AN APPROACH FOR HUMAN ACTIVITY RECOGNITION USING SUPERVISED MACHINE LEARNING

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Abstract: *In this paper ,we are trying to build a classification model which will recognise the activities through the mobile sensor like walking ,walking_upstairs ,walking_downstairs ,sitting ,standing,lying.The topic Human Activity recognition is in research and has its own advantages like anomaly detection, for healthy diet maintenance fitness bands are used , measuring stress level ,for monitoring employees ,for heartbeat pulse rate etc. We are going to focus on the dataset which was carried out through experiments with a group of 30 volunteers wearing a smartphone on the waist. Using its embedded accelerometer and gyroscope.The experiments have been video-recorded to label the data manually.The main motto is to use the dataset and work with the libraries like scikit learn and machine learning related libraries and algorithms while training .*

Keywords:Human Activity Recognition , accelerometer, gyroscope,scikit

1. INTRODUCTION

Human Activity Recognition is one of the active research areas in computer vision for various contexts like security surveillance, health care and human-computer interaction.

The topic has increased its importance in the last few decades in the domain of Computer Vision and A.I "Human Activity Recognition". As the concepts of human activity recognition help in understanding the concepts and issues of the human action understanding which majorly helps in medication, management, learning patterns, and many situations of video retrieval. The detection of the physical activities by different such sensors and recognition processes is a key topic of research in wireless, smartphones, and mobile computing.

Machine learning can be used to detect activities by reading and processing sensor data automatically.Machine Learning algorithms like Decision Trees Decision trees are one of the common algorithms for classification problems such as Human Activity Recognition. Decision Trees are easy to understand. However, if there is a non-linear relationship between predictors and outcome, accuracy will suffer. Another algorithm Adaptive Boost (AdaBoost) for Multiclass AdaBoost is a performance-boosting technique. This algorithm tends to assign more importance to the incorrectly classified examples by weak learners and so challenges weak learners to perform well. We used the AdaBoost technique with 10 decision trees to improve the classification accuracy of a single deep classification tree.Random Forest Random forest is also the algorithm that tends to combine weak learners to improve accuracy. It bootstraps different predictors and builds multiple weak trees from bootstrapped predictors. Bootstrapping of predictors ensures less correlated trees. And finally, it combines weak decision trees to predict the outcome. This algorithm also yields much better classification accuracy over decision trees.Support Vector Machine It is also a supervised learning algorithm. SVM model represents samples as points in space and separates the points based on outcome categories with a clear dividing gap. The category of new points is determined based on which side of the gap they fall on.

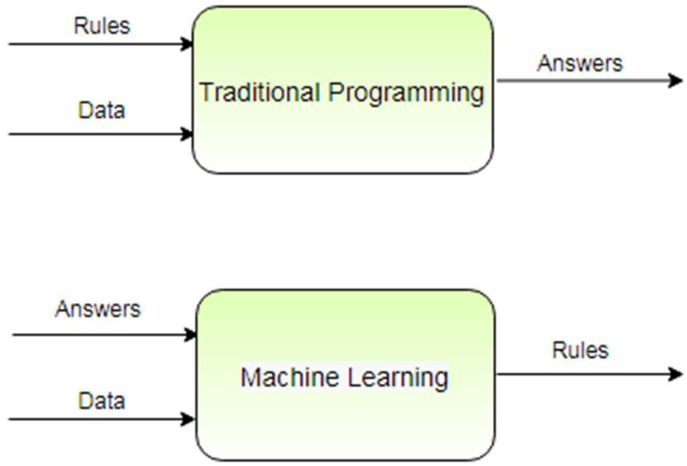

Fig 1.0 Difference in traditional programming and machine learning

In the past few decades, there have been drastic changes in the way, data is stored, perceived, and processed. A tremendous amount of data is generated every second and if this data is used and analyzed efficiently, it can reveal very important insights. A lot of data mining techniques have evolved in analyzing the huge amount of data.

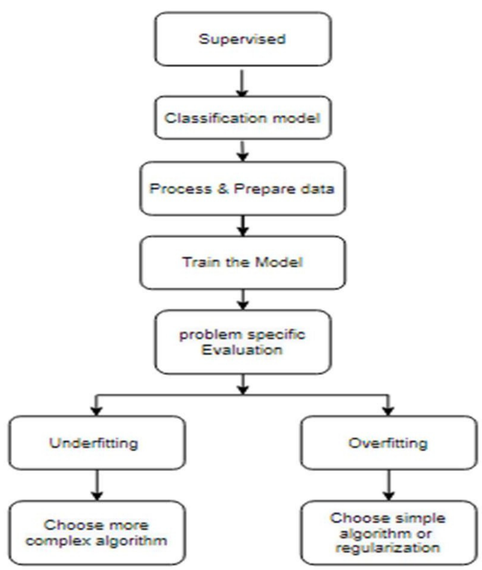

Fig 1.1 Basic steps in Machine Learning

Human activity recognition, or HAR for short, is a broad field of study concerned with identifying the specific movement or action of a person based on sensor data.Mobile devices have become an integral part of our daily life. This is due to an increase in the sophisticated development and the integration of quality sensors, high computational power, large storage capacity and continuous connectivity in mobile devices. People constantly interact with their low cost, small-sized smartphones in their day to day activities, which has led to the rise in the research of extracting knowledge from data acquired by pervasive sensors in mobile devices . Movements are often typical activities performed indoors, such as walking, talking, standing, and sitting. They may also be more focused activities such as those types of activities performed in a kitchen or on a factory floor.The sensor data may be remotely recorded, such as video, radar, or other wireless methods. Alternatively, data may be recorded directly on the subject such as by carrying custom hardware or smart phones that have accelerometers and gyroscopes.

Modern Machine Learning Techniques can be used to distinguish and recognize human activities based on data collection .A simple smartphone can help solve the problem of documenting a detailed history of a user's daily activity .Advancements in deep learning and methods of feature selection along with the inclusion of a variety of sensors can push the boundaries of human activity recognition on deeper ontological level.

