Distracted Driver Detection

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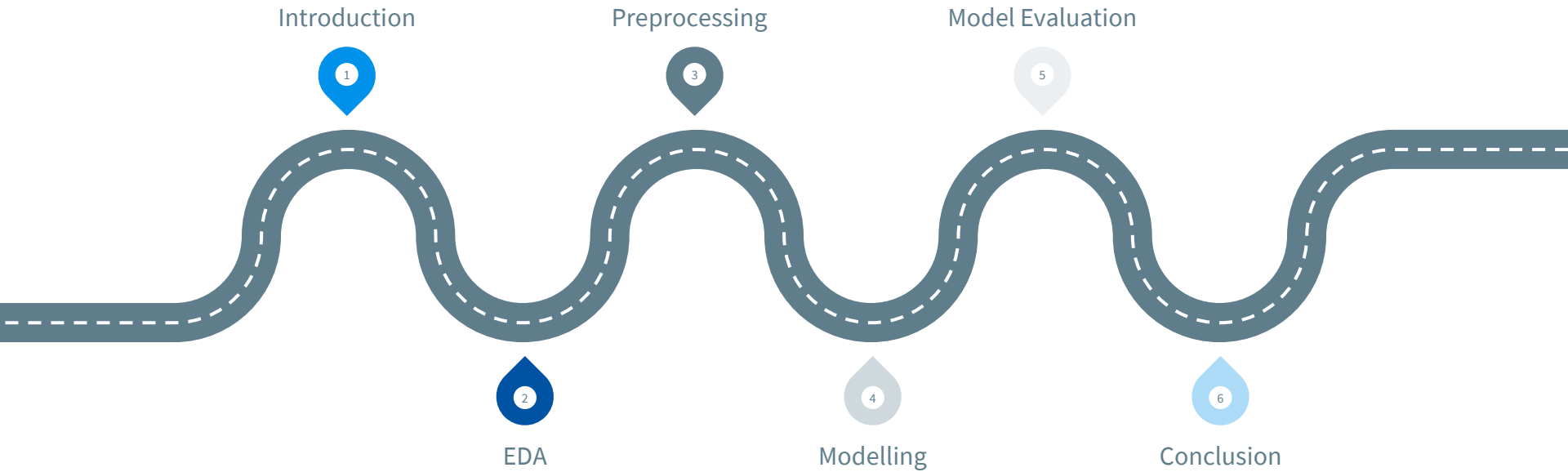
General Assembly DSI 20

Agenda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Introduction

Background

- High road fatality rates in Singapore
- Distracted driving a major cause of road accidents
- >80% of drivers admit to using phone while driving
- >90% think that it is unsafe

Problem Statement

- Explore use of dashboard cameras to improve these statistics
- Create an image classification model that can detect the distraction state of the driver

EDA

Data Source – Kaggle Competition

- Images of drivers in various states of distraction
- 10 Classes
- Images curated from controlled experiment
- Train and test data split on the drivers*
  - > 22,000 Train images
  - > 79,000 Test images
- Evaluated on multi-class log loss

Classes

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

Insights from Data

- Drivers' body position the most distinguishing feature
- Features consistent across classes
  - Type of car
  - Lighting
  - Quality of image
- Features inconsistent within same class
  - Driver features
  - Camera angle

Preprocessing

Distinct Driver Issue

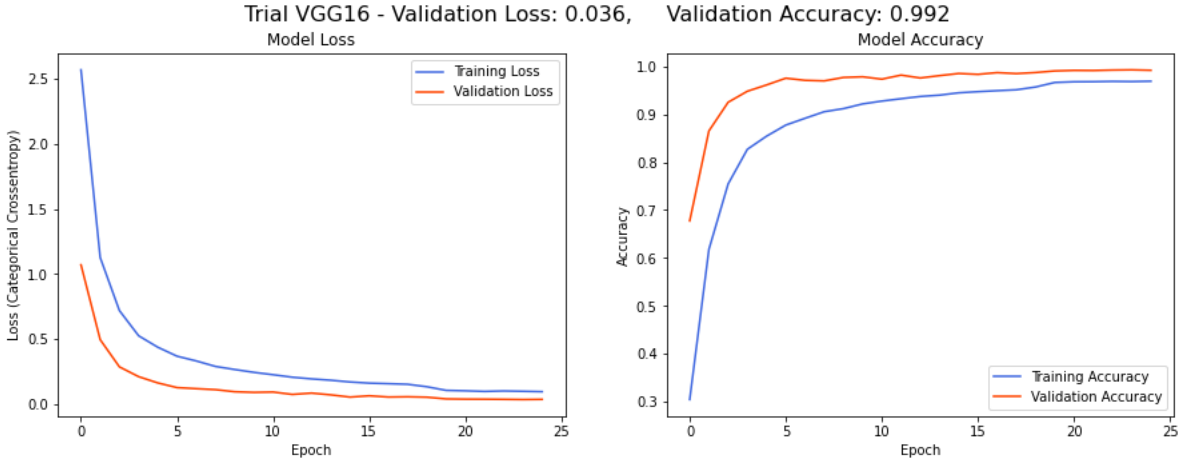
- Train and test data split on the drivers*
- Model must be able to generalize to new drivers
- Many similar images
- Might end up overfitting to drivers' features

