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Human Activity Recognition using Smartphones

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Abstract:

Activity recognition is one of the most important technologies behind various applications such as medical science, human survey system and it is an influential research subject in health care and smart homes. Human Activity Recognition(HAR) classifies a person's behavior using sensitive sensors that are influenced by human movement. Both users and mobile capabilities (sensors) are growing and users typically bring their mobile with them. These facts make HAR bigger and more famous. This research focuses on the identification of human behavior using smartphone sensors that use different approaches to classifying machine learning. To identify human activity, data obtained from the accelerometer and gyroscope sensors of smart phones are classified.

Keywords - Machine learning, smart phone, activity recognition, classification.

1. Introduction:

Nowadays smartphones became more and more popular in human daily life. Most of the people used it for searching news, watching videos, playing games and accessing social network but there were many useful studies on smartphones. Activity recognition is one of the most important technologies behind many applications on smartphone such as health monitoring, fall detection, context-aware mobile applications, human survey system and home automation etc., Smartphone-based activity recognition system is an active area of research because they can lead to new types of mobile applications.

Understanding human activities creating a demand in health-care domain, especially in rehabilitation assistance, physiotherapist assistance, and elder care support services and cognitive impairment. Sensors will record and monitor the patient „s activities and report automatically when any abnormality is detected, so, huge amount of resources can be saved. Other applications like human survey system and location indicator are all getting benefits from this study. Training process is always necessary when a new activity is added in to the system. The same algorithm parameters are needed to be trained and fine-tuned when the algorithm runs on different devices with various built-in sensors. However, labeling a training data (time-series data) is a time consuming procedure and it is not always possible to label all the training data by the users. As a result, we present an active learning technique to accelerate the training process.

HAR system takes the raw sensor readings from mobile sensors as inputs and predicts human motion activity, this can be done by leveraging smartphone with various sensors, including accelerometers, compass sensor, GPS, light sensors, gyroscope, barometer etc., Due to its unassertive, none/low installation cost and easy-to-use, smart phones are becoming the main platform for human activity recognition. In this paper, we focus on robust human activity recognition using 3-dimentional accelerometer and gyroscope on smart phones.

In this study a dataset consists 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 analyzed and compared in terms of precision and efficiency.

2. Literature Review:

Human activity recognition has been studied for years and researchers have proposed different solutions to attack the problem. Existing approaches typically use vision sensor, inertial sensor and the mixture of both. Machine learning and threshold-base algorithms are often applied. Machine learning usually produces more accurate and reliable results, while threshold-based algorithms are faster and simpler.

One or multiple cameras have been used to capture and identify body posture [1].

Multiple accelerometers and gyroscopes attached to different body positions are the most common solutions [2].

Approaches that combine both vision and inertial sensors have also been purposed [3]. Another essential part of all these algorithms is data processing. The quality of the input features has a great impact on the performance. Some previous works are focused on generating the most

useful features from the time series data set [4]. The common approach is to analyze the signal in both time and frequency domain. Active learning technique has been applied on many machine learning problems that are time-consuming and labor-expensive to label samples. Some applications include speech recognition, information extraction, and handwritten character recognition [5]. This technique, however, has yet been applied on the human activity problem before.

Jun Yang [6] extracted orientation-independent features from three feature sets, including horizontal, vertical and magnitude features. Each feature set consists of mean, standard deviation, zero cross rate, 75 percentile, interquartile, spectrum centroid, entropy. The authors used Attributed Selection filters to give 7 feature subsets and evaluate recognition accuracy on these subsets. As a result, the accuracy of classifiers on each subsets are lower than with all features, i.e. Decision Tree equals to 90.4% (all features: 90.6%), Naïve Bayes equals to 68.3% (all features: 68.7%).

