Task 1 and Task 2 (Done by Dhyanav)

Task 1

The CIFAR10 dataset is already clean, shuffled and neatly labelled. So, I directly moved to data augmentation. I divided 60,000 images of CIFAR-10 into 6 batches of 10,000 each. They were used for flipping, rotating, cropping, adding noise, cut-out and mixup.

Cut-out: I randomly cut a square of 6 by 6 from the image. Using this technique helps the model learn better since it tries to identify an image without a certain part. It reduces dependence on specific parts of the image. I decided to use 6 by 6 after some experimentation. I feel it was in the middle, not too small to be practically ineffective and not too large to remove all key features entirely.

Mixup: It selects a random image and imposes it on chosen images. The formula used is

Xnew = alpha*X1 + (1-alpha)*X2

Here, Xnew is the final result, X1 is the base image and X2 is the image that is being imposed. After some experimentation, I used alpha = 0.75.

Then, I combined it into the original dataset, doubling its size. Then, I split data. 95,000 images for training, 10,000 for validation and 15,000 for testing.

Now, I moved to task 2

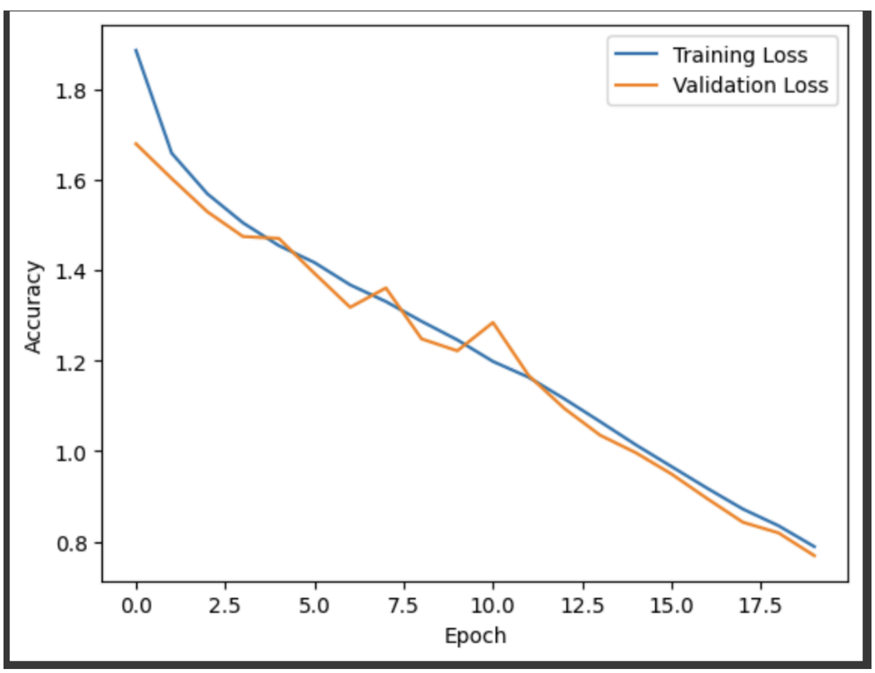
Task 2

ANN:

I started with 2 hidden layers, but gradually increased the layers so it was computationally viable. Finally, there are 4 layers. I also doubled the number of neurons in each layer and stuck with it since it increased accuracy without overfitting.

