Technocolabs Machine Learning Internship

Topic:- Machine Learning Techniques for Distracted Driver Detection

Date of Internship:- 15th May 2021- 15th June 2021

TEAM MEMBERS:

1. KSHITIJ JAISWAL (TEAM LEAD)
2. ANUSHIKA AGARWAL
3. SACHIN YADAV
4. ROSHAN KUMAR JANGID

MENTORS:

1. MR. YASIN SHAH
2. MR. UMER AYOUB

Machine Learning Techniques for Distracted Driver Detection

Abstract

Driving a car is a complex task, and it requires complete attention. Distracted driving is any activity that takes away the driver's attention from the road. Approximately 1.35 million people die each year because of road traffic crashes.

Road traffic crashes cost most countries 3% of their gross domestic product So, our aim/goal in this project is to detect if the car driver is driving safe or performing any activity that might result in an accident or any harm to others, by using various Machine Learning Models to classify the provided images into different categories of Distraction.

Furthermore, we can extend this work into comparing various Machine Learning Models to determine the accuracy based on respective models.

Importance of Project

Many states now have laws against texting, talking on a cell phone, and other distractions while driving. We believe that by applying Machine Learn- ing algorithms, we can detect the risk of accident by classifying the driver images in one of the distracted classes and hence prevent accidents caused by distracted driving. If this information can be known at real time, then a lot of accidents can be reduced with proper implementation.

1 Dataset

The dataset used is State Farm Dis- traced Driver Detection taken from *https://www.kaggle.com/c/state-farm-distracted- driver-detection/data.* The dataset contains 22424 driver images in total and has 10 classes. The 10 classes are Safe driving, Texting (right hand)

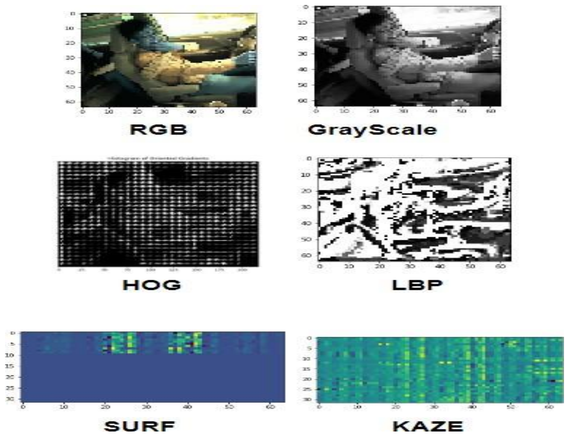
, Talking on the phone (right hand), Texting (left hand), Talking on the phone (left hand), Operating the radio, Drinking, reaching behind, Hair and makeup, Talking to passenger(s). Each image belongs to one of the classes above and are taken in a car with a driver doing something in the car. The images are colored and have 640*480 pixels each as shown below. For the training and testing purposes the images are resized to 64*64-colored images.

Stratified splitting is used to split the dataset into 80:10 Training-Testing ratio. The training dataset is further split into 90:10 Training-Validation set.

Figure 1: Data Visualization

2 Data Analysis

Images are resized to 64*64-colored images for training and testing purposes. Following feature ex- traction techniques are applied LBP, HOG, color Histograms, KAZE, SURF. The result of feature ex- traction can be visualized in figure 2. Normalization is performed over the extracted features.
Dimensionality reduction techniques like PCA and LDA are used to reduce the dimensions and avoid 'Curse of Dimensionality'. For deciding the n components of PCA, variance-components graphs are used (Figure 3).
All the features are stacked together to get complete image representation and ML algorithms are applied to obtain the accuracy.



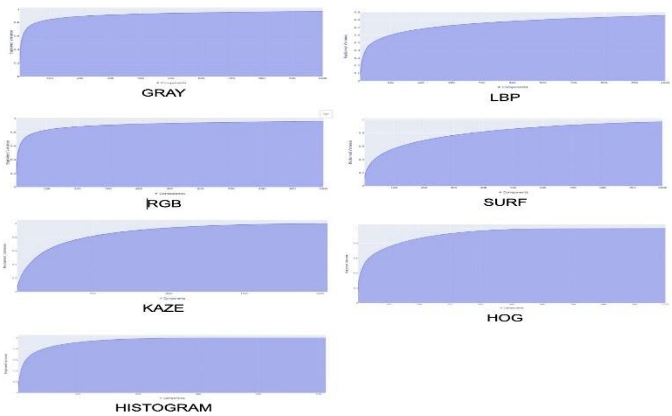
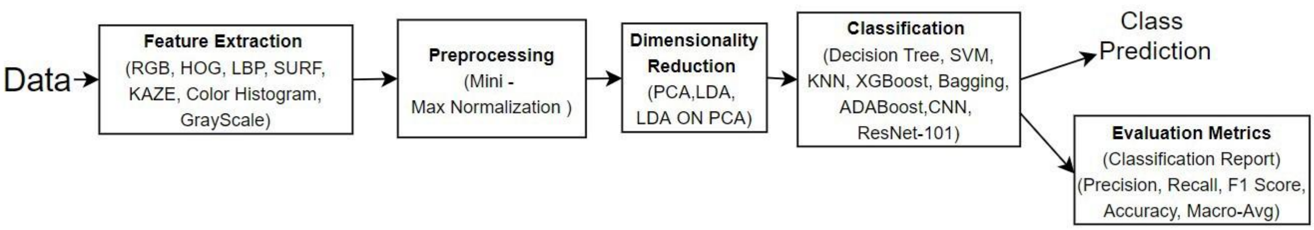


Figure 2: Feature Extraction Techniques graph

Figure 3: PCA variance and n components



3 Methods and Results

3.1 Traditional ML Models

The following traditional ML algorithms are used along with feature extraction and dimensionality reduction.

