Human Activity Recognition Using Smartphones

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***Abstract*— Human Activity Recognition(HAR) is classifying activity of a person using responsive sensors that are affected from human movement. Both users and capabilities(sensors) of smartphones increase and users usually carry their smartphone with them. These facts makes HAR more important and popular. This work focuses on recognition of human activity using smartphone sensors using different machine learning classification approaches. Data retrieved from smart phones' accelerometer and gyroscope sensors are classified in order to recognise human activity. Results of the approaches used are compared in terms of efficiency and presicion.**

Keywords—Machine learning, smartphone, activity recognition, classification

I. INTRODUCTION

Smartphones are the most useful tools of our daily life and with the advancing technology they get more capable day by day to meet customer needs and expectations. To make these gadgets more functional and powerful, designers add new modules and devices to the hardware. Sensors has a big role in making smartphones more functional and aware of the environment thus most smartphones comes with different embedded sensors and this makes it possible to collect vast amounts of information about the user's daily life and activities. Accelerometer and gyroscope sensors are amongst these devices too.

Accelerometer has been a standard hardware for almost all smartphone manufacturers. As it's name suggests accelerometer measures the change in speed; not the speed itself. Data retrieved from accelerometer may be processed in order to detect sudden changes in movement. Another sensor that has been a standard hardware for smartphones is gyroscope which measures orientation by using gravity. Signals retrieved by gyroscope can be processed to detect position and alignment of the device. Since there is a meaningful difference of characteristics between datas retrieved from these sensors, many features could be generated from these sensors data to determine activity of the person that is carrying the device.

Classification of smartphone user activities has been focused in different studies. Bayat et al. studied on human activity recognition with accelerator signals[1]. Attal et al. tried to classify activity depending on wearable multiple gyroscope and accelerometers[2]. Ronao et al. structured a convolutional artificial neural network in order to recognize user activity using smartphones accelerometer and gyroscope[3]. Kozina et al. worked on fall detection using accelerometer[4].

In this study a dataset consist of signals from accelerometer and gyroscope of a smartphone carried by different man and women volunteers while doing different activities are classified using different machine learning approaches. Performance of different approaches are analysed and compared in terms of presicion and efficiency.

II. METHOD

A. Dataset

Dataset consists of signals from a smartphone carried by 9 individuals performing 6 different activities. Activities performed are listed below with their corresponding codes.

- WALKING - 1
- CLIMBING UP THE STAIRS - 2
- CLIMBING DOWN THE STAIRS - 3
- SITTING - 4
- STANDING - 5
- LAYING - 6

Signals are recorded with a sampling rate of 50Hz and stored as time series for each dimension so 6 different signals obtained (3 are from accelerometer and other 3 are from gyroscope). The noise was filtered using median and 20Hz Butterworth[5] filters in order to get more precise results. A second 3hz Butterwoth filtering applied to eliminate effect of gravity in accelerometer signals. Values then normalized to (-1,1) interval. Euclid magnitudes of the values of 3 dimensions calculated to merge 3 dimensional signal into one dataset[5]. Finally class codes (activity codes) given above for each row are added at the end of them among with the number that is given to each individual. In the end dataset consists of 2947 records with 561 features.

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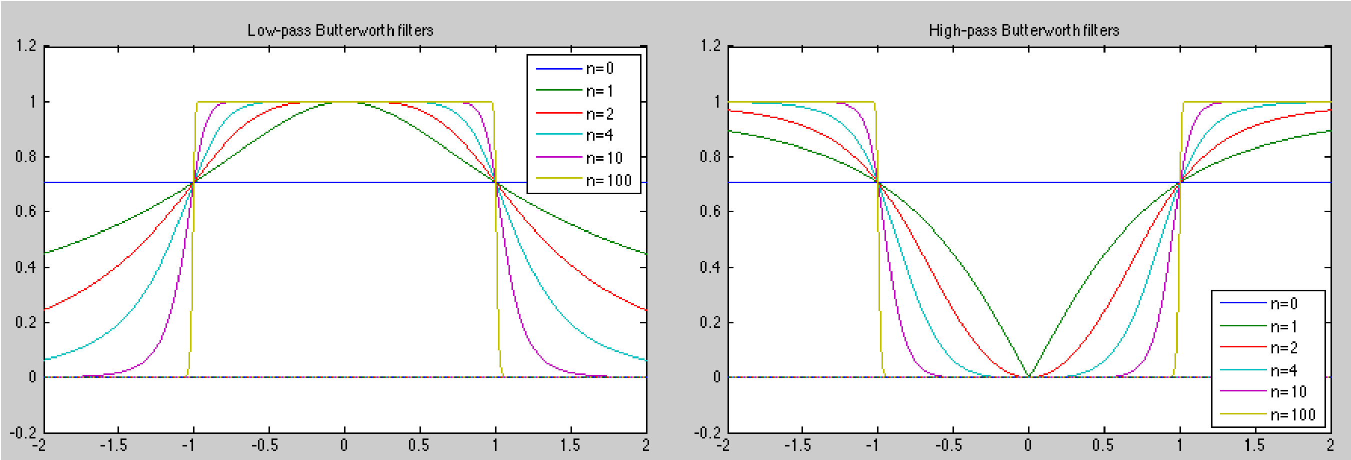