I trained for 15 epochs. Since, loss is steadily decreasing, implementing early stopping was not useful. Increasing epochs led to an increase in difference between training accuracy and test accuracy. I finally decided to use 15 epochs since the difference was only 5%.

```
Epoch 1/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 10s 8ms/step - accuracy: 0.2536 - loss: 2.0862 - val_accuracy: 0.3981 - val_loss: 1.679
Epoch 2/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.3936 - loss: 1.6859 - val_accuracy: 0.4287 - val_loss: 1.602
Epoch 3/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.4359 - loss: 1.5695 - val_accuracy: 0.4551 - val_loss: 1.529
Epoch 4/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.4602 - loss: 1.5097 - val_accuracy: 0.4736 - val_loss: 1.474
Epoch 5/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.4803 - loss: 1.4559 - val_accuracy: 0.4801 - val_loss: 1.470
Epoch 6/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.4901 - loss: 1.4178 - val_accuracy: 0.4946 - val_loss: 1.393
Epoch 7/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.5117 - loss: 1.3672 - val_accuracy: 0.5313 - val_loss: 1.317
Epoch 8/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.5262 - loss: 1.3283 - val_accuracy: 0.5214 - val_loss: 1.360
Epoch 9/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.5345 - loss: 1.2936 - val_accuracy: 0.5600 - val_loss: 1.248
Epoch 10/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.5547 - loss: 1.2391 - val_accuracy: 0.5637 - val_loss: 1.221
Epoch 11/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.5720 - loss: 1.1946 - val_accuracy: 0.5372 - val_loss: 1.284
Epoch 12/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.5868 - loss: 1.1579 - val_accuracy: 0.5885 - val_loss: 1.167
Epoch 13/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.6027 - loss: 1.1118 - val_accuracy: 0.6075 - val_loss: 1.094
Epoch 14/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.6242 - loss: 1.0528 - val_accuracy: 0.6281 - val_loss: 1.035
Epoch 15/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.6451 - loss: 0.9930 - val_accuracy: 0.6412 - val_loss: 0.996
Epoch 16/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.6584 - loss: 0.9508 - val_accuracy: 0.6611 - val_loss: 0.949
Epoch 17/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.6805 - loss: 0.9027 - val_accuracy: 0.6784 - val_loss: 0.895
Epoch 18/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.6954 - loss: 0.8527 - val_accuracy: 0.6981 - val_loss: 0.842
Epoch 19/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.7094 - loss: 0.8127 - val_accuracy: 0.7044 - val_loss: 0.819
Epoch 20/20
743/743 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - accuracy: 0.7290 - loss: 0.7683 - val_accuracy: 0.7202 - val_loss: 0.769
469/469 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.6772 - loss: 0.9278
[1.1586171388626099, 0.6033333539962769]
```

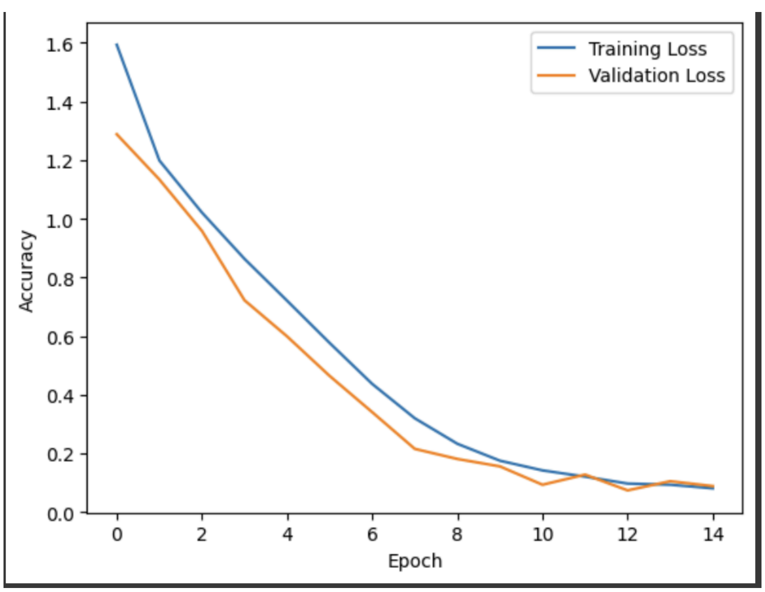


CNN:

I used a similar process as in ANN. Gradually increasing the number of layers and number of neurons in each layer till I was satisfied with the result. I tried implementing early stopping but it was useless as only the last three layers were showing signs of saturation and early stopping evaluates accuracy of three layers before stopping training.