SianLun Lau [7] used common four features mean, standard deviation, energy of the Fast Fourier Transformand correlation. They combined features to 3 groups: group G1 includes average and standard deviation of values of each axis and all three axes, group G2 includes the average and the standard deviation of FFT coefficients of each axis and all three axes, group G3 includes all four features of each axis and all three axes. However, they used simple features and combined features into groups manually.

Ville Kononen [8] used two feature selection methods, including Sequential Forward Selection and Selection to select features from accelerometer and heart rate signals and evaluate complex classification compared with simple classification. However, they used the feature selection method to select features and compared accuracy of classifier on that features and recognition accuracy of classifier range from about 60% to90%.

3. Working 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 [9] filters in order to get more precise results. A second 3hz Butterworth 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[10]. Finally, class codes (activity codes) given above for each row are added at the end of them along with the number that is given to each individual. In the end dataset consists of 2947 records with 561 features.

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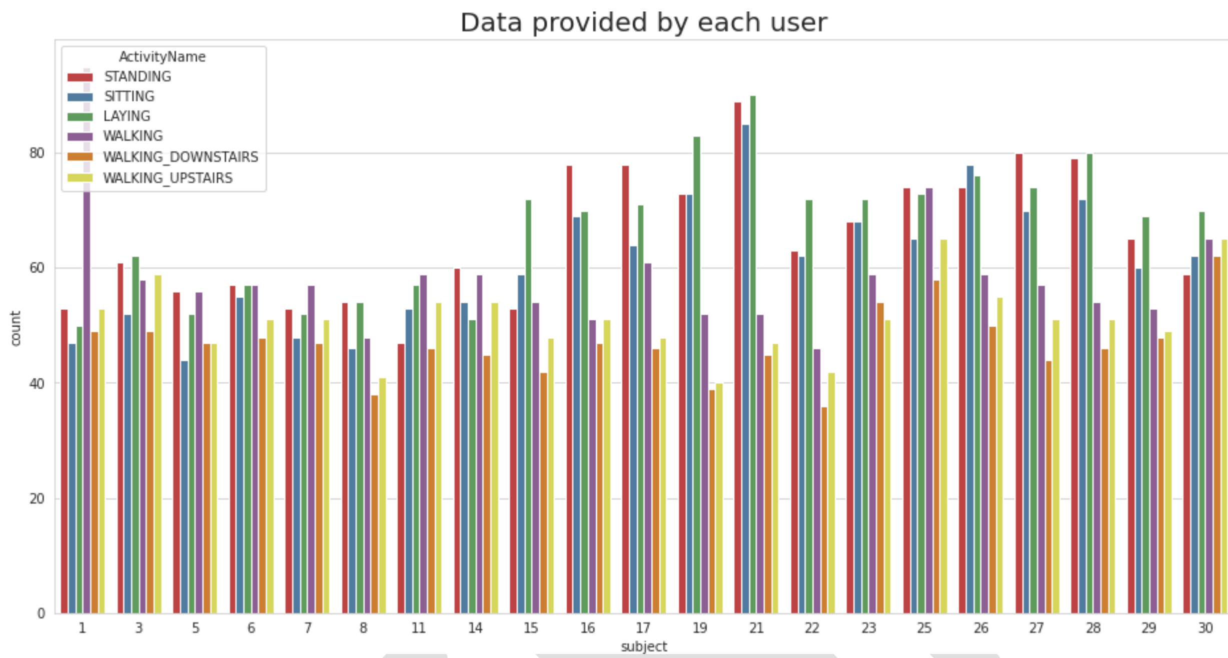

Fig 1. Data provided by each user

B. Learning

Methods Supervised machine learning is used to recognize activity from dataset records. Different supervised machine learning models designed using different classification approaches.

