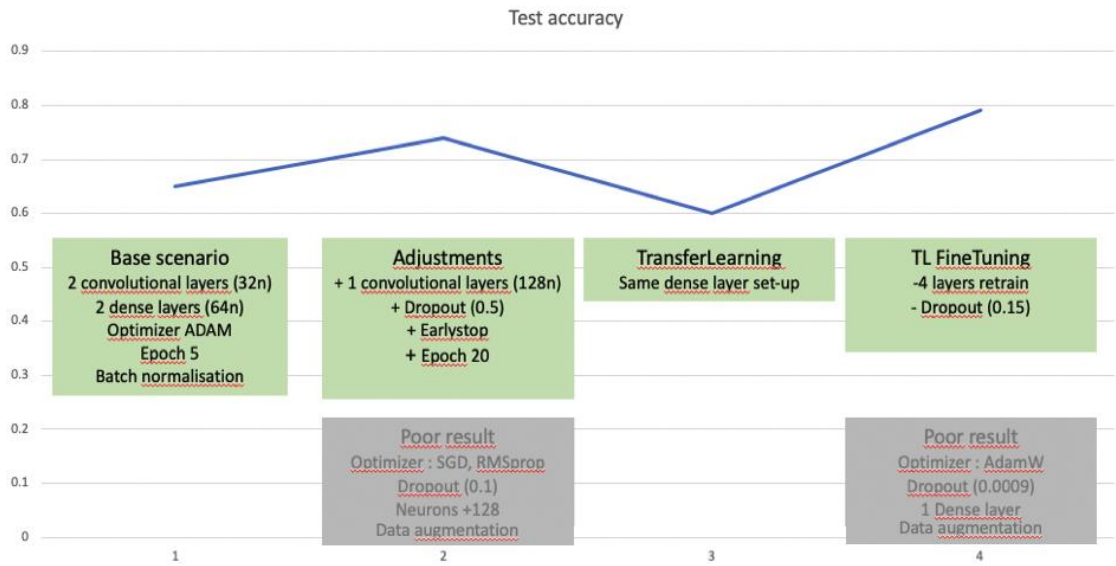
IronHack project 1: Deep learning image classification with CNN

Objective of this project is to build a convolutional neural network model, classify images and predict new images against the trained model.

Final result can be accessed below

Access the page from your home: https://af2f-87-209-237-170.ngrok-free.app/
Github: https://github.com/paulvble/project-1-deep-learning-image-classification-with-cnn.git



1. Project report

1.1 Dataset

The data used for this project is the CIFAR-10 dataset, which consists of 60,000 32x32 color images in 10 classes, with 6,000 images per class.
(https://www.cs.toronto.edu/~kriz/cifar.html)

1.2 Tools

- Python
- Visual Studio Code, Google Colab, NGROK
- Libraries: Numpy, Scikit-Learn, Matplotlib, Tensorflow, Keras

2. Data exploration

2.1 Data exploration

- Total images = 60.000 (32p x 32p)
    - Training set = 50.000
    - Test set = 10.000
- 10 elements = 10 classes
- Images already splitted for training and test, so no train_test_split function required

```
# Check images and their shapes
print(f"Training data shape:
{train_images.shape}")
print(f"Training labels shape:
{train_labels.shape}")
print(f"Testing data shape:
{test_images.shape}")
print(f"Testing labels shape:
{test_labels.shape}")

# Check the unique classes and
their counts
unique_classes, class_counts =
np.unique(train_labels,
return_counts=True)
print(f"Classes:
{unique_classes}")
print(f"Class counts:
{class_counts}")
```

```
Training data shape: (50000, 32,
32, 3)
Training labels shape: (50000, 1)
Testing data shape: (10000, 32,
32, 3)
Testing labels shape: (10000, 1)
Classes: [0 1 2 3 4 5 6 7 8 9]
Class counts: [5000 5000 5000 5000
5000 5000 5000 5000 5000 5000]
```

3. Model selection

3 approaches were taken into account

- CNN training from the start
- CNN with transfer learning
- CNN with transfer learning + finetuning