In both, I used ADAM optimiser, so learning rate was not a part of experimentation as ADAM adjusts learning rate accordingly. I increased batch size from 32 to 256 to speed up training while also maintaining accuracy. (After 256, accuracy started to drop.)

```
Epoch 1/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 22s 36ms/step - accuracy: 0.3192 - loss: 1.8257 - val_accuracy: 0.5380 - val_loss: 1.2884
Epoch 2/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 6s 17ms/step - accuracy: 0.5547 - loss: 1.2457 - val_accuracy: 0.5978 - val_loss: 1.1342
Epoch 3/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 9s 15ms/step - accuracy: 0.6289 - loss: 1.0507 - val_accuracy: 0.6544 - val_loss: 0.9589
Epoch 4/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 5s 14ms/step - accuracy: 0.6856 - loss: 0.8931 - val_accuracy: 0.7445 - val_loss: 0.7224
Epoch 5/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 11s 17ms/step - accuracy: 0.7452 - loss: 0.7242 - val_accuracy: 0.7935 - val_loss: 0.5991
Epoch 6/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 6s 15ms/step - accuracy: 0.8011 - loss: 0.5730 - val_accuracy: 0.8386 - val_loss: 0.4643
Epoch 7/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 6s 15ms/step - accuracy: 0.8474 - loss: 0.4388 - val_accuracy: 0.8813 - val_loss: 0.3407
Epoch 8/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 10s 14ms/step - accuracy: 0.8931 - loss: 0.3132 - val_accuracy: 0.9268 - val_loss: 0.2155
Epoch 9/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 10s 14ms/step - accuracy: 0.9237 - loss: 0.2235 - val_accuracy: 0.9379 - val_loss: 0.1811
Epoch 10/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 10s 14ms/step - accuracy: 0.9434 - loss: 0.1683 - val_accuracy: 0.9467 - val_loss: 0.1558
Epoch 11/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 10s 14ms/step - accuracy: 0.9570 - loss: 0.1266 - val_accuracy: 0.9681 - val_loss: 0.0932
Epoch 12/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 5s 14ms/step - accuracy: 0.9616 - loss: 0.1156 - val_accuracy: 0.9552 - val_loss: 0.1277
Epoch 13/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 10s 14ms/step - accuracy: 0.9689 - loss: 0.0928 - val_accuracy: 0.9745 - val_loss: 0.0739
Epoch 14/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 10s 14ms/step - accuracy: 0.9655 - loss: 0.1021 - val_accuracy: 0.9640 - val_loss: 0.1051
Epoch 15/15
372/372 ━━━━━━━━━━━━━━━━━━━━ 10s 14ms/step - accuracy: 0.9759 - loss: 0.0698 - val_accuracy: 0.9692 - val_loss: 0.0885
469/469 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.9271 - loss: 0.2719
[0.5354151129722595, 0.8613333106040955]
```



I also trained the same models, ANN and CNN on raw CIFAR10 data and the difference in accuracy was significant.

```
  super().__init__(**kwargs)
Epoch 1/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 6s 8ms/step - accuracy: 0.1764 - loss: 192.5728
Epoch 2/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.3281 - loss: 1.9206
Epoch 3/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.3685 - loss: 1.7916
Epoch 4/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.4040 - loss: 1.6968
Epoch 5/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.4141 - loss: 1.6505
Epoch 6/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - accuracy: 0.4289 - loss: 1.6159
Epoch 7/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4376 - loss: 1.5935
Epoch 8/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.4269 - loss: 1.6178
Epoch 9/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4427 - loss: 1.5682
Epoch 10/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4447 - loss: 1.5621
Epoch 11/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4545 - loss: 1.5468
Epoch 12/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - accuracy: 0.4561 - loss: 1.5256
Epoch 13/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4631 - loss: 1.5007
Epoch 14/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - accuracy: 0.4721 - loss: 1.4838
Epoch 15/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.4644 - loss: 1.4894
Epoch 16/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4696 - loss: 1.4905
Epoch 17/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - accuracy: 0.4823 - loss: 1.4414
Epoch 18/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4845 - loss: 1.4481
Epoch 19/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.4853 - loss: 1.4352
Epoch 20/20
391/391 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - accuracy: 0.4903 - loss: 1.4312
313/313 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.4469 - loss: 1.5485
[1.5541332960128784, 0.44449999928474426]
```

```
Epoch 1/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 9s 22ms/step - accuracy: 0.1260 - loss: 5.1147
Epoch 2/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 7s 13ms/step - accuracy: 0.2919 - loss: 1.8043
Epoch 3/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 5s 13ms/step - accuracy: 0.4495 - loss: 1.4742
Epoch 4/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 12ms/step - accuracy: 0.5496 - loss: 1.2520
Epoch 5/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 3s 12ms/step - accuracy: 0.6090 - loss: 1.0987
Epoch 6/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - accuracy: 0.6700 - loss: 0.9320
Epoch 7/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 5s 13ms/step - accuracy: 0.7162 - loss: 0.7970
Epoch 8/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 12ms/step - accuracy: 0.7590 - loss: 0.6782
Epoch 9/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - accuracy: 0.8057 - loss: 0.5491
Epoch 10/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - accuracy: 0.8435 - loss: 0.4444
Epoch 11/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - accuracy: 0.8769 - loss: 0.3582
Epoch 12/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - accuracy: 0.8971 - loss: 0.2993
Epoch 13/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - accuracy: 0.9286 - loss: 0.2087
Epoch 14/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - accuracy: 0.9367 - loss: 0.1879
Epoch 15/15
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 13ms/step - accuracy: 0.9466 - loss: 0.1638
313/313 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.6336 - loss: 1.7517
[1.766332983970642, 0.6341000199317932]
```

