State Farm Distracted Driver Detection

1.35 million people die in car accidents and most of the accidents happen because of drivers doing multiple tasks while driving. In other words, getting distracted. State Farm collected the data of several subjects in various situations(mentioned below) in a controlled environment.

Various Situations or class of images:

- 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

Business Understanding

State farm wants to make use of machine learning and deep learning techniques to predict the current state of the driver. We need to find the likelihood of what the driver is doing in each picture.

Data Description

- **imgs.zip** - zipped folder of all (train/test) images
- **sample_submission.csv** - a sample submission file in the correct format
- **driver_imgs_list.csv** - a list of training images, their subject (driver) id, and class id

Data Processing

- We are making use of ImageDataGenerator from keras package to do image augmentation, performed below operations:

  > - Shear image (0.2)
  > - Zoomed image (0.2)
  > - Horizontal flip
  > - Vertical flip

- We also used openCV for some minor image processing such as zooming in on drivers and resizing the image to 224x224.
- **Splitting of data:** Previously data was split randomly into test and train however after looking into the data we realized that same person's images were in both test and train sets with very slight variation in the images. Hence, there were chances of overfitting. So, we took different approach where splitting was done

based on subject. We used images of "p045", "p075", "p022", and "p012" subjects as test images and rest as train images.

- For traditional machine learning algorithm (random forest) we extracted features from the images and stored them in a data set. Following at the features extracted from the images:

  - Pixel values: Pixel vales were stored as on of the features.
  - Gabor filter: Gabor filter was used to analyze the texture of the images, it helps us to examine patterns in some particular direction. For example, presence of human subject in the image. Below is the mathematical equation of Gabor filter.

    $$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda}+\psi\right)$$

    where:

    - $x' = x\cos\theta + y\sin\theta and y' = -x\sin\theta + y\cos\theta.$
    - λ represents the wavelength.
    - θ represents the orientation.
    - ψ is the phase offset .
    - σ is the sigma/standard deviation.
    - γ is the aspect ratio.

  - Sobel filter: Sobel filter was used for edge detection. It is a matrix with certain values which upon convolution with the image pixel matrix highlights the edges present in the picture. Below are vertical and horizontal sobal filters.

