed all over the world. In this study, we explored the power of ensemble of classifiers approach for accelerometer-based activity recognition and built a novel activity prediction model based on machine learning classifiers. Our approach utilizes from J48 decision tree, Multi-Layer Perceptrons (MLP) and Logistic Regression techniques and combines these classifiers with the average of probabilities combination rule. Publicly available activity recognition dataset known as WISDM (Wireless Sensor Data Mining) which includes information from thirty six users was used during the experiments. According to the experimental results, our model provides better performance than MLP-based recognition approach suggested in previous study. These results strongly suggest researchers applying ensemble of classifiers approach for activity recognition problem.





## 1. Introduction

Activity recognition (AR) is a research topic under Human Computer Interaction (HCI) research area. Some of the researchers first focused on activity recognition from videos and images, but later when daily life was considered, researchers started to apply sensors such as accelerometers for activity recognition [1]. Although there are common research challenges between activity recognition and pattern recognition, several unique challenges which are explained in detail in Bulling et al.'s [1] study exist for AR.

Many machine learning approaches such as Hidden Markov Models (HMMs) [2], Decision Trees (DT) [3], Support Vector Machines (SVM) [4], Conditional Random Fields (CRFs) [5], k-nearest Neighbor (KNN) Ayu et al. [6] were successfully used in AR studies. There are many sensors which can be used for AR problem, and some of them which were used previously are given as follows: accelerometers, gyroscopes, magnetometer, GPS, RFID, light sensor, Inertial measurement units, skin temperature, ECG, EEG, and camera [1]. Recent studies showed that mobile phones can be effectively used for activity recognition and there is no need to use an extra sensor on the body [7]. In a mobile phone, several sensors such as gyroscope, camera, microphone, light, compass, accelerometer, proximity, and GPS can be used in conjunction with the wireless interfaces such as Bluetooth, Wi-Fi, or 3G/4G. In smartphones, accelerometers are generally used to show landscape or portrait views of the phone. For example, when you rotate your smartphone, accelerometer can detect changes in orientation, and the user interface can be updated appropriately. Also, there are different applications of accelerometers such as pedometers and games. A mobile application, which can be used as a pedometer, is used to count the steps a person takes and it uses the accelerometer of the smartphone. Accelerometer-based games are more fun compared to the other games because player only tilts the smartphone instead of using keys. As explained in these examples, accelerometers have a wide application area in smartphones.

Despite of these benefits of mobile phones, there are many limitations regarding to the hardware [8]. For example, battery limitation and resource consumption of classifiers must be taken into account when designing an activity recognition system.

In this study, we used the accelerometer sensor of a mobile phone and recognized specific activities which are walking, jogging, upstairs, downstairs, sitting, and standing. These activities were chosen because we perform them everyday in our daily life. Jogging means running at a slow pace, and running is a faster activity compared to jogging. Also, calorie burn and activation of muscles will be very different in these two activities. Downstairs and upstairs activities mean descending stairs and ascending stairs, respectively. For each activity, acceleration is recorded in three axes (*z*-axis: forward

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acceleration, $y$-axis: upward/downward motion, $x$-axis: horizontal movement of the leg). Kwapisz et al. reported that while walking, jogging, upstairs, and downstairs activities show periodic behavior, sitting and standing do not have such a property. During descending stairs, small peaks were reported for $y$-axis and during ascending stairs, peaks were reported for $z$-axis and $y$-axis. Sitting and standing do not have such a periodic behavior but the main difference between these activities is each axis's relative magnitude values [7].

We used a publicly available dataset which is known as WISDM (Wireless Sensor Data Mining) and it can be accessed from the following link: http://www.cis.fordham.edu/wisdm/dataset.php. There are activity information of thirty six users in this dataset. Therefore, this dataset is very appropriate for benchmarking studies.