2. LITERATURE REVIEW

A standard human activity recognition dataset for time series classification was proposed .Loading and preparing human activity recognition time series classification data.Exploring and visualizing time series classification data in order to generate ideas for modeling.A suite of approaches were seen for framing the problem, preparing the data, modeling and evaluating models for human activity recognition.[2]

Min-Cheol Kwon and Sunwoong Choi, proposed a human activity recognition system that collects data from an off-the-shelf smartwatch and uses an artificial neural network for classification. The proposed system was further enhanced using location information . We consider 11 activities, including both simple and daily activities. For the effective performance evaluation of the proposed system, four indicators: accuracy, precision, recall, and F1-score were used. The experiment tests and evaluates two models: one using the dataset with location information and the other using the dataset without location information has enhanced the performance of the system and shown that various activities can be classified with an accuracy of 95%.[1]

Another author has found in the survey about the recent advance in deep learning approaches for sensor-based activity recognition. Compared to traditional pattern recognition methods, deep learning reduces the dependency on human-crafted feature extraction which achieves better performance by automatically learning high-level representations of the sensor data.They have also highlighted the recent progress in three important categories: sensor modality, deep model, and application. Subsequently, they summarized and discussed the surveyed research in detail. Finally, several grand challenges on Online and mobile deep activity recognition,More accurate unsupervised activity recognition,Flexible models to recognize high-level activities, Light-weight deep models,Non-invasive activity sensing.,Beyond activity recognition assessment and assistant. and feasible solutions were presented for future research.[3]

3. DESIGN APPROACH

The overall design approach from collection of data till building of machine learning model is shown below:

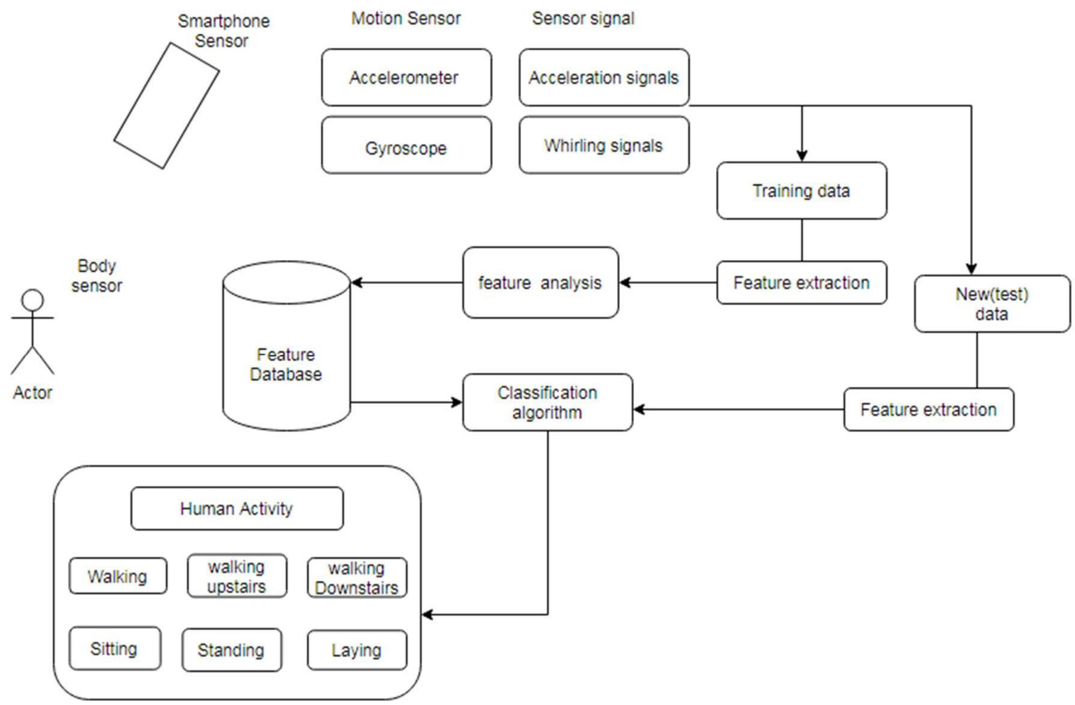

Fig 1.2 Flow diagram of Human Activity Recognition

The dataset can be fed into the modules for Random Forest, kNN, Neural Network, Logistic Regression, Stochastic Gradient Descent and Naive Bayes. Their Precision and Recall Values calculated.

4. METHODOLOGY

4.1 About Dataset

The experiments have been carried out with a group of 30 volunteers within an age bracket of 19–48 years. Each person performed six activities (WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, LAYING) wearing a smartphone (Samsung Galaxy S II) on the waist. Using its embedded accelerometer and gyroscope, we captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz. The experiments have been video-recorded to label the data manually. The obtained dataset has been randomly partitioned into two sets, where 70% of the volunteers were selected for generating the training data and 30% for the test data.

The sensor signals (accelerometer and gyroscope) were pre-processed by applying noise filters and then sampled in fixed-width sliding windows of 2.56 sec and 50% overlap (128 readings/window). The sensor acceleration signal, which has gravitational and body motion components, was separated using a Butterworth low-pass filter into body acceleration and gravity. The gravitational force is assumed to have only low-frequency components, therefore a filter with 0.3 Hz cutoff frequency was used. From each window, a vector of features was obtained by calculating variables from the time and frequency domain.

4.2 Attribute Information:

For each record in the dataset it is provided:

- Triaxial acceleration from the accelerometer (total acceleration) and the estimated body acceleration.

- Triaxial Angular velocity from the gyroscope.

- A 561-feature vector with time and frequency domain variables.

- It's an activity label.

- An identifier of the subject who carried out the experiment.

4.3 Dataset Classification

Overall 7,352 records are present in the dataset.

