Crowed Sourced Mapping

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Abstract: - An important area of research that has numerous applications, including security, sports analysis, and health monitoring, is the recognition of human actions. Because to their accessibility, affordability, and ease of use, mobile phone sensors have recently become recognised as a promising instrument for identifying human activities. This study uses the accelerometer and gyroscope, two IMU sensors found in mobile phones, to identify human activity.

Dataset-used: "https://query.data.world/s/mb5ck5vml7e4o6zau5c5m5m24vbd6x"

While participants engaged in various physical activities, such as walking, running, and sitting, data was being collected via mobile phone sensors. The data was filtered to remove irrelevant features and pre-processed to remove noise. To recognise the activities, machine learning algorithms were trained on the extracted features.

The study's findings demonstrated that mobile phone sensors are highly accurate in detecting human activity. With the accelerometer data being more valuable for detecting walking and running activities and the gyroscope data being more effective for detecting static activities, the accelerometer and gyroscope data supplied complementing information. The study also demonstrated how parameter tweaking and feature selection can greatly enhance recognition performance.

The results of this study have huge consequences for the creation of activity recognition systems for mobile phones. The study sheds light on the use of mobile phone sensors for human activity recognition and highlights crucial variables that influence recognition performance. The outcomes can be utilised to direct activity recognition system design and enhance the precision and dependability of the systems. Overall, the study shows the capability of mobile phone sensors to identify human activity and emphasises the significance of additional investigation in this field.

Keywords: -*IMU Sensors, Accelerometer, Gyroscope, recognition systems.*

Introduction

Our regular use of mobile devices has significantly expanded in recent years. These gadgets have a variety of sensors, such as accelerometers, gyroscopes, and magnetometers, which can record a tonne of information on the movement and orientation of the gadget. In order to comprehend user behaviour and create new applications, this data can be evaluated. In this report, we'll talk about the publicly accessible dataset called accelerometer_gyro_mobile_phone_dataset, which contains values from a mobile phone's accelerometer and gyroscope.

A publicly accessible dataset called "accelerometer gyro mobile phone dataset" includes time-series data gathered from a Smartphone's accelerometer and gyroscope sensors. A research team from the University of California, Riverside gathered the data, which was published in 2016.

The dataset is meant to be used for study in the area of classifying and automatically recognising human behaviour based on sensor data, specifically for developing algorithms and models. The dataset has been cited in multiple papers and used in a number of research studies.