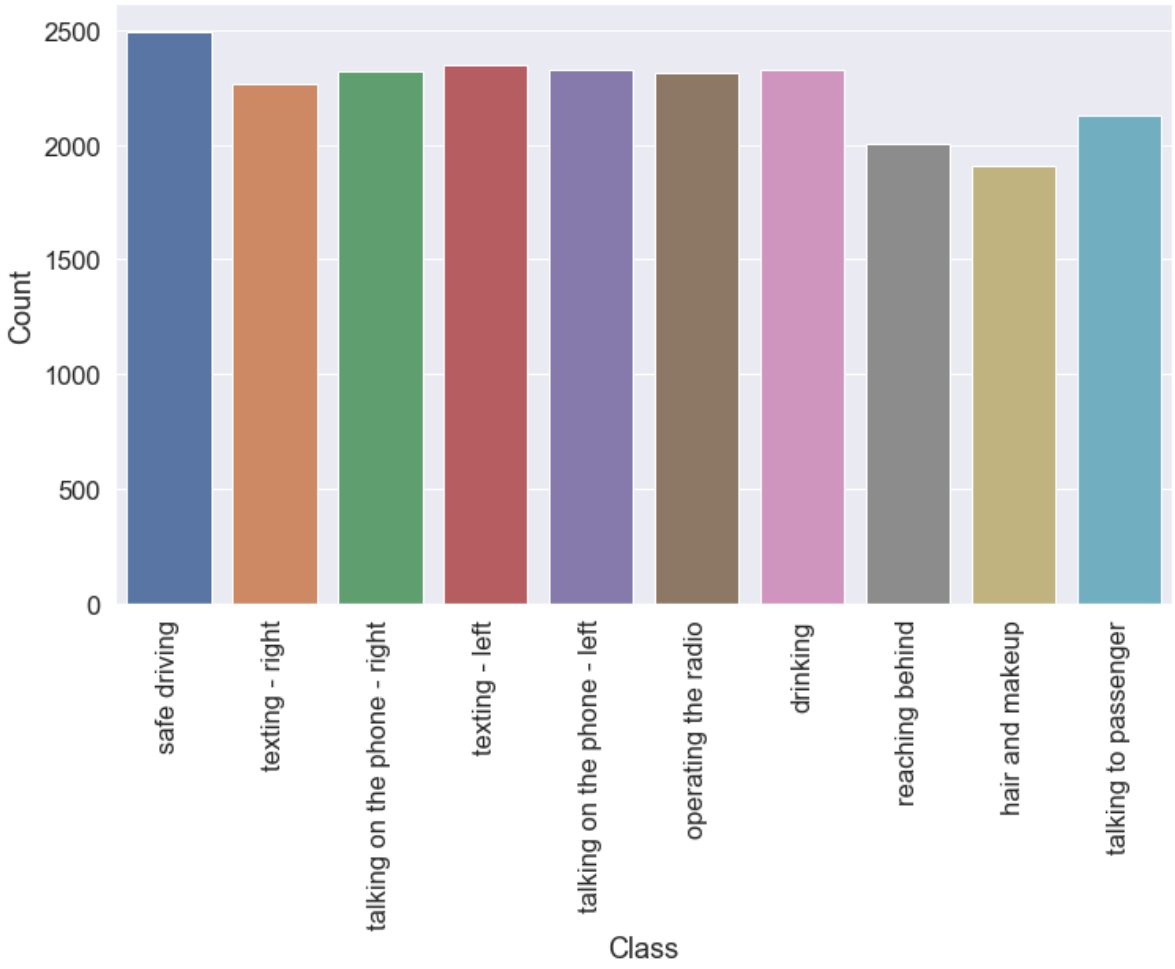
    $$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * \mathbf{A} \text{and} \mathbf{G}_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * \mathbf{A}$$

    where:

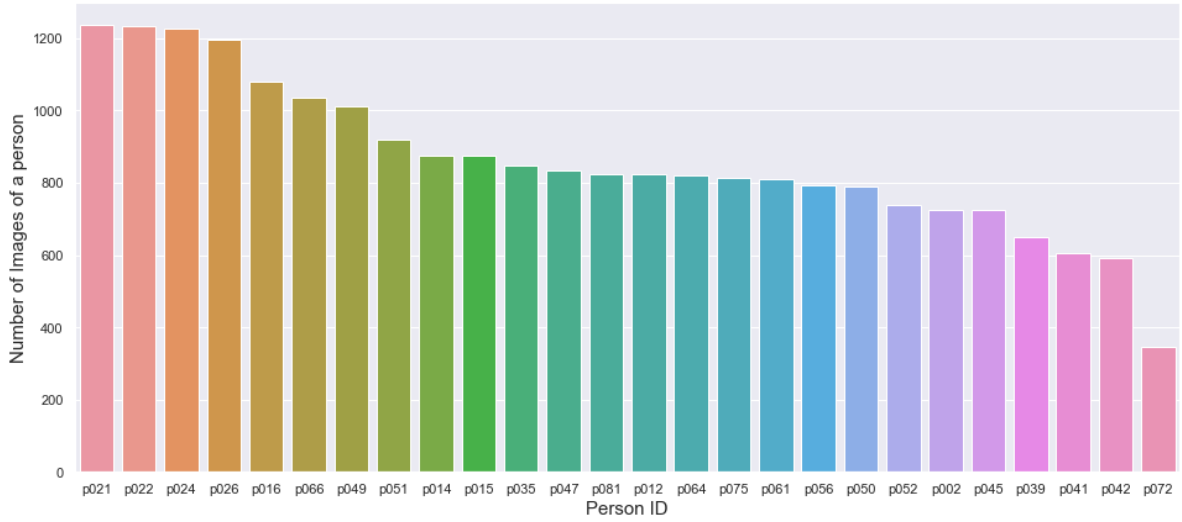
    - * is the convolution operation.
    - A is the original image.
    - G_x is the image with horizontal edges.
    - G_y is the image with vertical edges.

