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# FINAL PROJECT

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# INTRODUCTION

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- Our Project was the “Car Classification” task where we had to use transfer learning to solve our problem
- This involved classifying 196 classes of cars from 16,185 different images
- We have tested multiple models ranging from Efficient Net B4 to InceptionV3.
- These models were taken from TensorFlow Keras Pre-defined Models, and one model was created on our own
- We used these models as a base and then added dense layers for classification, and applied regularization techniques

# NETWORK ARCHITECTURE

Base Model: ResNet152V2

Global Average Pooling 2D layer (instead of Flatten)

Dense layer (with 2048 outputs and ReLu activation)

Dense layer (with 2048 outputs and ReLu Activation)

Batch Normalization layer

Dropout layer (rate = 0.6)

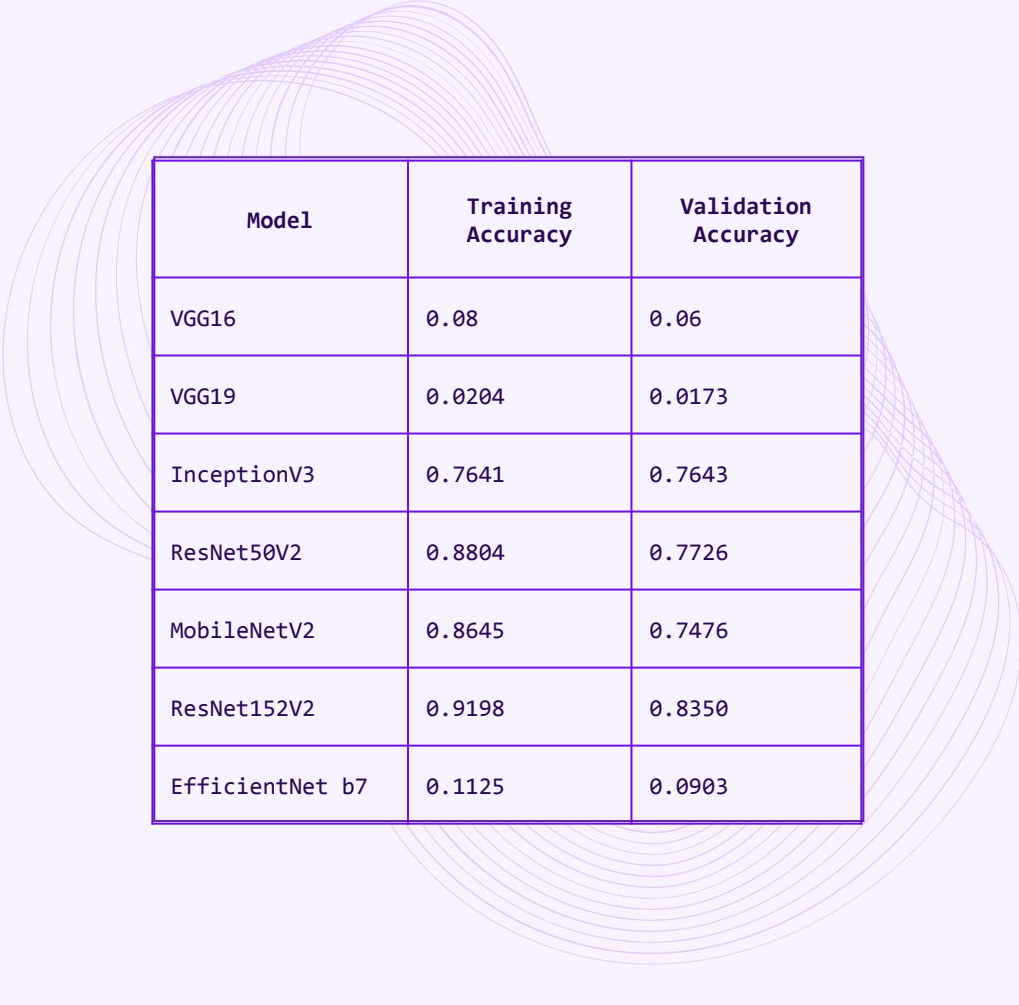
Dense layer (with 196 outputs and Softmax activation)



```
resnet = ResNet152V2(weights="imagenet", include_top=False, input_shape = (224, 224, 3))
x = (resnet.output)
x = GlobalAveragePooling2D()(x)
x = Dense(2048, activation='relu')(x)
x = Dense(2048, activation='relu')(x)
x = BatchNormalization()(x)
x = Dropout(0.6)(x)
predictions = Dense(196, activation='softmax')(x)

model = Model(inputs=resnet.input, outputs=predictions)

for layer in model.layers[:30]:
    layer.trainable=False
for layer in model.layers[30:]:
    layer.trainable=True
```



| Model           | Training Accuracy | Validation Accuracy |
|-----------------|-------------------|---------------------|
| VGG16           | 0.08              | 0.06                |
| VGG19           | 0.0204            | 0.0173              |
| InceptionV3     | 0.7641            | 0.7643              |
| ResNet50V2      | 0.8804            | 0.7726              |
| MobileNetV2     | 0.8645            | 0.7476              |
| ResNet152V2     | 0.9198            | 0.8350              |
| EfficientNet b7 | 0.1125            | 0.0903              |

## MODEL TESTING

we tested the performance of a number of different models and decided that **ResNet152V2** was the best one

# HYPERPARAMETERS

## DATA TRANSFORMATION

```
rescale=1./255,  
width_shift_range=0.1,  
height_shift_range=0.1,  
horizontal_flip=True,  
vertical_flip=True,  
zoom_range=0.2
```