Fig. 1. High and low pass Butterworth filters[6]

B. Learning Methods

Supervised machine learning is used to recognize activity from dataset records. Different supervised machine learning models designed using different classification approaches. Designed models first trained with a training data that consists of %80 of the total dataset and then tested with the rest. Classification presicion of models are tested and observed using 5-fold cross validation.

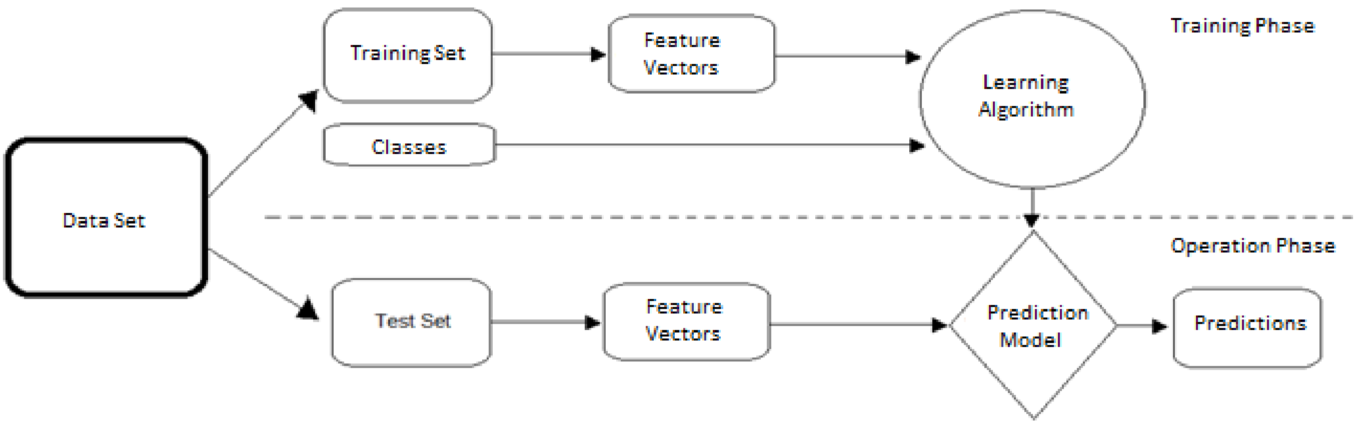

Fig. 2. Supervised machine learning model

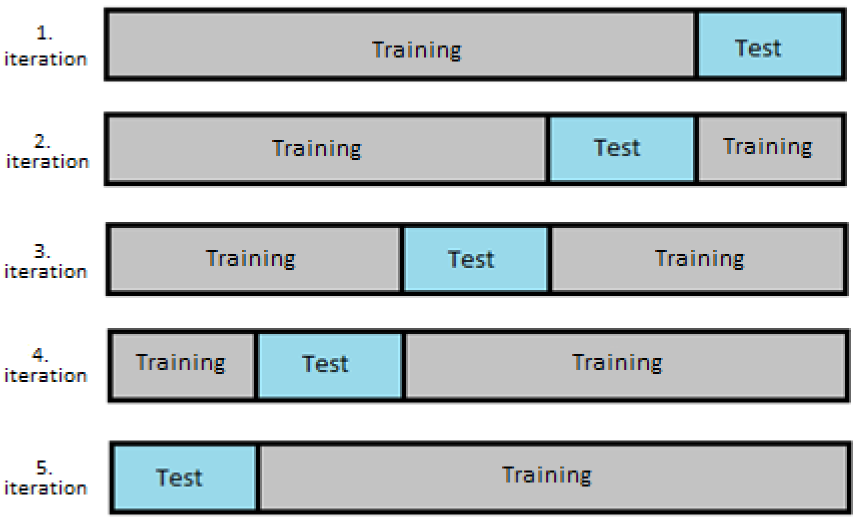

Fig. 3. 5-fold cross validation

Methods used for classification are as follows:

