Machine Learning (CSE543) Distracted Driver Detection

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End Term Presentation

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 , Deep Learning (CNN) Algorithms are 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:

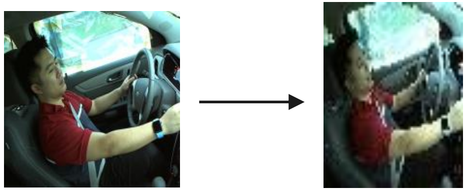
We have used the Dataset from Kaggle (State Farm Distracted Driver Detection)

1. The dataset contains 22424 driver images in total and has 10 classes
2. 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)
3. The images are coloured and have 640*480 pixels.
4. Approx 70k unlabelled images

Data Preprocessing:

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

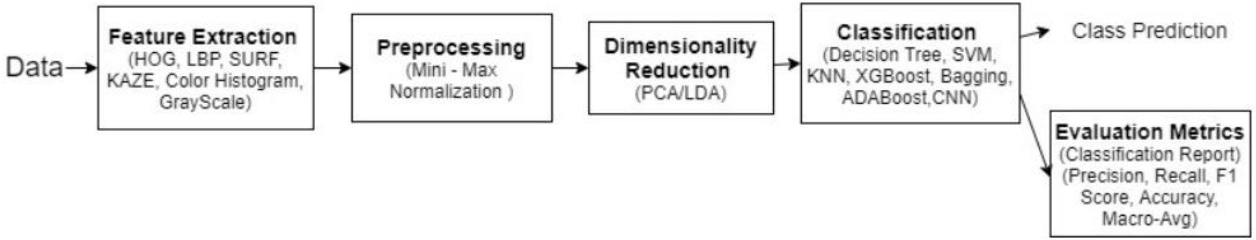
1. **Image Resize to 64x64 RGB Image**
2. **64x64 coloured Image will be used for Feature Extraction Algorithms (Below Figure shows original image and resize image)**
1. **Also For Deep Learning Algorithms (CNN)we have Performed on 224x224x3 as well as 64x64x3**



Dataset Visualization:

c0:Safe Driving
c1: texting-right
c2: talking on the phone - right
c3: texting - left
c4: talking on the phone - left
c5: operating the radio
c6: drinking
c7: reaching behind
c8: hair and makeup
c9: talking to passenger

Project Pipeline:



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)

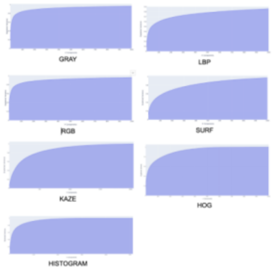
Algorithm Implementation : Steps

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

Applying PCA on Extracted Features to reduce Dimensions

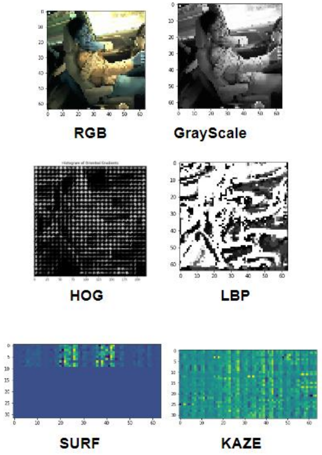
PCA Components vs. Variance

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



Visualization :

Feature Extraction Techniques:



Mid Sem Report Recap : Results

	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

	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.

Next Steps (Post mid term)

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

We have applied following Algorithms with Analysis :

- Decision Tree
- SVM
- KNN
- XGBoost
- Bagging
- ADABoost
- Transfer Learning
- CNN for [64x64x3]
- CNN for [224x224x3]
- ResNet

We have applied following Algorithms with Analysis :
Traditional ML, Ensembling, DeepLearning

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- SVM
- KNN
- XGBoost
- Bagging
- ADABoost
- Transfer Learning
- CNN for [64x64x3]
- CNN for [224x224x3]
- ResNet