LAYING	1407
STANDING	1374
SITTING	1286
WALKING	1226
WALKING_UPSTAIRS	1073
WALKING_DOWNSTAIRS	986

Fig:1.2 Individual Activities Classification

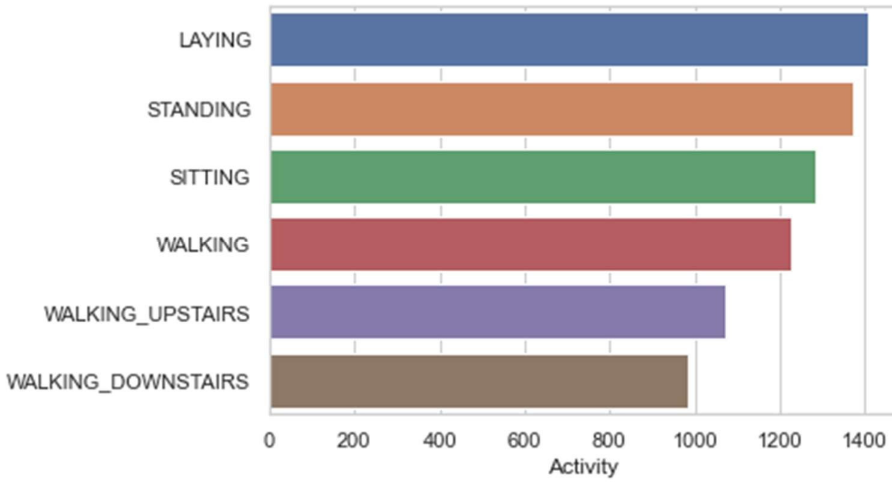

Fig 1.3 Activity Distribution

4.4 Packages Used

import pandas as pd

import numpy as np

import seaborn as sns

5. PREPROCESSING STEPS

5.1 Check for null values : In real world data, there are some instances where a particular element is absent because of various reasons, such as corrupt data, failure to load the information, or incomplete extraction. Handling the missing values is an important task in a machine learning dataset . we have used isnull()and isna()to check the missing values in our dataset.

5.2 Check for Outliers: Sometimes a dataset can contain extreme values that are outside the range of what is expected and unlike the other data. These are called outliers. To detect outliers we have used Box Plot .

5.3 Label Encoding

Label Encoding refers to converting the labels into numeric form so as to convert it into the machine-readable form. Machine learning algorithms can then decide in a better way on how those labels must be operated.

6. CLASSIFICATION OF DATASET INTO DEPENDENT AND INDEPENDENT VARIABLES

Independent variables (also referred to as Features) are the input for a process that is being analyzed (i.e. considered as y). Dependent variables are the output of the process.ie. X.

Activity is the column in our dataset which shows the activities and can be considered as Independent variable "y".Remaining all features can be considered as Dependent variables "X".

The shape of our dataset is (7352, 564).There are a total 564 features in our dataset.

7. APPLYING ALGORITHMS

7.1 Decision tree classifier:

Decision Tree is a Supervised learning technique that can be used for both classification and Regression problems, but mostly it is preferred for solving Classification problems. It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome.

After applying the DecisionTreeClassifier algorithm .The precision_score and recall_score.The precision_score is 95.04% and recall_score as 95.03%