Methods used for classification are as follows:

- Logistic Regression
- Decision Trees
- Support Vector Machines
- Ensemble classification methods
  - Random Forest
  - Gradient Boost

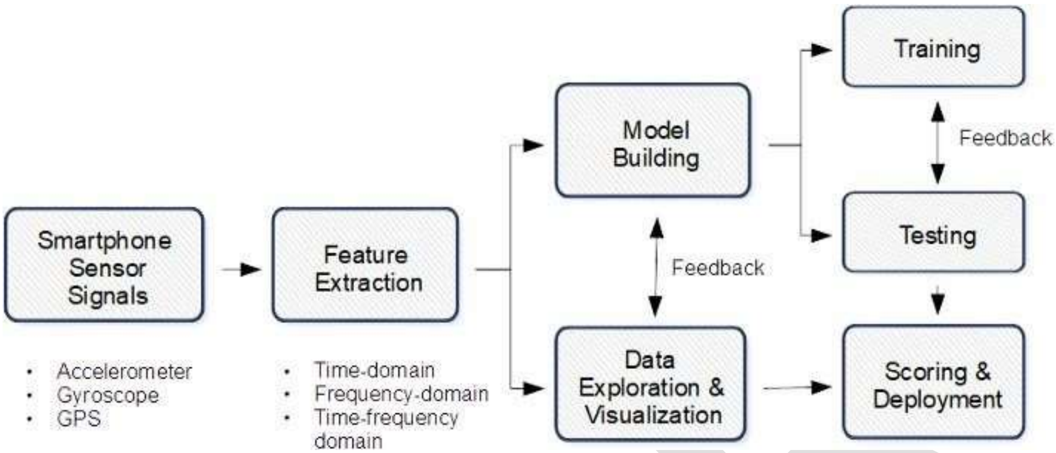

Fig 2. System Architecture

I. Logistic Regression:

In statistics, the logistic model (or logit model) is used to model the probability of a certain class or event existing such as pass/fail, win/lose, alive/dead or healthy/sick. This can be extended to model several classes of events such as determining whether an image contains a cat, dog, lion, etc. Each object being detected in the image would be assigned a probability between 0 and 1, with a sum of one. Logistic regression is a statistical model that in its basic form uses a logistic function to model a binarydependent variable, although many more complex extensions exist. In regression analysis, logistic regression[1] (or logit regression) is estimating the parameters of a logistic model (a form of binary regression). Mathematically, a binary logistic model has a dependent variable with two possible values, such as pass/fail which is represented by an indicator variable, where the two values are labeled "0" and "1". In the logistic model, the log-odds (the logarithm of the odds) for the value labeled "1" is a linear combination of one or more independent variables ("predictors"); the independent variables can each be a binary variable (two classes, coded by an indicator variable) or a continuous variable (any real value).Since dataset has 6 different activity records, final regression must have 6 different classes. Linearly classified and almost linearly classified factorsare very important factor for success of classification. When Logistic Regression is used for classification 96.54% success rate is achieved(see Fig. 4).

Fig 3. Confusion Matrix for Logistic Regression.

II. Decision Trees:

A decision tree is a decision support tool that uses a tree-likemodel of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm that only contains conditional control statements. Decision trees are commonly used in operations research, specifically in decision analysis, to help identify a strategy most likely to reach a goal, but are also a popular tool in machine learning. 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 [11]. 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 decision tree is used for classification 80.96% success rate is achieved (see Fig. 4).