We have Performed on 3 Different Variations for every ML Algorithm Given Below

1. PCA

Model	Precision	Recall	F1 Score	Acc
DT	0.8221	0.8213	0.8214	0.822
SVM	0.9973	0.9973	0.9973	0.997
KNN	0.9872	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 2: PCA

2. LDA On PCA

Model	Precision	Recall	F1 Score	Acc
DT	0.9638	0.9639	0.9638	0.964
SVM	0.9799	0.9791	0.9795	0.979
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 4: LDA on PCA

3. LDA

Model	Precision	Recall	F1 Score	Acc
DT	0.9753	0.9752	0.9751	0.974
SVM	0.9881	0.9876	0.9876	0.987
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 3: LDA

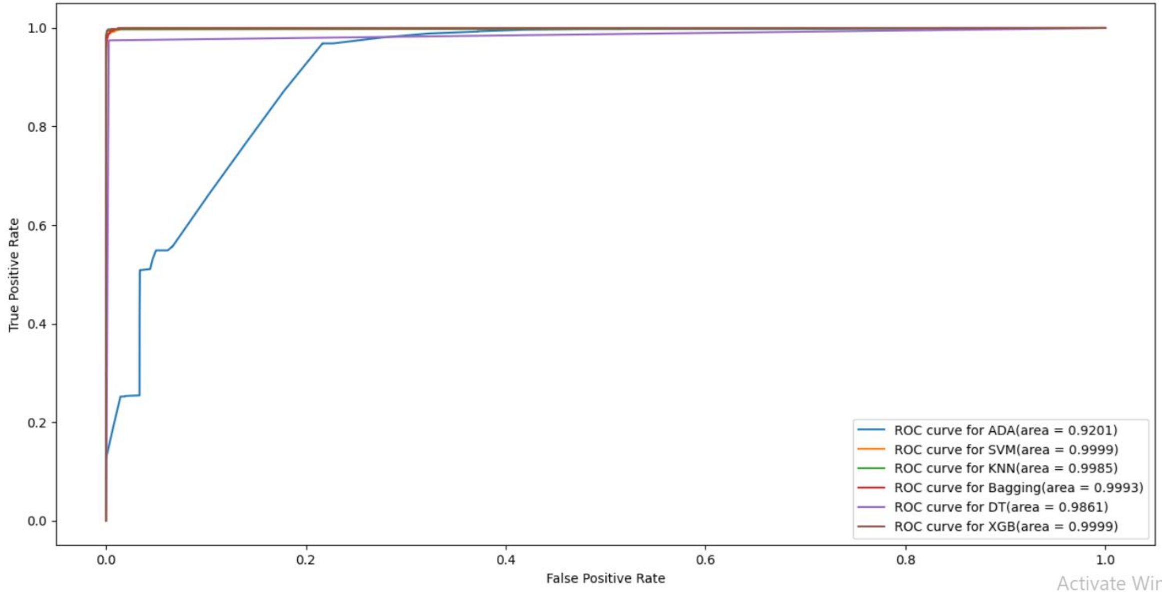
After Performing Hyperparameter Tuning For each ML Algorithms, Results are :

Model	Optimal Hyperparameters
DT	criterion = 'entropy', max-depth = 20
SVM	C=10 and kernel='rbf'
KNN	n-neighbours = 5
XGB	max-depth = 6, eta = 0.5
Bagging	n-estimators=40
Adaboost	n-estimators=200

