DISTRACTED DRIVER DETECTION USING MACHINE LEARNING AND DEEP LEARNING

Senior Design Project Report

CSE/EEE/ETE 499

Submitted By

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Agreement Form

It has been great pleasure for us to develop a Distracted driver detection using machine learning and deep learning. We have gathered sufficient knowledge and experience during this project. The authors of this paper would like to thank specially Dr. Shahnewaz Siddique to give us the opportunity on this noble project as well as helping us to establish this project. He encouraged us to seek out the clearest and deepest description of theoretical ideas as well as experimental findings. We are very grateful to him for his continuous support, advice and guidance.

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Abstract

One of the main reason of most car accidents is distracted driving, which is the act of driving while engaging in other such as texting, talking on the phone, etc. activities. Activities of that nature distract the driver from paying attention to the road. These distractions in turn compromise the safety of the driver, passengers, bystanders and others in other vehicles. 7,796 deaths due to accidents in 2018, a report of Bangladesh Passengers Welfare Association said at least 7,796 people were killed and 15,980 were injured in 6,048 accidents. The United States Department of Transportation states that one in five car accidents are caused by distracted drivers. This work looks at various images of distracted drivers taken from people performing different actions, some of which can be deemed as distracting whilst behind the wheel of a car. A mixture of various neural network is used in order to more accurately predict what activity a driver is being distracted by.

Introduction

Distracted driving is an event that occurs when a driver diverts their primary focus of driving to another task or activity. Distracted driving is an ongoing problem that seems to only be getting worse with the dependence on technology. Not only is the general public becoming more reliant on vehicles, but also on distractions like cell phones and GPS systems within them. Most modern day vehicles come with touch screen navigation that requires some level of interaction to operate. Cellphones, too, are a big part of everyday life interactions, with constant incoming notifications and calls. These upward trends in dependence seem to have a correlation to the number of crashes as a result of distracted driving. In the province of Ontario, the deaths from crashes as a result of distracted driving have doubled since the year 2000, with one person being injured every half hour as a result of a distracted driver1. Furthermore, in the United States alone, 425,000 people are injured and 3,000 are killed as a result of distracted driving, according to the Centers for Disease Control and Prevention (CDC) in 2015. The U.S. Department of Transportation National Highway Traffic Safety Administration (NHTSA) published a Research Note regarding Distracted Driving in 2015.

With our increased dependence on technology and cellphones, distracted driving is becoming an increased concern. Distracted driving does not just involve the use of cellphones but also includes eating, drinking, and even talking to a passenger whilst driving. This work aims to help amend this issue by automatically predicting if drivers are distracted, and what action in specific is resulting in the distracted driving. Three different models are implemented, from simple Convolutional Neural Networks (CNNs) to more complex ones involving Transfer Learning from other pre-trained models. The success of the models will hopefully, one day, aid combat the ongoing and increasing issue of distracted drivers on the roads.

Problem Statement

The problem that we are trying to solve is a multi-class classification problem. We are tasked to properly predict and classify driver's behavior given the dashboard images of people doing 10 different actions, 9 of which are considered actions of distracted behavior. The 10 classes are as follows: 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.

A solution to this problem is using machine learning computer vision models to classify driver actions. Working with Hybrid model would be a good idea because Hybrid models are known to yield the most accurate results in the computer vision field. Keras application models with pre-trained weights could reduce the time it takes to train while still maintaining good results.

Reducing image size and dividing the images into the RGB channels could make processing of the images more manageable. Pre-processing the images may be necessary to reduce overfitting and improve generalization. Once the model is fit, we will need to predict the labels of the test set to determine which of 10 categories each picture belongs to. The validation results and benchmark result will then tell us if we still need to improve the model.

Number of road disasters is continuously increasing in last few years worldwide. This makes it imperative to take measures to curb the number of road fatalities. The major cause of these accidents is due to driver's error. We attempt to develop an accurate and robust system for detecting distracted driver and warn them against it. We focus on detecting manual distractions where driver is engaged in other activities than safe driving and also classify the cause of distraction.

We input images of the driver to our model. Each image belongs to one of the 10 classes mentioned in the dataset section. The model then predicts the class of an image by giving as an output a probability for each class.

Literature review:

- **Machine Learning Techniques for Distracted Driver Detection by Demeng Feng and Yumeng Yue**
  This paper explored driver distraction activities detection via images using different kinds of machine learning techniques. Their objective was to build a high-accuracy model to distinguish whether drivers is driving safely or conducting a particular kind of distraction activity. The input of our model is images of driver taken in the car. We first preprocess these images to get input vectors, then use different classifiers (linear SVM, sofrmax, naive bayes, decision tree, and 2-layer neural network) to output a predicted type of distraction activity that drivers are conducting. As unlabeled training data can be

collected from drivers' naturalistic driving records with little extra resource, semisupervised methods, which utilize both labeled and unlabeled data, can enhance the efficiency of model development in terms of time and cost.

- **Real-Time Detection of Driver Cognitive Distraction Using Support Vector Machines**
  In this paper they applied support vector machines (SVMs), which is a data mining method, to develop a real-time approach for detecting cognitive distraction using drivers' eye movements and driving performance data. Data were collected in a simulator experiment in which ten participants interacted with an IVIS while driving.

- **Distracted Driver Detection: Deep Learning vs Handcrafted Features** In this paper they applied the traditional features include a blend of Histogram of Oriented Gradients and Scale-Invariant Feature Transform descriptors used to create Bags of Words. The deep convolutional methods use transfer learning on AlexNet, VGG16, and ResNet-152.

- **Driver Distraction Detection Using Semi-Supervised Machine Learning** This paper explored semi-supervised methods for driver distraction detection in real driving conditions to alleviate the cost of labeling training data. Laplacian support vector machine and semi-supervised extreme learning machine were evaluated using eye and head movements to classify two driver states: attentive and cognitively distracted.

Dataset:

State Farm is a large group of insurance and financial services companies throughout the United States. They released their dataset of 2D dashboard camera images for a Kaggle challenge. The dataset had 22400 training images and 79727 testing images. Resolution was 640 x 480 pixels. We also collected 90 training images in which there was also pictures of local bus.

The training images had corresponding labels attached. Labels belonged to one of the ten classes as mentioned below: c0: normal 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

A sample input is shown:

We propose a reliable model that achieves a 95% driving posture classification accuracy. We build a custom code model from scratch and also implemented pre-trained models to compare the accuracy of the test data. Finally, we present the best version of our model that could achieve a 95 % classification accuracy and operate in a real-time environment.

Dataset Details

The dataset contains a total of 102150 images split into a training set of 22424 images and a testing set of 79726 images. Here is a sample of the dataset images:

C3-texting C6-drinking C9- Talking to the passenger C5- Operating the radio

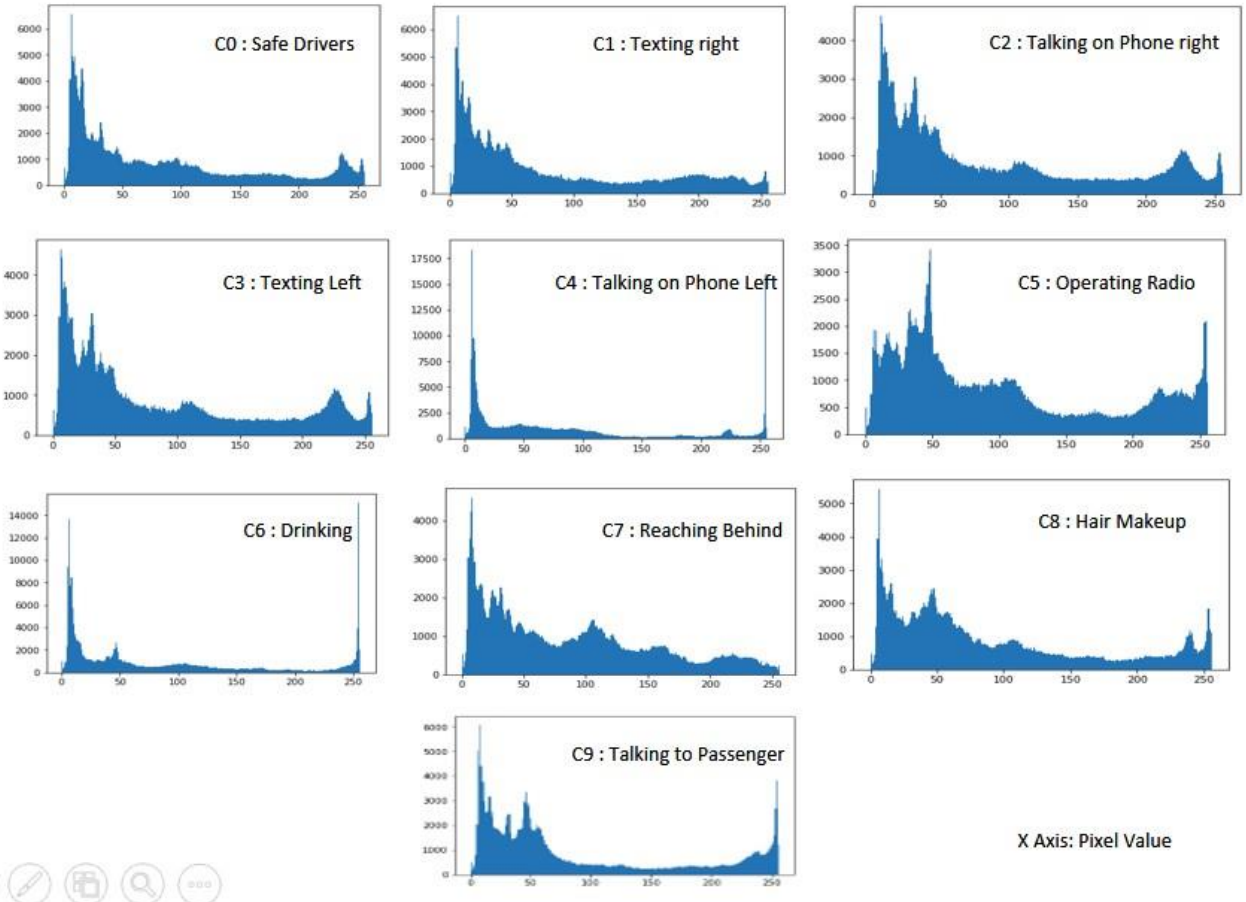
Learning

Our important learning while executing the project was

1. We had to use optimal sample size to evaluate different types of models. Using all of the input data was not possible.
2. Applying pre-processing techniques, especially converting to gray scale helped improve performance a lot. Also, helped attain accuracy at a faster pace.
3. Visualizing the images in between the layers, helped understand the emphasis on the section of images being learnt during the course of training.
4. Regular machine learning models should be analyzed for initial understanding before using neural network models and also can be ensembled for better accuracy.