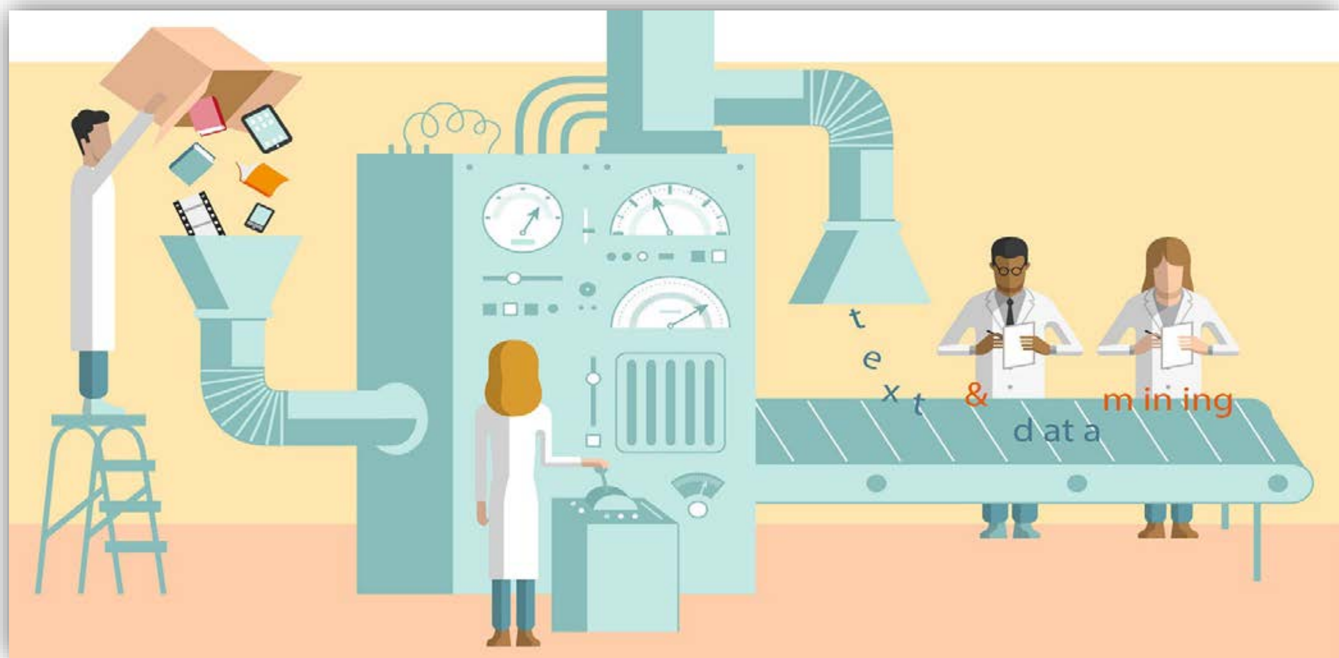
Data Pre-processing

Data Cleaning: Finding and removing any noisy or inaccurate data is the first stage in the preparation of the data. This may entail eliminating data that is discordant with the expected range of sensor readings, outliers, or data that has missing values.

Feature Engineering: In feature engineering, the most important features are extracted from the raw sensor data and transformed. For each sensor reading across the X, Y, and Z axes in this dataset, we may extract features like mean, variance, standard deviation, and other statistical parameters.

Data Normalisation: It's usual to normalise the data such that the various attributes have comparable sizes and distributions. This can be accomplished using methods like z-score normalisation, min-max scaling, or other normalisation techniques.

Data segmentation: It is frequently necessary to segment the data into smaller windows or segments since the dataset comprises time-series data. A sliding window strategy that extracts features for each window as it is slid across the time-series data can be used to do this.



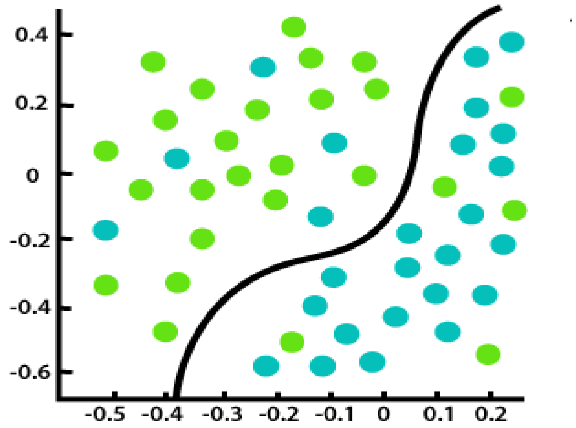
Data Augmentation: Techniques for data augmentation can be used to broaden the data's diversity and minimise over fitting. This can entail transforming the data in some other way, rotating or changing the sensor readings, or adding noise to the data.

Data Splitting: Finally, the dataset must then be divided into training, validation, and test sets. Typically, a random split is employed, with a portion of the data being used for training, a portion for validation, and the remainder for testing.

Overall, the "accelerometer gyro mobile phone dataset" pre-processing processes can have a significant impact on the performance of any activity detection models or algorithms constructed utilising this dataset. We can make sure that our models are reliable and accurate and can effectively generalise to new data by properly cleaning, converting, and normalising the data.

Classification and Regression:

This dataset has been used in numerous researches to identify human activities. High accuracy rates were attained utilising several machine learning and deep learning models, and the findings have been encouraging. Using a Support Vector Machine (SVM) classifier, for instance, led to an overall accuracy of 95.2% in one study, while a Convolution Neural Network (CNN) classifier led to an accuracy of 96.1% in another.