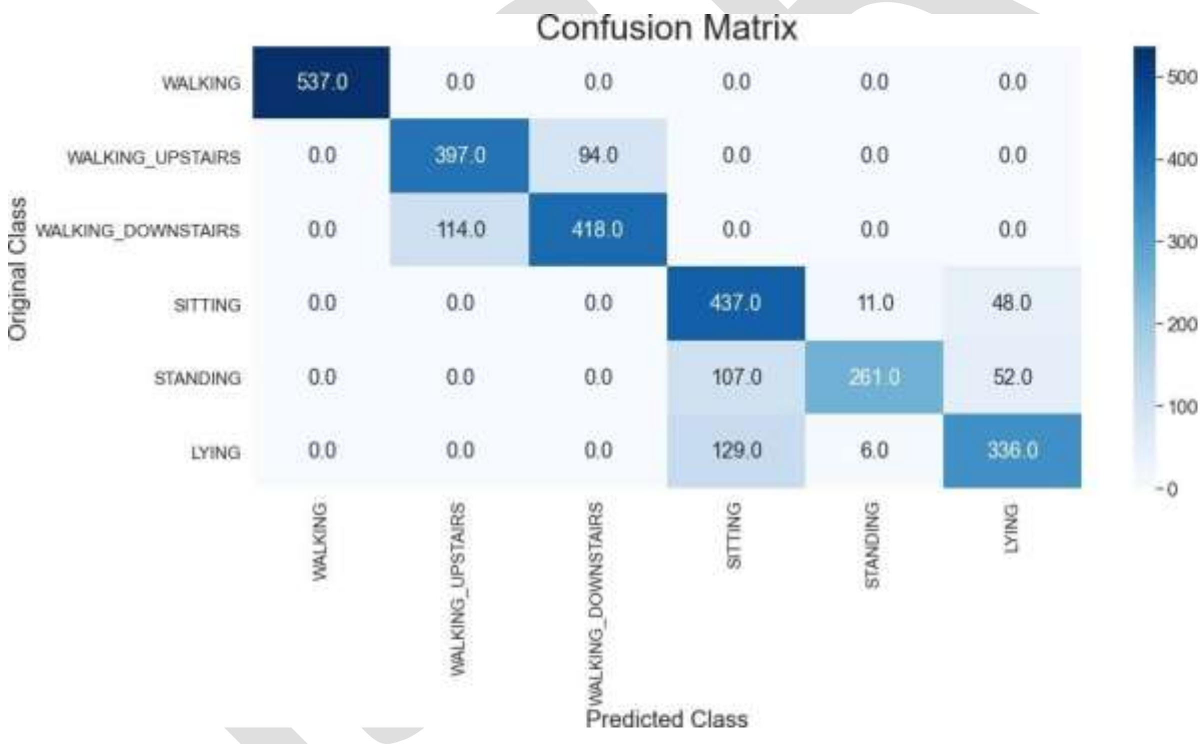

Fig 4. Confusion Matrix for Decision Trees

III. Support Vector Machines:

Classifying data is a common task in machine learning. Suppose some given data points each belong to one of two classes, and the goal is to decide which class a new data point will be in. the case of support-vector machines, a data point is viewed as a p -dimensional vector (a list of p-

numbers), and we want to know whether we can separate such points with a $(\boldsymbol{p}-1)$- dimensional hyperplane. This is called a linear classifier. There are many hyperplanes that might classify the data. One reasonable choice as the best hyperplane is the one that represents the largest separation, or margin, between the two classes. So we choose the hyperplane so that the distance from it to the nearest data point on each side is maximized. If such a hyperplane exists, it is known as the maximum-margin hyperplane and the linear classifier it defines is known as a maximum-margin classifier; or equivalently, the perceptron of optimal stability.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 successful [12]. When supervised SVM with a cubic polynomial kernel used for classification of tuples in the dataset, high level success with rate of 96.64% was achieved (see Fig. 5).

