Sensor Based Human Physical Activities Evaluation on Multiple Classifiers

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Abstract:- Recognition of human activities has become a very popular problem that has been widely studied with the development of sensors embedded in mobile devices and increasingly widespread methods of machine learning. For the solution of this problem, the sensor data of the different movements collected are labeled with the movements performed and turned into a classification problem. Different human activities are tried to be distinguished by applying Gradient Boosting, Random Forest, AdaBoost, Gaussian Naive Bayes classification algorithms on the collected data. Performance examinations and accuracy values are evaluated with the combination confusion matrix. It is observed that Gradient Boosting showed the best performance overall analysis. Human activity recognition is used in health practices, calculating personal daily calories, analyzing the health status, monitoring the movements performed by the elderly people in their environment, human position tracking, and various security applications.

Keywords:- *Human activity recognition; Sensor; Gradient Boosting; Random Forest; AdaBoost; Gaussian Naive Bayes.*

I. INTRODUCTION

The new generation of mobile devices includes a wide variety of sensors for the analysis of human activity and behavior. This sensor data allows it to be used in smart applications to make inferences about different aspects of human life. Health checking, life control, fitness monitoring and safety practices are examples of traditional applications. Information gathering and sensation has been an effective research area with the extensive usage of cellular phones and advances in microelectronics and sensor technologies. Human activity recognition (HAR) using sensors on smartphones is a classic multiple-variable time series classification issue that applies vector sensor signals and distinctive features to diagnose movements using a classifier. Such a tight one-dimensional structure needs highly interrelated measurements. Motion features and the different forms and styles people show in the same activities are used as time series signals and are very useful information if handled correctly by a classifier.

Automatic identification of human physical activities (HAR) has become a major research area inaccessible computing (ubiquitous computing), human-computer interaction (HCI), and human behavior analysis. In this problem, human activities are defined from real-time sensor signals that are worn on or in the body. The main factor in the success of HAR systems is the effective evaluation of time series data collected over the body. Commonly used features in HAR systems are basic transform coding, wavelet and Fourier transform signals, statistics of basic signals (mean and variance of time series), and symbolic representations. Although these features are widely used in many time series problems, they are intuitive and not specific to the problem. It should be noted that HAR operations have their challenges, such as in-class variability, the similarity between classes, NULL class dominance, and complexity and diversity of physical activities.

Recognition of human behavior can usually be broken down into two levels. The initial step is separation in time series. Simplest application for this process is to apply a fixed-size sliding window and always equally splitting the series. The second step is the extraction and classification of effective properties from the raw sections obtained. This is highly important for HAR problems because the quality of features usually determines the completion of an entire system. Although this approach performs well in practice, it is often mediocre to rely on area-specific information and generalize to new data sources and experimental setups. Another way is by applying deep learning architectures. The essential idea is based on the extraction of the required features straightly from the data. Along with its consistency and generalization, the key value of this strategy is that it provides end-to-end training by eliminating manual feature extraction after the deep learning model is created.

Human activity recognition has attracted intense interest in a variety of fields, such as widespread, mobile, and context-sensitive computing, due to the advancement of techniques such as smart mobile devices, wireless networks, and machine learning. The main component for the recognition of successful human activity may be to learn how to efficiently represent sensor signals (corresponding to feature extraction) so that the properties of predefined actions are well defined by classifiers on mobile devices.

II. RELATED WORK

In the literature, studies that consider the human activity recognition issue as a classification problem. Based on these studies, each human activity is based on the detection of class labels with the attributes they obtain from the sensor data, as different class labels.

Bao and Intille collected data from 20 different subjects by placing them in different parts of the human body such as 5 uniaxial accelerometers, hips, wrists and ankles [2]. They trained 20 different human activities which collected from 20 different subjects using the Fourier Transform attribute with sample-based learning, decision trees, Naive Bayes classifiers, and achieved success. Similarly, Banos et al also tried to detect walking, running, standing, and sitting movements using accelerometers located in different parts of the body [3].