Table 1: Hyperparmeter Tuning

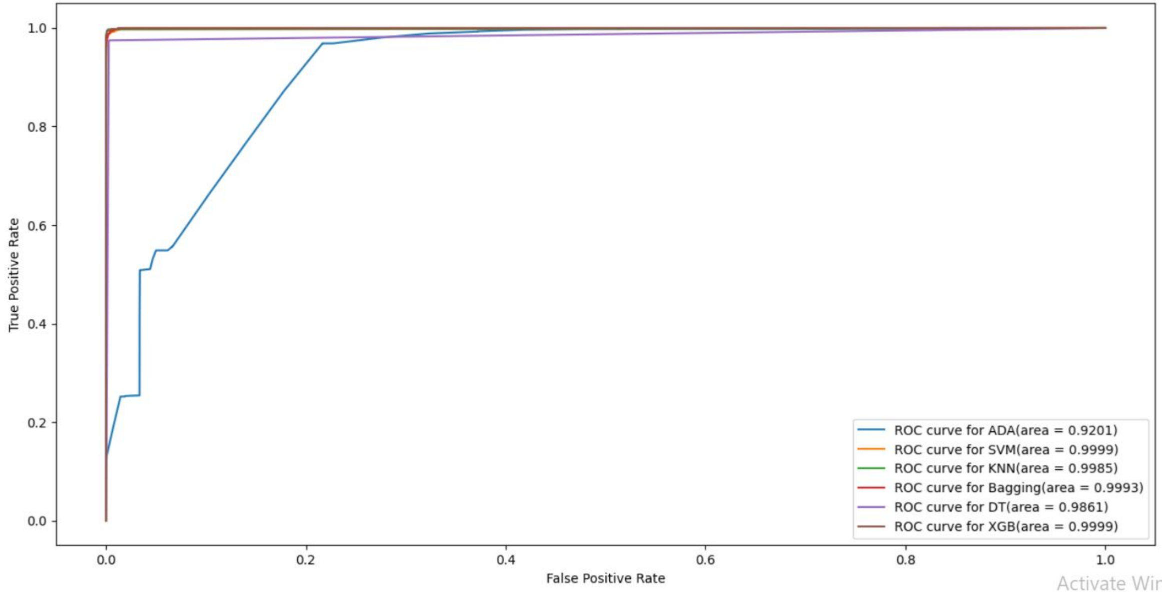
ROC Curve For the Applied Algorithms for 3 Variations.

1. LDA ROC Curve



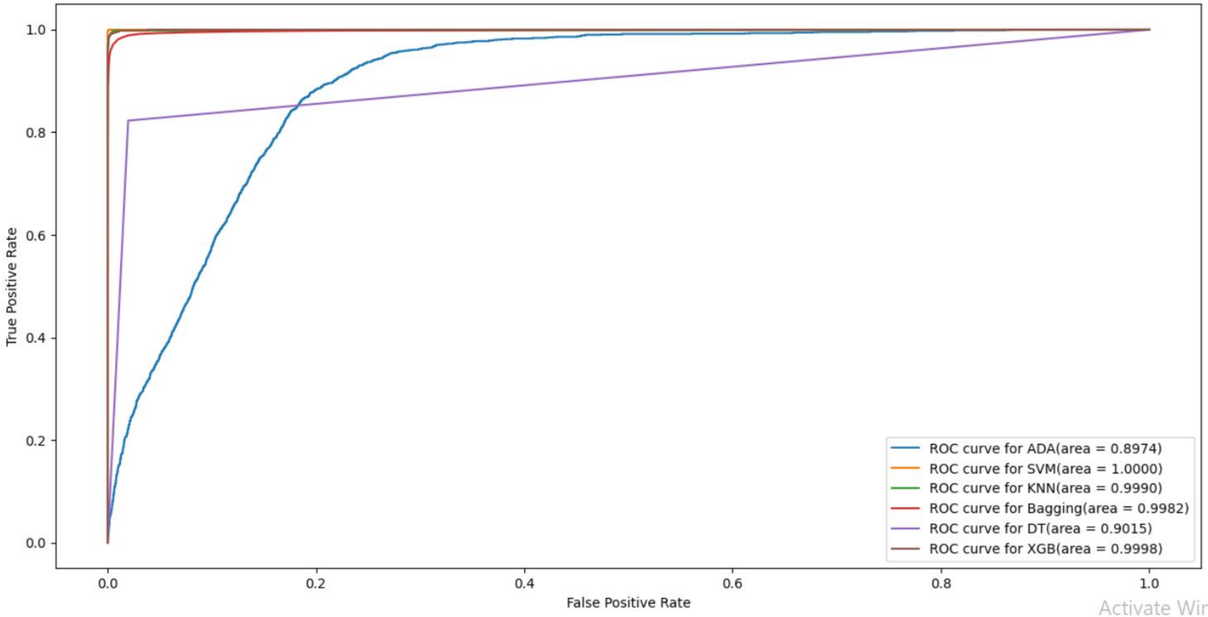
ROC Curve For the Applied Algorithms for 3 Variations.