On the CNN model, I implemented one-pixel attack. THis is a type of attack where the attacker randomly selects a pixel and manipulates it. It is known to reduce accuracy of the model by a significant margin. But since I implemented cutout in data augmentation, model accuracy only dropped from 91.24% to 83.34

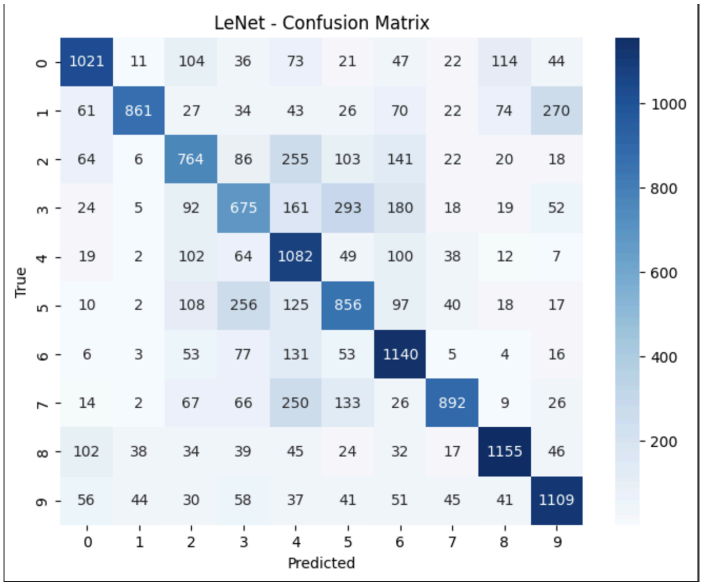
```
one_pixel_attack(test_images, test_labels, model_cnn)
```

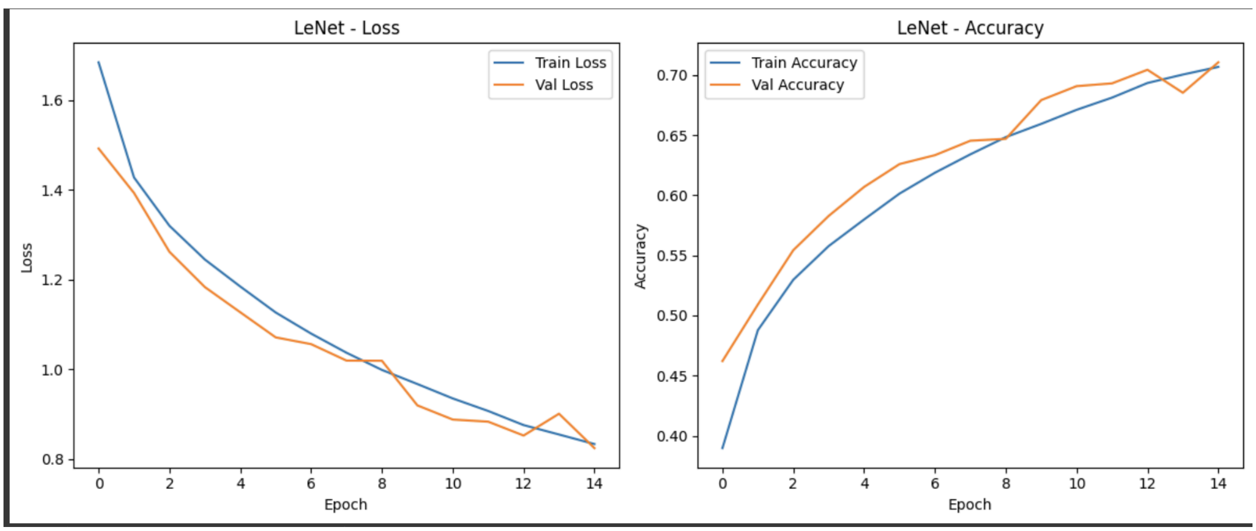
```
0.843
```

Task 3-6(Sumit and Shikhar)
AlexNet, LeNet, VGG16(Sumit)