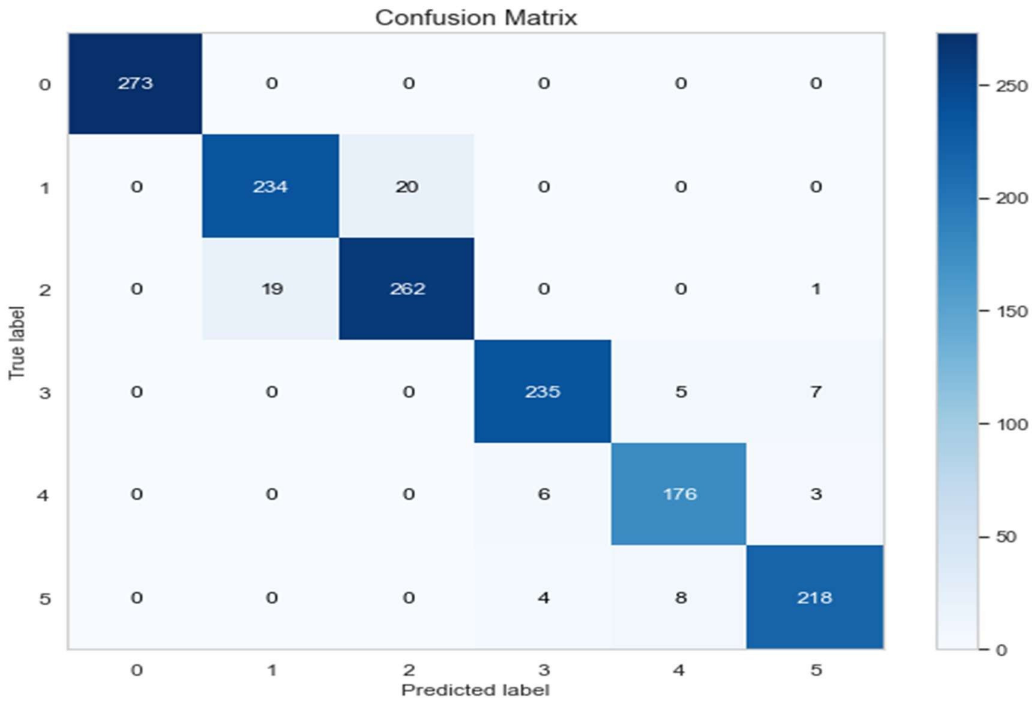

Fig 1.4 Confusion matrix based on Decision Tree Classifier

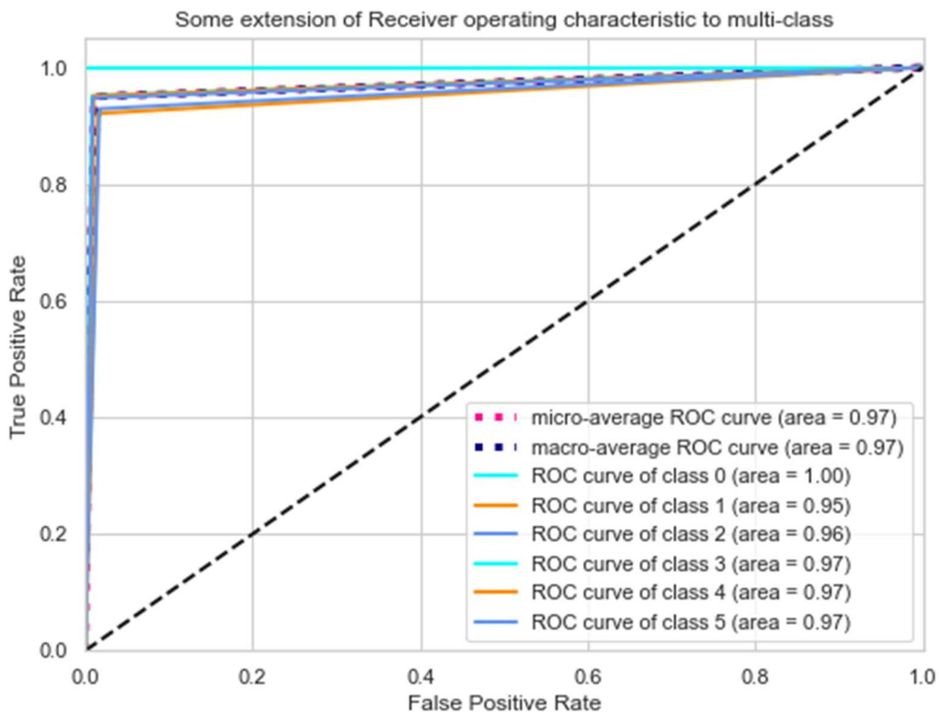

Fig 1.5 ROC Curve based on DecisionTreeClassifier

Random Forest Classifier:

Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset.

RandomForestClassifier shows precision_score as 97.69% and recall_score as 97.68%.

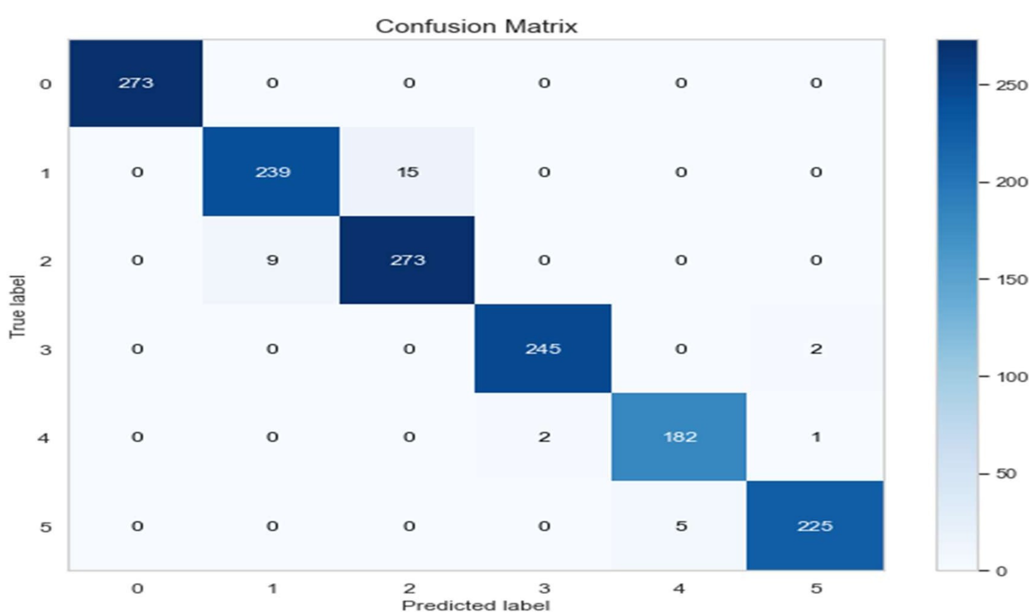

Fig 1.6 Confusion Matrix based on RandomForestClassifier

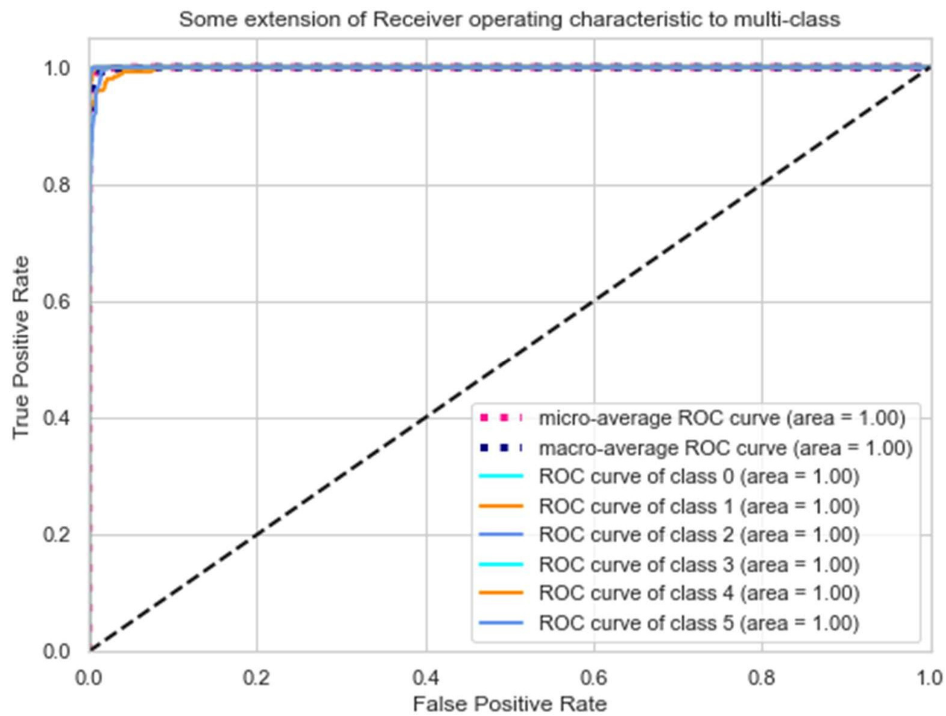

Fig 1.7 ROC Curve based on RandomForestClassifier

8. COMPARE TIME AND ACCURACY OF DIFFERENT ALGORITHMS

Using sklearn library comparison between different algorithms like K-Nearest-Neighbour, SupportVectorClassifier,DecisionTreeClassifier,RandomForestClassifier,GaussianNB,Ridge Classifier,LogisticRegression was done based on Time and Accuracy.

```
Score: 0.975     Time(in secs): 0.301    Classifier: KNeighborsClassifier
Score: 0.976     Time(in secs): 2.826    Classifier: SVC
Score: 0.943     Time(in secs): 2.933    Classifier: DecisionTreeClassifier
Score: 0.978     Time(in secs): 6.504    Classifier: RandomForestClassifier
Score: 0.728     Time(in secs): 0.143    Classifier: GaussianNB
Score: 0.979     Time(in secs): 0.12     Classifier: RidgeClassifier
Score: 0.99      Time(in secs): 1.735    Classifier: LogisticRegression
```