Class: c0, File: img_208.jpg

Class: c0, File: img_231.jpg

Trial Model

- Transfer learning from pre-trained CNN model: VGG16



- Kaggle score – 1.78549

Split by Driver

- Random train-validation split leads to poor generalization
- Split by unique driver instead
  - 26 unique drivers in train data
  - 19 – 7 split
- Model should train on non-driver related features

Modelling

Methodology

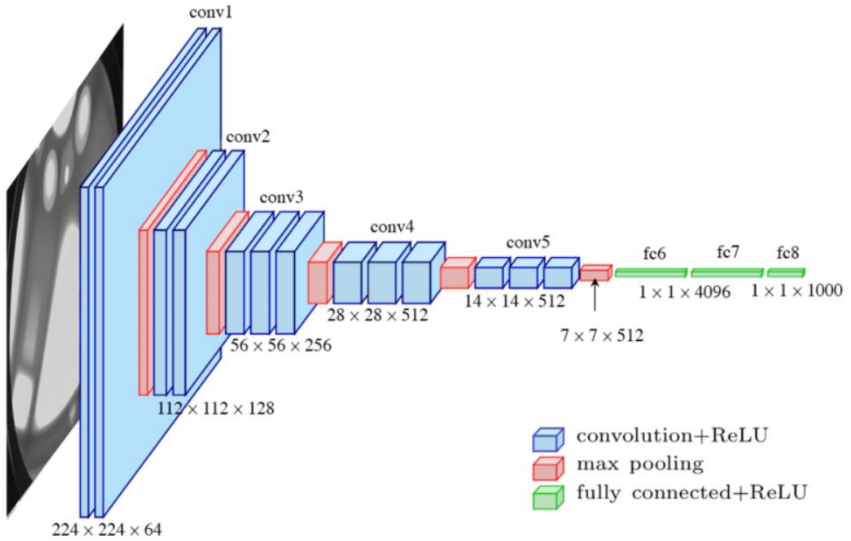
- Transfer Learning
  - Build classifier on pre-trained CNN Models
    - VGG16
    - EfficientNetB4
- Fine-tuning
  - 2 rounds
- Optimised on categorical cross-entropy
- 25 Initial epochs + 25 Fine-tuning epochs per round
- Callbacks
  - Checkpoint, EarlyStopping, ReduceLROnPlateau