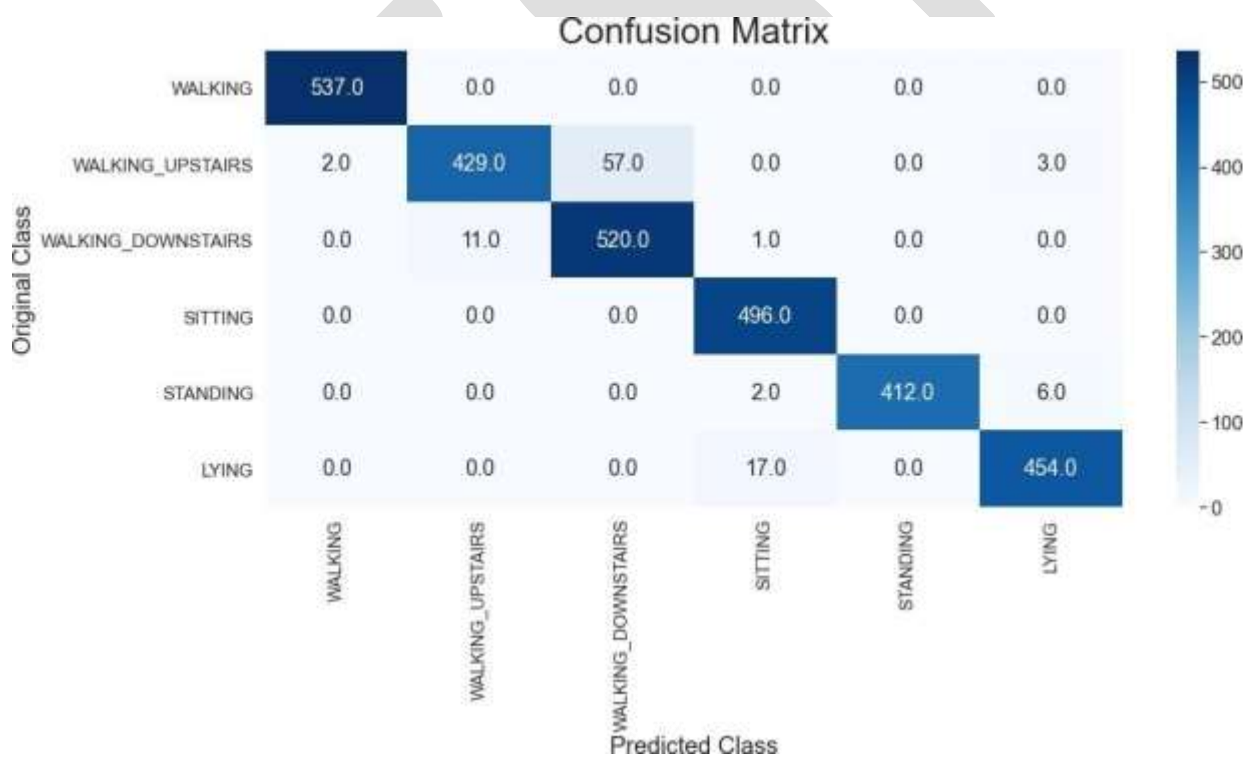

Fig 5. Confusion Matrix for Decision Trees

IV. Random Forest:

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.Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.Random decision forests correct for decision trees' habit of overfitting to their training set.

When Random Forest with bagging and decision trees used for classification of tuples in the dataset, high level success with rate of 92.04% was achieved(see Fig. 6).

Fig 6. Confusion Matrix for Random

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V. Gradient Boosting:

Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees. It builds the model in a stage-wise fashion like other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiableloss function.Gradient boosting is typically used with decision trees (especially CART trees) of a fixed size as base learners. For this special case, Friedman proposes a modification to gradient boosting method which improves the quality of fit of each base learner.When Gradient Boosting with boosting and decision trees used for classification of tuples in the dataset, high level success with rate of 90.8% was achieved

Fig 7. Confusion Matrix for Gradient Boosting

Conclusion:

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

	Model	Accuracy(%)
0	Logistic Regression	96.54
1	Linear SVM	96.64
2	Random Forest	92.4
3	Decision Trees	80.96
4	Gradient Boosted DT	90.8

Table 1. Success Rate of Model Accuracies

While SVM is the most precise approach tested in this work as seen in Table 1, most of the methods create effective models. 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 smartphonesto the dataset. Some of these devices are magnetometer, light sensor, proximity

sensor, barometer, accelerometer, 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.

Fig 8. Visualization of Success Rate of Model Accuracies

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