3.1 CNN training from the start

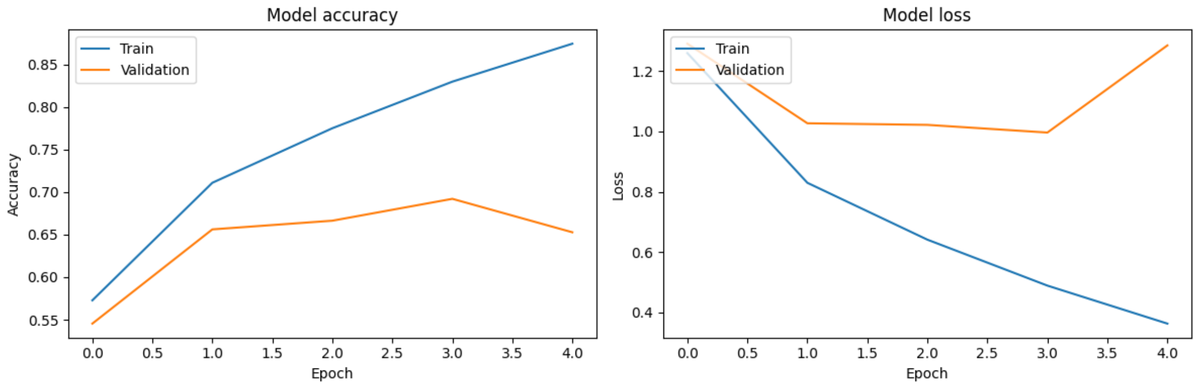
Base attempt & running locally

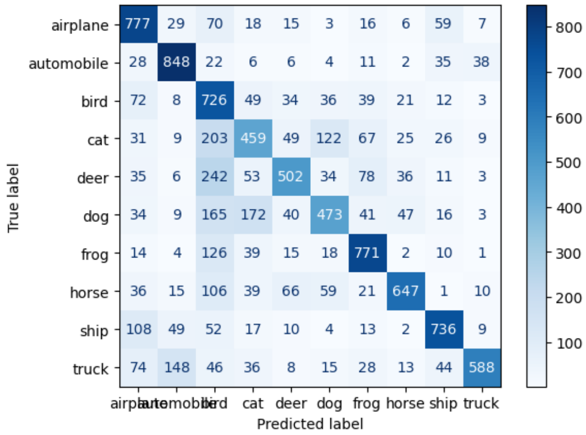
- 2 convolutional layers (1 input, 1 hidden)
    - Conv2D: we are working with images where the input and the following spatial hierarchies is required to understand the patterns in the images. Leveraging the kernels/filters reduces complexity and makes it work train for efficiently.
- 2 dense layers
    - Started of with 128 to absorb image complexity in general. Also because the images appeared to be small and vague.
- Activation layers
    - Selected ReLU to have non-linearity to the output. Did not go for sigmoid, because that's mainly usefull for binary classifications.
    - Softmax used in the output layer to be able to define the probability scores of the classification.
    - Batch normalization, to enhance efficiency between the layers.
- Epochs: started of with 5 for the speed to test the code
- Optimizer: selected ADAM. Shortly tested with SGD, but that didn't go anywhere.

```
def build_cnn_model():
  cnn_model = models.Sequential([

    # Define convolutional layer nbr.1
    layers.Conv2D(filters=32, kernel_size=(3, 3), activation='relu', input_shape=(32, 32, 3)),
    layers.MaxPool2D(pool_size=(2, 2)),
    layers.BatchNormalization(),


    # Define convolutional layer nbr.2
    layers.Conv2D(filters=64, kernel_size=(3, 3), activation='relu'),
    layers.MaxPool2D(pool_size=(2, 2)),
    layers.BatchNormalization(),

    # Flatten and Dense layers
```

```
        layers.Flatten(),
        layers.Dense(128, activation='relu'),
        layers.Dense(10, activation='softmax')

    ])

    return cnn_model

cnn_model = build_cnn_model()

# Print the summary of the layers in the model.
print(cnn_model.summary())

optimizer = tf.keras.optimizers.Adam()

cnn_model.compile(optimizer=optimizer,
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

```
Accuracy: 0.6527
Precision: 0.678541004259845
Recall: 0.6527
F1 Score: 0.6541426761277805
Classification Report:
              precision    recall  f1-score   support

    airplane       0.64      0.78      0.70      1000
  automobile       0.75      0.85      0.80      1000
        bird       0.41      0.73      0.53      1000
         cat       0.52      0.46      0.49      1000
        deer       0.67      0.50      0.58      1000
         dog       0.62      0.47      0.54      1000
        frog       0.71      0.77      0.74      1000
       horse       0.81      0.65      0.72      1000
        ship       0.77      0.74      0.75      1000
       truck       0.88      0.59      0.70      1000