Niskham and Nikhil have attempted to detect walking, running, standing, sitting, ladder descending, ladder climbing, tooth brushing, and sweeping movements using a three-axis accelerometer [8]. They concluded that the classifiers based on majority voting were more successful than other classifiers. They also stated that it was impossible to distinguish between toothbrushing and ladder descending activities.

Kwapsiz and friends made an activity determination using the three-axis accelerometer data they received on an android device [6]. They produced different features such as mean acceleration, standard deviation, and mean absolute deviation. They used the data set they obtained for the training of 3 different classifiers (Logistic Regression, Decision Tree, and MLP). They stated that the decision tree algorithm has higher performance than other models. In the results obtained, it is observed that the performance is low due to the similarity between the stair descending and stair climbing movements.

Another study is to identify 5 different human activities using 13 different wave attributes in total, in time and frequency space [5]. The data set was collected from a total of 7 different subjects, females and males, between the ages of 27-35. After obtaining 13 different time and frequency attributes from 69400 sensor data, they trained their systems with the C4.5 algorithm and Artificial Neural Networks. According to their results, they achieved a success rate of \%94.13 with the C4.5 algorithm. Wu et al. used gyro data together with their accelerometer data for their human activity systems [10]. When used together with the accelerometer data, gyroscope data contributes to the establishment of more successful models.

III. CLASSIFIERS

A. Gradient Boosting

Gradient boosting is used for both regression and classification techniques. It generates a high-level prediction model by combining weak models like decision trees. As a boosting method, it constructs the model in several phases and allows optimization of loss function optionally.

Principal objective here is to get a function $F^*(x)$ that for every (y,x) pairs on joint distribution minimizes the presumed values of determined loss function $\psi\ (y,F(x))$.

$$F^*(x) = argminF(x\ )E_{y,x}\ \psi\ (y,\ F(x)) \qquad (1)$$

Boosting approaches $F^*(x)$ through a supplement growth of the function

$$F(x) = \Sigma m = 0M\beta_m h(x;a_m) \qquad (2)$$

where $h(x;a)$ are mostly selected to be plain functions of x having variables $a=\{a1,a2,...\}$. The expansion coefficients βm and the variables are together complied to training data by an onward wisely way [4].

Gradient Boosting is a strong method for establishing predictive models. It is feasible to numerous various risk functions and improves projection precision. It is useful for conventional fitting techniques and lets comfort in model construction. It also deals with possible multiple correlation problems that may occur between variables [11].

B. Random Forest

Random forests are a kind of ensemble learning method. It can be used for both classification and regression. It works by building a large number of decision trees in the training process. It gives the mode of the classes for classification or means of separate trees for regression as output. Random decision forests rectify the drawback of decision trees' overfitting problem on training data.

The random forest classifier is composed of tree classifiers mixture. Every unit is created by a random vector illustrated separately from the input vector. Each tree uniquely votes for the best-accepted category to label an input vector. The random forest classifier utilized in this work made up stochastic chosen attributes or integration of attributes at every node that expands tree [12].

The most common quantifiers for feature selection are the Information Gain Ratio criterion and the Gini Index. The random forest classifier takes a Gini Index as a feature selection unit that calculates the impureness of a feature related to classes [7]. For a particular training data T, choosing one class incidental and assigning to category Ci, the Gini index can be expressed as:

$$\sum\sum_{j\neq i}(f(C_i,T)/T|T|)(f(C_j,T)/|T|) \quad (3)$$

where $f(C_j,T)/|T|$ is the probability that selected case belongs to class C_i.

C. AdaBoost

Adaptive Boosting can be implemented by a combination of different machine learning algorithms to enhance efficiency. The throughput of distinct weak algorithms is weighted summed to a concluding boosted classifier output. AdaBoost is adaptable such that consecutive poor learners are adjusted to samples classified improperly by former classifiers. It is susceptible to dirty data and extreme values. In some situations, it is less sensitive to over-fitting rather than alternative learning algorithms. Even though the singular learners should be poor, as far as the performance of every member is marginally preferable than random estimation, the eventual model can become a powerful learner.