Before we explain the features in this dataset, we must address how the dataset was prepared by those researchers. Raw time-series data was divided into 10-s segments and features were identified for 200 readings in each 10-s segment. Researchers reported that they compared the 10-s and 20-s example duration and since 10-s duration was slightly better, they used this example duration for their dataset. They created features based on 200 readings and 43 features, which are mainly variations of six basic features, were identified. Six feature types are: Average-A (3), Standard Deviation-SD (3), Average Absolute Difference-AAD (3), Average Resultant Acceleration-ARA (1), Time Between Peaks-TBP (3), Binned Distribution-BD (30). The numbers which are shown in parenthesis indicate how many features were generated from this feature-type. Therefore, we have 43 features in total. The number three (3) in parenthesis represents different feature values for each axis. Average shows the average acceleration, and SD represents the standard deviation. AAD is the difference between each value in 200 readings and the mean of 200 values. ARA is computed by calculating the average of square root of the sum of the squared values of each axis. TBP represents the time between peaks. BD is calculated by dividing the range of values into 10 bins and recording the fraction of 200 values which fall within each bin [7].

In Fig. 1, we depict the activity recognition problem. After the data from accelerometer sensor of the smart phone is read, this time series data is transformed into 43 features and the class label of this exercise is recorded in the dataset. In our datasets, we have exercises of 36 people and there are different number of exercises for each exercise type. By using a machine learning classifier, it is possible to build some hypothesis and new activity's exercise type can be predicted based on new 43 features' values. There are many benefits of this challenging problem. For example, when user is in running mode, the smart phone may automatically send an SMS to the caller about this issue or when user is in walking mode, ring tone may increase. Also, if he/she is in sitting mode, location must not be updated due to the battery power considerations.

There are many application areas of activity recognition such as targeted advertisement, health monitoring, and ambient assisted living [8]. From this application perspective, we should consider not only recognition of simple activities such as climbing stairs, sitting, and running but also complex ones such as cleaning, cooking, and sweeping. Dernbach et al. [9] reported that although they achieved 93% accuracy by using Multi-Layer Perceptron for simple activities, they only reached to 50% accuracy for complex activities. This shows that a mobile phone can be a part of a system which can recognize complex activities, but we should take into account extra sensor or devices for a better prediction result.

In this study, we made several experiments with J48, Logistic Regression, and Multi-Layer Perceptron algorithms. Our novel recognition model applied Voting algorithm by combining the power of these three methods. We used these classifiers because we aimed to compare the performance we reached with the performance reported in the recent study of Kwapisz et al. [7]. Although many approaches were suggested for activity recognition in literature, there was no clear consensus which approach is the best one for this problem because researchers mostly used proprietary datasets instead of public ones. However, we applied the public dataset released by Kwapisz et al. [7], but we had to repeat the experiments since the dataset was updated after their publication. Our aim was to provide a better model compared to the model suggest in Kwapisz et al.'s study and therefore, we made experiments with the algorithms used in their study. Miluzzo et al. [10] used J48 classifier for activity recognition task by applying various sensors in smart phones. Al-Bin-Ali and Davies [11] showed that simple Logistic Regression can be used for activity recognition. Mantyjarvi et al. [12] applied Multi-Layer Perceptron for this problem and reported that it can provide acceptable performance. We empirically observed that we can achieve better performance with ensemble of classifiers approach. The detail of our approach is explained in Section 3.