    accuracy                           0.65     10000
   macro avg       0.68      0.65      0.65     10000
weighted avg       0.68      0.65      0.65     10000
```





Conclusion: starting point to tackle

- The model is overfitting where the training loss is much lower compared to the test.
- Low accuracy on the test set

Options explored

- Adding convolutional layer -> to address the model memorizing noise data since it's blurry and small.
- Adding dropout -> randomly remove neurons to hopefully remove unnecessary features
- Early stopping -> stop the learning with cycle to prevent the model learning things that do not matter.
- Batch normalization -> improves the learning efficiency of the model
- Adjustment of the learning rate -> decrease the rate so it does not try to learn everything.
- Data augmentation -> increase the data set

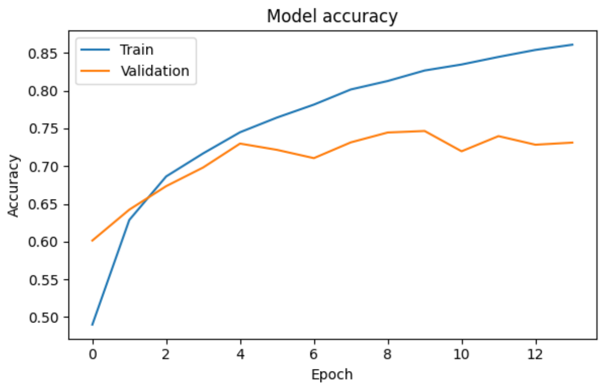
Result of the options explored

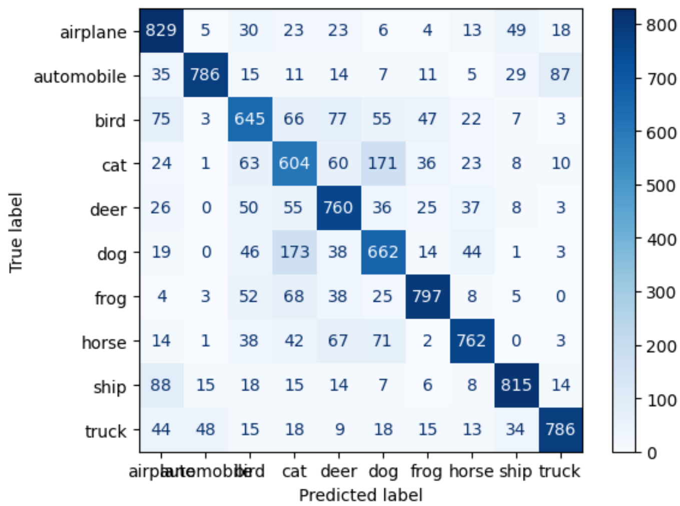
Increased the accuracy rate, and reduced the overfitting. Though not there yet.