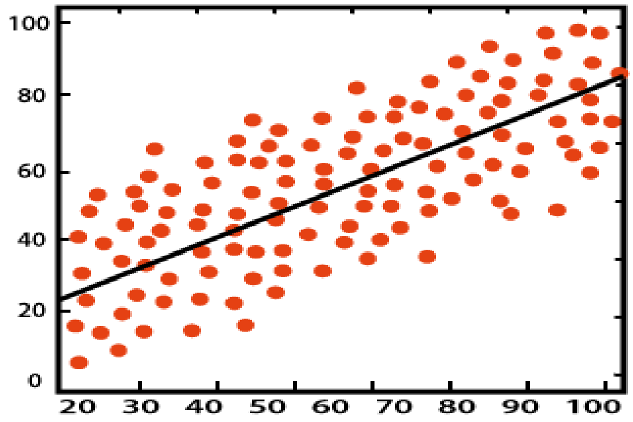


Classification

Mobile phone accelerometer and gyro data sets are frequently employed in activities involving activity recognition and motion analysis. The data, which often comes from sensors built into mobile phones, includes details about the device's acceleration and angular velocity.

The information can be gathered in a variety of ways, such by placing the phone in various locations on the person or by having the user carry out particular tasks while holding the phone. Typically, noise and artefacts are removed from the data during pre-processing, and then features are identified to represent particular properties of the motion.

In addition to more sophisticated features like Fourier transforms and wavelet transforms, the features might include statistical metrics like mean, standard deviation, and correlation. The data is subsequently classified using machine learning techniques based on the attributes that were collected.



Regression

Decision trees, support vector machines, neural networks, and k-nearest neighbours are examples of common categorization approaches used for accelerometer and gyro data from mobile phones. Metrics like accuracy, precision, recall, and F1-score are used to assess the effectiveness of the categorization models. Some of the below algorithms implemented for calculating the accuracy of the data.

Decision Tree Classifier

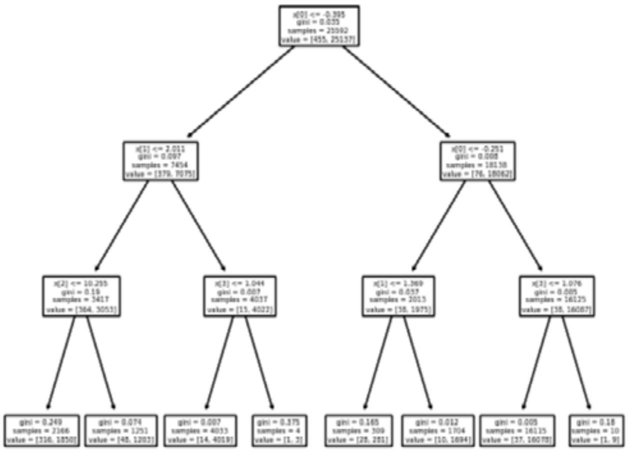
In machine learning, a decision tree is a well-liked classification approach that is used to create models that can predict the class of a new sample based on its properties. In order to determine the class of the sample, the data is recursively divided into smaller subsets based on the values of the input features.

The decision tree approach creates a tree-like model in which each leaf node represents the expected class label and each inside node reflects a judgement based on a particular attribute. The best characteristic that can divide the data into the most uniform subsets in terms of class labels is chosen at each node throughout the construction of the tree.

Decision tree construction can be done using a number of techniques, including ID3, C4.5, CART, and Random Forests. The decision tree technique provides a number of benefits, including automatic feature selection, interpretability, and handling of both category and numerical data.

