Machine Learning (CSE543) Distracted Driver Detection

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Introduction :

Our Goal in this Project is to 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

Various Machine Learning Models used to classify the Provided images into Different category of Distraction

Problem Domain:

1. Approximately 1.35 million people die every year as a result of road traffic crashes
2. Road traffic crashes cost most countries 3 % of their gross domestic Product
3. Road traffic injuries are the leading cause of death for children and young adults aged 5-29

Source : World Health Organization

Dataset:

We have used the Dataset from Kaggle (State Farm Distracted Driver Detection)

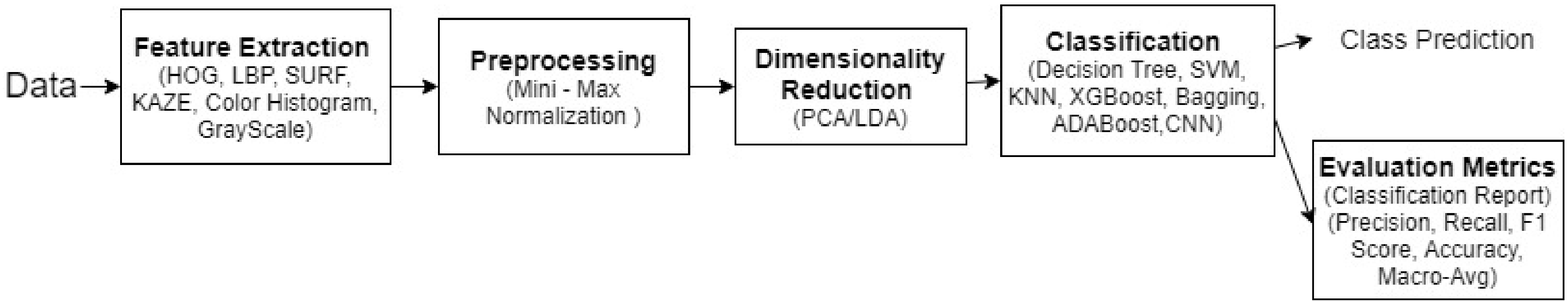
1. The dataset contains 22424 driver images in total and has 10 classes

1. 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)

1. The images are coloured and have 640*480 pixels.
2. Approx 70k unlabelled images

Dataset Visualization:

Project Pipeline:



Data Preprocessing:

Here we will use pixels as features for our Training Algorithms :

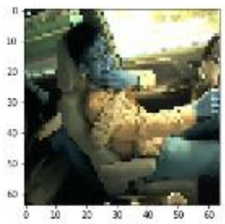
1. Image Resize to 64x64 RGB Image
2. 64x64 coloured Image will be used for Feature Extraction Algorithms (Below Figure shows original image and resize image)

Feature Extraction Techniques:

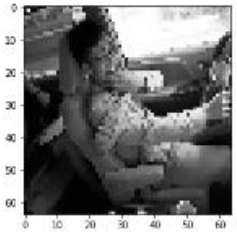
1. HOG (Histogram of Oriented Gradients)
2. LBP (Local Binary Pattern)
3. SURF
4. KAZE
5. Color Histogram

(For Dimensionality Reduction we have used PCA and LDA)

Visualization :
Feature Extraction Techniques:

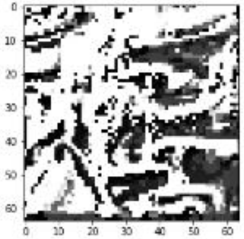


RGB

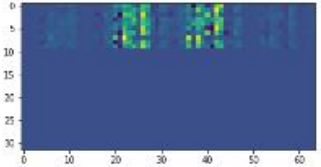


GrayScale

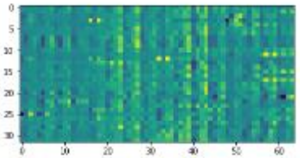
HOG



LBP



SURF

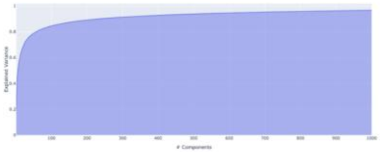


KAZE

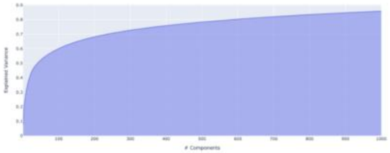
Applying PCA on Extracted Features to reduce Dimensions

PCA Components vs. Variance

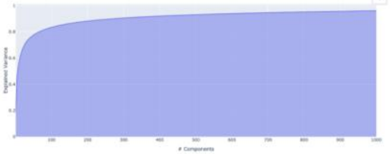
We choose PCA Components
Such that we get Higher variance
With less components



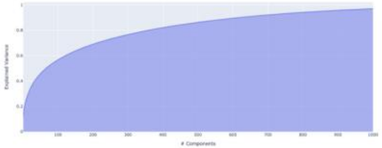
GRAY



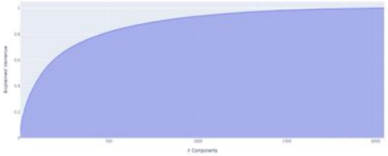
LBP



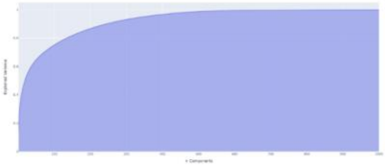
RGB



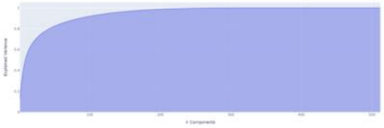
SURF



KAZE



HOG



HISTOGRAM

Algorithm Implementation : Steps

1. Dividing Train dataset into Train and Test DataSet by stratified split
2. Again we Split Train Dataset to Train and Validation Set
3. We apply Feature extraction Technique
4. Normalizing the Extracted Features using min-max Normalization
5. Dimensionality Reduction Techniques (PCA/LDA) on normalized Extracted Features
6. Combining the Extracted Features
7. We apply our Classifier and Fitting it on train_imgs and Testing it on val_imgs
8. Predicting the Class label
9. Evaluation Metrics

Model Evaluation : Decision Tree

	Precision	Recall	F1 Score	Acc
LDA	0.8754	0.8755	0.8753	0.8754
PCA	0.7869	0.7862	0.7863	0.7876
HOG	0.7415	0.7405	0.7409	0.7408
Color Hist.	0.6655	0.6629	0.6635	0.6638
KAZE	0.5639	0.5629	0.5629	0.5668

Table 2: DT

Model Evaluation : SVM

	Precision	Recall	F1 Score	Acc
LDA	0.9088	0.9081	0.9082	0.9077
PCA	0.8955	0.8955	0.8955	0.8955
HOG	0.8511	0.8510	0.8510	0.8510
Color Hist.	0.4110	0.3805	0.3818	0.3823
KAZE	0.7927	0.7848	0.7861	0.7898

Table 1: SVM

Conclusion

- As PCA was not able to capture class information so accuracy obtained with LDA is better as compared to PCA .

- As there are huge number of dimensions so Decision tree tends to overfit and performs bad over the test set.

- Combination of features from various feature extractions give better accuracy than taking individual features.

Key Learnings

- Feature Extraction is an important step
- Dimensionality Reduction is important when we have a large number of features
- Good features are needed for Dimensionality reduction
- “No Free Lunch” - Grid search is required to find the best parameters for classifiers.

Next Steps

- Training with other models
- Comparison between performance of traditional ML algorithms and advanced algorithms