## EPOCHS

```
epochs: 50  
batch_size: 32
```

## LEARNING RATE

```
lr = 0.0001
```

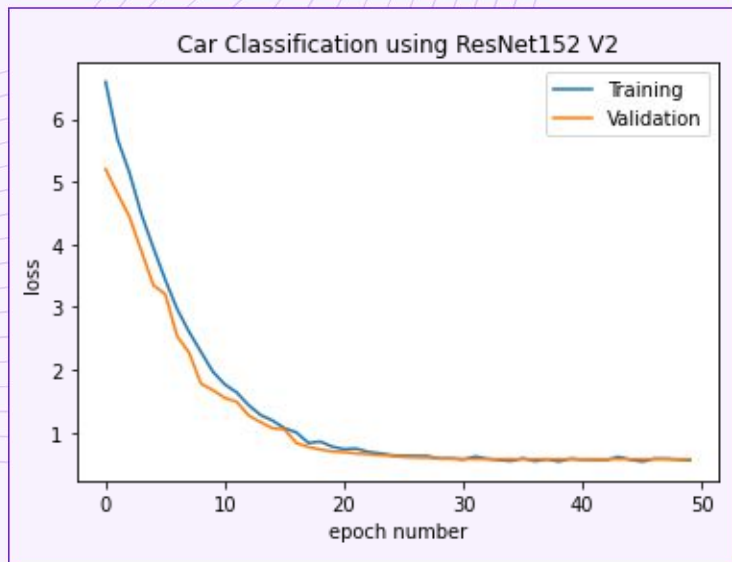
```
ReduceLROnPlateau  
( 'val_accuracy',  
factor = 0.1,  
patience = 1)
```

## OPTIMISER

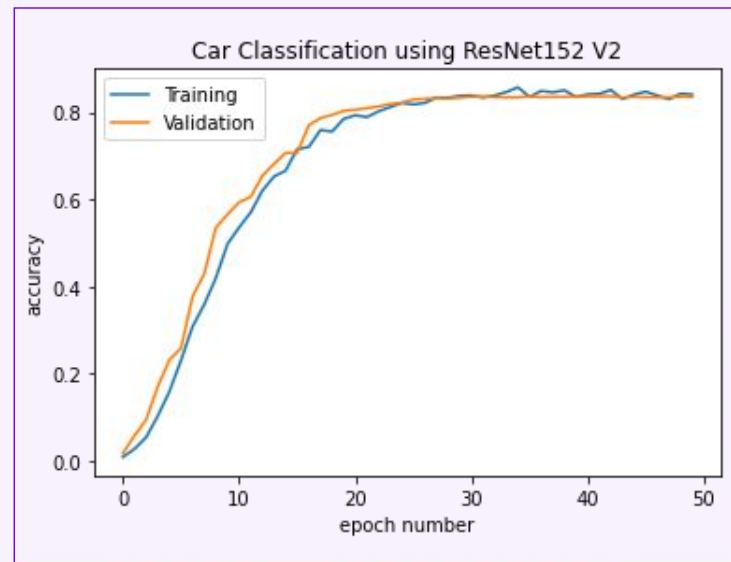
```
optimizer =  
Adam(lr=0.0001)
```

# MODEL PERFORMANCE

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LOSS



ACCURACY

Training Accuracy: 91.98%  
Validation Accuracy: 83.50%

# CLASS ACCURACY

| Class                                       | Accuracy |
|---|----------|
| 1: Acura RL Sedan 2012                      | 0.9286   |
| 2: Acura TL Sedan 2012                      | 0.7143   |
| 3: Acura TL Type-S 2008                     | 0.8667   |
| 4: Acura TSX Sedan 2012                     | 0.7500   |
| 5: Acura Integra Type R 2001                | 0.5000   |
| 6: Acura ZDX Hatchback 2012                 | 0.8824   |
| 7: Aston Martin V8 Vantage Convertible 2012 | 0.8462   |
| 8: Aston Martin V8 Vantage Coupe 2012       | 0.6500   |
| 9: Aston Martin Virage Convertible 2012     | 0.7059   |
| 10: Aston Martin Virage Coupe 2012          | 0.6667   |



# CHALLENGES

- The dataset had trouble downloading onto Google Colab and made the computer very slow
- For the first few hours the accuracy was stuck at 0.3 to 0.5 percent (VGG19)
- After another hour, the accuracy went up to 2 to 3 percent (model created from scratch)
- The problem was resolved when the accuracy started climbing to 25 and 50 percent accuracy with the usage of different models.
- We had to test an assortment of models, which was troubling, because our computers could not handle the immense workload, therefore, making the process tedious and time-consuming

# SOURCES

- 3D Object Representations for Fine-Grained Categorization.  
Jonathan Krause, Michael Stark, Jia Deng, Li Fei-Fei4th IEEE  
Workshop on 3D Representation and Recognition, at ICCV 2013  
(3dRR-13). Sydney, Australia. Dec. 8, 2013. [
- Identity Mappings in Deep Residual Networks]  
(<https://arxiv.org/abs/1603.05027>) (CVPR 2016)
- Brownlee, Jason. "Transfer Learning in Keras with Computer Vision  
Models." Machine Learning Mastery, 2 Sept. 2019,  
[machinelearningmastery.com/how-to-use-transfer-learning-when-developing-convolutional-neural-network-models/](http://machinelearningmastery.com/how-to-use-transfer-learning-when-developing-convolutional-neural-network-models/).