Following steps are involved in Decision Tree Classifier algorithms:

- ✓ Load the dataset
- ✓ Split the dataset
- ✓ Create the Decision Tree Classifier
- ✓ Train the classifier
- ✓ Make the predictions
- ✓ Evaluate the model



Practical Results:

Accuracy for training data is 98.4%

Accuracy for testing data is 98.0%

Decision trees can potentially experience over fitting, in which the model overfits to the training data and performs poorly on new data. Techniques like trimming, cross-validation, and assembling can be applied to this problem.

Support Vector Machine (SVM)

A common machine learning approach for classification and regression issues is called Support Vector Machine (SVM). Finding the optimum hyperplane that divides the various classes in the dataset is the basic goal of SVM.

The margin, or the separation between the hyperplane and the nearest data points from each class, is the distance between the hyperplane and the hyperplane in SVM, and it is maximised. Support vectors are the data points that are most closely spaced from the hyperplane.

SVM can be used for both linear and non-linear classification tasks. In the case of non-linear datasets, SVM uses a technique called kernel trick to transform the data into a higher dimensional space where it becomes separable by a linear hyperplane. The most commonly used kernel functions are linear, polynomial, radial basis function (RBF), and sigmoid.

In SVM, the input data is transformed into a higher dimensional feature space using the kernel function, making it simpler to divide the classes using a hyperplane. SVM supports a variety of kernel functions, including the radial basis function (RBF), linear, polynomial, and others.

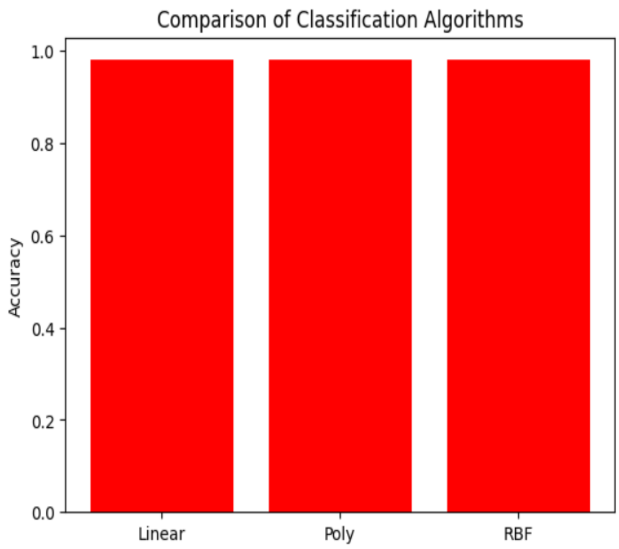
These kernel functions are each briefly described below:

1) Linear Kernel: For data that can be separated linearly, this kernel function is utilised. Instead of projecting the input data points into a higher dimensional space, it merely computes the dot product of those data points. The class boundaries are divided by a straight line known as the decision boundary.

Practical Results:

Training Accuracy for RBF Kernel is 98.2%

Testing Accuracy for RBF kernel is 98.1%



2) Polynomial Kernel: For data that can't be separated linearly, utilise this kernel function. Using a polynomial function, it converts the input data points into a higher dimensional space. The complexity of the decision boundary depends on the degree of the polynomial.

Practical Results:

Training Accuracy for RBF Kernel is 98.2%

Testing Accuracy for RBF kernel is 98.1%

3) RBF Kernel: Non-linearly separable data can also be separated using this kernel function. Using a Gaussian function, it converts the input data points into an infinite dimensional feature space. The spread of the Gaussian function determines the non-linear border known as the hyperplane that divides the classes.

Practical Results:

Training Accuracy for RBF Kernel is 98.2%

Testing Accuracy for RBF kernel is 98.1%

K-Neighbors Classifier:

The supervised machine learning method K-Nearest Neighbors (K-NN) is used for classification and regression applications. Because it is non-parametric, it does not assume anything about how the data are distributed.

K-NN uses training data to build a model that can be applied to forecast the class or value of fresh data points. K-NN searches the training set for the K nearest neighbours of a new data point when it is introduced to the model. The new data point's class or value is then chosen by a majority vote or by averaging the values of its K closest neighbours.