Dataset Exploration

Pixel Intensity (Gray Scale Images):

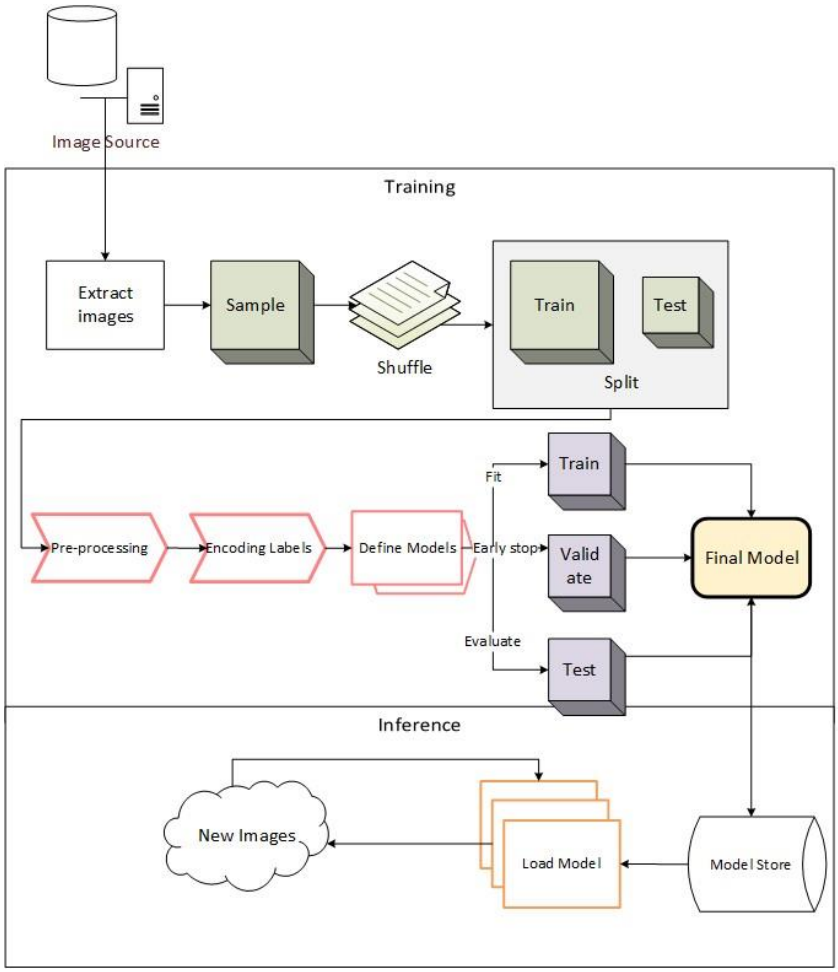


Overview of the final process

We attempted to solve the problem by using two different approaches.

1. By developing our own custom model
2. By using multiple pre-trained models and choosing the best from those

The goal is to arrive at a model to achieve lowest log loss and best accuracy possible, with the selected samples. The actual result could be visually observed by looking at the predictions given by the chosen models for few images that are unseen by the model.



Approach -1:

For feature extraction, convolution layers are being used for image recognition and then functional approach of using dense layers and max pool layers to create and train a model which will help us classify into one of the ten types.

We developed custom code to try multiple combinations of convolution and dense layers. 9 models were generated and trained for varying number of samples.

The best model resulted in test accuracy of approximately 96%, which was achieved after applyi ng image pre-processing and regularization techniques.

1. Images were converted to Gray scale for faster execution. This also enabled including mo re number of images for better and faster prediction. For our problem statement, there is l ess emphasis on information from color, hence converting to Gray scale seemed to be ide al.

2. DropOut - Dropout is an efficient way of reducing overfitting by randomly dropping out / ignoring some neurons. We have applied standard dropouts across all convolution layers.
3. Batch Normalization - Batch normalization helps to improve the performance and stabilit y of neural networks by explicitly forcing the activations through a layer of network to fo llow a unit Gaussian distribution [6]. It reduces strong dependence on weight initializatio n, improves gradient flow through the network as well as allows higher learning rates. In our work, activations of all convolutional layers are normalized.

Approach -2:

Transfer learning is the idea of using a CNN model pre-trained on a large dataset as an initialization. It gave us a significant boost in terms of speed and performance. For each model we tried, we only modified the last FC layer to output 10 class predictions instead of 1000 or more. We then use our own training set as the input images to train the whole neural network. The below pre-trained models have been trained for the distracted driver image set. The models load a set of weights pre-trained on ImageNet.

1. VGG 16 and VGG 19
2. AlexNet
3. ResNet50
4. MobileNet

Following are the observations from each model.

VGG 16 and 19:

The architecture of VGG is characterized by its simplicity using 3X3 convolution layers stacked on top of each other in increasing depths.

The major drawbacks observed with VGGNet:

1. It is very slow to train.
2. The network architecture weights themselves are quite large in bandwidth.

Due to its depth and number of fully-connected nodes, VGG is over 533MB for VGG16 and 574MB for VGG19. Also, we could observe that for the image sample provided, the networks either could not be adequately trained or did not give a good accuracy for each class. This could be because of the sample size we had chosen.

These models resulted in varying accuracies and predictions for every run and hence were not reliable for our case.

ResNet50:

ResNet50 is a 50 layer Residual Network. ResNet does subtraction of feature learned from input of that layer using shortcut connections (directly connecting input of nth layer to some (n+x) th layer. It has proved that training this form of networks is easier than training simple deep convolutional neural networks and also the problem of degrading accuracy is resolved.

For our image set, we could observe the best accuracy and prediction using ResNet50 pretrained model. The model training was faster in comparison to VGG.

MobileNet:

MobileNet is an architecture which is more suitable for mobile and embedded based vision applications where there is lack of compute power. This architecture uses depthwise separable convolutions which significantly reduces the number of parameters when compared to the network with normal convolutions with the same depth in the networks. This results in light weight deep neural networks.

By using depthwise separable convolutions, there is some sacrifice of accuracy for low complexity deep neural network

For our set of images, the accuracy was average using this model.

AlexNet:

AlexNet is relatively simpler model with less number of convolution and fully connected layers. This helps to quickly train the model. AlexNet is designed to be used to execute in parallel in multiple GPUs. Since it uses Relu instead of Tanh to add non-linearity. It accelerates the speed by 6 times at the same accuracy theoretically. Use dropout instead of regularization to deal with overfitting

For our image set, AlexNet model seemed to train the fastest. However, the test accuracy was bit jittery for different runs.