1. LDA ROC Curve



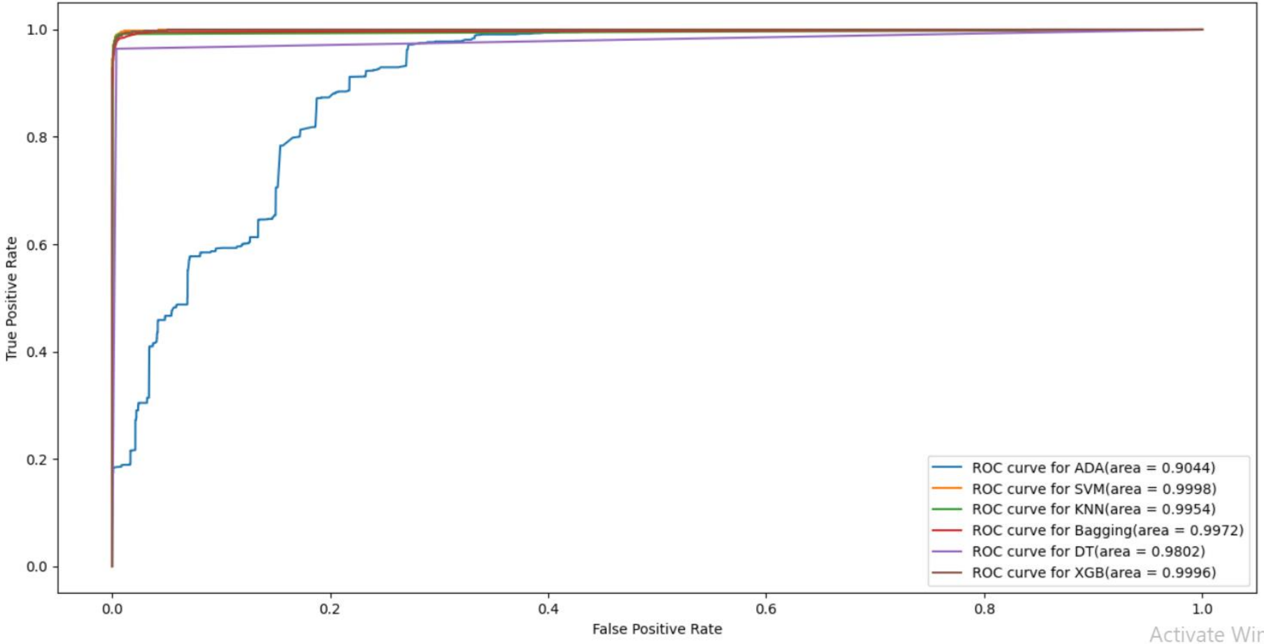
ROC Curve For the Applied Algorithms for 3 Variations.

