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Prediction of Body Motion Changes in Humans with Neural Networks

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ABSTRACT

Smartphone's now include a broad variety of sensors, making them more powerful and flexible. Cameras, audio sensors (such as microphones), light and temperature sensors, and direction sensors (such as compass) are among examples (i.e., accelerometers). The incorporation of these sensors in mass-market communication devices offers up exciting new avenues for data mining and machine learning. This project's purpose is to create and evaluate an accelerometer-based phone system for activity identification, a task that recognizes the physical activity in which a user is involved. We gathered accelerometer data from 30 users as they went about their daily activities, including walking, running, climbing stairs, sitting, and standing, and then grouped this time series data into examples that explain human behavior over 10-second intervals. Using the training data, a predictive model for activity recognition was created. With the activity detection approach, we can passively collect relevant information about the behaviors of millions of individuals as they keep their phones in the pockets.

Keywords - Machine learning, smartphone, activity recognition, classification.

1.INTRODUCTION

Since they first became widely available, cellphones have become a ubiquitous part of almost everyone's daily routine. The majority of smartphone users, according to research, browsed news, gaming, and social networking sites on their handheld devices. [*] Many smartphone applications, including health monitoring, fall detection, context-aware mobile apps, human survey systems, and home automation, use activity recognition as a foundation technology. As a result of this, new mobile applications may be developed employing smartphone activity detection algorithms.

There must be a knowledge of the human behaviours that lead to the need for health care services such as rehabilitation aid, physiotherapy assistance, and assistance for persons with cognitive impairment. Recording and monitoring patients' actions will save a significant amount of money in the long run. From this work, we should expect to see improvements in human survey systems and location-based services. Training is required for each new activity that is introduced to a system. There must be an understanding of the same algorithm parameters over a wide range of sensors if the algorithm is to be used on several devices with different sensors. As a result, users may not have the resources to create labels for every training set that they get. The use of an active learning technique may also help to expedite the training procedure.

Sensors from mobile devices may be used to predict human behaviour based on raw sensor data. Among these sensors are accelerometers, gyroscopes, and barometers, all of which monitor movement (which measure altitude). Because of their inexpensive installation and operating costs and simplicity of use, smart phones are swiftly displacing other platforms as the major way of tracking human activities. In this study, we want to establish the reliability of 3-D accelerometer and gyroscope-based mobile phone activity recognition.

Data from an accelerometer and gyroscope on a smartphone used by male and female participants while engaged in different tasks is classified using numerous machine learning techniques. Various methods are examined and compared in terms of accuracy and efficiency.

2. LITERATURE REVIEW:

After a long period of research, several answers to the issue have developed. There are a number of current techniques that use vision sensors, inertial sensors, or a combination of both. Automated learning and threshold-based algorithms are often used. Threshold-based algorithms, on the other hand, are faster and easier to implement than other algorithms.

The body posture of a person has been recorded and identified using one or more cameras. [2] In many cases, the best option is to place dozens or even hundreds of accelerometers and gyroscopes throughout the body[2.]

Inertial sensors and vision sensors have been used together in certain designs. All of these algorithms depend on efficient data processing to function. Input attributes quality is significant in a number of ways. The most relevant parts of this data collection have already been studied by other academics. An active learning approach has proven useful in many machine learning situations that need lengthy and labor-intensive labelling of data sets. Handwriting character recognition and speech recognition are further viable uses. There has been no effort to deal with the problem of human activity with this technology.

An approach developed by Jun Yang [6] used three different feature sets to extract orientation-independent properties from the dataset. Each dataset's feature set includes the average, standard deviation, zero cross rate, 75 percentile, interquartile, spectrum centroid, and entropy. Using Attributed Selection filters, the researchers divided the total number of features into seven groups and then tested how well each subset could be recognised. Naive Bayes, on the other hand, has just 68.3% accuracy when all characteristics are taken into account, which is lower than Decision Tree's 90.44% accuracy (all features are taken into account) (all features: 68.7 percent).

In her study, SianLun Lau used the mean, standard deviation, Fourier Transform energy, and correlation [7]. They categorised the traits into three primary groups: G1 and G2 include the average and standard deviation of FFT coefficients for all three axes, while G3 contains all four features of the relevant analogue axes. Instead, they relied on simple characteristics and groups that could be simply controlled by the user's hands.

The Sequential Forward Selection and Selection [9] method was used by Ville Kononen to choose features from accelerometer and heart rate data and to compare complex classification with a basic classification. In contrast, they used a feature selection strategy and compared their classification and identification accuracy, which ranged from 60% to 90%.