  - Final resultant image can be obtained by below equation: $\mathbf{G} = \sqrt{\mathbf{G}_x{}^2 + \mathbf{G}_y{}^2}$

Exploratory Data Analysis



From the above plot we can see that on an average all the classes have around 2000 images. Hence, the dataset is balanced.



From the above plot we can see some subjects have significantly more images than others. However this will not affect our model and results as we are dividing our dataset based on subjects, i.e., keeping "p045", "p075", "p022", and "p012" in test and rest in train set.

Modeling and comparing results

NOTE: For core modelling code refer ./src/modelling/model.py

Traditional Machine Learning Algorithm (Random Forest)

Why Traditional Machine Learning when CNNs are preferred on image data?

- CNNs work very well when there are tons of data. In our case we have 10 classes and only 2000 images on an average per class. So, we wanted to compare traditional machine learning algorithm's performance with CNN. However, feature extraction was taking extended period of time so, we end up using only 4000 images out of 18000 test images.

Why Random Forest?

- Random forest can implicitly carry out feature selection which makes it one of the better options when there are lots of features. It builds different decision trees by randomly selecting the subset of features.
- There is less to no effect of outliers on random forest. There are chances some of the images might have dirty pixels or while processing them we have introduced some errors. So, it will be taken care by binning of variables in Random Forest.
- Random forest can handle bias-variance trade-off well as it makes multiple decision trees and then takes average of all the trees, hence, averages the variance too.

Why Gabor Filter as feature?

- Gabor filter does a very good job in picking out loose edges present in the images. So, by applying gabor filter we will be able to extract the features like where the hands are, what might be the face orientation etc. For detailed explanation of gabor filter equation refer Data Processing Section above in this notebook.

Why Sobel Filter as feature?

- Sobel filters are mainly used for edge detection. In our case when edge detected by sobel is combined with gabor filter we can expect them to work well in detecting the hand, head and body position so that the right state of the driver can be predicted. For detailed explanation of the equation refer Data Processing Section above in this notebook.

```
Accuracy of Traditional machine learning approach on very limited data point
s is: 13.20%
```

From above result we can see we only managed to get 13.20% of accuracy, however, we only considered 22% of data points i.e., 4000 images out of around 18000 images. So, definitely model can be improved to a greater extent when more images are used. That can be tried in the future, for now to reduce the computation overhead we are only considering 4000 images for traditional machine learning model.

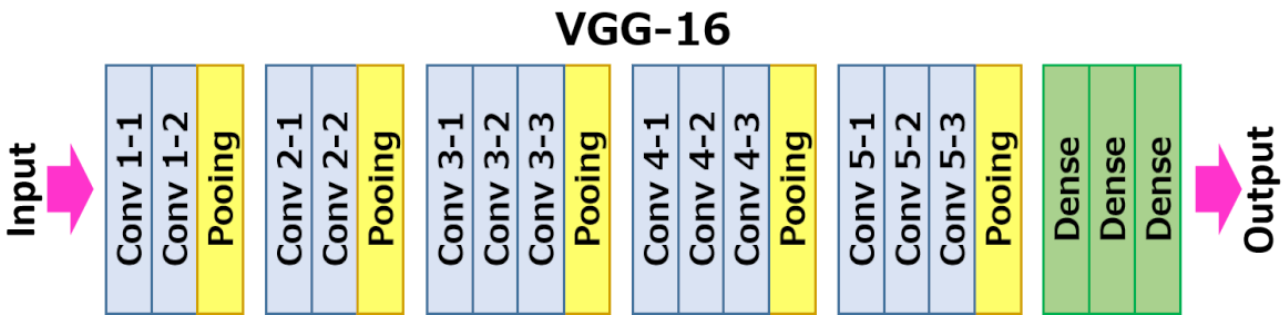
CNN Trained from Scratch (VGG16 architecture)

Why CNNs are good for image data?