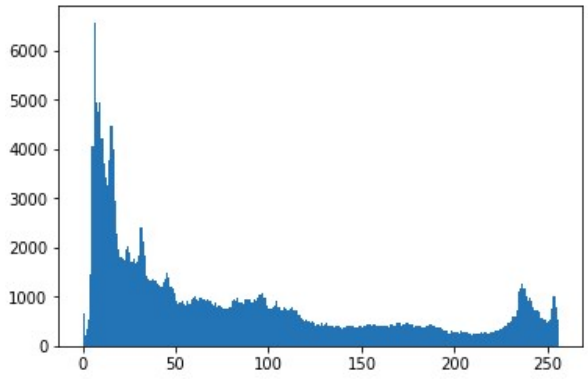
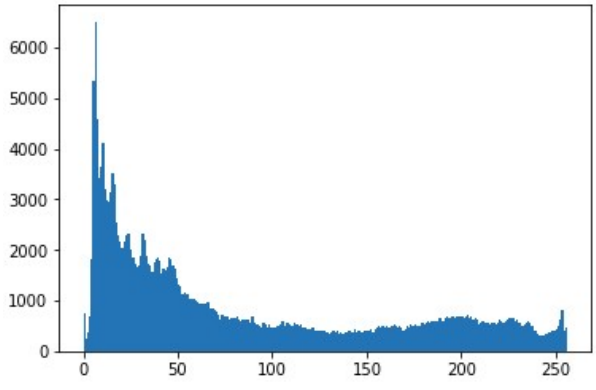
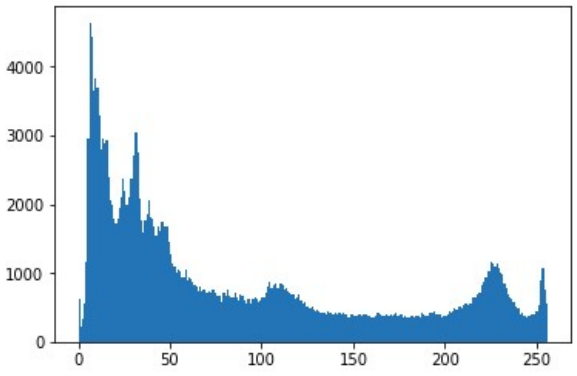
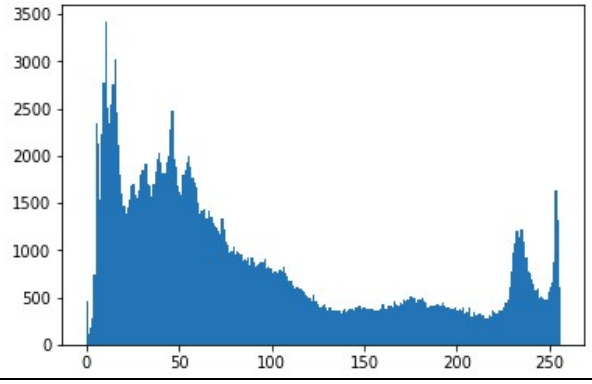
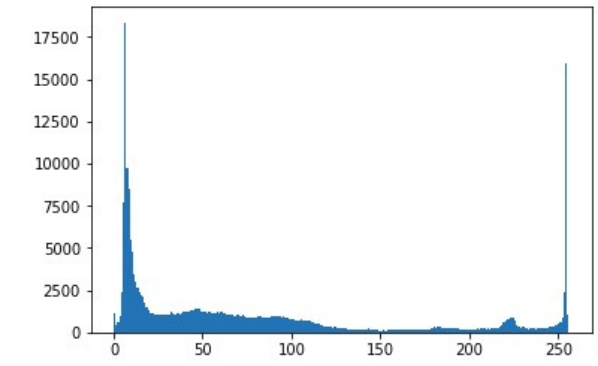
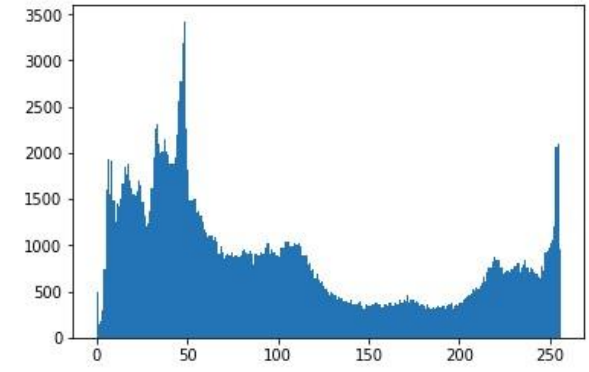
Approach – 3:

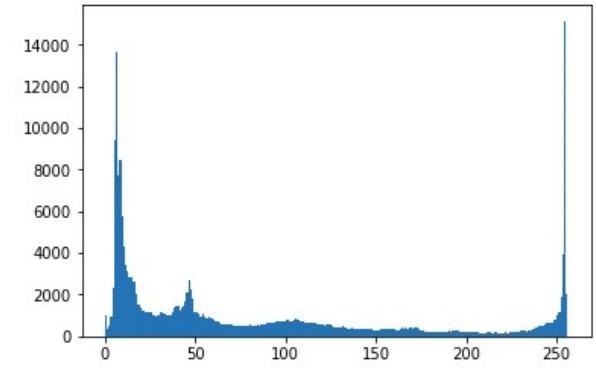
Value addition: In addition, we had also tried using machine learning and ensembling techniques, after extracting features. For classifier boosting, SVM is used as an alternative to softmax to enhance generalization ability CNN works as a trainable feature extractor and SVM performs as a recognizer.

Salient Features of Data:

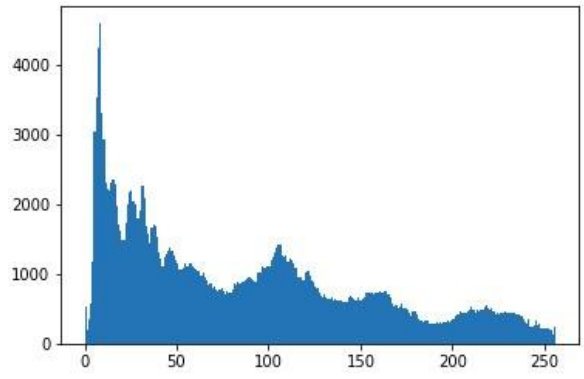
The distribution of images in various classes is mentioned in the above section. On analyzing random images, the visibility and brightness seems optimal (though bit on the dark side) for images in different classes. Following are histograms of sample images from each category.

c0: safe driving	c1: texting - right

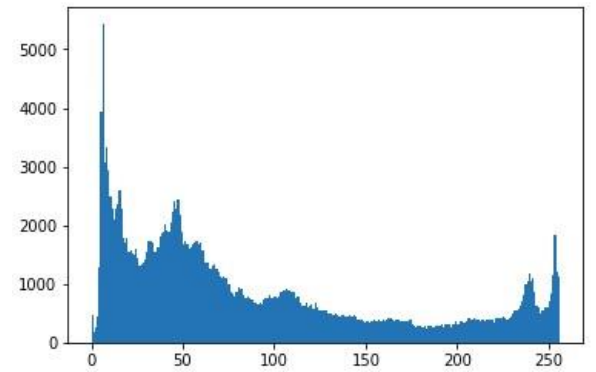
	
c2: talking on the phone - right	c3: texting - left
	
c4: talking on the phone - left	c5: operating the radio
	
c6: drinking	c7: reaching behind

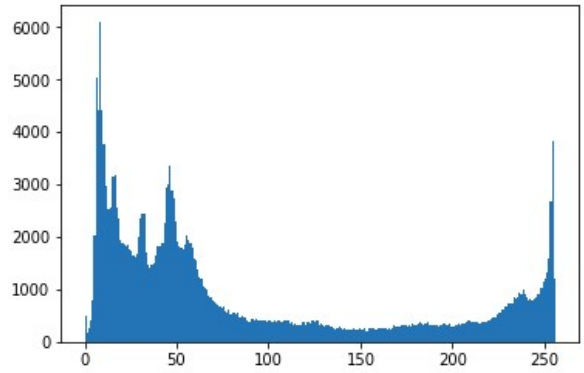


c8: hair and makeup



c9: talking to passenger





Data Pre-processing

Two main Techniques Normalization and Augmentation (mirroring, rotation, scaling, and Color modifications) have been considered for pre-processing.

The purpose is to correct the deficiencies that may damage the learning process, such as omissions, noise and outliers and adapting the data to simplify and optimize the training of the learning model. However, high abstraction capacity of CNNs allows them to work on the original high dimensional space, which reduces the need for manually preparing the input

Data augmentation increases the volume of the training dataset by applying several transformations to the original input. However since we had adequate samples in acceptable quality for the sample size used for training. This technique could be used when higher computing capacity is available.

The major pre-processing applied to the samples were to resize, normalize and convert to gray scale in case of custom model.

Step by step walkthrough of solution

Approach -1

Custom Models have been used for the prediction. Both the Convolution and Max_Pooling Layers have been listed on our own.

Grid Search for the Convolution and Denser Layers combinations are not available in Keras. Hence, we have developed a custom code that could run multiple variations and combinations of the Convolution and Dense Layers.

Initially the channels used was very low and as the number of channels were increased, we could see an improvement in accuracy. Below are couple of the models tried.

Convolution Layer – 1:

layer_size	c_filter_no	c_filter_dim	c_stride_dim	activation
480	32	3	3	relu
158	64	3	3	relu
50	128	3	3	relu
14	256	3	3	relu

Dense Layer -1:

layer_size	activation	drop_prob
20	relu	0.1
30		
30	relu	0.1
10	relu	0.1
	softmax	0.1

The above combination did not provide satisfactory accuracy.

Convolution Layer -2:

layer_size	c_filter_no	c_filter_dim	c_padding_no	c_stride_dim	activation
224	96	3	0	2	relu
56	188	3	0	2	relu

14	256	3	0	1	relu
11	384	3	0	1	relu
8	768	3	0	1	relu

Dense Layer- 2:

layer_size	activation	drop_prob
4500	relu	0.1
2250	relu	0.1
1250	relu	0.1
600	relu	0.1
300	relu	0.1
150	relu	0.1
75	relu	0.1
30	relu	0.1
10	softmax	0.1

This combination provided an overfit on training and 97% accuracy on test.

Convolution Layer- 3:

layer_size	c_filter_no	c_filter_dim	c_padding_no	c_stride_dim	activation
224	96	3	0	2	relu
56	188	3	0	2	relu
14	256	3	0	1	relu
11	384	3	0	1	relu
8	768	3	0	1	relu

Dense Layer- 3:

layer_size	activation	drop_prob
16000	relu	0.1
8000	relu	0.1
4000	relu	0.1

2000	relu	0.1
1000	relu	0.1
500	relu	0.1
250	relu	0.1
125	relu	0.1
60	relu	0.1
30	relu	0.1
18	relu	0.1
10	relu	0.1
	relu	0.1
	relu	0.1

For the above combination, learning Rate was quite low. The train accuracy was 95% and Test Accuracy was 94%.

From the observations, the second model is the best.

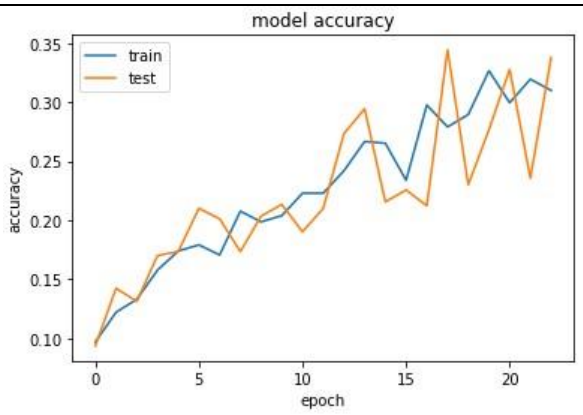
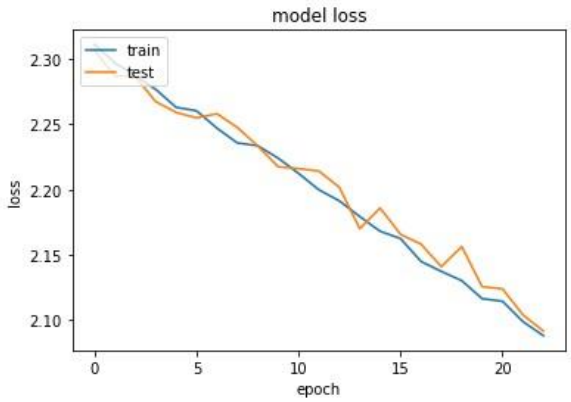
Approach-2:

Similar sample and hyperparameter were applied for various pre-trained models and the observations are as below.