```
Accuracy: 0.7446
Precision: 0.7517972128563107
Recall: 0.7446
```

F1 Score: 0.7467254999132825
Classification Report:

	precision	recall	f1-score	support
airplane	0.72	0.83	0.77	1000
automobile	0.91	0.79	0.84	1000
bird	0.66	0.65	0.65	1000
cat	0.56	0.60	0.58	1000
deer	0.69	0.76	0.72	1000
dog	0.63	0.66	0.64	1000
frog	0.83	0.80	0.81	1000
horse	0.81	0.76	0.79	1000
ship	0.85	0.81	0.83	1000
truck	0.85	0.79	0.82	1000
accuracy			0.74	10000
macro avg	0.75	0.74	0.75	10000
weighted avg	0.75	0.74	0.75	10000





3.2 Transfer learning with VGG16

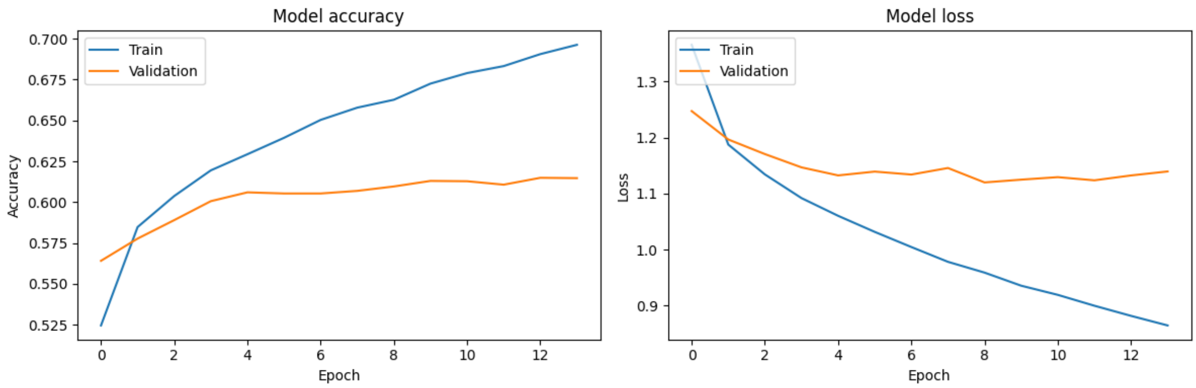
Explore VGG16 and Inception
One of my limitation was the processing power. Since VGG16 was relatively simple in set-up and more efficient than others, I choose to go for VGG16. In articles it was mentioned that it

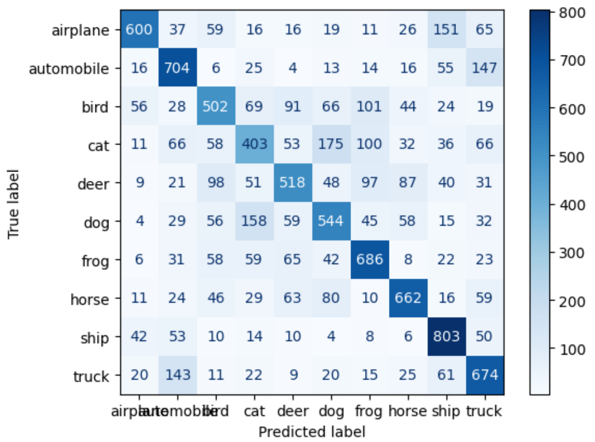
was prone for overfitting with smaller datasets, so that was something to take into account going forward. I need to control this factor in the finetuning.

Potential action: open up part of the layer to retrain with the CIFAR dataset.

Result

```
Accuracy: 0.6096
Precision: 0.6099438891771447
Recall: 0.6096
F1 Score: 0.6065246061066646
Classification Report:
              precision    recall  f1-score   support

    airplane       0.77      0.60      0.68      1000
  automobile       0.62      0.70      0.66      1000
        bird       0.56      0.50      0.53      1000
         cat       0.48      0.40      0.44      1000
        deer       0.58      0.52      0.55      1000
         dog       0.54      0.54      0.54      1000
        frog       0.63      0.69      0.66      1000
       horse       0.69      0.66      0.67      1000
        ship       0.66      0.80      0.72      1000
       truck       0.58      0.67      0.62      1000

    accuracy                           0.61     10000
   macro avg       0.61      0.61      0.61     10000
weighted avg       0.61      0.61      0.61     10000
```





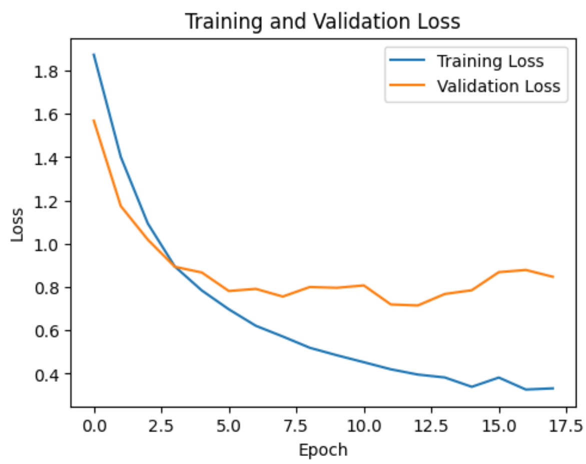
3.3 CNN training with transfer learning VGG16 + finetuning

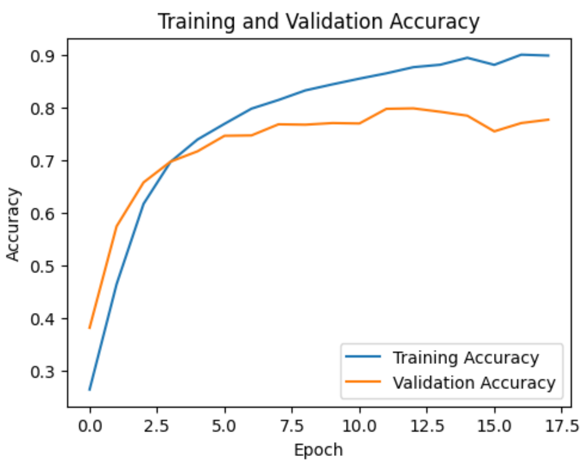
- Re-train weights of the last 4 layers of the base VGG16
- Adjusted learning rate 20 -> 15%

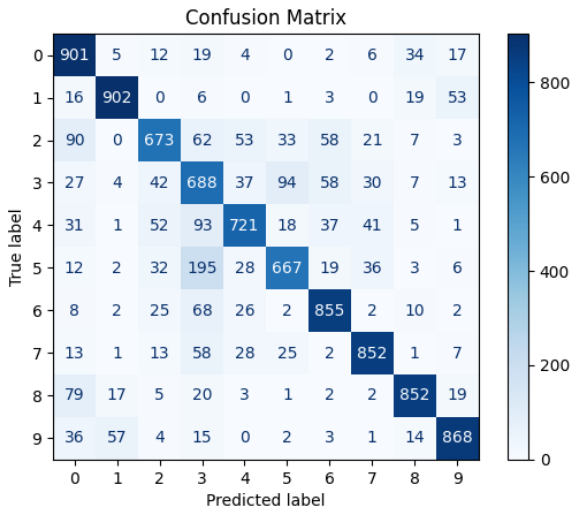
Result