LeNet: ~60K parameters. A shallow network with 2 convolutional layers.
Epochs-15
Batch Size-128

```
LeNet - Classification Report
              precision    recall  f1-score   support

           0       0.74      0.68      0.71      1493
           1       0.88      0.58      0.70      1488
           2       0.55      0.52      0.53      1479
           3       0.49      0.44      0.46      1519
           4       0.49      0.73      0.59      1475
           5       0.54      0.56      0.55      1529
           6       0.61      0.77      0.68      1488
           7       0.80      0.60      0.68      1485
           8       0.79      0.75      0.77      1532
           9       0.69      0.73      0.71      1512

    accuracy                           0.64     15000
   macro avg       0.66      0.64      0.64     15000
weighted avg       0.66      0.64      0.64     15000

ROC AUC Score (OvA): 0.9401
```



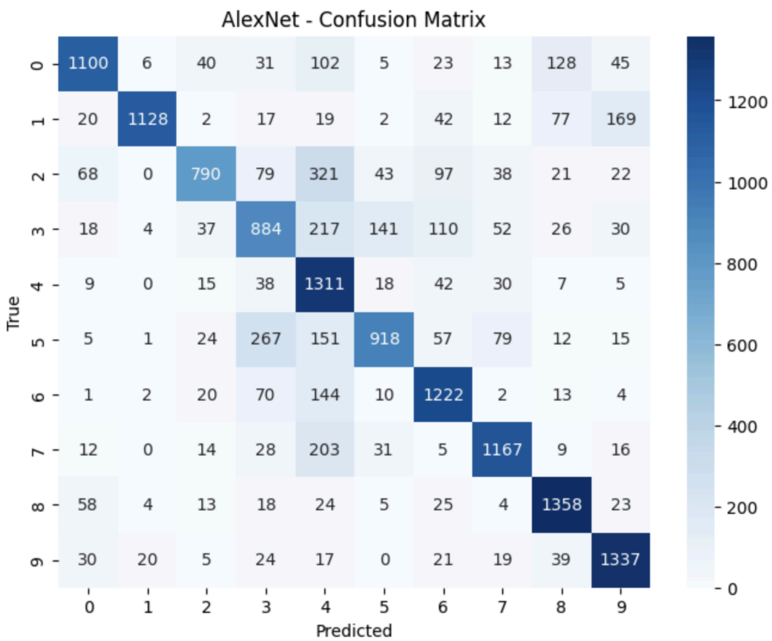


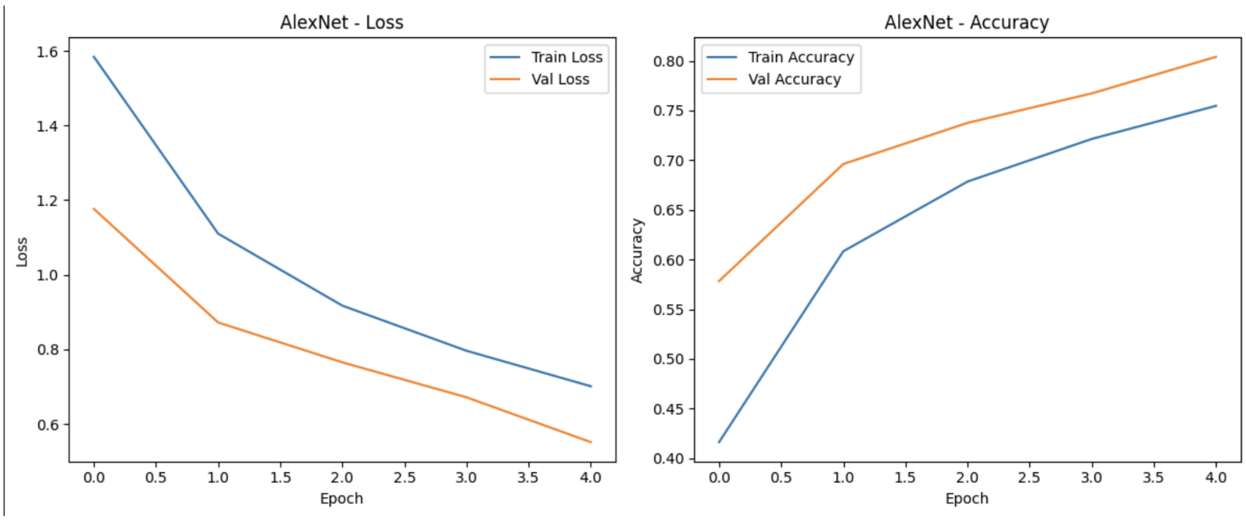
AlexNet: ~60M parameters. A deeper architecture with 5 convolutional layers. It handles larger input variations better.