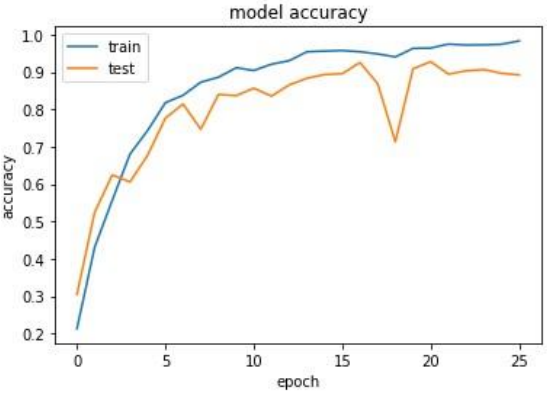
Model	No. of Samples	Batch Size	No. Of Epochs	Optimizer	Results	
VGG16	3000	32	25	SGD	Accuracy Score Train – 1.000 Test - 0.9622	Loss Train - 0.0011 Test - 0.1651
VGG19	3000	32	25	SGD	Accuracy Score Train – 0.3100 Test - 0.3377	Loss Train - 2.0878 Test - 2.0914
ResNet50	3000	32	50	adam	Accuracy Score Train – 1.0000	Loss Train - 5.0345e-05
					Test - 0.9677	Test - 0.1149

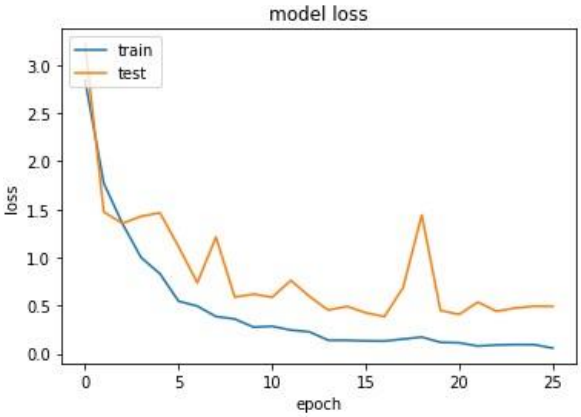
MobileNet	3000	32	50	adam	Accuracy Score Train – 0.6214 Test - 0.5822	Loss Train - 0.8248 Test - 1.0023
AlexNet	3000	32	50	adam	Accuracy Score Train – 0.9833 Test - 0.8922	Loss Train - 0.0596 Test - 0.4927

Accuracy and Loss:

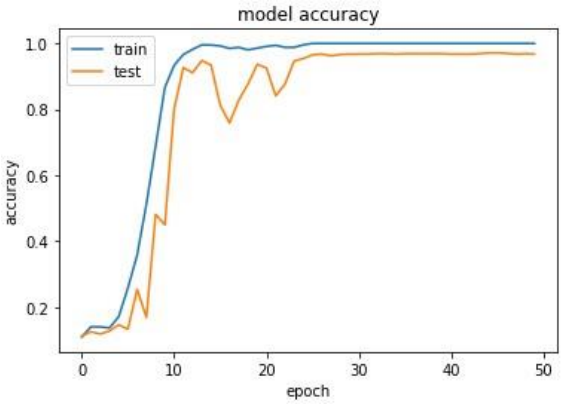
VGG	
	

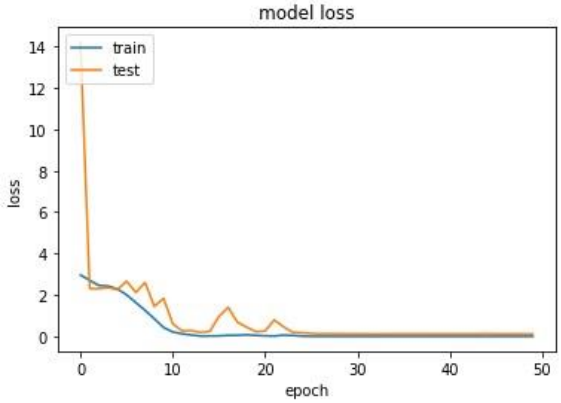
AlexNet



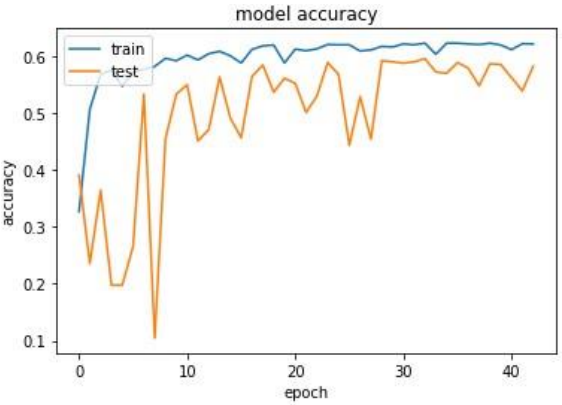


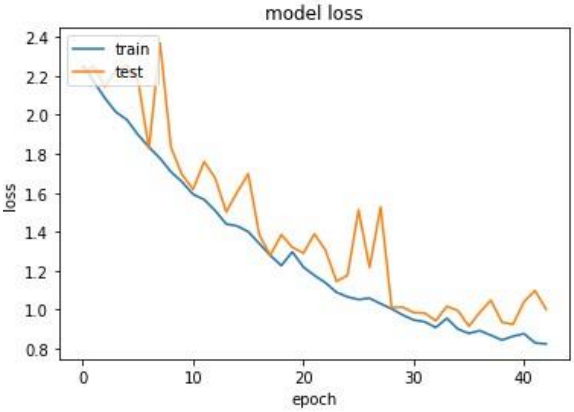
ResNet50





MobileNet





Approach – 3:

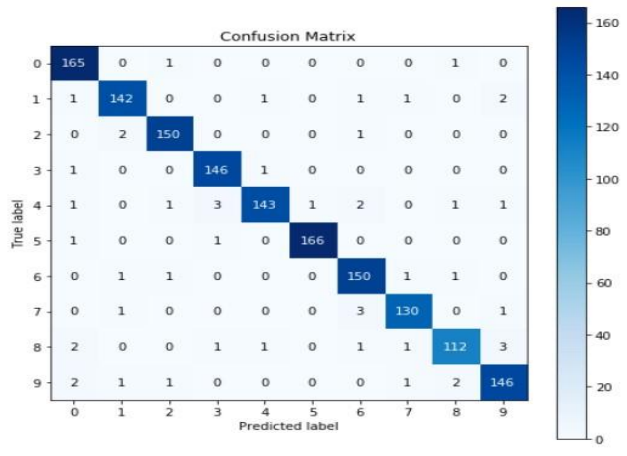
Following are the observations on using machine learning models and ensembling techniques.

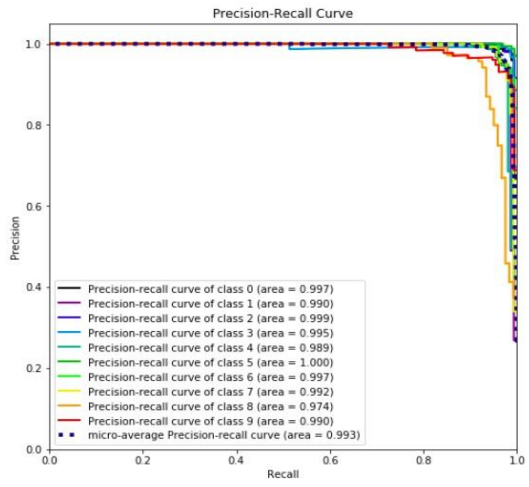
Method – 1: By directly feeding images in the form arrays, without using CNN layers.