2. PCA ROC Curve



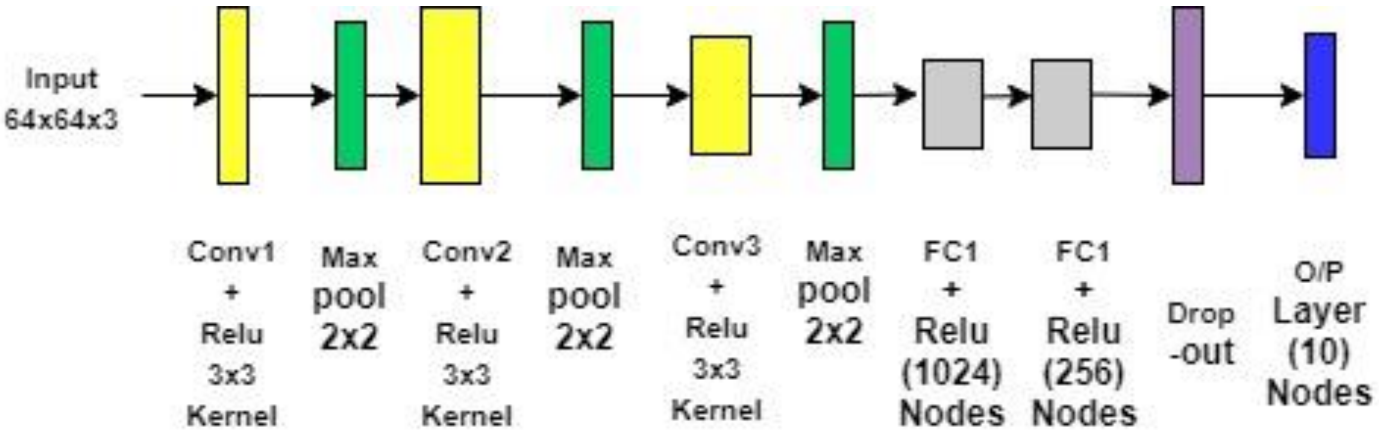
ROC Curve For the Applied Algorithms for 3 Variations.

3. LDA on PCA ROC Curve



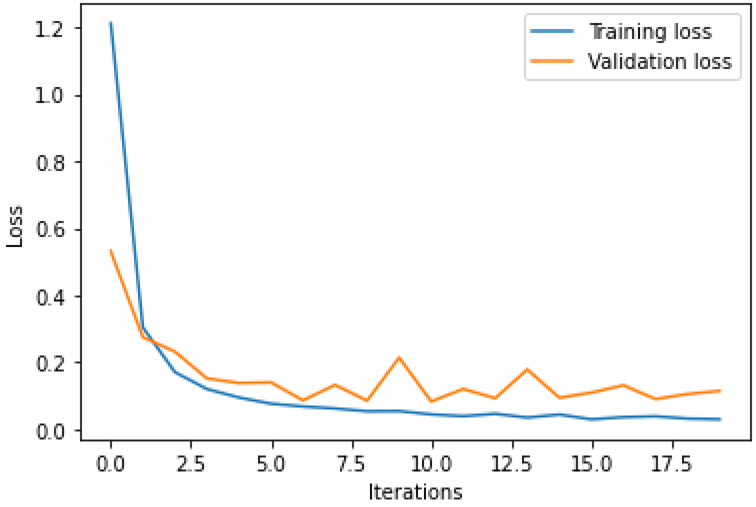
Deep Learning Techniques : CNN

(a) Optimal CNN architecture for image size [64x64x3]



