



# Task is Simple....

- Build a classification model to correctly identify what the driver is doing while driving the car.
- The driver could be:
- Insert the table related to class labels

# But Challenging...

- Technical Challenges

- A particular subject can only appear either in the training or the testing dataset

- Resource Challenges

- CNN model with millions of trainable parameters on a local machine was resource intensive and was taking hours to finish the model

# Our Solution....

- Technical Challenge
  - Use a pre-trained model – VGG16, VGG19, EfficientNetB0
  - Image Augmentation to add more variations to our dataset to make the model more generalizable
- Resource Challenge
  - Used Google CoLab to run our models

# Modeling Workflow

- Establishing a baseline score with a 2-layer CNN model
- Run iterations using the three pre-trained models to improve the log-loss on the testing dataset
- Parameters varied and investigated:
  - Number of nodes in the FNN
  - Number of hidden layers in the FNN
  - Regularization- dropout/l2
  - Learning rate for the ADAM optimizer
- For all the models, the best model was saved using a model checkpoint option in Keras

# Pre-Trained Models

- What is a Pre-trained Model?
  - A pre-trained model is a model created by some one else to solve a similar problem. We use this model as a starting point.
- Why use Pre-trained Models?
  - To “transfer” the learning from the pre-trained model to our model to avoid having to train our model from scratch
- How to use a Pre-trained Models?
  - Define the objective of our problem
  - Use a pre-trained model which was trained for a similar problem. For e.g. Image classification pre-trained model for an Image classification problem

# Pre-Trained Models and Transfer Learning

- Using a pre-trained model to our specific problem is called Transfer Learning
- Use of pre-trained models takes 3 different forms:
  - Feature Extraction:- Directly use the weights and architecture and apply that learning to our problem. The only modification that would be required in this case is changing the output layer depending on our class labels
  - Transfer Learning:- Use the weights and architecture of the convolutional layers and train the user-defined FNN layers
  - Fine-tuning:- Tweak the already trained convolutional layers and train the model

# Our Approach

- Transfer Learning using Pre-trained model
  - Since we did not have a large dataset to train on, we decided not to train the convolutional layers and set these layers to not-trainable in our model
  - Set up our own FNN architecture connected to the pre-trained convolutional architecture and train the datasets on this model



# Modeling Results

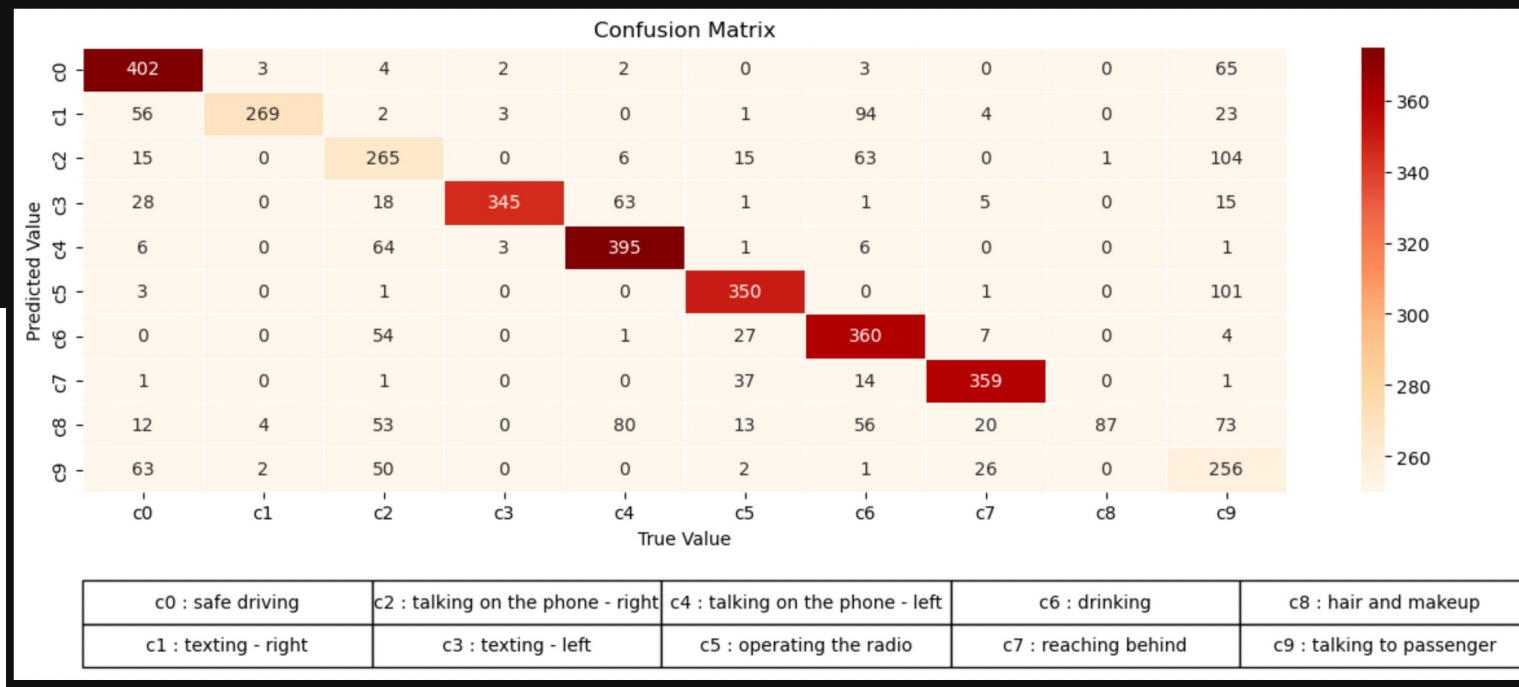
|   | Model                                 | Training Loss | Training Accuracy | Validation Loss | Validation Accuracy | Kaggle Testing Loss | Model Type     |
|---|---------------------------------------|---------------|-------------------|-----------------|---------------------|---------------------|----------------|
| 0 | base_model_kfold                      | 0.000         | 1.000             | 0.005           | 0.999               | 26.643              | Base-Kfold     |
| 1 | base_model_gkfold                     | 0.746         | 0.855             | 3.525           | 0.315               | 23.763              | Base-Gkfold    |
| 2 | best_model_vgg16_dropout_1024         | 0.193         | 0.937             | 0.929           | 0.690               | 0.731               | VGG16          |
| 3 | best_model_vgg16                      | 0.181         | 0.944             | 0.891           | 0.718               | 0.752               | VGG16          |
| 4 | best_model_vgg19_l2_4096_1024_adam_lr | 0.512         | 0.943             | 1.181           | 0.719               | 0.806               | VGG19          |
| 5 | best_model_vgg16_l2_1024              | 0.433         | 0.926             | 1.324           | 0.645               | 0.837               | VGG16          |
| 6 | best_model_vgg16_l2_4096_1024_adam_lr | 0.574         | 0.944             | 1.280           | 0.720               | 0.850               | VGG16          |
| 7 | best_model_EfficientNetB0_v2_base     | 0.090         | 0.984             | 0.949           | 0.686               | 0.857               | EfficientNetB0 |
| 8 | best_model_EfficientNetB0_v2_augment  | 0.205         | 0.952             | 0.983           | 0.693               | 0.878               | EfficientNetB0 |