Epochs: Initially tried 15 but it was taking much longer than LeNet so switched to 5.

Batch Size-128

```
AlexNet - Classification Report
              precision    recall  f1-score   support

           0       0.83      0.74      0.78      1493
           1       0.97      0.76      0.85      1488
           2       0.82      0.53      0.65      1479
           3       0.61      0.58      0.59      1519
           4       0.52      0.89      0.66      1475
           5       0.78      0.60      0.68      1529
           6       0.74      0.82      0.78      1488
           7       0.82      0.79      0.80      1485
           8       0.80      0.89      0.84      1532
           9       0.80      0.88      0.84      1512

    accuracy                           0.75     15000
   macro avg       0.77      0.75      0.75     15000
weighted avg       0.77      0.75      0.75     15000

ROC AUC Score (OvA): 0.9706
```



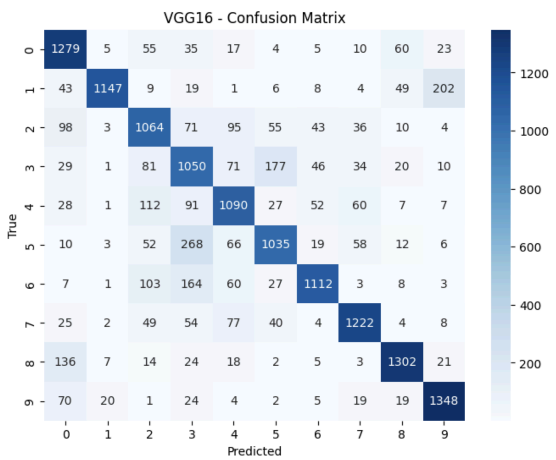


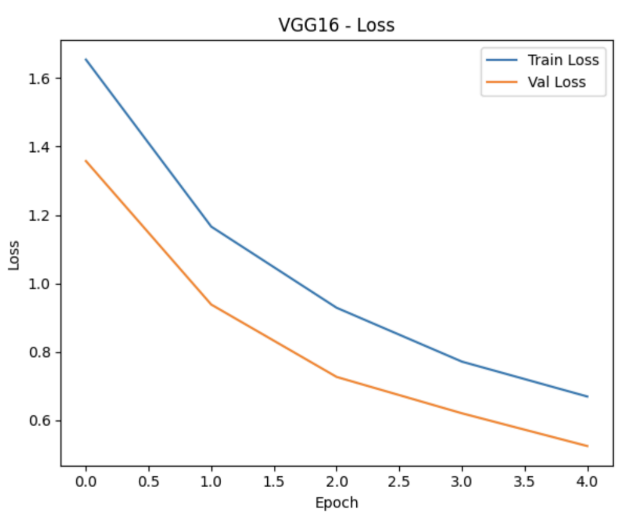
VGG16: ~138M parameters. A very deep model with 13 convolutional layers.

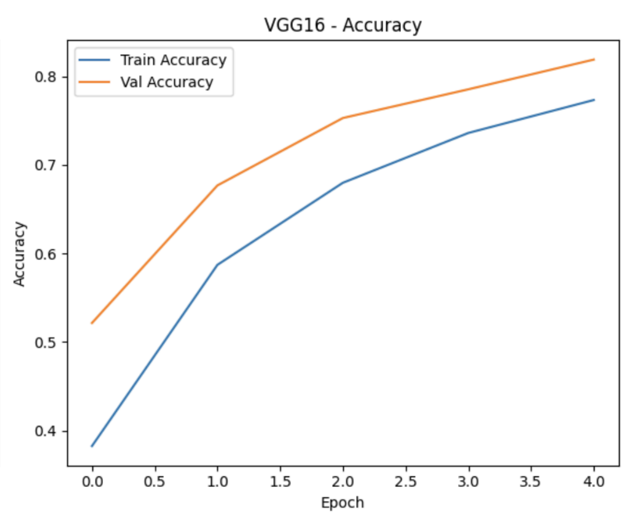
Epochs: 5(same problem as AlexNet)