Deep Learning Techniques : CNN

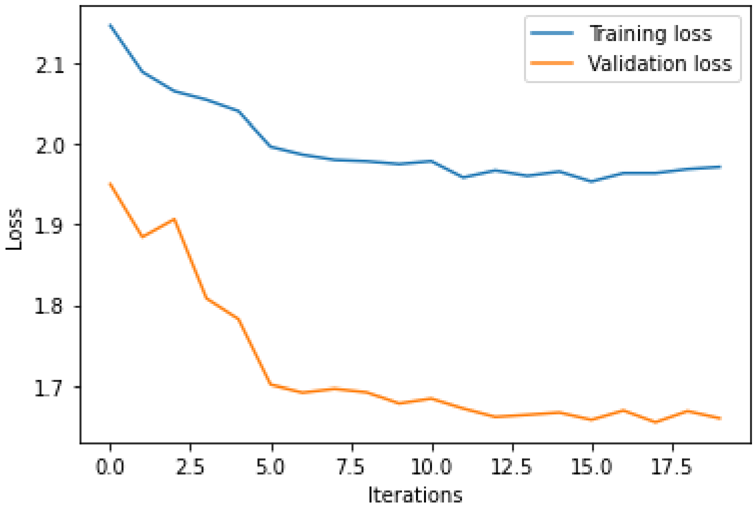
(b) Epochs vs. Loss Graph of CNN-64



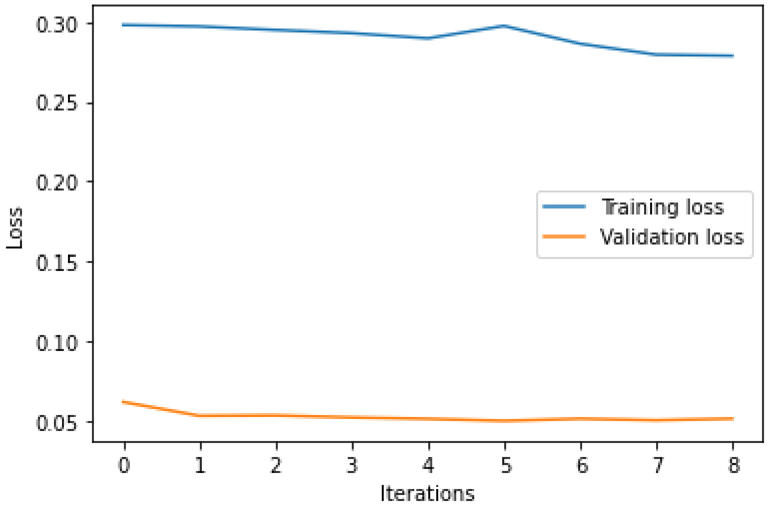
Deep Learning Techniques : Transfer Learning

(c) ResNet (101) Analysis : Loss vs. Iteration Graph

(i) Strategy-1 : S1



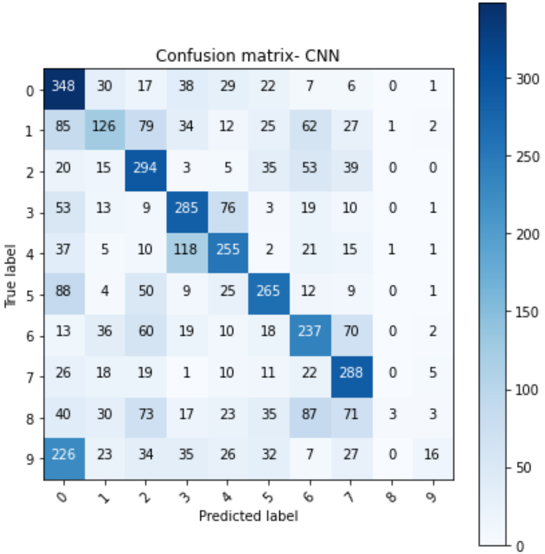
(ii) Strategy-2 : S2



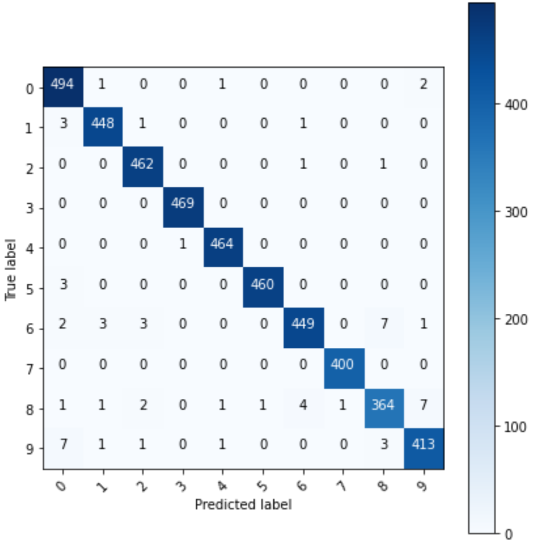
Deep Learning Techniques : Transfer Learning