Method – 2: By using CNN for feature extraction

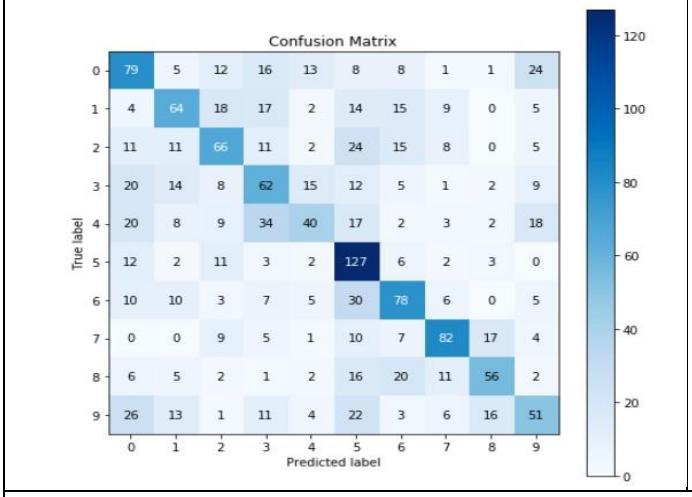
Model_Name	Model_Type	Training_Score	Test_Prediction_Score
Logistic Regression	Normal	1.000000	0.9712
Bagging Classifier	Ensemble	0.999200	0.8768
Voting Classifier	Ensemble	0.990933	0.9016
Random Forest Classifier	Ensemble	0.977067	0.8312
KNN Classifier	Normal	0.976000	0.9616
Naive Bayes Classifer	Normal	0.560800	0.4776
Decision Tree Classifier	Normal	0.465867	0.3928
Support Vector Machine Classifier	Normal	0.464000	0.4112
Ada Boosting Classifier	Ensemble	0.269600	0.2280