Baseline Model

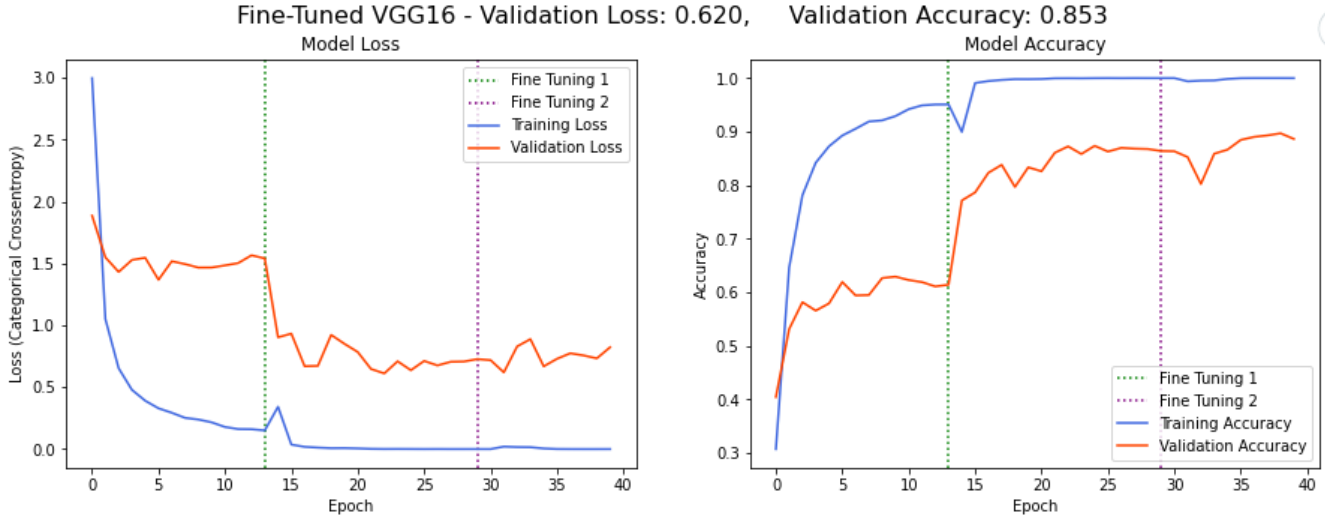
- Predict all classes to have same probability
- Baseline score: **2.303**

VGG16

- Trained on ImageNet
  - 90.1% Top-5 Acc
- 5 Convolutional blocks
- 3 Fully connected layers
- Simple architecture
- Large size