Each learning algorithm aims to comply with some cases better than other algorithms. To accomplish an optimal solution, they regulate numerous variant parameters and compositions. AdaBoost is generally preferred as a prepared classifier. Conjunction with decision trees, the knowledge gained in every step of AdaBoost algorithm supplies for expanding tree. In this way, later trees bear to focalize on much harder classification samples [13].

$$H(x) = sign(\textstyle\sum_{t=1}^{T}\alpha_t h_t(x)) \quad (4)$$

The output of poor classifier t is $h_t(x)$ is input x and α_t is weight allocated on classifier. It is computed as $\alpha_t = 0.5 * ln((1|E)/E)$. Weight of classifier is depending on the error rate E [9]. At first, whole input training samples have same significance. Later on, weak classifier is trained, the weight of every training peer is reformed by below formula

$$D_{t+1}(i) = \frac{D_t(i)\exp(-\alpha_t y_i h_t(x_i))}{Z_t} \quad (5)$$

where D_t is weight at previous level.

D. Gausssioan Naïve Bayes

When working with continuous data, the ordinary presumption is the values related to each category are concerning normal or Gaussian distribution. Such as, let x is a continuous feature. Initially, data is divided into categories and then the mean and variance of x in every class are calculated. Suppose k be the mean of x values corresponding with class Ck and v is observation value gathered [14]. Thereafter, the probability distribution of v of a class is determined using v in the parameterized normal distribution equation.

$$\hat{y} = argmax\ p(C_k)\textstyle\prod_{i=1}^{n}p(x_i|C_k) \quad (6)$$

A different conventional method for dealing with continuous values is to apply binning to discretize the attributes and to get a new group of Bernoulli distributed variables. Occasionally, the dispersion of class-related marginal intensities is not normal. In these situations, kernel density prediction can be applied for a better reasonable evaluation for marginal densities of every rank. This technique can improve the correctness of classifiers significantly. The Naive Bayes classifier assembles this type with a decision rule. Generally, the most prospective hypothesis is selected and referred to as the maximum a posterior or MAP decision rule.

IV. METHOD AND MATERIAL

Fig. 1. Axis orientation of the accelerometer embedded in smartphone

Source for data is obtained from Human Activity Recognition Using Smartphones Data Set [1]. The research is done with a group of 30 participants in a 19-48-year age group. Every individual achieved six actions with a Samsung I9100 Galaxy S II smartphone. Each of them executed the steps two times and every action made at least twice to reproduce repetition. Besides, 5 seconds break is given between activities to move apart from each assignment and make it easier to label throughput. The data is divided into two sets where \%70 is train data whereas %30 is test data. The partitioning is done randomly but it was assured that no instances from the same occupant were in both subsets. The smartphone had an embedded triaxial accelerometer which used for experiments. A rate of constant 50 Hz is used for logging acceleration signals. This rate is enough speedy to get a person's movement information. The data marking process is done manually by choosing the videos saved through experiments as ground truth and checking with inertial signal logs.