- Decision Trees
- Support Vector Machines
- K-nearest neighbors(KNN)
- Ensemble classification methods
    - o Boosting
    - o Bagging
    - o Stacking

a) Decision Trees: Decision trees are based on the logic of dividing complex decisions by features to create simpler ones. It classifies data by flowing through a query structure from the root until it reaches the leaf, which represents one class[7]. Since dataset has 6 different activity records, final decision tree must have 6 kind of leafs. Branching level is an important factor for success of classification. When binary decision tree is used for classification %53.1 success rate is achieved (see Fig. 4).

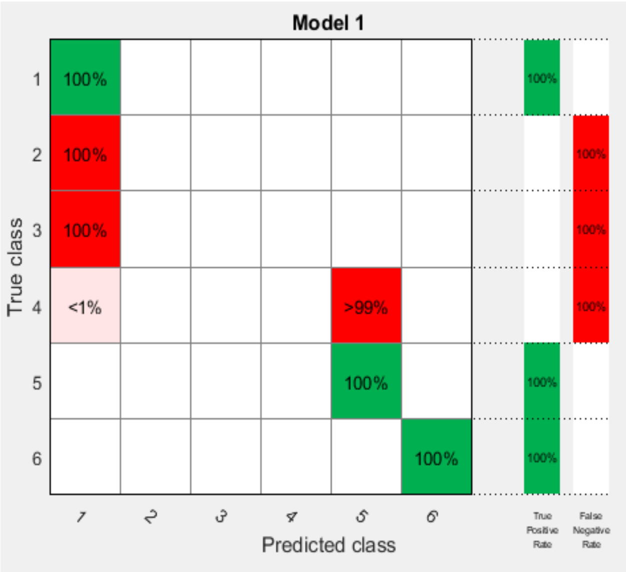

Fig. 4. Confusion matrix of binary tree classification.

When branching is limited to two, model can't create leafs for each activity class and classifies tuples as STANDING, WALKING and LAYING as seen in Figure 6.

After braching limit is raised to 20 a significant increase in classification success is observed. In this model classification success rate is %91.7 (see Fig. 5).

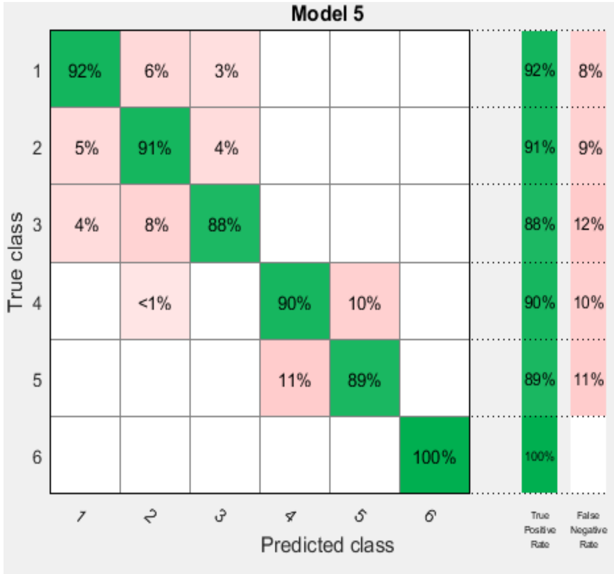

Fig. 5. Confusion matrix of the decision tree classification with branching limited with 20

As branching increases success rate and calculation time increases. When branching limit is set to 100, success rate increases to %94.4 (see Fig. 6).