Batch Size: 128

```
VGG16 - Classification Report
              precision    recall  f1-score   support

           0       0.74      0.86      0.79      1493
           1       0.96      0.77      0.86      1488
           2       0.69      0.72      0.70      1479
           3       0.58      0.69      0.63      1519
           4       0.73      0.74      0.73      1475
           5       0.75      0.68      0.71      1529
           6       0.86      0.75      0.80      1488
           7       0.84      0.82      0.83      1485
           8       0.87      0.85      0.86      1532
           9       0.83      0.89      0.86      1512

    accuracy                           0.78     15000
   macro avg       0.79      0.78      0.78     15000
weighted avg       0.79      0.78      0.78     15000

ROC AUC Score (OvA): 0.9746
```







Model	Accuracy	Precision	Recall	F1-score	ROC-AUC(OvA)
LeNet	0.64	0.66	0.64	0.64	0.9401
AlexNet	0.75	0.77	0.75	0.75	0.9706
VGG16	0.78	0.79	0.78	0.78	0.9746

(here precision, recall, and f1 score are the macro avg)

Factor	**LeNet**	**AlexNet**	**VGG16**
Overfitting	High	Medium	Low
Training Time	Low	Medium	High
Generalization	Poor	Decent	Good

Conclusion:

-VGG16 gave the best results in terms of accuracy, F1-score, and AUC.

-LeNet was unsuitable for CIFAR-10 due to its simplicity.

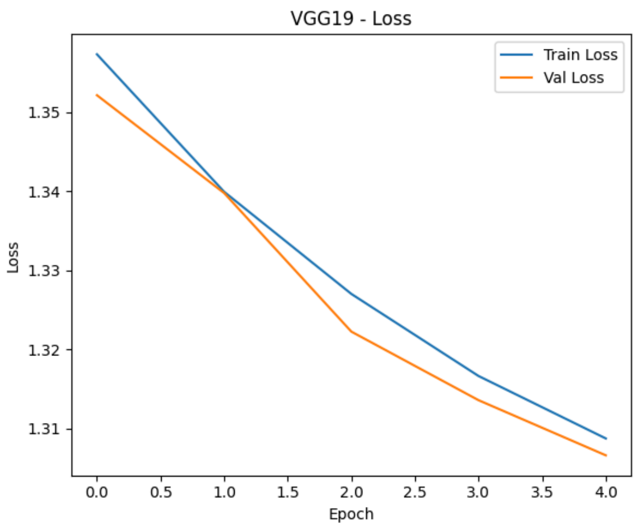
-AlexNet was a good balance between complexity and performance.

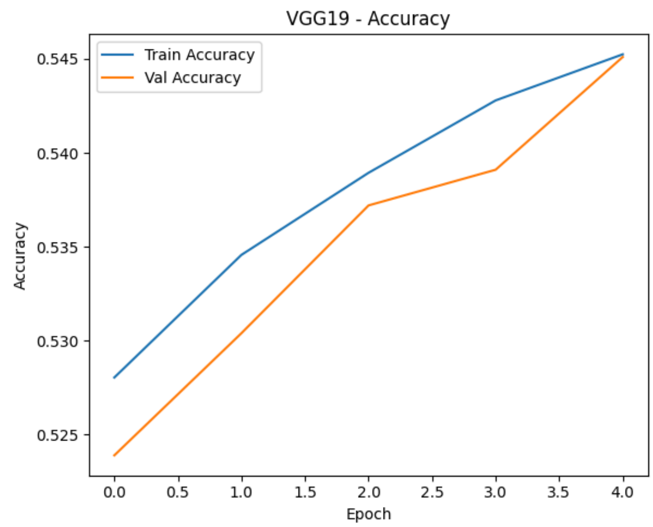
TRANSFER LEARNING IMPLEMENTATION

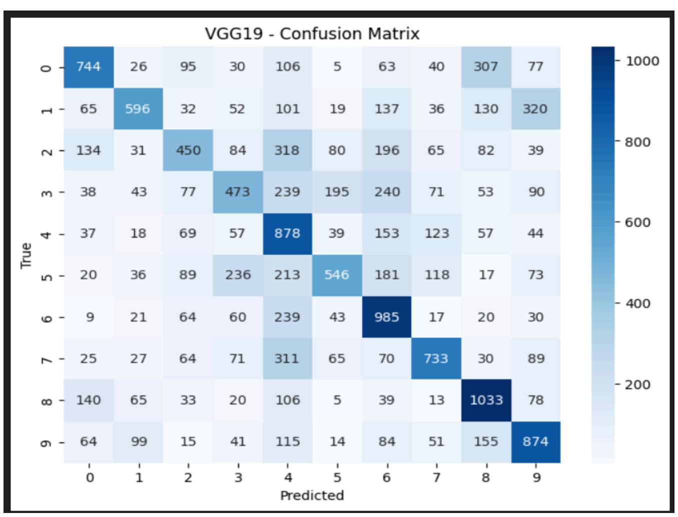
VGG 19, ResNet50, ResNet152 (Shikhar)