Fig 1.8 Comparison of Time and Accuracy between different algorithms

8.1 GRADIENT BOOSTING CLASSIFIER

Boosting is a method of converting weak learners to strong learners.Gradient Boosting trains many models in a gradual, additive and sequential manner.Gradient boosting performs by using gradients in the loss function (*y=ax+b+e , e needs a special mention as it is the error term)*. The loss function is a measure indicating how good the model's coefficients are at fitting the underlying data.

f1_score after applying GradientBoostingClassifier Algorithm is 99% and the time consumed by this algorithm is 247.074 .

8.2 REDUCING THE NUMBER OF FEATURES

As we have 561 features in our dataset which can cause overfitting in our dataset.So, there is a need to remove the features which do not depend on independent variable.

Using the get_support( ) of sklearn features are reduced from 560 to 130.

Now, after reducing the features our results based on comparison between different algorithms can be seen below:

```
[ ]  f_score(X_train, X_test, y_train, y_test)

     Score: 0.975     Time(in secs): 0.297    Classifier: KNeighborsClassifier
     Score: 0.976     Time(in secs): 3.422    Classifier: SVC
     Score: 0.943     Time(in secs): 3.26     Classifier: DecisionTreeClassifier
     Score: 0.98      Time(in secs): 6.95     Classifier: RandomForestClassifier
     Score: 0.728     Time(in secs): 0.163    Classifier: GaussianNB
     Score: 0.979     Time(in secs): 0.153    Classifier: RidgeClassifier
     Score: 0.99      Time(in secs): 1.95     Classifier: LogisticRegression
```

Fig 1.9 Comparison between different algorithms after reducing the features

8.3 ENSEMBLE LEARNING - BAGGING

The main principle behind the ensemble model is that a group of weak learners come together to form a strong learner, thus increasing the accuracy of the model.Bootstrap Aggregation (or Bagging for short), is a simple and very powerful ensemble method. Bagging is the application of the Bootstrap procedure to a high-variance machine learning algorithm.

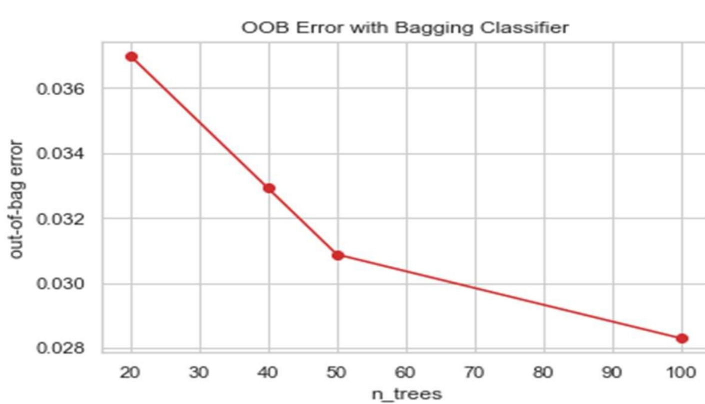

Fig 2.0 Elbow Shaped graph Bagging

	precision	recall	f1-score	support
0	1.00	1.00	1.00	273
1	1.00	1.00	1.00	254
2	1.00	1.00	1.00	282
3	1.00	1.00	1.00	247
4	1.00	1.00	1.00	185
5	1.00	1.00	1.00	230
accuracy			1.00	1471
macro avg	1.00	1.00	1.00	1471
weighted avg	1.00	1.00	1.00	1471

Fig 2.1Bagging Classifier with 50 estimator

Confusion matrix after applying bagging classifier.