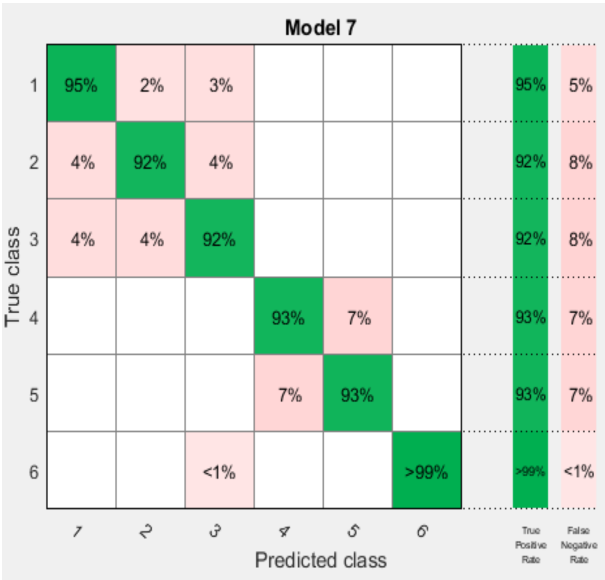

Fig. 6. Confusion matrix of decision tree classification with branching limit 100

b) Support Vector Machines(SVM): Support Vector Machines uses hyper dimensional planes to separate examples in best way possible. Although SVN can be used both with and without supervising, using supervised SVN is usually faster and more succesful[8]. When supervised SVM with a cubic polinomial kernel used for classification of tuples in the dataset, high level success with rate of %99.4 was achieved (see Fig. 7).

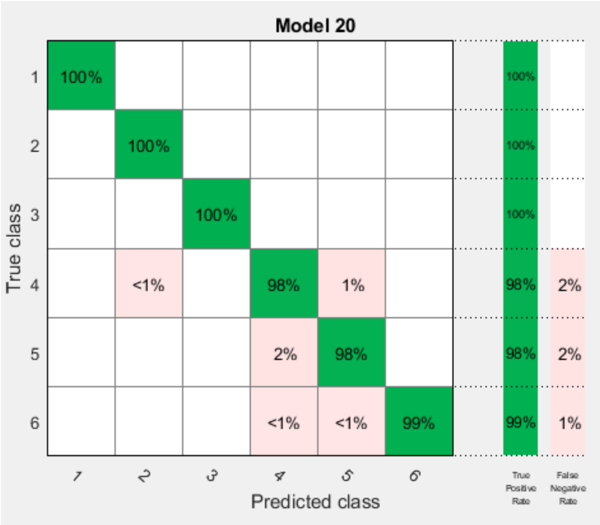

Fig. 7. Confusion matrix of Cubic SVM

c) K-Nearest Neighbors(k-NN): k-NN is a widely used classification method that uses clustering examples depending on their coordinates on the feature space. In this method an example is classified by checking its previously classified k neighbours. Choosing the right value for k value is crucial. A low k value may be affected by noise. On the other hand a high k value may cause inclusion of different class members to base group. Since the dataset is noise-filtered twice, risk of choosing lower k values have less risk. For k=1 success rate is %97.1. When k is set to 3 success rate is %97.5 (see Fig. 8).

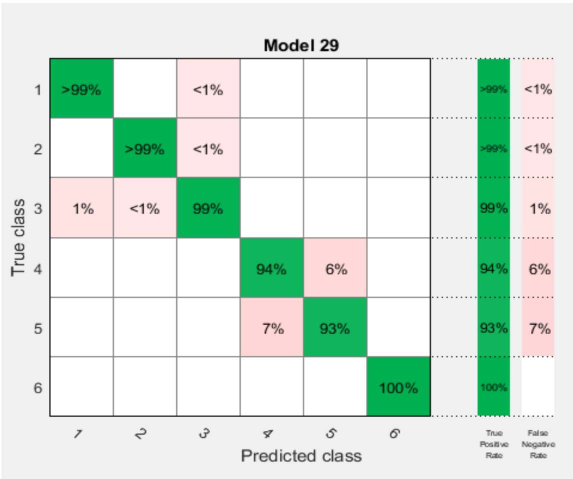

Fig. 8. Confusion matrix of kNN when k=3

d) Ensemble Classifiers: Ensemble classifiers are combinations of different machine learning algorithms and have many different approaches. One of these approaches is boosting. Boosting requires a training set with N members created with all tuples has the same probability. After first classifier classifies the tuples, misclassified records probability are increased to make sure they are picked and correctly classified by the next classifier and so on. One of the most common forms of boosting machine learning is AdaBoost(Adaptive Bootsrapping) algorithm. AdaBoost uses a sequential set of classifiers and aims to create a strong classifier out of weaker ones[9]. After each classification phase it boosts miscalculated tuples probability by calculating them with the coefficient below.

$$(1-Ek)/Ek \qquad (1)$$

Where Ek is the total probability of the miscalculated tuples. Finally it normalizes all weights that the sum would be equal to 1[10]. In our tests AdaBoost classifies %97.4 of the records succesfully (see Fig. 9).