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

Using a sample rate of 50 Hz, six distinct signals were collected and stored in time series for each dimension (3 are from accelerometer and other 3 are from gyroscope). Median and 20Hz Butterworth [9] filters were used to reduce the amount of noise in the data. Additional Butterworth filtering is used to remove the gravitational impact from accelerometer signals.. It was

then adjusted to the (-1,1) range. The magnitudes of the values in each of the three dimensions of a three-dimensional signal are integrated into a single dataset using Euclid magnitude. Individual numbers are placed at the end of each row with the class codes (activity codes) provided above for each row, as seen in the following example. The final collection includes 2947 records and 561 characteristics.

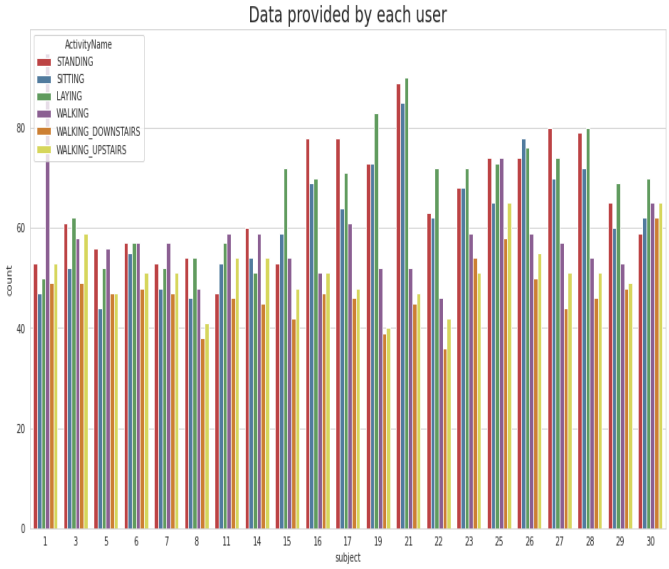

Fig 1. Data provided by each user

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

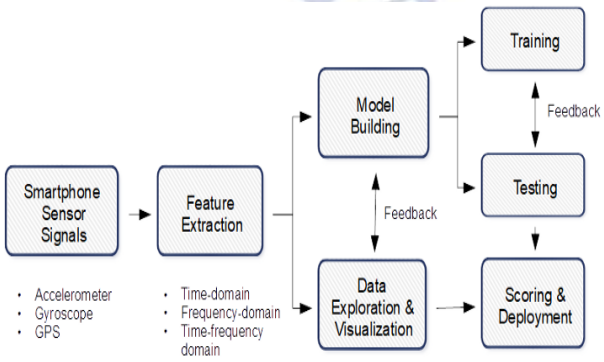

Fig 2. System Architecture

4. LOGISTIC REGRESSION:

The logistic model (or logit model) is used to represent the likelihood of a certain class or event, such as passing or failing, winning or losing, being alive or dead, or healthy or ill. For example, you might use this to determine if a picture includes a cat, dog, lion, or another animal. With a probability ranging from 0 to 1, the image's identified objects would be allocated individual probabilities. The final result would be 1. To put it simply, logistic regression is a model that uses an exponential logistic function to explain a binary dependent variable and many more advanced expansions. Using logistic regression (also known as logit regression), the logistic model's parameters may be estimated[1]. [1] (a form of binary regression). There are only two potential outcomes in a binary logistic model, namely "0" and "1". To calculate the log-odds for the value marked "1," you may use a linear combination of one or more independent variables, each of which can be either binary or continuous; this linear combination is called the independent variable (any real value).Since the dataset contains six distinct records of activity, the final regression must contain six distinct classes. Linearly categorised and nearly linearly classified components are critical to classification success. With Logistic Regression for categorization, 96% of the time, the results are accurate (see Fig. 4).

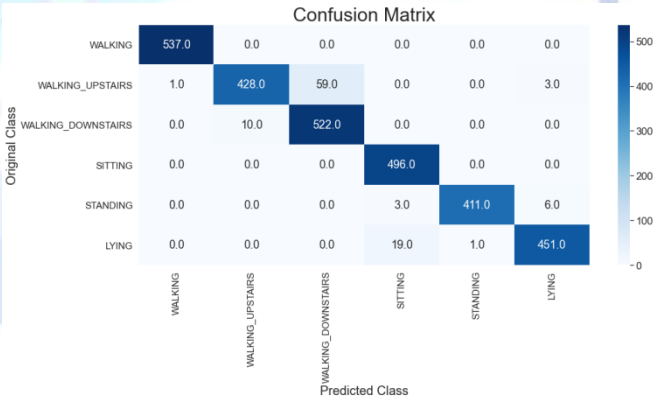

Fig 3. Confusion Matrix for Logistic Regression.