- CNNs are fully connected feed forward neural networks.
- In deep neural networks usually there are lots of parameters to be tuned which can be very computation intensive and take considerable amount of time. That time can be reduced with CNNs.
- CNNs are good with large number of features and in images we have many features as each pixel is considered as a feature. CNNs make use of kernels or filters for dimensionality reduction. Sliding operation is performed using kernels and convolution operation is done this reduces the size of the image without losing much useful information hence, dimension reduced.

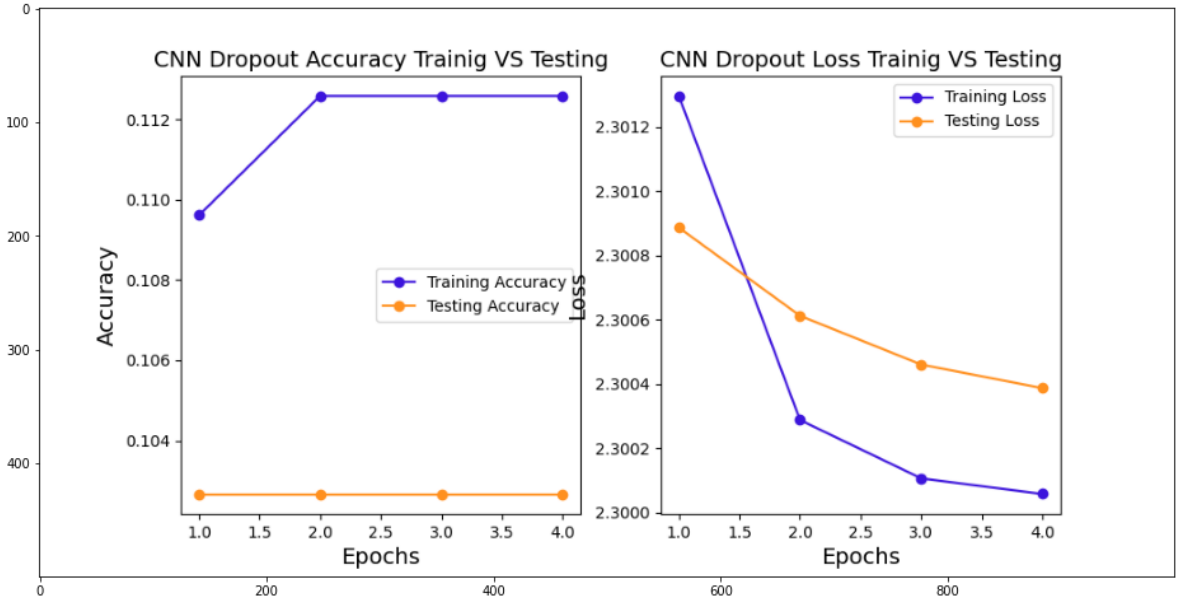
Why VGG16 Architecture?

- We have around 2000 images per class which is not a lot of data to properly train a very deep network and if we train a very shallow network it will not be able to pick up important features from the image and hence will perform poorly. VGG16 has 16 layers, it's not at all shallow at the same time it's not too deep, which suits our requirement. Below is the architecture of VGG16. (image source: https://neurohive.io/en/popular-networks/vgg16/ (https://neurohive.io/en/popular-networks/vgg16/))



Out[13]:

<matplotlib.image.AxesImage at 0x2007a3f5640>



From above accuracy and loss plot we can observe following points:
- Training accuracy is increasing but not by much. We are only achieving 11% accuracy, whereas, test accuracy is not improving at all.
- Training and testing loss is reducing but again not by much and loss is still high at the end of 4th epoch.
- Model is clearly underfit because it is performing poorly on both train as well as test set. We tried to improve it by increasing the complexity of the network by adding more filters, by adding more nodes, by increasing the number of epochs, by reducing the learning rate, with and without Dropout layers. Also tried various optimizers like adam, rmsprop, sgd, adagrad and activation functions like relu, elu, tanh, etc., but nothing seemed to be working so, we decided to move towards transfer learning using VGG16 pre-trained model, discussed next.