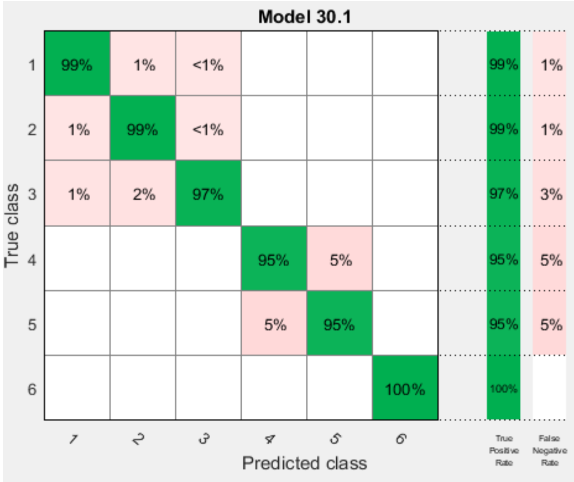

Fig. 9. Confusion matrix of AdaBoost classifier

Another ensemble approach is Aggregation(Bagging). This method requires training data to be divided into subgroups and distributed to classifiers of the ensemble structure[11]. Aggregation is usually used to get more decisive results from sensitive learning algorithms like decision trees[12]. Using aggregation %98.1 successful classification ratio is achieved (see Fig. 10).

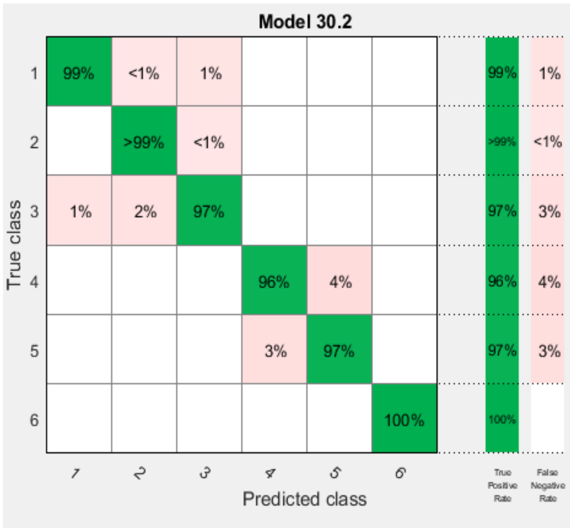

Fig. 10. Confusion matrix of Aggregation(Bagging) classifier

Third ensemble approach covered in this work is stacking. Unlike other ensemble classifiers stacking always have two training phases. Training data is divided and distributed to first phase classifiers and a classifier in the second phase is trained by output of the first phase classifiers, using them like generated new features.