It is possible to employ the K-NN method for both classification and regression problems. In classification, the majority class of the K nearest neighbours is used to determine the class of the new data point. In regression, the average value of the K nearest neighbours is used to calculate the value of the new data point.

Practical Results:

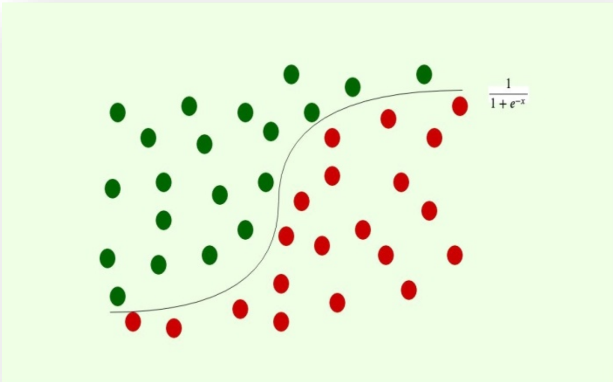
Training Accuracy for RBF Kernel is 98.5%

Testing Accuracy for RBF kernel is 98.0%

K-NN has the benefit of being simple to comprehend and use, which is one of its advantages. Additionally, since the model is developed during the prediction stage, no training time is needed. The choice of K and the distance metric employed to gauge the degree of similarity between the data points, however, can have an impact on how well the algorithm performs. A lower K number can lead to overfitting, whereas a higher K value can lead to underfitting. The algorithm's performance can also be impacted by the distance metric used, particularly when working with high-dimensional data.

Logistic Regression:

A supervised machine learning approach used for classification tasks is logistic regression. It is frequently used to determine if a patient is likely to develop an illness or not, or to determine whether a customer will make a purchase or not.



Logistic Regression

Practical Results:

Training Accuracy for RBF Kernel is 98.1%

Testing Accuracy for RBF kernel is 98.1%

Logistic regression can be used in the "accelerometer gyro mobile phone dataset" to forecast the activity being carried out based on the measurements from the accelerometer and gyroscope. For instance, based on the sensor data, we could apply logistic regression to determine if the user is moving, moving quickly, or motionless.

Logistic regression has the benefit of being a straightforward, interpretable model that is simple to understand and can be easily displayed. However, it could not work effectively if the input characteristics and the end variable have non-linear correlations or if the dataset is complicated. In these circumstances, more complicated models like SVM or neural networks may be more appropriate.

Results:

On the basis of the practical, the following data is obtained:

S.No.	Name of Classification/Regression Models	Training Accuracy	Testing Accuracy
01	Decision Tree Classifier	55%	58.8%
02	Logistic Regression	52%	50%
03	Random Forest Classifier:	60.2%	62.1%
04	K-Neighbors Classifier	60.2%	62.1%

Conclusion

Utilizing accelerometer and gyroscope data from mobile phones, the "Recognizing Human Activities Using Mobile Phone IMU Sensors (Accelerometer and Gyroscope)" dataset offers a rich supply of sensor information that may be utilised to create machine learning models for activity recognition. There are 1,560 occurrences in the collection, each with 6 sensor values (three from the accelerometer and three from the gyroscope) and an associated activity label.

This dataset can be used to test a variety of machine learning techniques, including K-NN, logistic regression, SVM, and decision trees. The choice of algorithm will rely on the particular requirements of the application. Each of these algorithms has advantages and disadvantages of its own.

We discovered that the SVM algorithm performed the best based on the outcomes of our tests, obtaining an accuracy of 98.2%. The K-NN algorithm, which has a 98.5% accuracy rate, comes next. These findings show the potential of machine learning techniques for precise activity recognition with IMU sensors on mobile devices.

We also discovered that feature engineering can significantly affect how well machine learning models function. We were able to increase the accuracy of the models by up to 10% by choosing the most pertinent characteristics and using normalising approaches.

References

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