- 1<sup>st</sup> model is the base model with usual train\_test\_split gave accuracy of 1 for both training and validation but a testing loss of 26.64
- 2<sup>nd</sup> model is the base model with Group Kfold train test split reduced the validation accuracy to 30% and improved the testing loss to 23.7
- Our best model performance with pre-trained model was for VGG16 model with a single hidden layer of 1024 nodes. The testing loss was 0.73

# Classification Report and Confusion Matrix

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| c0           | 0.69      | 0.84   | 0.75     | 481     |
| c1           | 0.97      | 0.60   | 0.74     | 452     |
| c2           | 0.52      | 0.57   | 0.54     | 469     |
| c3           | 0.98      | 0.72   | 0.83     | 476     |
| c4           | 0.72      | 0.83   | 0.77     | 476     |
| c5           | 0.78      | 0.77   | 0.78     | 456     |
| c6           | 0.60      | 0.79   | 0.69     | 453     |
| c7           | 0.85      | 0.87   | 0.86     | 413     |
| c8           | 0.99      | 0.22   | 0.36     | 398     |
| c9           | 0.40      | 0.64   | 0.49     | 400     |
| accuracy     |           |        | 0.69     | 4474    |
| macro avg    | 0.75      | 0.68   | 0.68     | 4474    |
| weighted avg | 0.75      | 0.69   | 0.69     | 4474    |

Class labels c8 and c9 have the lowest f1-score and c3 and c7 have the highest



# Mislabeled Prediction Analysis

## Mislabeled Predictions

Original label: talking on the phone - left  
Prediction :talking on the phone - right  
confidence :0.625



Original label: hair and makeup  
Prediction :drinking  
confidence :0.347



Original label: texting - right  
Prediction :drinking  
confidence :0.433



Original label: talking on the phone - right  
Prediction :talking to passenger  
confidence :0.688



Original label: safe driving  
Prediction :talking to passenger  
confidence :0.539



Original label: talking to passenger  
Prediction :safe driving  
confidence :0.557



Original label: texting - right  
Prediction :safe driving  
confidence :0.850



Original label: hair and makeup  
Prediction :drinking  
confidence :0.728



Original label: talking to passenger  
Prediction :safe driving  
confidence :0.443



Original label: talking to passenger  
Prediction :reaching behind  
confidence :0.449





# Mislabeled Prediction Analysis

Original label: reaching behind  
Prediction :operating the radio  
confidence :0.578



Original label: texting - right  
Prediction :drinking  
confidence :0.734



Original label: hair and makeup  
Prediction :drinking  
confidence :0.496



Original label: talking on the phone - right  
Prediction :drinking  
confidence :0.908



Original label: talking on the phone - right  
Prediction :drinking  
confidence :0.504



Original label: reaching behind  
Prediction :operating the radio  
confidence :0.406



Original label: hair and makeup  
Prediction :talking to passenger  
confidence :0.913



Original label: talking to passenger  
Prediction :safe driving  
confidence :0.871



Original label: hair and makeup  
Prediction :talking on the phone - right  
confidence :0.658



Original label: texting - right  
Prediction :drinking  
confidence :0.497



# Conclusions

- Use of pre-trained models significantly improved the predictions of the CNN model
- A CNN model using a VGG16 pre-trained model gave testing loss on Kaggle of 0.73