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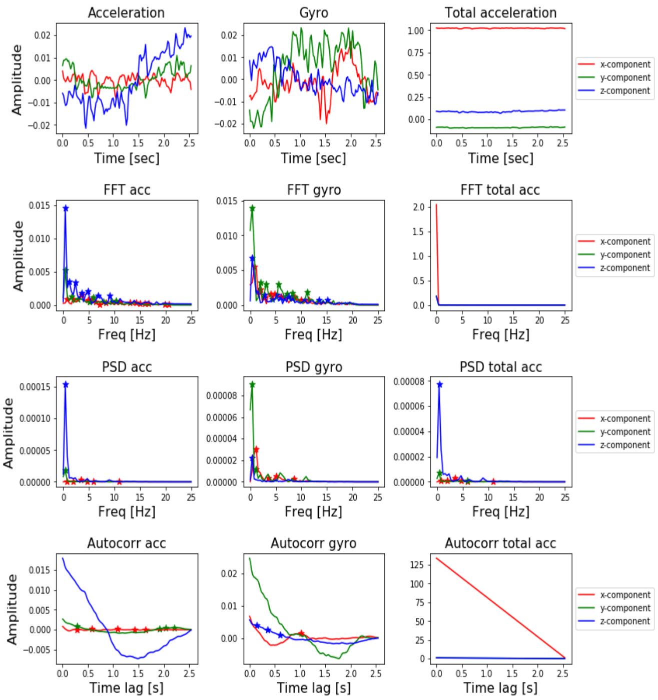

Fig. 2. Amplitudes signals for activities

Sensor signals are firstly filtered several times for adjustment. Noise is decreased by a median filter and a 20 Hz cutoff frequency Butterworth filter. The energy spectrum of a human being is between 0 Hz and 15 Hz. After this operation, a pure triaxial aggregate acceleration is achieved. Gravitational component G is the summation of two acceleration vectors. Body action acceleration BA is partitioned by a spare low pass filter and considered as that G exclusively affects the lowest frequencies. 0.3 Hz is measured as the ideal cutoff frequency to reach a stable gravity. Besides, a derivate of time and acceleration (dA/dt) is predicted acknowledged as jerk. All received signals are formatted by implementing noise filters by 2.56 sec fixed-width sliding windows with \%50 convergence. Consequently, to get shake signals, body linear acceleration, and angular velocity extracted.

The amplitude of 3D signals is measured by the Euclidean norm. Thereafter, a Fast Fourier Transform (FFT) is implemented to designate frequency-domain signals. These indicators are used to predict vector-function parameters for each sequence. In every window, attribute vectors are received with 17 features that predicted from values set in time-frequency domain applying beforehand proposed features. After every trial window example, a vector of features is computed and given as input for the learning algorithm of the model.

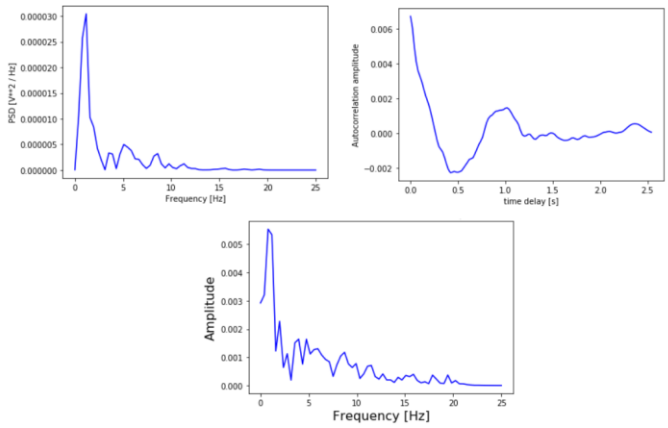

Fig. 3. Frequency domain of the signal

TABLE I. ACCURACY OF CLASSIFIERS.

Classifier	Value
Gradient Boosting Classifier	0.8995
Random Forest Classifier	0.8819
AdaBoost Classifier	0.4798
Gaussian Naïve Bayes	0.7108

Gradient Boosting showed the best performance with 0.8995 whereas AdaBoost is the worst with 0.4798. Precision is the proportion of truly estimated positive values to the entire estimated positive values. High precision values depend on a low false-positive ratio. Recall also referred as sensitivity is the proportion of truly estimated positive values to whole observations in exact class. Recall is useful when false negatives are high. F1 Score is a weighted mean of precision and sensitivity. Consequently, false positives and false negatives are considered together. Heuristically, it is difficult to figure out like accuracy but particularly if the class distribution is unbalanced then F1 is generally further helpful than accuracy. Accuracy is ideal when false positive and false negative have a like amount. If they are very distinct, taking precision and recall is much more effective. The accuracy values of the model are shown in Table 1.