CNN Trained using Transfer Learning (VGG16 Pretrained Model)

Why transfer learning?

- As we saw previously, when we are training our network from scratch it is underfitting even after increasing the complexity of the network. So, we decided to try transfer learning because rather than assigning random weights to start with we are using weights from VGG16 pre-trained model and expecting it to work better as it will have prior knowledge(weights from imagenet dataset). This also helps in faster training of model as weights are not assigned randomly.

- VGG16 is a convolutional neural network model that was trained on imagenet dataset which contains around 14 million images belonging to 1000 classes. This model achieved around 95% accuracy on imagenet dataset. It a step forward on AlexNet model. AlexNet's Larger kernels were replaced by smaller 3x3 kernel in VGG16 and was trained on NVIDIA Titan GPUs for weeks.
- In addition to VGG16 pre-trained layers we added below layers:

Layer (type)	Output Shape	Param
img_input (InputLayer)	[(None, 224, 224, 3)]	0
vgg16 (Functional)	(None, 7, 7, 512)	14714688
conv2d_13 (Conv2D)	(None, 5, 5, 128)	589952
global_average_pooling2d (G lobalAveragePooling2D)	(None, 128)	0
dense_3 (Dense)	(None, 1024)	132096
dropout (Dropout)	(None, 1024)	0
dense_4 (Dense)	(None, 512)	524800
batch_normalization (BatchN ormalization)	(None, 512)	2048
dropout_1 (Dropout)	(None, 512)	0
dense_5 (Dense)	(None, 512)	262656
dense_6 (Dense)	(None, 10)	5130

Total params: 16,231,370

Trainable params: 1,515,658

Non-trainable params: 14,715,712

Why ReLU activation function?

- ReLU stands for Rectified Linear Unit, following is the equation of ReLU.
  $f(x) = x^+ = \max(0, x)$
  where, x is the input to a neuron.
  ReLU started getting popularity for feature extraction of image data and is argued to show biological motivation and also mathematically justified, because of these reasons ReLU is most widely used activation function in deep neural networks.

Why He Initialization?

- He initialization is good for activation functions like ReLU which are non-linear.

Why valid padding?

- Valid padding is used because pixels at the boundary are getting only one convolution operation with kernel hence, not much information can be extracted from them plus when we use lot of filters, chances are image will reduce so much that we will lose most of the information. To avoid this problem we are using zero padding (valid padding).

Why GlobalAveragePooling2D?

- In GlobalAveragePooling2D the pool size is set to the input size and it outputs the average of the pool. It is closely related to convolution structure. It makes close links between feature map and categories.

Why Dropout layer?

- Dropout layer helps in avoiding overfitting of model by deactivating some of the neurons to nullify their effect on decision making.

Why BatchNormalization?

- In neural network operation performed on the data is done in batches. So, normalization of data is done batch wise. It helps the model to avoid overfitting.

Why Stochastic Gradient Descent (SGD) optimizer?