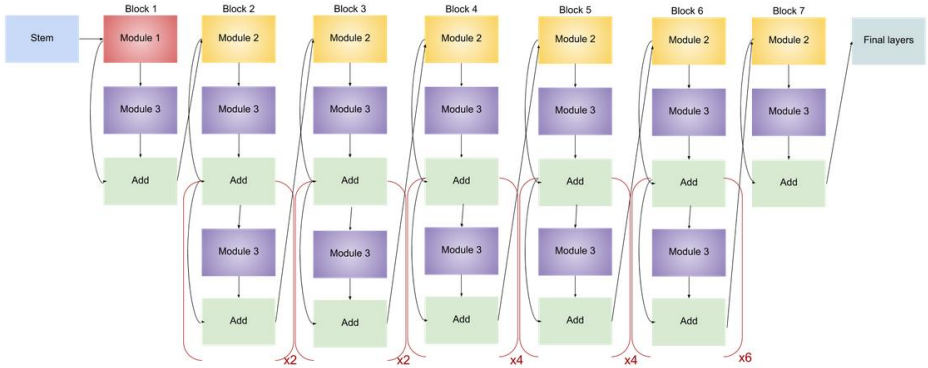
VGG16



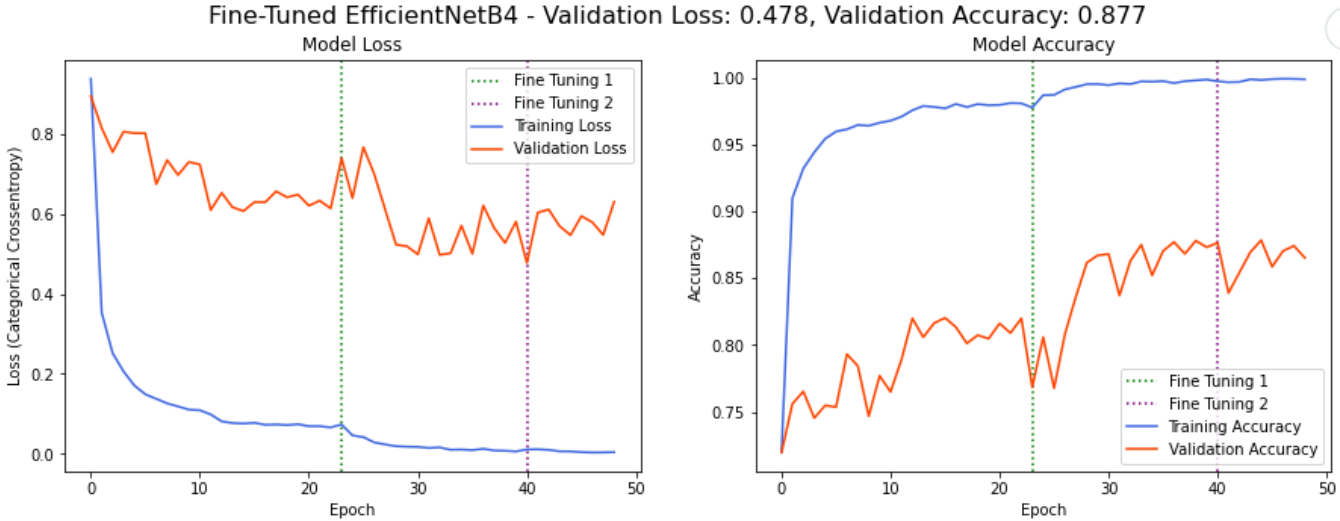
- Kaggle Score: **0.68395**

EfficientNetB4

- Trained on ImageNet
- Focused on efficiency of parameters
- Repeated modules linked in blocks
- 8 different architectures
- B4 provides good balance



EfficientNetB4



- Kaggle Score: **0.59852**

Selection of Best Model

Model	Data	Fine-Tuning	Test Score (Kaggle)	Val Loss	Val Accuracy	Initial Epochs	Fine-Tuning Epochs	Total Epochs
VGG16	Randomly Shuffled	No	1.78549	0.049	0.987	25	-	25
VGG16	Split by Driver	Yes	0.68395	0.62	0.853	13	17 + 8	38
EfficientNetB4	Split by Driver	Yes	0.59852	0.478	0.877	24	16 + 9	49

- EfficientNetB4 performs best
- Splitting by driver reduced overfitting

Final Kaggle Submission

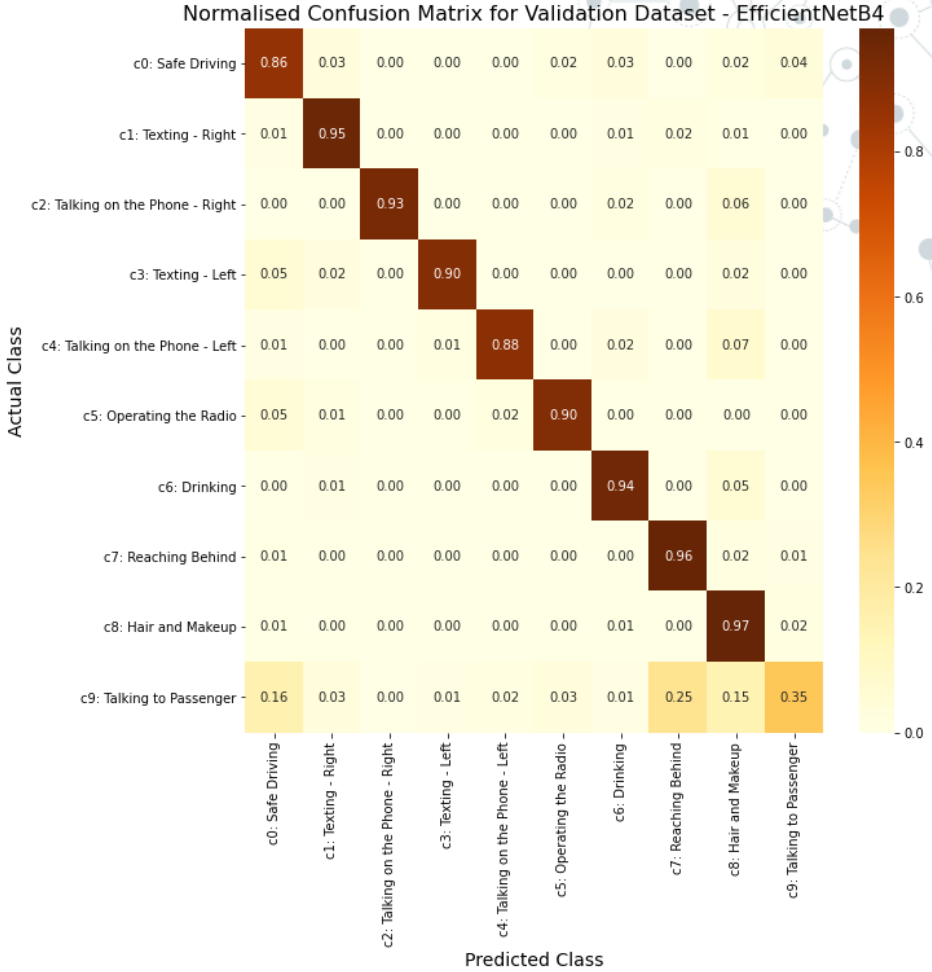
- Ensemble method
- Cross-validate best model over 4 folds
  - Data is not randomly shuffled
  - Expose the model to maximum amount of information
- Fine-tuned EfficientNetB4