The main contribution of this paper is two-fold:

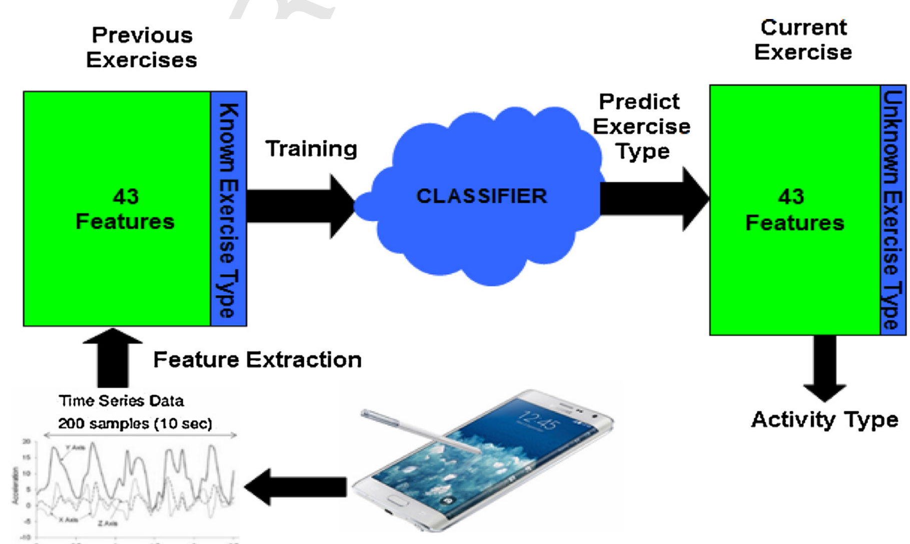


**Fig. 1.** Activity recognition problem.

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- A new high-performance recognition model was proposed and validated.
- Ensemble of classifiers approach was evaluated and its benefits were observed for the near future research studies. For example, ensemble of classifiers approach might be used for recognition of complex activities.

In addition to these contributions, we also developed a mobile activity recognition application for Google Android platform. SensorEventListener interface has been implemented and Activity class was extended in our class declaration. SensorManager class was used to access the sensors of the device and several functions such as getDefaultSensor were used to implement the application.

This paper is organized as follows. Section 2 explains the related work. Section 3 describes the methodology. Section 4 shows experiment results and Section 5 provides conclusion and future work.

## 2. Related work

Activity recognition (AR) has been applied in many application areas such as surveillance environments, entertainment environments, and healthcare systems. When healthcare systems are taken into account, activity recognition might contribute to the development of new rehabilitation systems [13]. Also, we can utilize from AR to design systems for elderly care or health/fitness monitoring [14]. In this study, we developed a novel AR model which can be used to monitor and categorize the activities performed in daily life and this new approach has many contributions for mobile healthcare. Major contributions in this area are explained as follows:

Kwapisz et al. [7] designed a system to recognize activities such as walking, climbing stairs (upstairs and downstairs), sitting, and standing by using the accelerometer of a smartphone. They showed that over 90% accuracy can be reached and activities can be identified quickly. They applied J48 decision tree, Logistic Regression, Multi-Layer Perceptron (MLP), and reported that MLPs provide better performance than the other algorithms. Dataset includes information from twenty nine users and 43 features were used during the experiments. They emphasized that the benefit of accelerometers in smartphones in this study. Lockhart et al. [15] documented the activity recognition (AR) applications and stated that few applications were developed for AR so far. These applications are fitness tracking, health monitoring, self-managing systems, targeted advertising, corporate management, social networking, and activity-based crowdsourcing. Weiss and Lockhart [16] investigated the performance of personal and impersonal AR models. They showed that personal models provide much better performance than impersonal models and personal models also achieve better performance than hybrid models using personal and impersonal information. MLP performed best for personal models and Random Forests (RF) was the best approach for impersonal models. Lockhart and Weiss [17] reported that most of the AR datasets are very limited. For example, some of them consist of very few subjects and data is collected under laboratory conditions. Also, there is no information about the model type such as personal, impersonal, and hybrid although model type impacts the performance dramatically. They analyzed 34 AR papers and observed that several critical issues. In this study, we used the dataset prepared by these authors because the dataset satisfies the requirements explained in the paper.