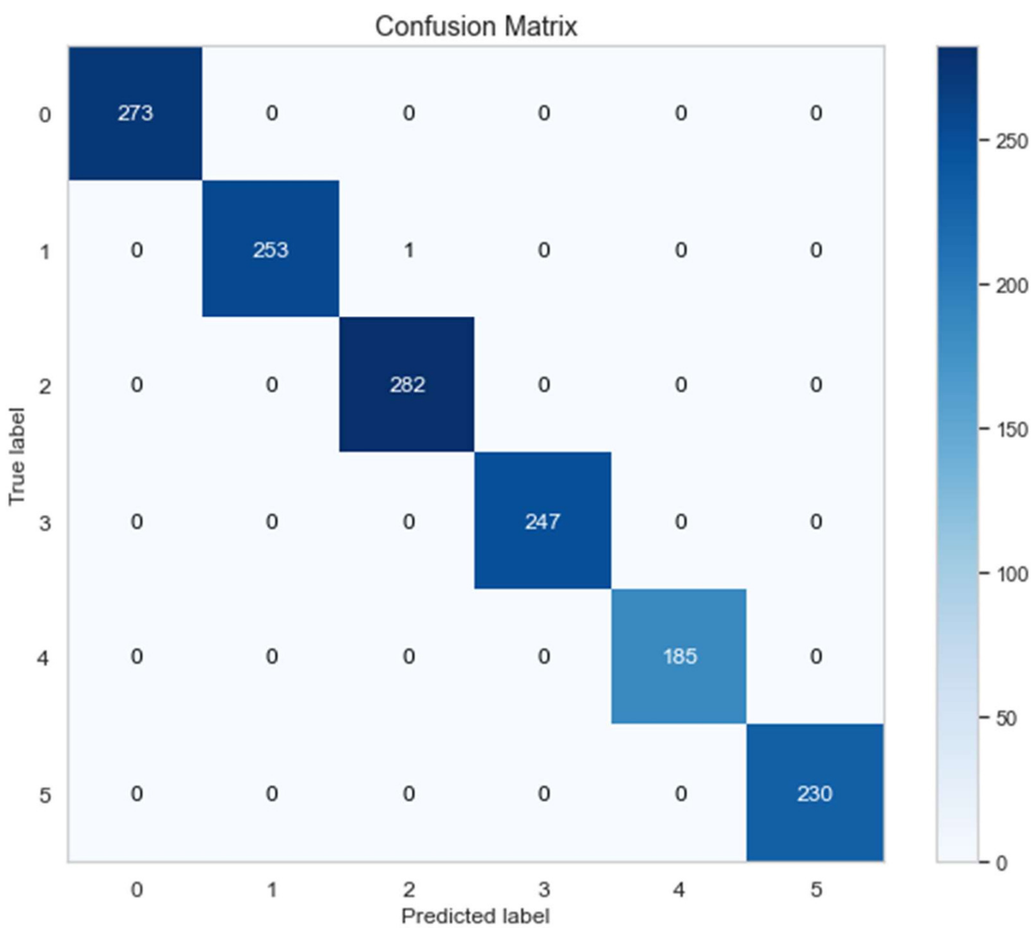

Fig 2.2 Confusion matrix after applying bagging_classifier

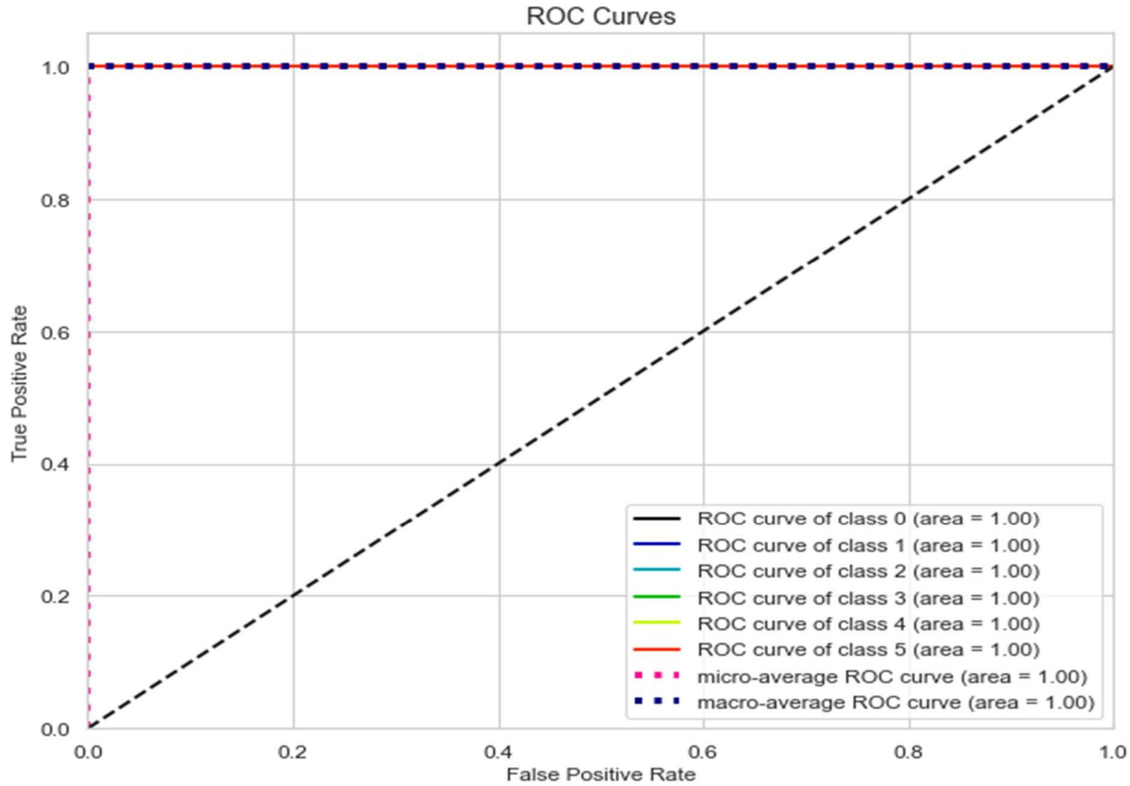

Fig 2.3 ROC Curve After Applying Bagging

8.4 RANDOM FOREST CLASSIFIER

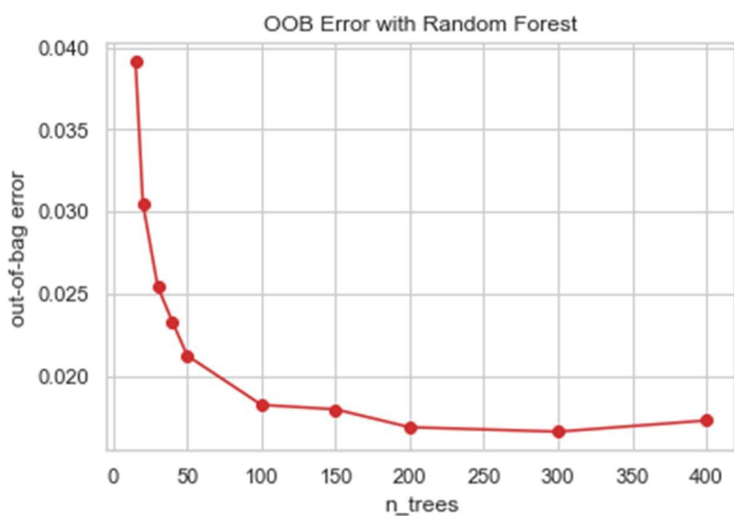

Fig 2.4 Result after applying RandomForestClassifier

	precision	recall	f1-score	support
0	1.00	1.00	1.00	273
1	1.00	1.00	1.00	254
2	1.00	1.00	1.00	282
3	1.00	1.00	1.00	247
4	1.00	1.00	1.00	185
5	1.00	1.00	1.00	230
accuracy			1.00	1471
macro avg	1.00	1.00	1.00	1471
weighted avg	1.00	1.00	1.00	1471