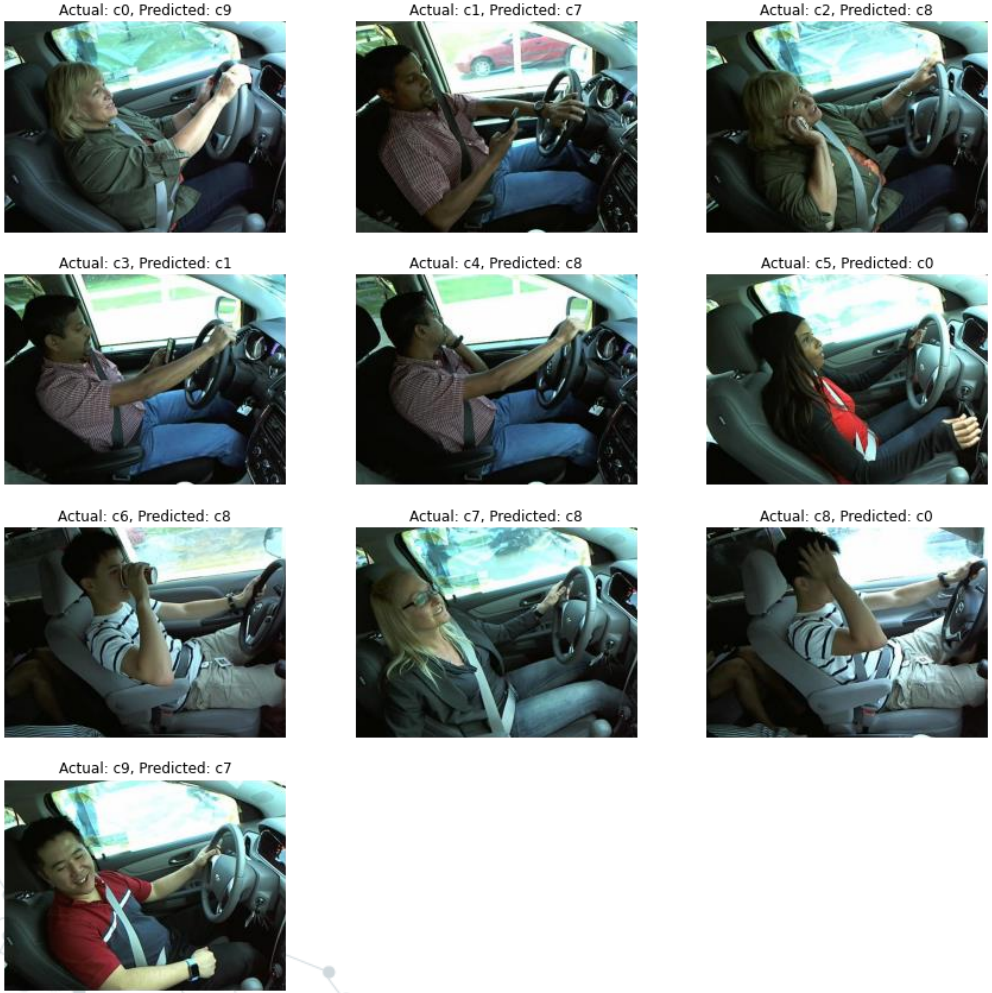
- Final Score: **0.30096**
  - Improvement from single fold (0.598)