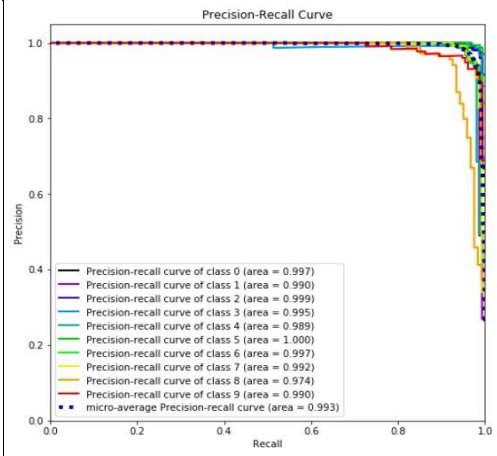
Logistic Regression



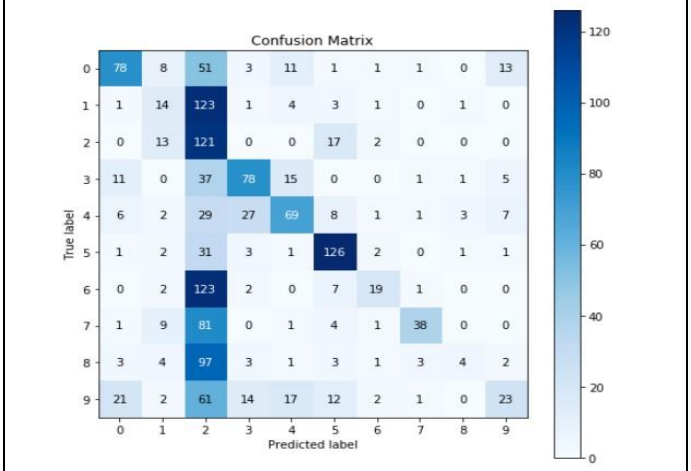


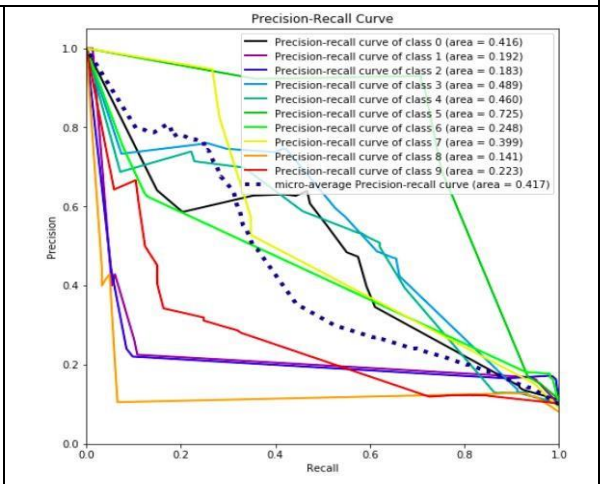
Naive Bayes Classifier



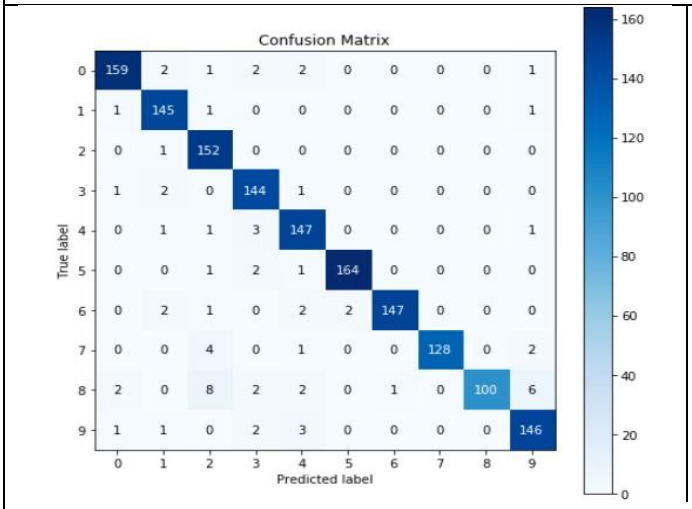


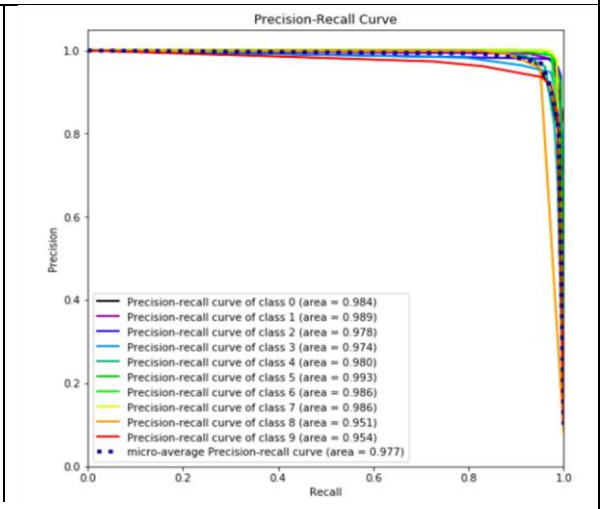
Decision Tree Classifier



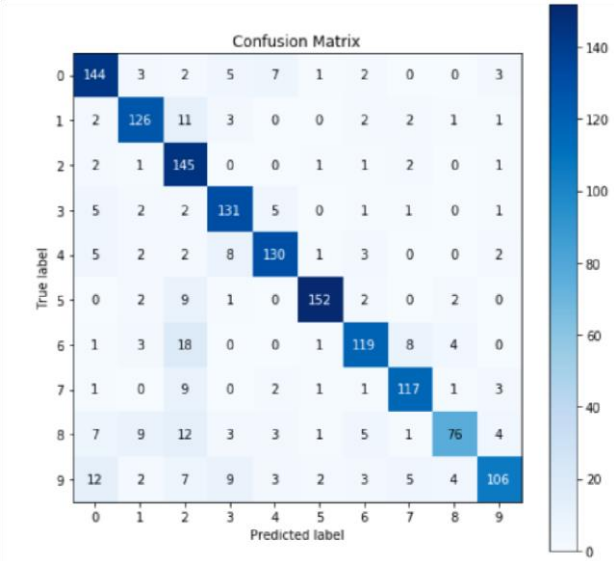


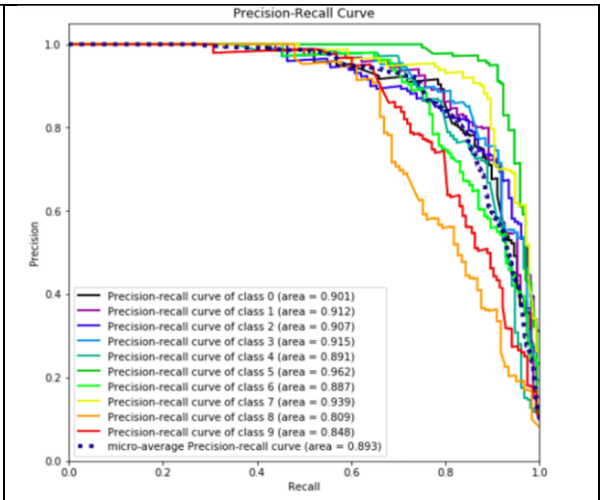
KNN Classifier



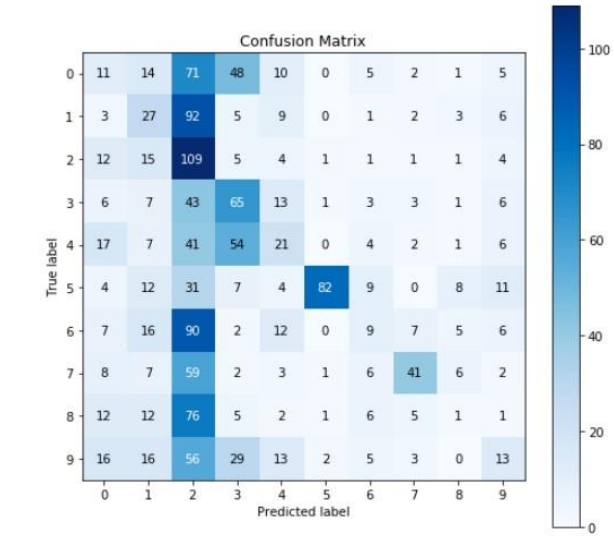


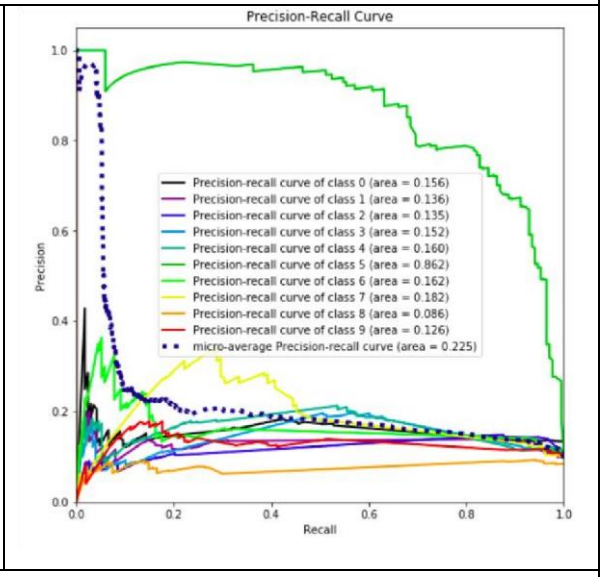
Random Forest Classifier



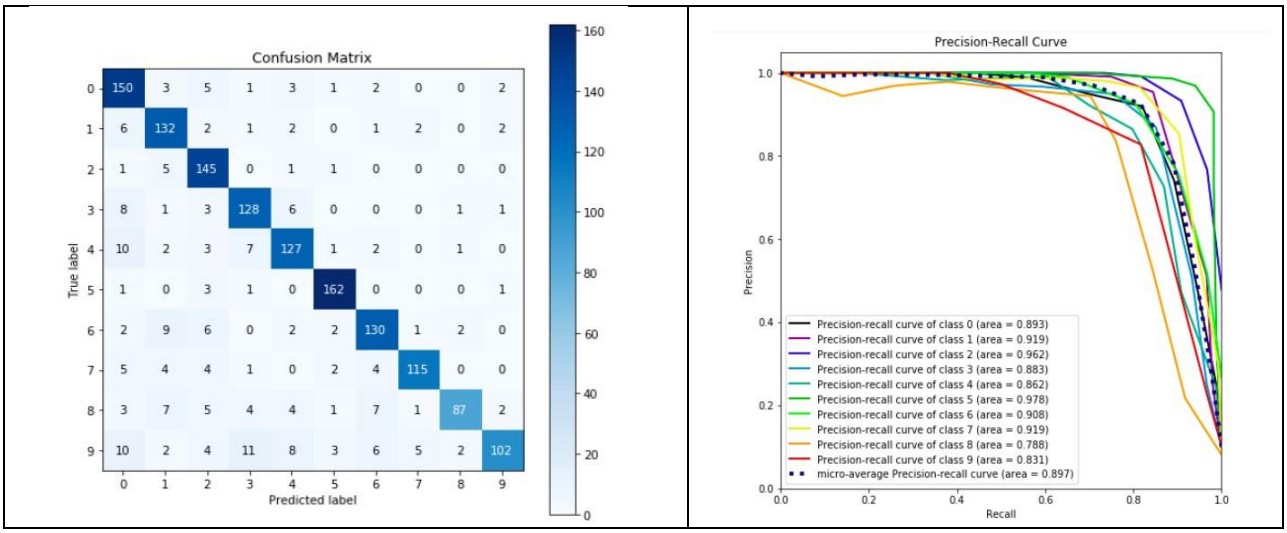


Ada Boosting Classifier





Bagging Classifier



Sample Predictions using Logistic Regression Model:

Method – 2: Results

	Best C Value	Best Gamma	Best Kernel
0	0.025	0.5	poly

3		0	Normal Driving
4		5	Operating the radio
5		1	Texting - right

Model evaluation

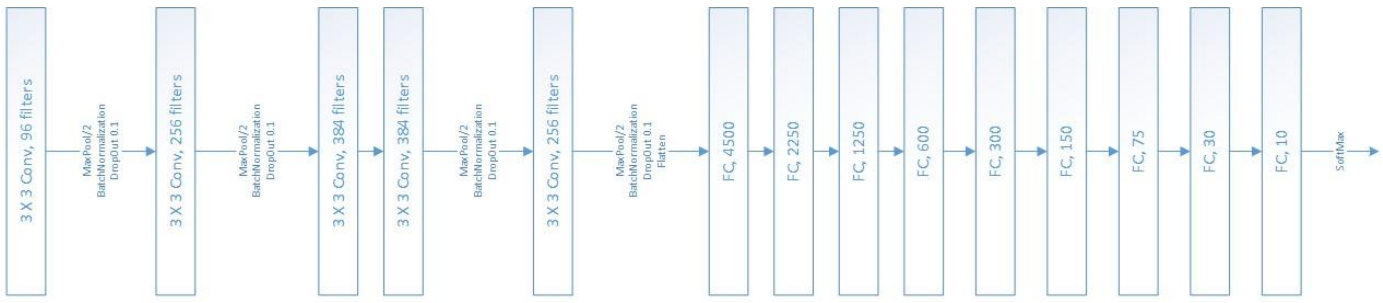
The best model we have arrived at from various trials is below Convolution Layers:

Layer Size	**No. of Filters**	**Filter Dimension**	**Stride Dimension**	**Activation**	**MaxPool Dimension**	**MaxPool Stride**
224	96	3	2	relu	2	2
56	188	3	2	relu	2	2
14	256	3	1	relu	2	1

11	384	3	1	relu	2	1
8	768	3	1	relu	2	1

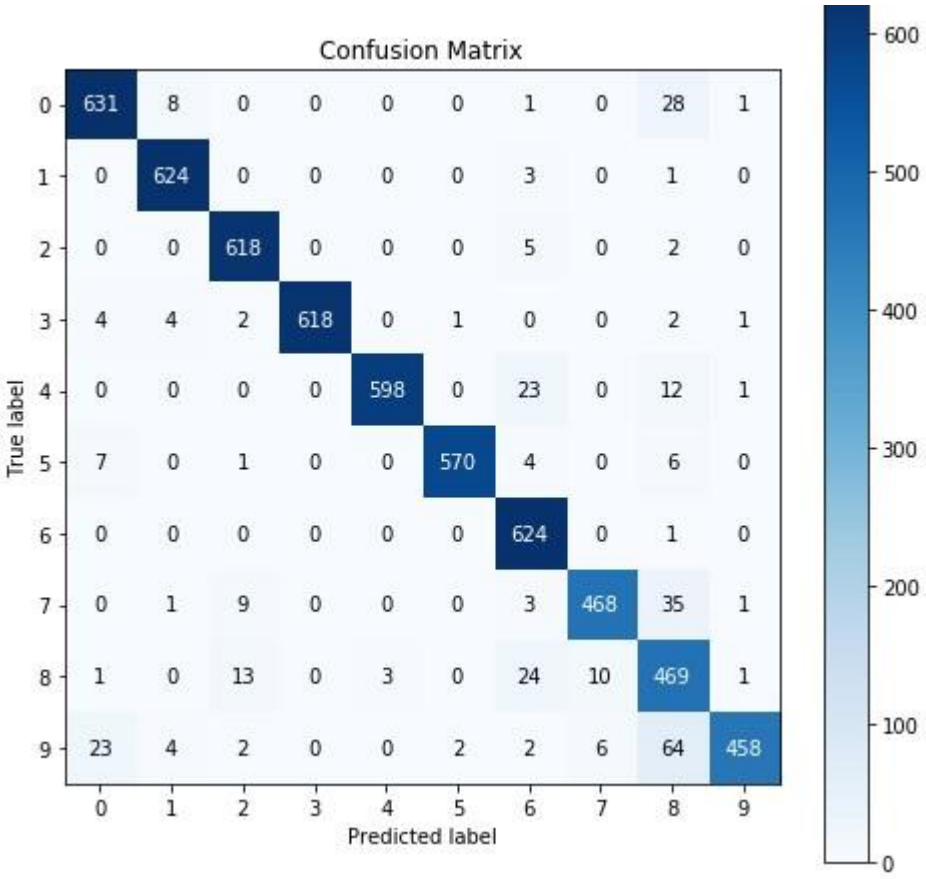
Dense Layers:

Number of Neurons	Activation	Drop Probability
4500	relu	0.1
2250	relu	0.1
1250	relu	0.1
600	relu	0.1
300	relu	0.1
150	relu	0.1
75	relu	0.1
30	relu	0.1
10	softmax	0.1

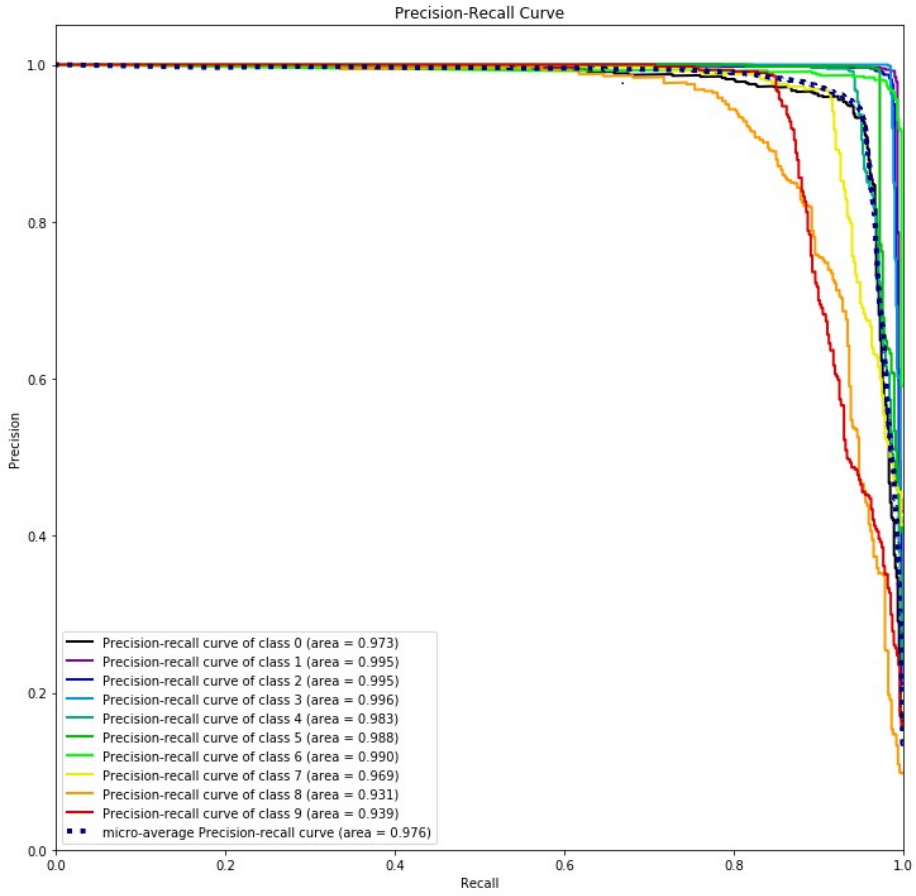


The results from this model are

Confusion matrix



Precision- Recall curve



Comparison to benchmark

This problem was a public challenge hosted on Kaggle by State Farm insurance company two years ago and many approaches were followed by the contributors to achieve better accuracy.