Bayat et al. [18] made several experiments with four users who performed six activities (slow walking, fast walking, running, stairs-up, stairs-down, dancing) and built a recognition model having 91.15% accuracy. They combined three classifiers (MLP, SVM, LogitBoost) for in-hand phone position and they achieved the best performance with this model. MLP + RF + SimpleLogistic combination performed best for in-pocket phone position. They reported that the best combination rule for fusion method was average of probabilities instead of majority voting. Wang et al. [19] suggested an algorithm based on Hidden Markov Model (HMM) for AR by using acceleration signals. Selected activities are walking, standing, running, jumping, sitting-down, and falling-down. Thirteen subjects were used for the experiments. 94.8% accuracy was achieved with the proposed approach. Kwon et al. [20] suggested unsupervised learning algorithms for AR problem by using smartphone sensors. If the number of activities are known previously, the mixture of Gaussian method works properly. DBSCAN algorithm reached to 90% accuracy when k is selected with Calinski–Harabasz index. Ayu et al. [6] performed several experiments for activity recognition by using machine learning algorithms and reported that the best algorithm for hand palm's position is IBk which is a k-nearest Neighbor (kNN) classifier. Rotation Forest algorithm was reported as the best approach for shirt pocket's position. They focused on five activities and emphasized that the location of the position of the phone affects the performance of the prediction models. Gao et al. [21] evaluated the effect of multiple sensors on body for AR and stated that decision tree classifier was the best algorithm for this problem. They explained that ANN, KNN, and SVM classifiers are computational expensive although they provide good performance. The proposed approach achieved 96.4% accuracy when multiple sensors were used. Hong et al. [22] suggested a method for AR by using three accelerometers and RFID technology. Two accelerometers were used to classify the activities with the help of decision tree algorithm. The prediction performance was around 95% which is quite acceptable. They noted that current phones have already built-in accelerometer so that the suggested model can easily be deployed on a smartphone without using extra devices.

## 3. Methodology

This section explains our activity recognition technique and describes the individual classifiers used in our technique.

We used Weka machine learning software for the experiments and our activity recognition model was built after an extensive number of experiments. The proposed model applies Vote classifier which is an ensemble of classifiers method. Individual classifiers used for Vote classifier are J48, which is a decision tree algorithm, Logistic Regression, and an artificial neural network method known as Multi-Layer Perceptron. The average of probabilities combination rule was integrated into the model for the decision step.

During the experiments, 10-fold cross-validation (CV) approach was used. After testing phase, confusion matrices for each technique (J48, Logistic Regression, and Multi-Layer Perceptron) were calculated. Later, the new model's validation was performed and confusion matrix was prepared for the proposed model. In order to see the performance variances, a separate table was designed and the performance results of each approach were filled.

*J48*: J48 is Java implementation of C4.5 algorithm. It creates a decision tree which can be used for classification problems. The attribute which has highest information gain is selected and a decision node is created based on this attribute. The algorithm goes on working recursively on the remaining attributes.

*Logistic Regression*: Logistic Regression is a statistical classification method. Relationship between dependent variable and independent variables can be modeled by using this method. Ordinary regression and logistic regression are two different approaches and logistic regression predicts the probability of an event.

*Multi-Layer Perceptron (MLP)*: MLP is a very popular artificial neural network technique which maps inputs onto outputs. Input layer,

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**Table 1**
Confusion matrix of J48-based recognition approach.

| Walking | Jogging | Upstairs | Downstairs | Sitting | Standing | Accuracy | AUC | F-measure |
|---|---|---|---|---|---|---|---|---|
| 1988 | 19 | 37 | 34 | 2 | 1 | 95.53 | 0.972 | 0.946 |
| 17 | 1563 | 31 | 13 | 0 | 1 | 96.18 | 0.98 | 0.958 |
| 59 | 37 | 427 | 106 | 1 | 2 | 67.56 | 0.86 | 0.68 |
| 53 | 14 | 126 | 334 | 1 | 0 | 63.26 | 0.868 | 0.657 |
| 3 | 1 | 2 | 1 | 295 | 4 | 96.41 | 0.985 | 0.975 |
| 2 | 3 | 1 | 0 | 0 | 240 | 97.56 | 0.99 | 0.972 |