Model Evaluation

Confusion Matrix

- Generally performs well
- Class c9: Talking to Passenger



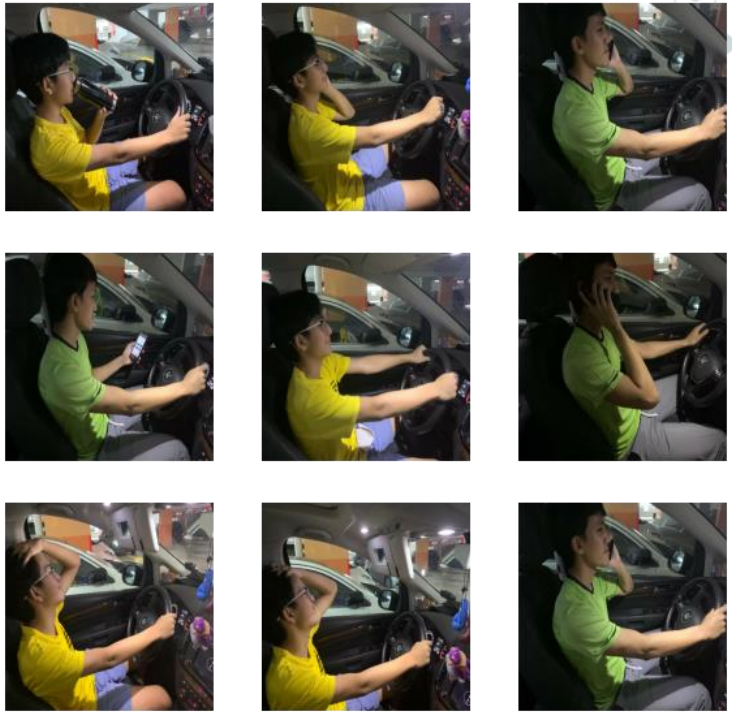


Misclassifications

- Sources of ambiguity for each class
- Particularly noticeable for c9
- Class labels not always consistent

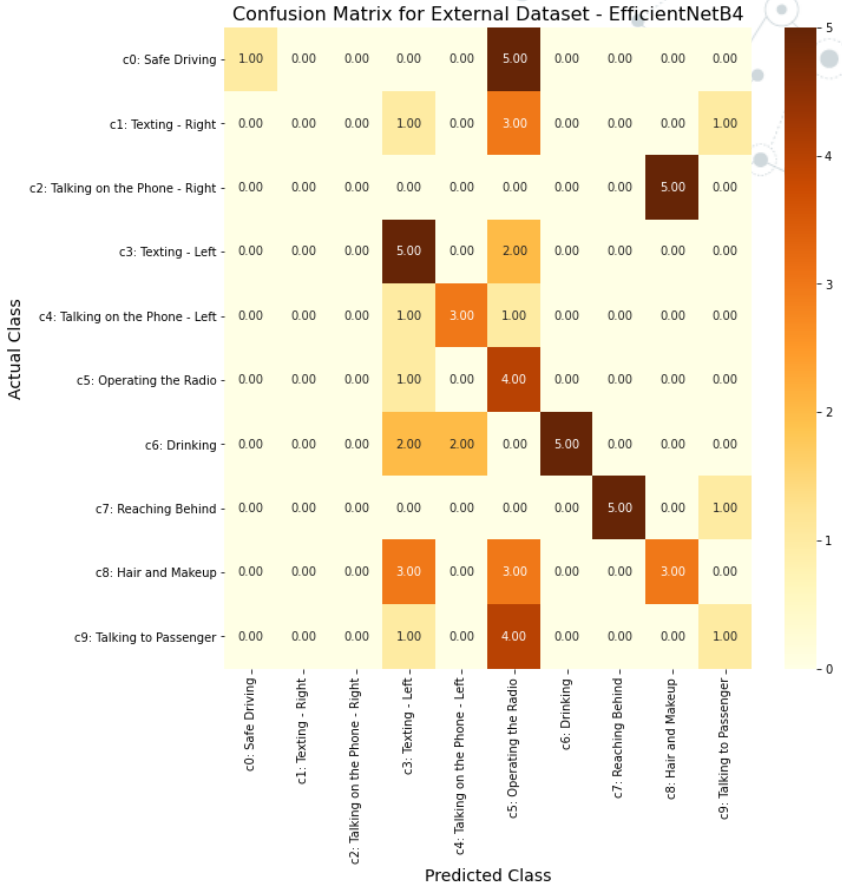
Test on Unseen Data

- Images outside the experiment
- Different lighting, car, location, camera angle



Test on Unseen Data

- Does not perform well
  - 43% accuracy
- Some classes 100% wrong



Conclusion

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- Successfully created model that predicted well for test set
- Not robust enough to be useful in real life
- Shows that detecting distraction with dashboard cameras is feasible
- Can be applied to improve road safety
  - Useful information for insurance companies
  - Real time feedback to drivers

Recommendations for Future Development

- Improve performance on unseen external data
  - Grayscale photos to reduce effect of driver features
  - Image augmentation
  - Gather more varied data
- Further development
  - Apply model to videos

Thank You