Some of the solutions were based on SVM, face and hand segmentation using RCNN, handcrafted features (HOG and BoWs), and quite a few approaches based on Deep CNN models which are pre-trained on ImageNet such as AlexNet, ResNet152, VGG-16.

The American University in Cairo, Egypt presented a model using a similar dataset that follows the same postures as kaggle. They used weighted ensemble of classifiers using a genetic algorithm to yield 96.4% classification accuracy. Considering this as our benchmark we ensued our try-outs implementing various stratagems. We accomplished 96% accuracy by using custom model which is little less than our benchmark.

We only used CPU systems for this project. If we would have had access to more computing resources, we could have tried to improve our results by implementing L2 regularization and ensemble techniques.

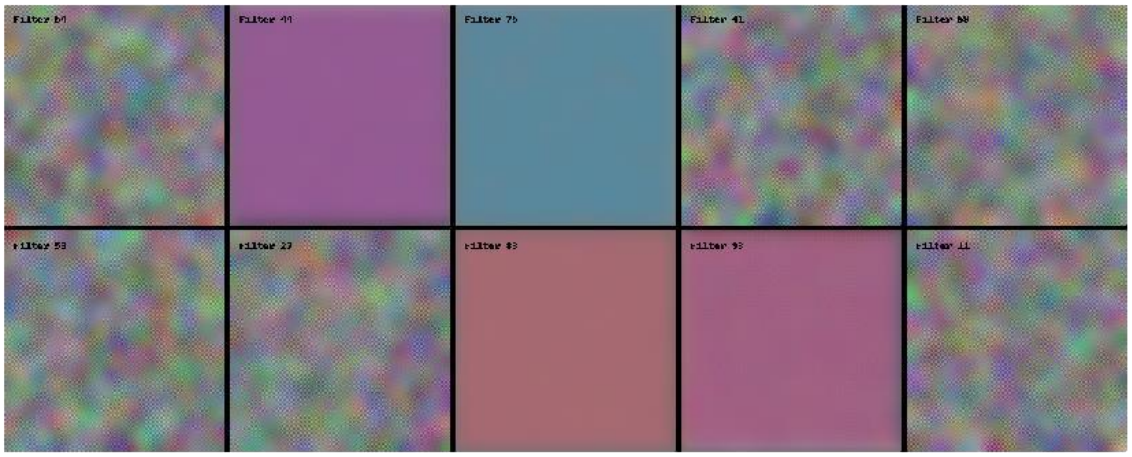
Visualization (s)

This Keras-Vis helps to visualize the activations of each unit of a neural network based image classifier as a graphical plot. The hidden layers use the ReLU activation function and the output layer uses the softmax activation function. Although the custom model trained works with about 97% accuracy in grayscale format and 87% accuracy in RGB and the primary concern of this experiment is to visualize the activations in each unit of a trained model.

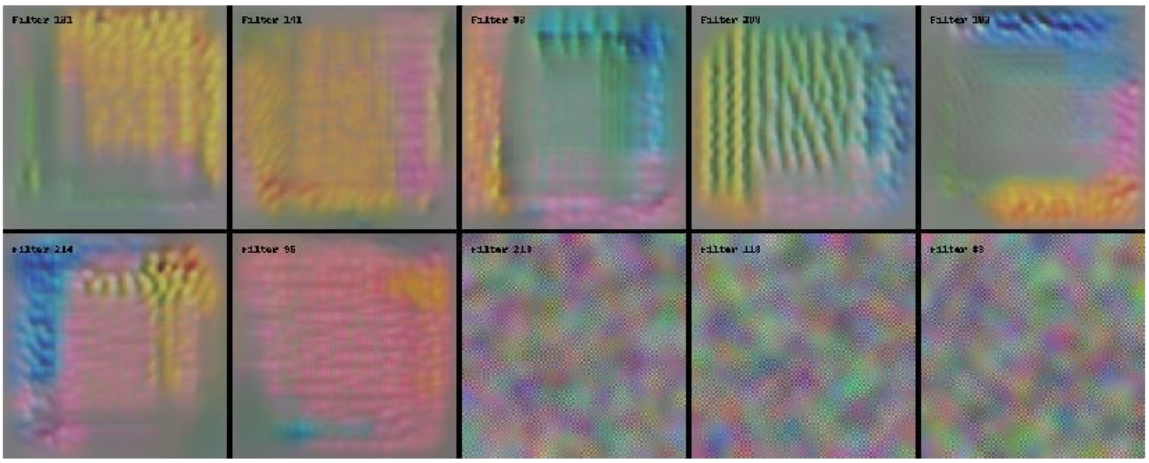
The below are the graphical plots of activations in each unit in each layer for every pixel component (i.e. R, G and B format). Each image is a visualization of what the activations in a specific unit looks like. For example, the first image for layer 1 is the visualization of the activations of the first unit in the first hidden layer.

Each pixel in an image below represents the activation in a specific unit for the corresponding pixel in the input image. The activation for each component (red, green and blue) for each pixel in each unit is computed separately. Then the activations of red, green and blue components in each pixel is combined and shown as a single pixel in an image below.