**Table 2**
Confusion matrix of Logistic Regression-based recognition approach.

| Walking | Jogging | Upstairs | Downstairs | Sitting | Standing | Accuracy | AUC | F-measure |
|---|---|---|---|---|---|---|---|---|
| 1980 | 9 | 57 | 34 | 0 | 1 | 95.15 | 0.969 | 0.902 |
| 18 | 1603 | 1 | 2 | 0 | 1 | 98.65 | 0.999 | 0.988 |
| 177 | 6 | 317 | 128 | 4 | 0 | 50.16 | 0.912 | 0.519 |
| 129 | 2 | 203 | 190 | 3 | 1 | 35.98 | 0.893 | 0.428 |
| 0 | 0 | 5 | 5 | 288 | 8 | 94.12 | 0.995 | 0.94 |
| 4 | 0 | 6 | 0 | 12 | 224 | 91.06 | 0.996 | 0.931 |

**Table 3**
Confusion matrix of Multi-Layer Perceptron based recognition approach.

| Walking | Jogging | Upstairs | Downstairs | Sitting | Standing | Accuracy | AUC | F-measure |
|---|---|---|---|---|---|---|---|---|
| 2027 | 2 | 25 | 26 | 0 | 1 | 97.41 | 0.995 | 0.976 |
| 6 | 1609 | 6 | 3 | 1 | 0 | 99.02 | 0.999 | 0.994 |
| 14 | 1 | 520 | 93 | 3 | 1 | 82.28 | 0.957 | 0.77 |
| 21 | 2 | 161 | 340 | 1 | 3 | 64.39 | 0.933 | 0.685 |
| 3 | 0 | 2 | 0 | 292 | 9 | 95.42 | 0.998 | 0.962 |
| 3 | 0 | 5 | 2 | 4 | 232 | 94.31 | 0.994 | 0.943 |

**Table 4**
Confusion matrix of our proposed model.

| Walking | Jogging | Upstairs | Downstairs | Sitting | Standing | Accuracy | AUC | F-measure |
|---|---|---|---|---|---|---|---|---|
| 2054 | 8 | 10 | 8 | 0 | 1 | 98.70 | 0.999 | 0.987 |
| 14 | 1598 | 9 | 4 | 0 | 0 | 98.34 | 0.998 | 0.986 |
| 3 | 4 | 538 | 85 | 2 | 0 | 85.13 | 0.983 | 0.813 |
| 9 | 5 | 129 | 384 | 1 | 0 | 72.73 | 0.981 | 0.76 |
| 1 | 0 | 3 | 0 | 300 | 2 | 98.04 | 1 | 0.985 |
| 2 | 1 | 3 | 2 | 0 | 238 | 96.75 | 0.995 | 0.977 |

hidden layer, and output layer are the basic building blocks of a MLP model. Backpropagation learning technique is used for the training of this network.

*Vote*: Vote is an example for ensemble of classifiers concept. It uses the power of several individual classifiers and applies a combination rule for the decision. For example, minimum probability, maximum probability, majority voting, product of probabilities, and average of probabilities are different examples for combination rules.

## 4. Experimental results

In this section, we explain the experimental results we reached during the experiments. We used 10-fold cross-validation for the experiments and applied accuracy parameter for evaluation of the models. Since the dataset is not unbalanced, we can use accuracy parameter and researchers applied this parameter previously in their studies. In addition to the accuracy parameter, we calculated Area Under ROC Curve (AUC) and *F*-measure performance evaluation parameters. These additional measures are shown in different columns in our tables. In Table 1, we present the confusion matrix of the proposed model. We compared this matrix with the confusion matrices of the other standalone classifiers such as J48, Logistic Regression, and Multi-Layer Perceptron. Since Kwapisz et al.'s [7] paper uses a dataset having twenty nine users and the dataset we downloaded from their website includes thirty six users, we had to repeat those calculations from the scratch.