5. Decision Trees:

Decision trees are decision support systems that employ a tree-like model of choices and their numerous implications, such as chance event outcomes, resource costs, and utility. They have a purpose. This is a way to illustrate an algorithm that only comprises control statements. In operations research, decision trees are often used in decision analysis to find the most

probable path to a goal, but they are also a popular machine learning tool. Decision trees are built on the notion of splitting difficult decisions into features in order to make them easier to understand and implement. It uses a query structure to classify data from the root to the leaf, which represents one class [11]. We need six different types of leaves in our final decision tree because the dataset contains 6 different activity records. For categorization to be successful, the branching level must be high enough. Decision trees have an 80.96 percent success rate when utilised as categorization tools (see Fig. 4).

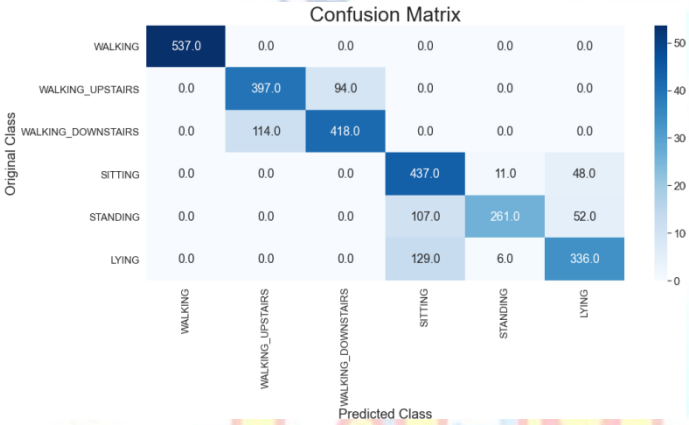

Fig 4. Confusion Matrix for Decision Trees

6. SUPPORT VECTOR MACHINES:

Machine learning relies heavily on the ability to categorise and organise information. It's important to know which of two groups of data points a new data point will fall into. It's important to know whether or not we can separate data points that are represented by an n-dimensional hyperplane (a list of n-numbers) in support-vector machines. We're use a linear classifier in this instance. There are a variety of ways to organise this data. Hyperplane selection may be easier if you take into account the distance between the classes. Using this method, the distances between the hyperplane and the nearest data points on each side are maximised. When looking for the perceptron of optimal stability, one may locate a maximum-margin hyperplane and classifier. Data may be identified more effectively using hyper-dimensional data planes used by Support Vector Machines (SVM). When used under supervision, SVN is more efficient and faster than when it isn't. At least 96% of test cases were correctly classified using a cubic polynomial kernel SVM for dataset classification (see Fig. 5).

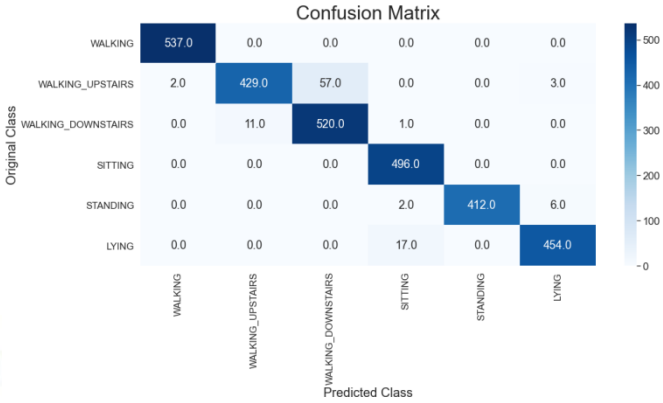

Fig 5. Confusion Matrix for Decision Trees

7. RANDOM FOREST:

Different machine learning methods and approaches can be used to create a classifier called an ensemble classifier. Boosting is one of the methods. It is necessary to have a training set with N members in which each tuple has the same probability. To ensure sure misclassified records are picked up by the next classifier and correctly classified, the likelihood of a misclassification is increased after the first classifier has categorised the tuples. There are a variety of ensemble learning methods that use decision trees to create several decision trees during training and then output the class that is the average of the classes (classification) or a mean prediction (regression). In order to prevent decision trees from overfitting their training set, random decision forests are used. Results were 92.04% accurate when Random Forest with bagging and decision trees were used to classify the dataset's tuple-level categorization (see Fig. 6).