VGG19 -
144M Parameters
Has Three more convolution layers than VGG16.
Epochs - 5

```
Epoch 1/5
743/743 ━━━━━━━━━━━━━━━━━━━━ 26s 33ms/step - accuracy: 0.5271 - loss: 1.3625 - val_accuracy: 0.5239 - val_loss: 1.3522
Epoch 2/5
743/743 ━━━━━━━━━━━━━━━━━━━━ 39s 31ms/step - accuracy: 0.5346 - loss: 1.3445 - val_accuracy: 0.5304 - val_loss: 1.3398
Epoch 3/5
743/743 ━━━━━━━━━━━━━━━━━━━━ 22s 30ms/step - accuracy: 0.5406 - loss: 1.3257 - val_accuracy: 0.5372 - val_loss: 1.3222
Epoch 4/5
743/743 ━━━━━━━━━━━━━━━━━━━━ 41s 30ms/step - accuracy: 0.5450 - loss: 1.3145 - val_accuracy: 0.5391 - val_loss: 1.3136
Epoch 5/5
743/743 ━━━━━━━━━━━━━━━━━━━━ 41s 30ms/step - accuracy: 0.5461 - loss: 1.3056 - val_accuracy: 0.5451 - val_loss: 1.3066
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - accuracy: 0.7599 - loss: 0.6906
```








```
VGG19 - Classification Report
              precision    recall  f1-score   support

           0       0.58      0.50      0.54      1493
           1       0.62      0.40      0.49      1488
           2       0.46      0.30      0.36      1479
           3       0.42      0.31      0.36      1519
           4       0.33      0.60      0.43      1475
           5       0.54      0.36      0.43      1529
           6       0.46      0.66      0.54      1488
           7       0.58      0.49      0.53      1485
           8       0.55      0.67      0.60      1532
           9       0.51      0.58      0.54      1512

    accuracy                           0.49     15000
   macro avg       0.50      0.49      0.48     15000
weighted avg       0.51      0.49      0.48     15000

ROC AUC Score (OvA): 0.8785
```

Resnet50 and 152

Resnets employ something called skip connections, which makes some neurons bypass some layers in the middle, minimising the exploding gradient problem and allowing deeper richer feature extraction.
While they are generally better than VGG, for a problem simple like MNIST, it is **overkill** and leads to lesser accuracy than VGG and simpler models.

ResNet50 - Classification Report

	precision	recall	f1-score	support
0	0.52	0.27	0.36	1493
1	0.44	0.34	0.38	1488
2	0.45	0.04	0.08	1479
3	0.25	0.27	0.26	1519
4	0.26	0.48	0.34	1475
5	0.44	0.25	0.32	1529
6	0.35	0.41	0.38	1488
7	0.29	0.63	0.40	1485
8	0.42	0.48	0.45	1532
9	0.48	0.29	0.36	1512
accuracy			0.35	15000
macro avg	0.39	0.35	0.33	15000
weighted avg	0.39	0.35	0.33	15000

ROC AUC Score (OvA): 0.8030

ResNet152 - Classification Report

	precision	recall	f1-score	support
0	0.28	0.22	0.24	1493
1	0.25	0.34	0.28	1488
2	0.18	0.42	0.25	1479
3	0.12	0.00	0.01	1519
4	0.19	0.42	0.26	1475
5	0.29	0.21	0.24	1529
6	0.27	0.23	0.25	1488
7	0.21	0.08	0.11	1485
8	0.36	0.21	0.26	1532
9	0.23	0.19	0.21	1512
accuracy			0.23	15000
macro avg	0.24	0.23	0.21	15000
weighted avg	0.24	0.23	0.21	15000

ROC AUC Score (OvA): 0.6930

Also, another conclusion that we can take from this is, that training models from scratch would always lead to better results than transfer learning since we lose feature extraction in compensation of computation cost.

We could also train for more epochs to further illustrate benefits of transfer learning.