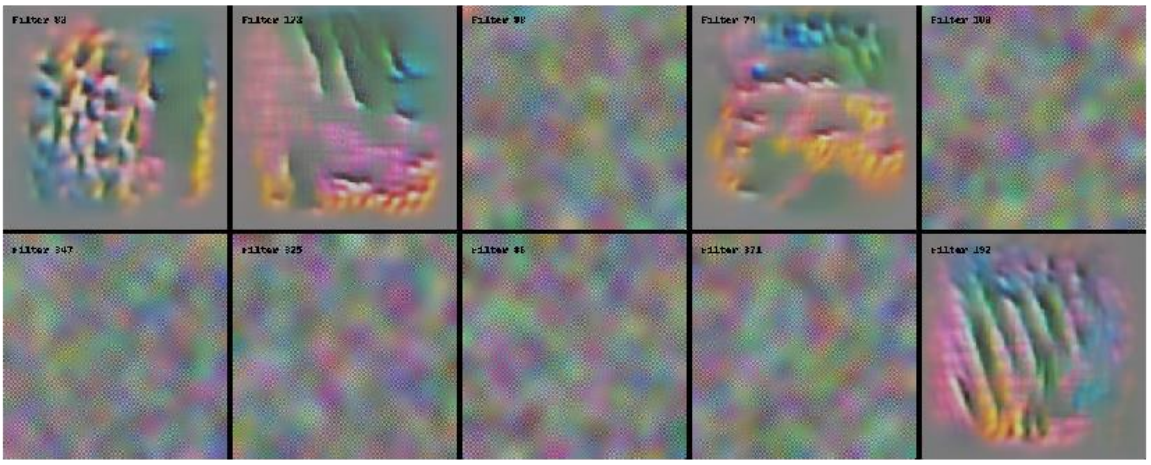
Layer 1 Activations - conv2d_1



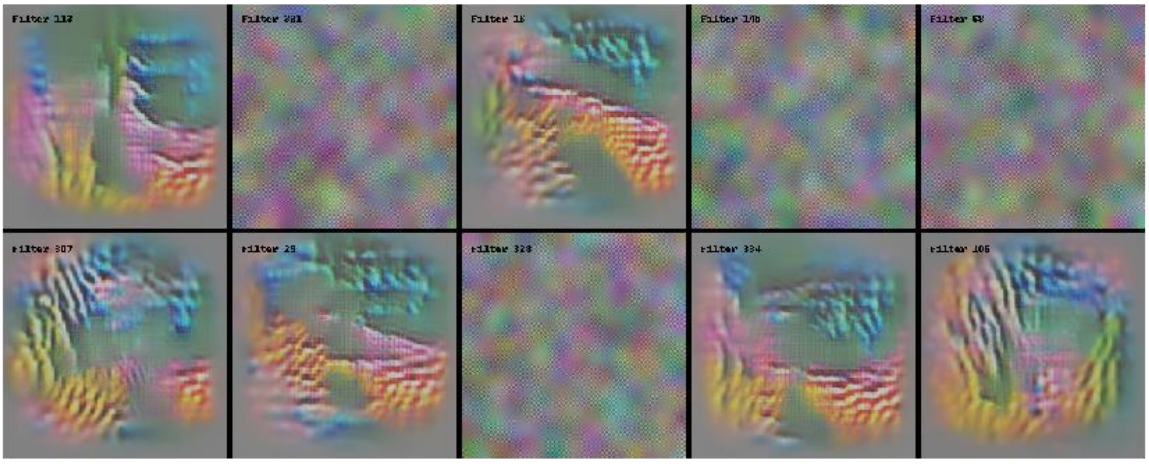
Layer 2 Activations - conv2d_2



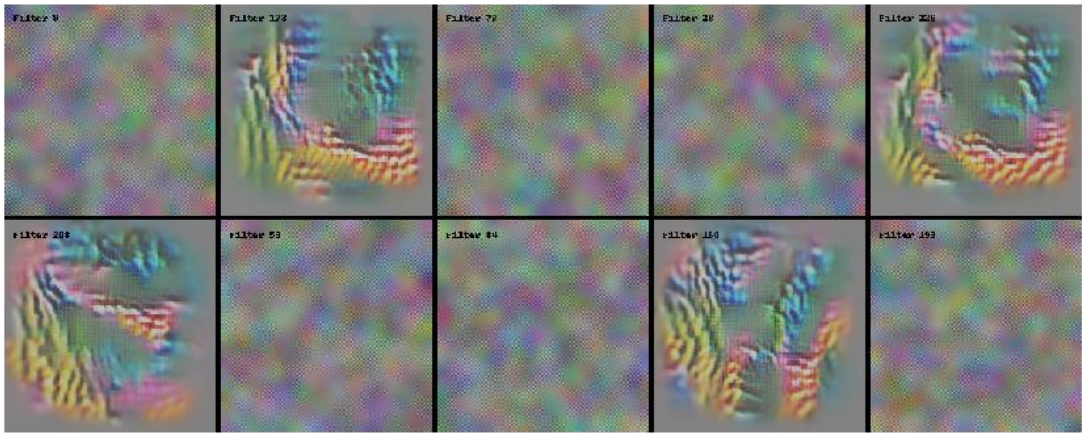
Layer 3 Activations - conv2d_3



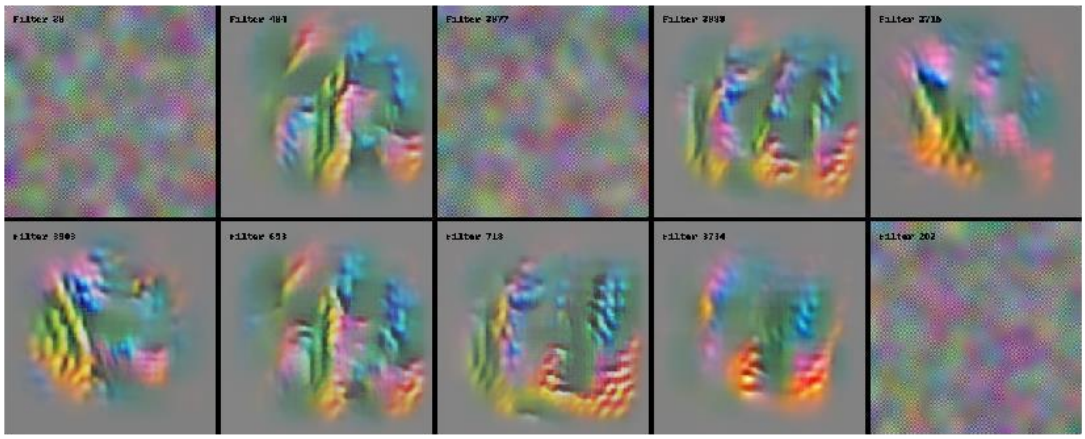
Layer 4 Activations - conv2d_4



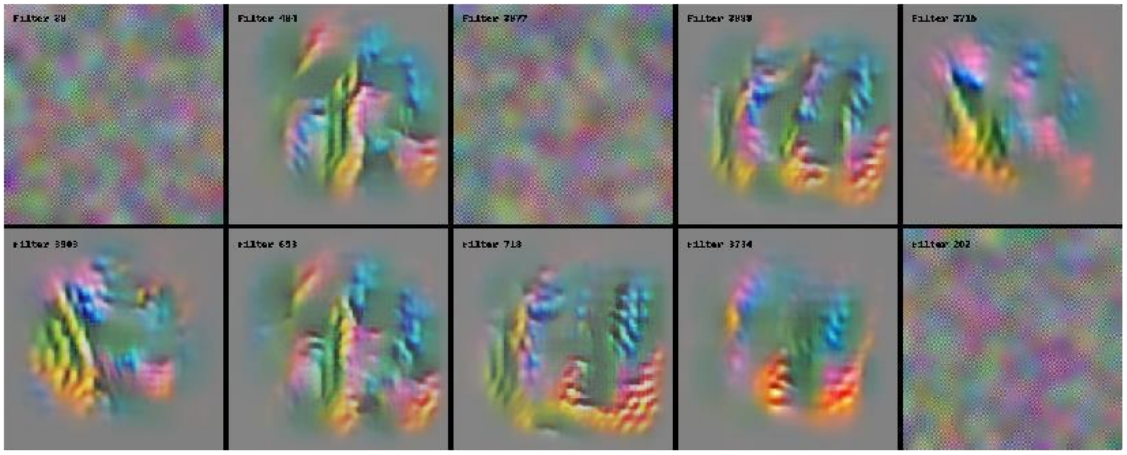
Layer 5 Activations - conv2d_5



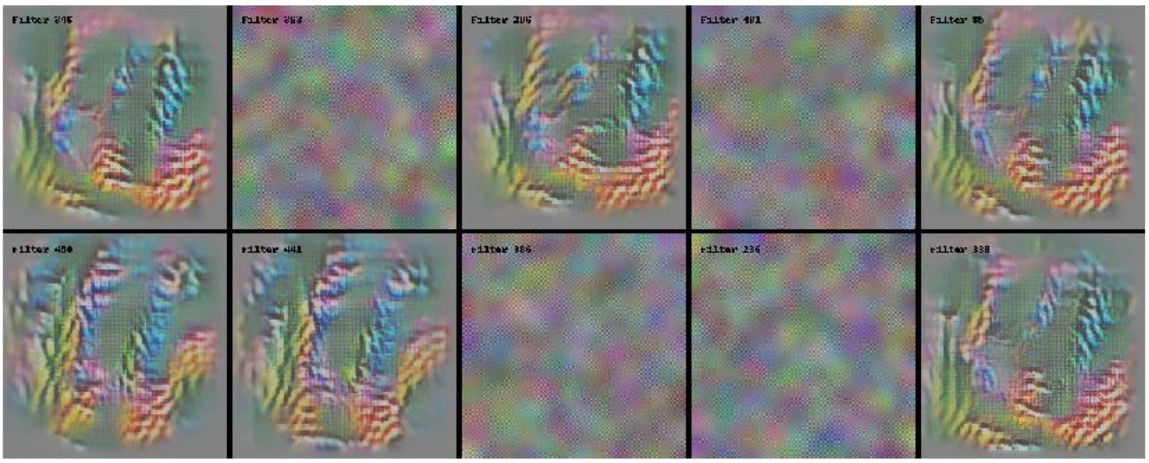
Layer 6 Activations - dense_1



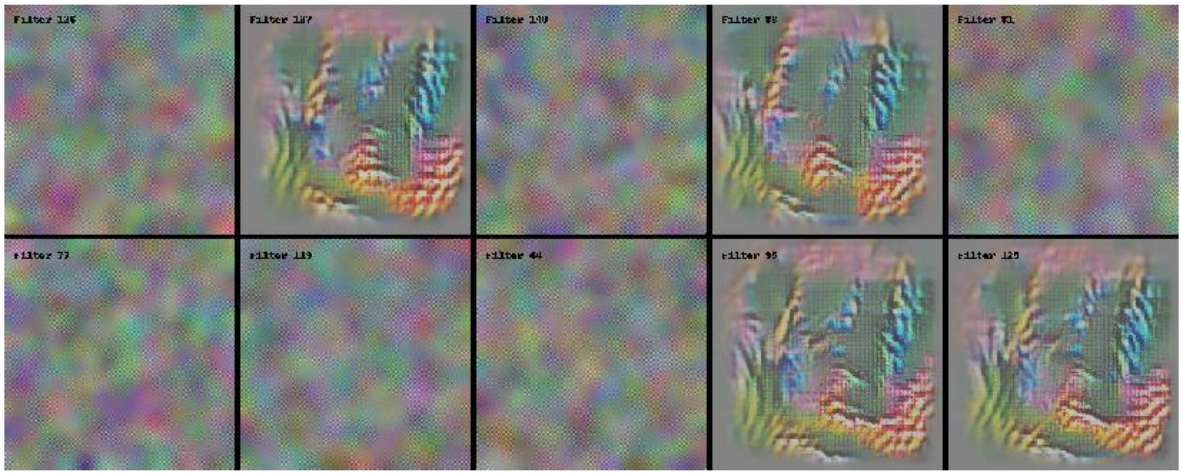
Layer 7 Activations - dense_4



Layer 8 Activations - dense_6



Layer 9 Activations - dense_9



Implications

The model we proposed can be used as real-time distracted driver posture estimation system and also can be used as an important system component in self-driving vehicles. Since, the custom model yields a very good accuracy of 97% with given limited number of train and test, we expect it to work better in production environment with 90-95% level of confidence when adequately trained. Further we recommend to use wide spectra of images from different countries to train and test the model.

Limitations

The challenging part of our project is that it is very easy to overfit our training model due to limited number of drivers in our dataset and also due to trivial dataset. Because of high similarities between two images with the same driver, it is more likely for the training model to over-emphasize on the drivers' features instead of their driving behaviors.

Since the test images are highly correlated and our training data set is small, it is beneficial to try data augmentation including color shifting and rotating to avoid overfitting problem, in real time systems.

Closing Reflections

Learning:

Visualizing the output is also important, once you can see the image, you have a better understanding whether the model is doing a reasonable job or not. Splitting of train and validation set such that images of drivers in the validation set are not in the training set.

Confusion matrix is a really nice visualization for small number of class classifications. Instead of running the entire 20k images, it's better to kick start with subset of data (around 20%).Starting with barebones model (without any convolutional layer) and then adding layers gradually and fine tuning will help to improve the model better in CNN.

Future Enhancement:

Another step that we would like to try in the future for better and safe roads is to implement this into a real time distracted driver detection device which will be able to detect clearly about the state of the driver in real time and indicate or warn the driver to drive safely. Which will be able reduce the number of death due to distracted driving significantly.

References:

Liu, Tianchi, et al. "Driver distraction detection using semi-supervised machine learning." *IEEE transactions on intelligent transportation systems* 17.4 (2015): 1108-1120.

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