```
Test Accuracy: 0.7979000210762024
Test Precision: 0.8047041390003009
Test Recall: 0.7979
Test F1 Score: 0.7986512694685315
Classification Report:
```

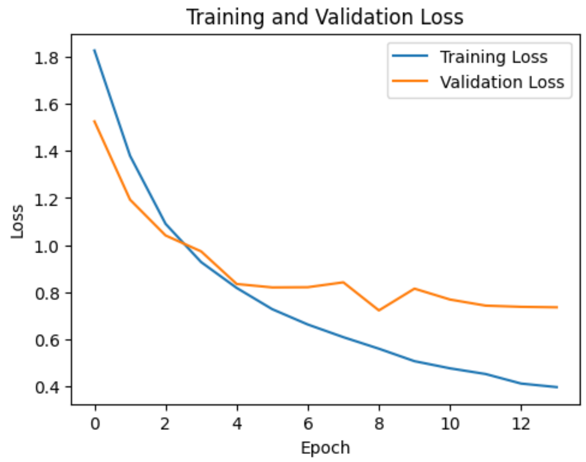
	precision	recall	f1-score	support
0	0.74	0.90	0.81	1000
1	0.91	0.90	0.91	1000
2	0.78	0.67	0.72	1000
3	0.56	0.69	0.62	1000
4	0.80	0.72	0.76	1000
5	0.79	0.67	0.72	1000
6	0.82	0.85	0.84	1000
7	0.86	0.85	0.86	1000
8	0.89	0.85	0.87	1000
9	0.88	0.87	0.87	1000
accuracy			0.80	10000
macro avg	0.80	0.80	0.80	10000
weighted avg	0.80	0.80	0.80	10000

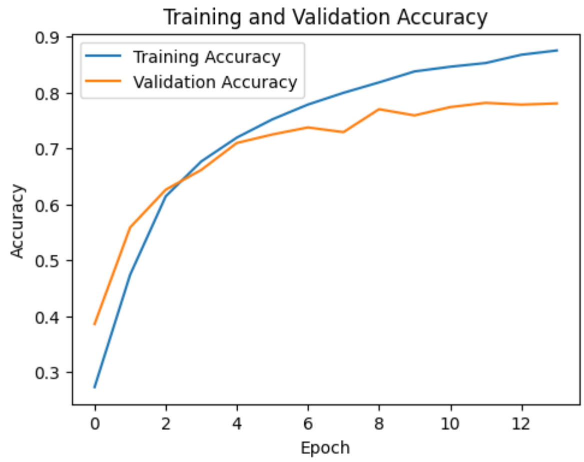






- Adjusted the optimizer to AdamW. Apparently this helps preventing overfitting by penelizing large parameter values therefore improving generalization performance. However the results did not increase for this dataset.
- Test Accuracy: 0.7703999876976013
- Test Precision: 0.7813474139705266
- Test Recall: 0.7704
- Test F1 Score: 0.7714482591095648





4.0 Deployment

- From Google Colab; generated a H5 file stored in google drive.
- Set-up the environment locally by using Flask
- Leverage NGROK to tunnel the application onto the internet. So the application runs locally from the laptop.