Fig 2.5 Output of Random Forest with 100 estimators

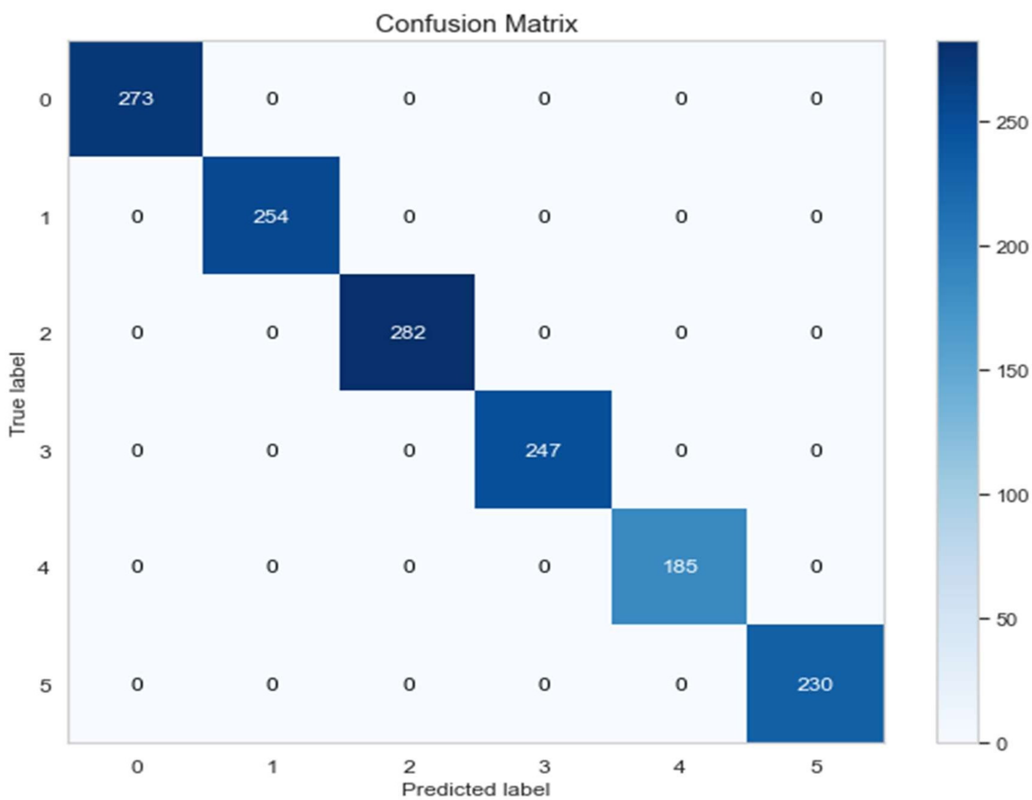

Fig 2.6 Confusion matrix after applying

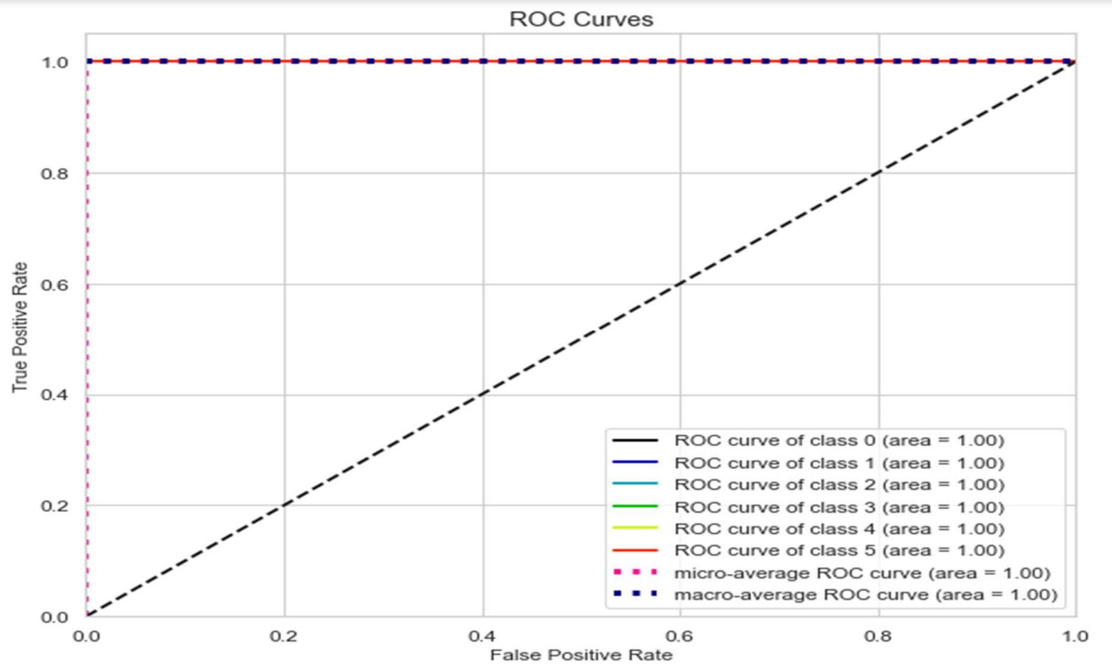

Fig 2.7 ROC Curve after applying RandomForestClassifier

9. EXTRA TREE CLASSIFIER

An extra-trees classifier. This class implements a meta estimator that fits a number of randomized decision trees (a.k.a. extra-trees) on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. The number of trees in the forest.

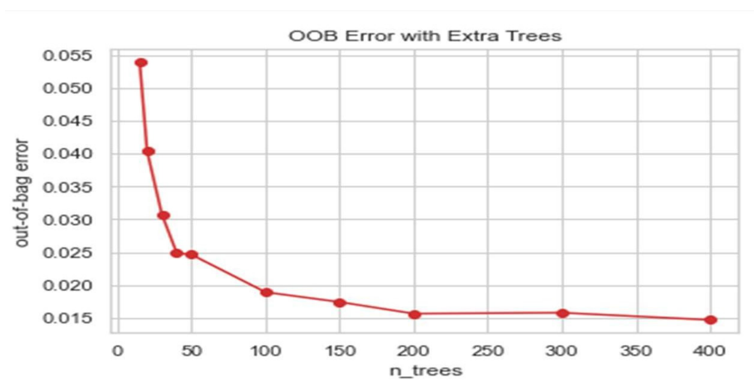

Fig 2.8 Output of elbow curve after applying ExtraTreeClassifier

	precision	recall	f1-score	support
0	1.00	1.00	1.00	273
1	1.00	1.00	1.00	254
2	1.00	1.00	1.00	282
3	1.00	1.00	1.00	247
4	1.00	1.00	1.00	185
5	1.00	1.00	1.00	230
accuracy			1.00	1471
macro avg	1.00	1.00	1.00	1471
weighted avg	1.00	1.00	1.00	1471