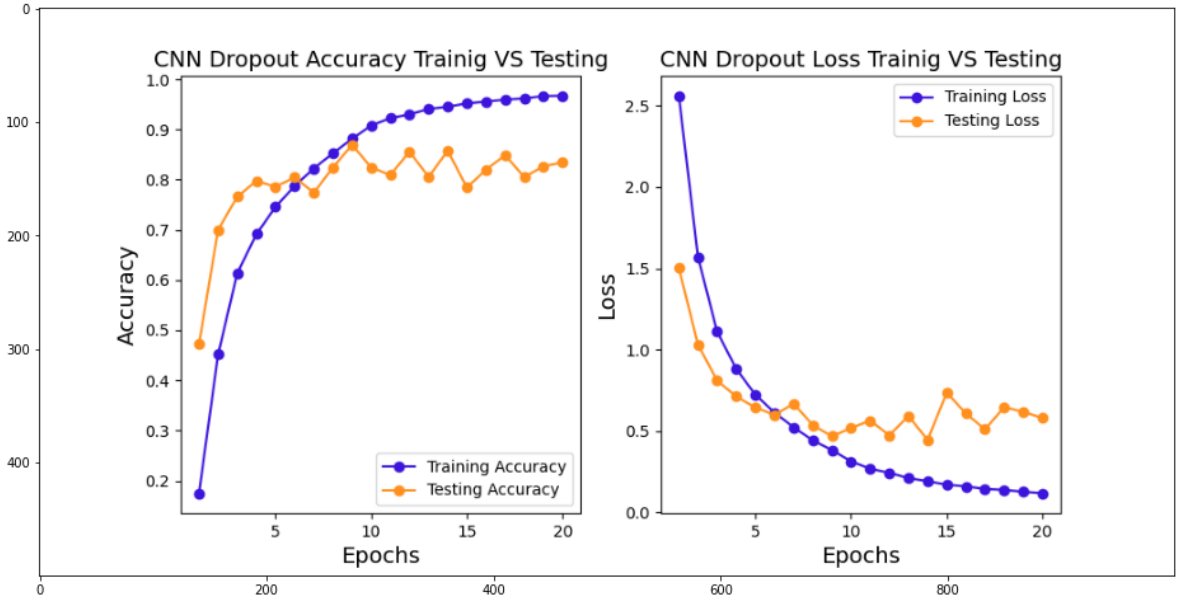
- Earlier preferred optimizer was Adam as it uses adaptive learning rate where as normal SGD keeps the same learning rate through out. However, while training it was observed that Adam was shooting very fast and model was overfitting. Hence, SGD was preferred to avoid overfitting.

Other important terms:

- **categorical_crossentropy:** As it is a multiclass classification problem we are using loss as categorical_crossentropy. It is the measure of error which the model would want to minimize.
- **accuracy:** As a performance evaluation metric, accuracy is being used. It is very interpretable and hence easy to compare multiple models especially when comparing machine learning and deep learning models.

Out[12]:

```
<matplotlib.image.AxesImage at 0x201e4829bb0>
```



From above plot we can infer below results:

- Training accuracy is 95% whereas test accuracy is 80%.
- Training loss is 0.1 where as test loss is 0.5.
- Clearly we can see that, this model is working very good as compared to other models we tested before. So, this model will be our final model and we will further test this model on test images that are provided

separately in the test directory.

Final model tested on test images

- 20 images randomly selected from the test folder that has over 70K images. These 20 images are stored in ./data/imgs/small_test directory.

From above grid we can see that most of the images are correctly classified(15). There are some misclassifications(5) that can be improved in the future models.

Conclusion and Future Scope

S.No.	Model	Accuracy
1	Traditional ML Algorithm (Random Forest)	13%
2	CNN VGG16 Architecture from Scratch	11%
3	CNN Transfer Learning (VGG16 Pre-Trained Model)	80%

From above table following key points can be inferred:

- CNN with transfer learning using VGG16 pre-trained model is performing the best as our model could use adjusted weights from the final layers of VGG16 pre-trained model which gave good learning starting point.
- CNN model trained from scratch performed the worst because it was underfitting this can be improved by making more complex model and trying different sizes of kernel.
- Random forest model can be improved to a greater extent by using all the images for feature extraction.
- Ensemble technique can also be used such as, using deep neural network for feature extraction and then applying traditional machine learning algorithm on top of it.

References

- https://en.wikipedia.org/wiki/Sobel_operator (https://en.wikipedia.org/wiki/Sobel_operator)
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- https://towardsdatascience.com/deep-learning-3-more-on-cnns-handling-overfitting-2bd5d99abe5d (https://towardsdatascience.com/deep-learning-3-more-on-cnns-handling-overfitting-2bd5d99abe5d)
- https://towardsdatascience.com/overfitting-vs-underfitting-a-complete-example-d05dd7e19765 (https://towardsdatascience.com/overfitting-vs-underfitting-a-complete-example-d05dd7e19765)