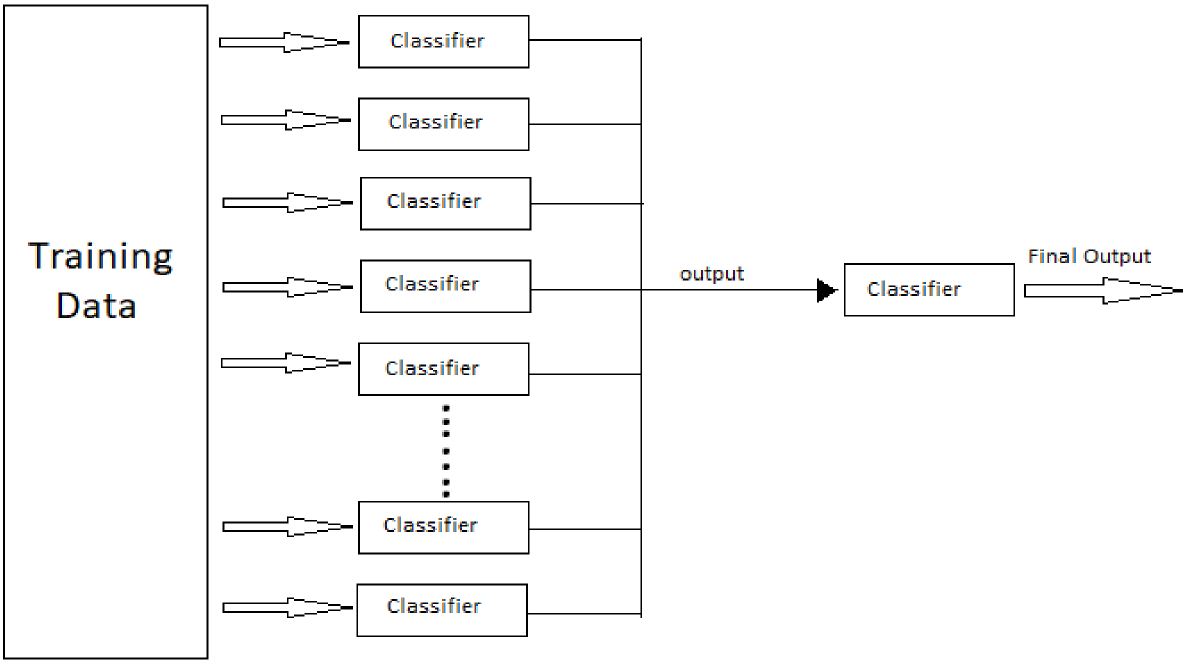

Fig. 11. Stacking Classifier Structure

With stacking classifier that consists of 30 k-NN classifiers %98.6 of the tuples' classes were succesfully predicted (see Fig. 12).

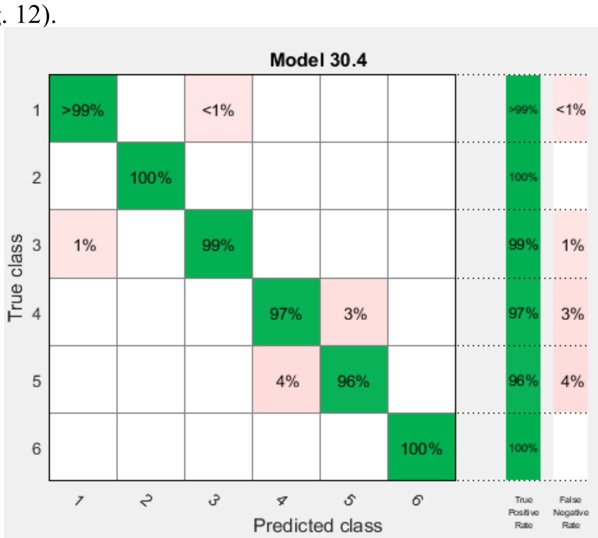

Fig. 12. Confusion matrix of stacking classifier

III. CONCLUSION

Success rates of tested models are given in Table 1 below.

TABLE I. SUCCESS RATES OF TESTED MODELS

Model	Success rate(%)
Binary Decision Tree	53,1
Decision Tree(20)	91,7
Decision Tree(100)	94,4
SVM	99,4
k-NN(k=1)	97,1
k-NN(k=3)	97,5
AdaBoost	97,4
Bagging	98,1
Stacking	98,6

While SVM is the most precise approach tested in this work as seen in Table 1, most of the methods create effective models. Bayat et.al. achieved %91.15 succesfull classification rate by using accelerator data. Anguita et. al. has used the dataset in this work and achieved %96 true positive rate using multi-class SVM. Another study that has used deep learning neural networks achieved %94.79 success rate[3]. Considering these comparisons it can be said that methods evaluated in this work highly successful at detecting activity performed by the smartphone user.

Dataset used in this study contains data generated from solely accelerometer and gyroscope signals. This work could be improved by increasing the number of activities and situations to classify and to add data received from other sensors and devices that are commonly used in smartphones to the dataset. Some of these devices are magnetometer, light sensor, proximity sensor, barometer, termometer, pedometer, heart pulse monitor, GPS and microphone. With help of these devices it would be possible to get information about condition and location of the user and situation of the environment in order to classify much more complex activities and situations.

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