The analysis of human activity recognition algorithms is primarily accomplished by statistical studies of models implementing the present data. The prevalently used technique is a confusion matrix that shows the performance by plainly figuring out the false positive and negative type errors. In collaboration with accuracy, multiple evaluation measures can be provided from data such as precision, recall, F1 Score. Alternative comparison metrics like speed and memory consumption can be also used.

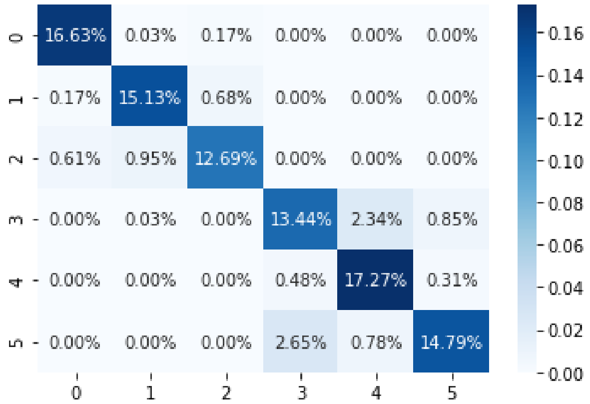

Fig. 4. Confusion Matrix for Gradient Boosting Classifier

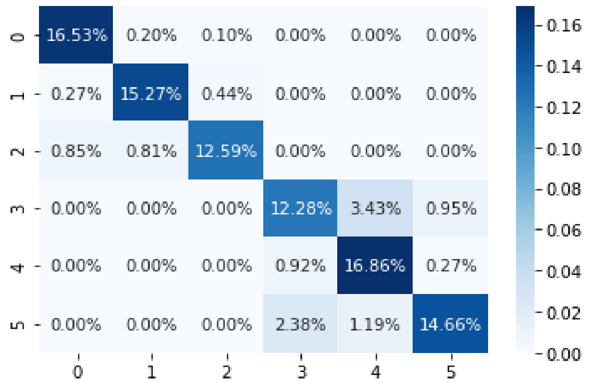

Fig. 5. Confusion Matrix for Random Forest Classifier

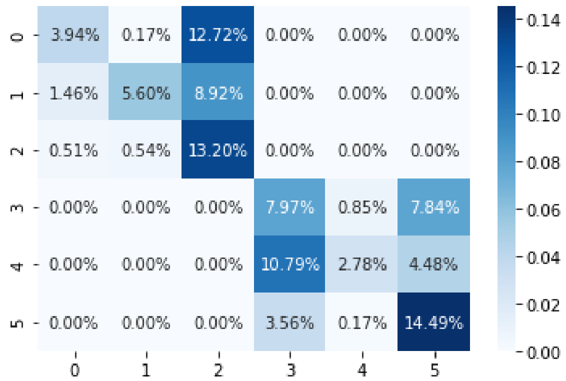

Fig. 6. Confusion Matrix for AdaBoost Classifier

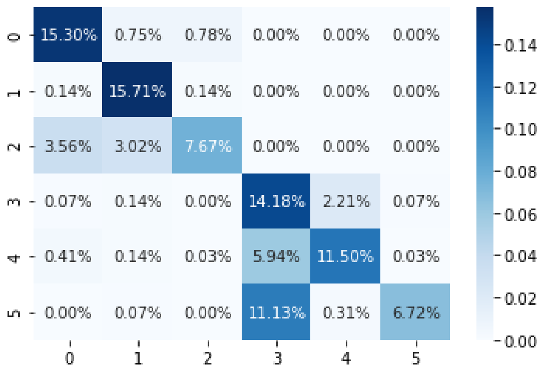

Fig. 7. Confusion Matrix for Gaussian Naïve Bayes

Fig. 8. Precision Metrics

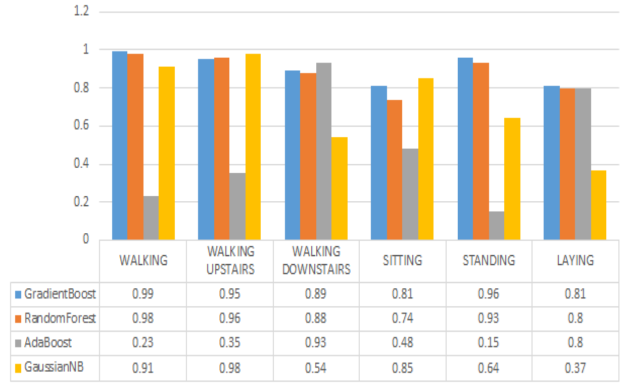

Fig. 9. Recall Metrics

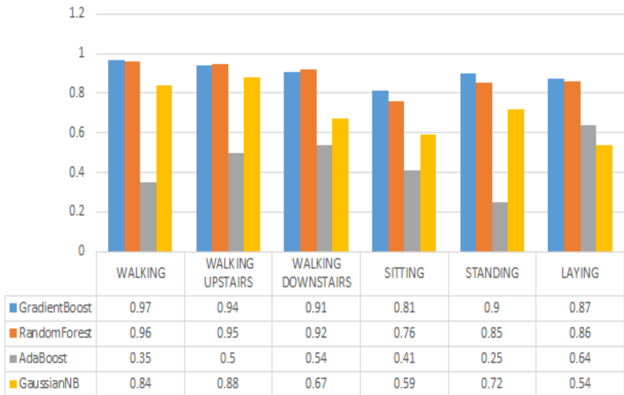

Fig. 10. F1 Score Metrics

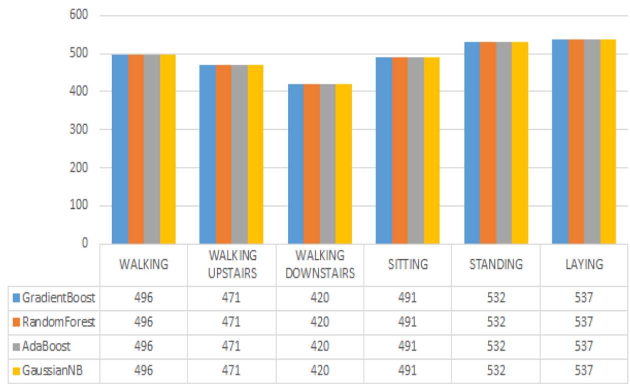

Fig. 11. Support Metrics

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V. CONCLUSION

Depending on the hardware developments, applications in smartphones have become available for the solution of different and specific problems. One of these studies is the detection of human activities using smartphones. Recognition of human activities is a research area that is used in a wide variety of fields and is still difficult to implement. It is used in a wide range of areas such as analyzing the daily movements of people in the field of health, fall detection applications for elderly people, smart homes, ensuring home security.

There are basically two approaches to defining human activity. The first of these approaches is to detect the movements of persons in the environment using image processing methods through various cameras placed in different locations in an environment. However, this method causes the cameras to be placed in a limited space, so an application to be developed can be developed in a limited space. Although image processing methods are used in large areas, they need infrastructure support. Besides, system installation costs are higher than the data mining methods to be mentioned.

Another method used in the field of human activity and becoming more and more common is the use of data mining methods in the solution of the problem. This method is based on the principle of solving this problem by converting the related problem into a classification problem by processing the data obtained from the sensors placed in different parts of the body in accordance with the data mining methods while performing different types of movement. It is attempted to determine different types of motion by using different classification algorithms over the data set created on raw data obtained from mobile sensors. In this study, continuous time wave features are extracted from human activities and successful models are examined. Performance measurements of various machine learning classifiers were performed on the data set from a human activity detection system using 3-axis accelerometer data for a mobile device. For future studies using larger datasets with deep learning algorithms would increase the accuracy of models.

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