Fig2.9 Output of ExtraTree with 100 estimator

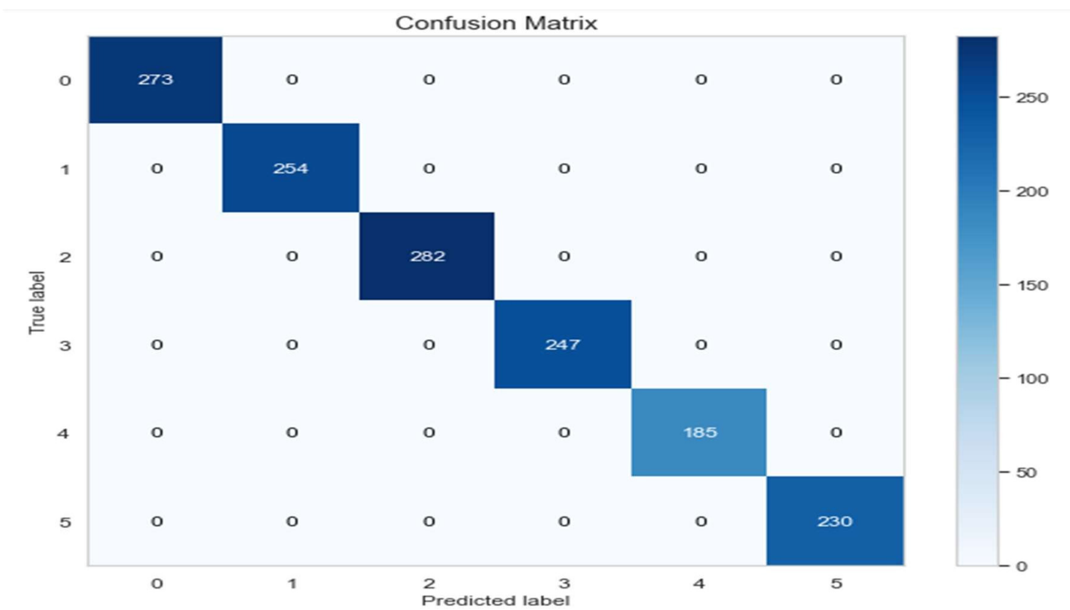

Fig 3.0 Confusion Matrix after applying Extra Tree

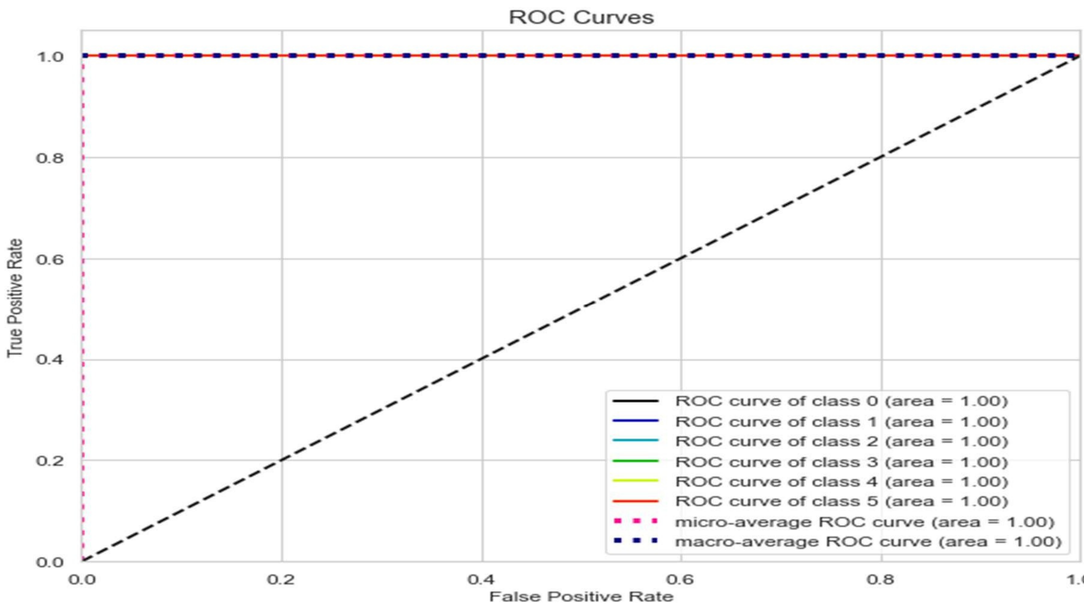

Fig 3.1 Output of ROC Curve after applying ExtraTreeClassifier

CONCLUSION

In fig 1.8 we can see without applying any preprocessing Ridge classifier is taking time of 0.12sec and 0.97%and giving better results than other classifiers . The models gave the same accuracy before applying gradient boosting algorithm and after applying gradient boosting algorithm but the time can be compared .Gradient Boost Classifier took 247.07sec and 99% .After Feature Reduction the performance of K Nearest Classifier was best.

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12Human Activity Recognition on Smartphones for Mobile Context AwarenessDavide Anguita, Alessandro Ghio, Luca Oneto, DITEN Department, University of Genova Via Opera Pia 11A, I-16145 Genova, Italy {Davide.Anguita,Alessandro.Ghio,Luca.Oneto} @unige.it Xavier Parra CETpD - Universitat Politecnica de Catalunya ` Vilanova i la Geltru 08800, Spain ´ xavier.parra@upc.edu Jorge L. Reyes-Ortiz□ CETpD - Universitat Politecnica de Catalunya ` Vilanova i la Geltru 08800, Spain ´ and DITEN Department, University of Genova Via Opera Pia 11A, I-16145 Genova, Italy jorge.luis.reyes@estudiant.upc.edu

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