(c) ResNet (101) Analysis : Classification Matrix

(i) Strategy-1 : S1



(ii) Strategy-2 : S2

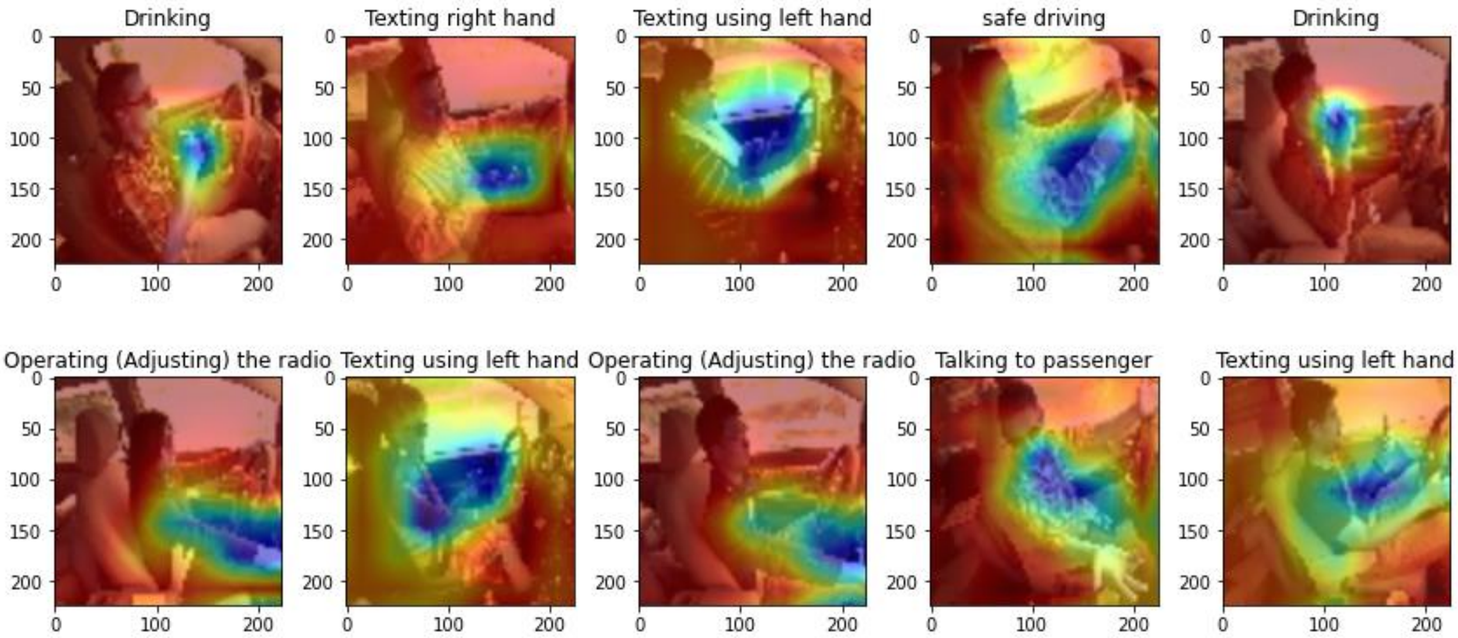


Deep Learning Techniques : Transfer Learning

(c) ResNet (101) Analysis : Prediction Visualization

Deep Learning Techniques : Transfer Learning

(c) ResNet (101) Analysis : Class Activation Mappings

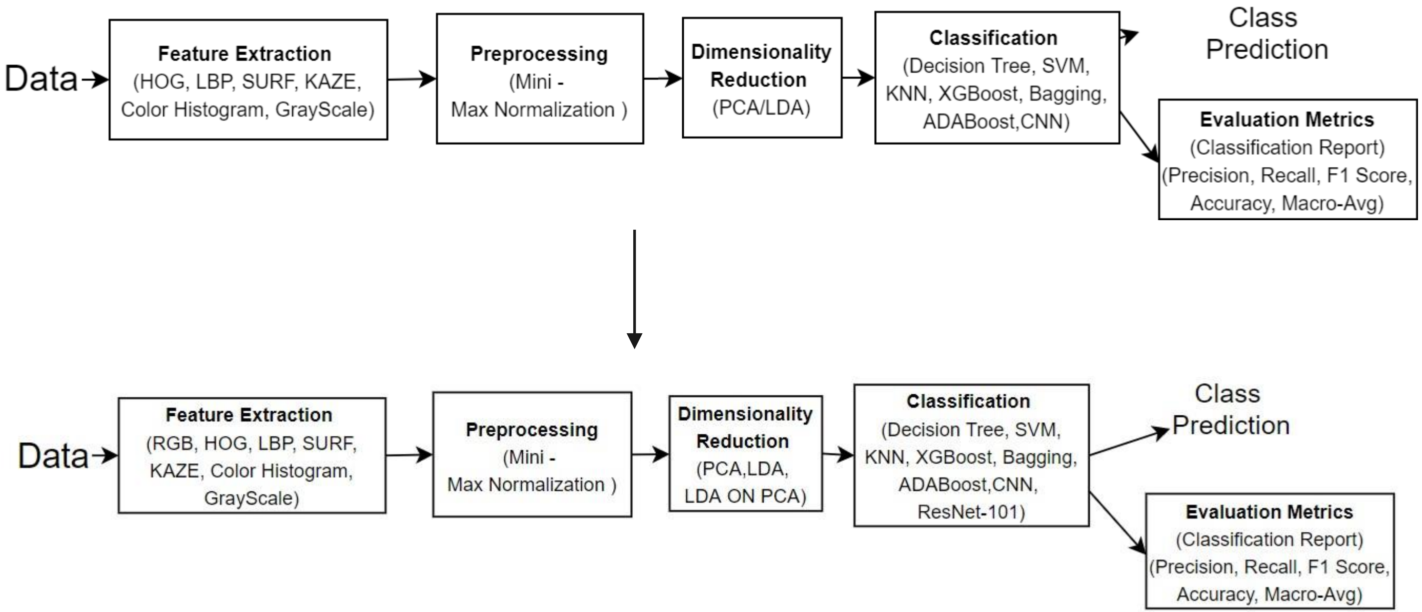


Deep Learning Techniques : Results

Model	Precision	Recall	F1 Score	Acc
CNN	0.98	0.98	0.98	0.98
ResNet-101(S1)	0.50	0.46	0.42	0.47
ResNet-101(S2)	0.99	0.99	0.99	0.99

Table 5: Deep Learning models

Comparison : Proposed Pipeline vs. Implemented Pipeline



Inference :

- PCA gave better results than LDA and LDA on PCA.
- After plotting the ROC curves for various models, best auc_roc score was found for SVM after applying PCA.
- ResNet-101 S2 performed much better than ResNet-101 S1 which is also higher than the accuracy obtained using CNN.
- Adaboost performed poorly for classification on this dataset as boosting techniques perform better on high variance datasets which is contrary to our data set which has low variance.
- Data Augumentation and Data Extraction techniques helps the classifier to perform better.
- Combining various feature extraction techniques gave much better results than using these techniques individually.

Learnings :

- Implementing various Feature Extraction Techniques like HOG, LBP, SURF, KAZE etc.
- Combining various features.
- How to use classification report as a metric for a model.
- Implementing traditional ML models like Decision Tree, SVM,KNN etc.
- Implementing Deep Learning techniques like CNN, ResNet-101.
- Plotting ROC curves for multi label classification.
- Hyperparameter tuning using GridSearchCV.

Future Work

- Given more time and processing power, we can use ResNET-152 to classify the dataset.
- More parameters can be tuned for different models.
- Our model works on images which are taken from one angle. To increase the robustness of the model for real time detection, further work can be done on images which are taken from other angles.
- More dataset can be collected containing images of drivers from different angles.
- More feature extraction techniques can be implemented.