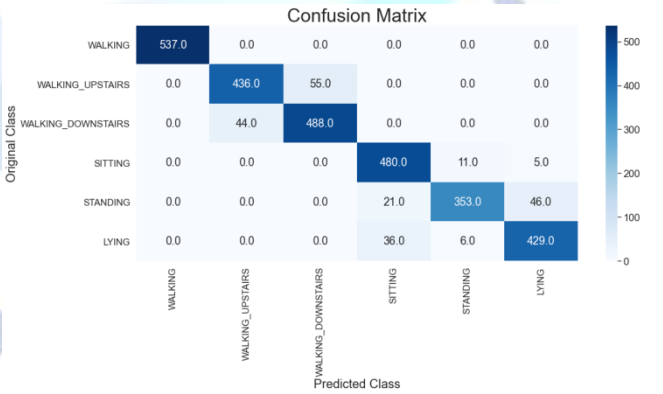

Fig 6. Confusion Matrix for Random Forest

8. GRADIENT BOOSTING:

An ensemble of weak prediction models, such as decision trees, is created using the regression and classification problem-solving technique known as

"gradient boosting". By permitting optimization of any differentiable loss function, it generalises other boosting approaches that build the model step-by-stage. CART trees of fixed size are frequently employed as base learners for gradient boosting. Friedman provides a modification to the gradient boosting method that enhances the quality of fit for each base learner in this specific scenario. A high success rate of 90.8% was attained when tuples in the dataset were classified using gradient boosting and decision trees with boosting and decision.

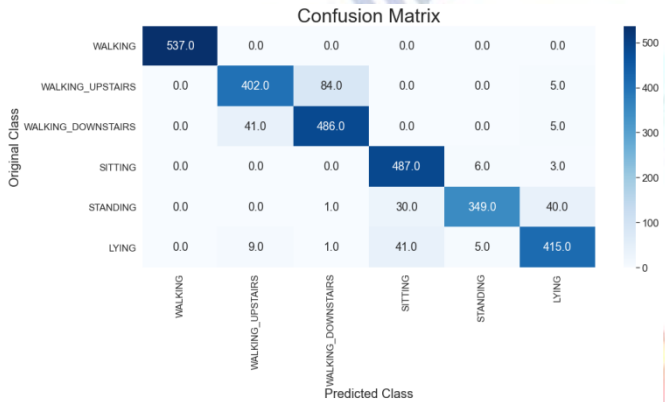

Fig 7. Confusion Matrix for Gradient Boosting

9. CONCLUSION:

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

Table 1. Success Rate of Model Accuracies

	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 shows that while SVM is the most exact way explored in this work, the majority of approaches build useful models. In light of these comparisons, it can be concluded that the approaches assessed in this paper are quite effective at identifying smartphone user activity. There are only accelerometer and gyroscope signals in this dataset. Increasing the amount of activities and circumstances to identify and adding data from other sensors and devices typically used in smartphones to the dataset could improve this study. This includes sensors such as a magnetometer and a proximity sensor as well as others such as accelerometers and pedometers, as well as microphones and GPS devices. In order to identify considerably more complicated behaviours and circumstances, these devices may gather information about a user's state, position, and status in relation to the surrounding environment.

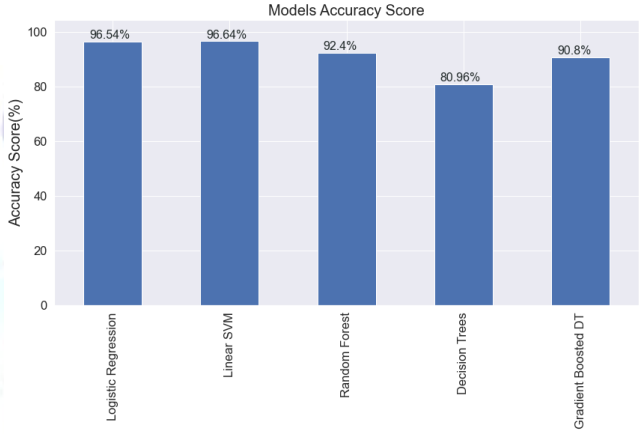

Fig 8. Visualization of Success Rate of Model Accuracies

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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