In Tables 1–3, we show the confusion matrices of J48, Logistic Regression, and MLP-based activity recognition models. In Table 4, we show the confusion matrix of our proposed model. In Table 5, we show the accuracy values of each model for each activity type. For four activities (walking, upstairs, downstairs, sitting), our new

**Table 5**
Comparison of various activity recognition models based on accuracy.

| | J48 | Logistic Regression | Multi-Layer Perceptron | Our model |
|---|---|---|---|---|
| Walking | 95.53 | 95.15 | 97.41 | 98.7 |
| Jogging | 96.18 | 98.65 | 99.02 | 98.34 |
| Upstairs | 67.56 | 50.16 | 82.28 | 85.13 |
| Downstairs | 63.26 | 35.98 | 64.39 | 72.73 |
| Sitting | 96.41 | 94.12 | 95.42 | 98.04 |
| Standing | 97.56 | 91.06 | 94.31 | 96.75 |

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**Table 6**
Comparison of various activity recognition models based on Accuracy.

| | Average of probabilities | Majority voting | Product of probabilities | Minimum probability | Maximum probability |
|---|---|---|---|---|---|
| Walking | 98.7 | 98.65 | 97.53 | 97.53 | 97.55 |
| Jogging | 98.34 | 98.03 | 97.82 | 97.82 | 97.48 |
| Upstairs | 85.13 | 82.75 | 79.81 | 79.32 | 79.11 |
| Downstairs | 72.73 | 72.92 | 72.64 | 72.64 | 67.61 |
| Sitting | 98.04 | 97.06 | 96.7 | 96.7 | 97.39 |
| Standing | 96.75 | 95.53 | 94.14 | 94.14 | 97.15 |

model provided the highest performance results compared to the other standalone classifiers. In jogging and standing activities, the performance of MLP and J48 is slightly better than our model but, when we consider most of the cases and the difference between performance values for two cases, we suggest our new model for activity recognition.

According to Table 5, very high results were achieved for walking and jogging activities. The reason of this high result is related with the number of samples in these categories. In the dataset, there are lots of samples having this category. According to this table, it is clear that the worst performance is taken for upstairs and downstairs activities which cannot be easily distinguished. However, the performance of our model for downstairs activity (72.73%) is much better than the other classifiers' performance (63.26%, 35.98%, and 64.39%). Also, the performance of our model is better for upstairs activity is better than the other classifiers' performance.

In Table 6, it is observed that the best performance is achieved with the average of probabilities combination rule for most of the activities. Therefore, we decided to apply this aggregation method in our new model.

## 5. Conclusion and future work

Activity recognition is a very important research area and a small increase in the performance may dramatically impact the performance of existing recognition systems. Since some of these recognition systems are used in health domain, the performance of these systems is vital from the perspective of patients. With the widespread usage of mobile phones, the research in AR domain shifted toward the application of them for this problem. Previous studies applied different sensors and devices to recognize the activities but now, most of the researchers focus on developing systems based on the sensors which exist in a mobile phone.

In this study, we proposed and validated a novel activity recognition technique which utilizes from J48, Logistic Regression, and MLP classifiers. We used these classifiers in a Vote algorithm and based on average of probabilities combination rule, an appropriate class was assigned to each sample during the testing phase. All the experiments were performed on a publicly available dataset and therefore, our results are reproducible. Experimental results showed that this new model achieved better performance than the standalone MLP-based recognition approach.

As a future work, we are planning to use different machine learning approaches and apply different combinations of classifier parameters for optimization. We will apply this model on different proprietary datasets and the other public datasets if we can reach them. One near future plan is to create our own dataset and include more users to create recognition information. In addition, we will use this model to be able to recognition complex activities such as sweeping and cooking.



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