- **KNN:**
  The KNN algorithm assumes that similar things exist in close proximity. In other words, similar things are near to each other KNN captures the idea of similarity (sometimes called distance, proximity, or closeness)

3.2 Ensembling Methods

- **XGBoost**
  XGBoost is a decision-tree-based ensemble Machine Learning algorithm that uses a gradient boosting framework. In prediction problems involving unstructured data (images, text, etc.) artificial neural networks tend to outperform all other algorithms or frameworks.

- **Bagging**
  Bootstrap aggregating, also called bagging (from bootstrap aggregating), is a machine learning ensemble meta-algorithm designed to improve the stability and accuracy of machine learning algorithms used in statistical classification and regression. It also reduces variance and helps to avoid overfitting.

- **ADABoost**
  AdaBoost algorithm, short for Adaptive Boost- ing, is a Boosting technique that is used as an Ensemble Method in Machine Learning. It is called Adaptive Boosting as the weights are re-assigned to each instance, with higher weights to incorrectly classified instances.

Table: Optimal Hyperparameters Obtained

Model	Optimal Hyperparameters
KNN	n-neighbours = 5
XGB	max-depth = 6, eta = 0.5
Bagging	n-estimators=40
Adaboost	n-estimators=200

4. Dimensionality Reduction

We have used three dimensionality reduction techniques which are stated below:

PCA

Principal component analysis (PCA) is a technique for reducing the dimensionality of datasets, increasing interpretability but at the same time minimizing information loss.

After applying feature extraction techniques, PCA with **n_components** = 100 components is applied to features extracted from each extraction technique individually and then later combined together to form a combined feature set of 700 features.

LDA

Linear discriminant analysis (LDA) is a generalization of Fisher's linear discriminant, a method used in statistics and other fields, to find a linear combination of features that characterizes or separates two or more classes of objects or events.

LDA over PCA

LDA is applied on combined features which are obtained after applying PCA to further reduce the features, get a better class separation and to increase computational efficiency.

Model	Precision	Recall	F1 Score	Acc
KNN	0.9935	0.9870	0.9870	0.987
XGB	0.9856	0.9849	0.9852	0.985
Bagging	0.7927	0.7848	0.7861	0.789
Adaboost	0.7197	0.6957	0.7010	0.693

Table 1: PCA

Model	Precision	Recall	F1 Score	Acc
KNN	0.9922	0.9924	0.9923	0.992
XGB	0.9912	0.9912	0.9912	0.991
Bagging	0.9825	0.9826	0.9825	0.982
Adaboost	0.5160	0.5785	0.5191	0.574

Table 2: LDA

Model	Precision	Recall	F1 Score	Acc
KNN	0.9806	0.9793	0.9799	0.979
XGB	0.9757	0.9756	0.9756	0.976
Bagging	0.9720	0.9710	0.9714	0.971
Adaboost	0.6880	0.6634	0.6304	0.658

Table 2: LDA on PCA

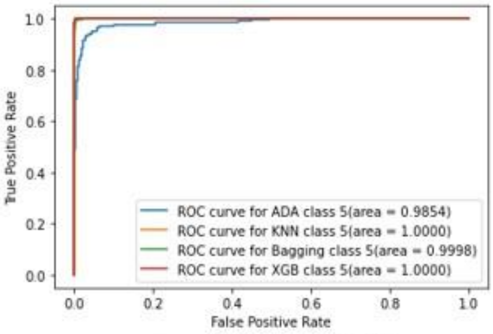


Figure 1: ROC curve for PCA Table

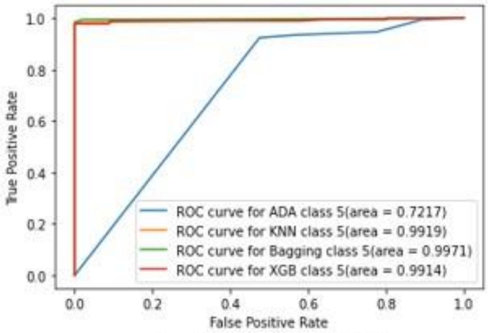


Figure 2: ROC curve for LDA Table

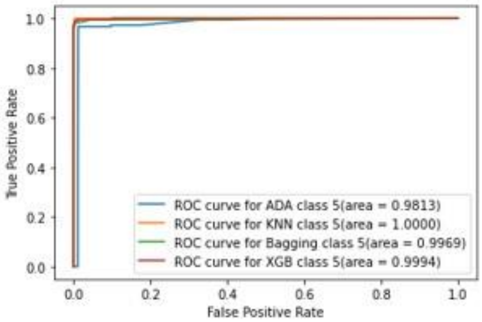


Figure 3: ROC curve for LDA on PCA Table

A short explanation of project-relevant terms

- **HOG** - The histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image.

- **LBP** - Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number.

- **Color Histogram** - A color histogram is a representation of the distribution of colors in an

- **Normalization** - In this technique of data normalization, linear transformation is performed on the original data. Minimum and maximum value from data is fetched and each value is replaced according to the following formula.

- **ROC curve** - An ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters: True Positive Rate and False Positive Rate.

- **PCA** - Principal component analysis (PCA) is a technique for reducing the dimensionality of datasets, increasing interpretability but at the same time minimizing information loss.

- **LDA** - Linear discriminant analysis (LDA) is a generalization of Fisher's linear discriminant, a method used in statistics and other fields, to find a linear combination of features.

Conclusion

Successfully modelled the problem statement and got the result. Deployed it on the local server. Got accurate results and optimal parameters. Overall learnt many new technologies and implemented them as well.