

Project 2: Deep Learning - Resnets

1. Experimental Results for cifar10 dataset

The model summary for Resnet20 is given in Figure 1

Layer (type)	Output Shape	Param #	Connected to
input_19 (InputLayer)	[(None, 32, 32, 3)]	0	[]
conv2d_118 (Conv2D)	(None, 32, 32, 16)	448	['input_19[0][0]']
batch_normalization_99 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_118[0][0]']
activation_86 (Activation)	(None, 32, 32, 16)	0	['batch_normalization_99[0][0]']
conv2d_119 (Conv2D)	(None, 32, 32, 16)	2320	['activation_86[0][0]']
batch_normalization_100 (Batch Normalization)	(None, 32, 32, 16)	64	['conv2d_119[0][0]']
activation_87 (Activation)	(None, 32, 32, 16)	0	['batch_normalization_100[0][0]']
conv2d_120 (Conv2D)	(None, 32, 32, 16)	2320	['activation_87[0][0]']
batch_normalization_101 (Batch Normalization)	(None, 32, 32, 16)	64	['conv2d_120[0][0]']
add_32 (Add)	(None, 32, 32, 16)	0	['activation_86[0][0]', 'batch_normalization_101[0][0]']
activation_88 (Activation)	(None, 32, 32, 16)	0	['add_32[0][0]']
conv2d_121 (Conv2D)	(None, 32, 32, 16)	2320	['activation_88[0][0]']
batch_normalization_102 (Batch Normalization)	(None, 32, 32, 16)	64	['conv2d_121[0][0]']
activation_89 (Activation)	(None, 32, 32, 16)	0	['batch_normalization_102[0][0]']
conv2d_122 (Conv2D)	(None, 32, 32, 16)	2320	['activation_89[0][0]']
batch_normalization_103 (Batch Normalization)	(None, 32, 32, 16)	64	['conv2d_122[0][0]']
add_33 (Add)	(None, 32, 32, 16)	0	['activation_88[0][0]', 'batch_normalization_103[0][0]']
activation_90 (Activation)	(None, 32, 32, 16)	0	['add_33[0][0]']
conv2d_123 (Conv2D)	(None, 32, 32, 16)	2320	['activation_90[0][0]']
batch_normalization_104 (Batch Normalization)	(None, 32, 32, 16)	64	['conv2d_123[0][0]']
activation_91 (Activation)	(None, 32, 32, 16)	0	['batch_normalization_104[0][0]']
conv2d_124 (Conv2D)	(None, 32, 32, 16)	2320	['activation_91[0][0]']
batch_normalization_105 (Batch Normalization)	(None, 32, 32, 16)	64	['conv2d_124[0][0]']
add_34 (Add)	(None, 32, 32, 16)	0	['activation_90[0][0]', 'batch_normalization_105[0][0]']

activation_92 (Activation)	(None, 32, 32, 16)	0	['add_34[0][0]']
conv2d_125 (Conv2D)	(None, 16, 16, 32)	4640	['activation_92[0][0]']
batch_normalization_106 (Batch Normalization)	(None, 16, 16, 32)	128	['conv2d_125[0][0]']
activation_93 (Activation)	(None, 16, 16, 32)	0	['batch_normalization_106[0][0]']
conv2d_126 (Conv2D)	(None, 16, 16, 32)	9248	['activation_93[0][0]']
conv2d_127 (Conv2D)	(None, 16, 16, 32)	544	['activation_93[0][0]']
batch_normalization_107 (Batch Normalization)	(None, 16, 16, 32)	128	['conv2d_126[0][0]']
add_35 (Add)	(None, 16, 16, 32)	0	['conv2d_127[0][0]', 'batch_normalization_107[0][0]']
activation_94 (Activation)	(None, 16, 16, 32)	0	['add_35[0][0]']
conv2d_128 (Conv2D)	(None, 16, 16, 32)	9248	['activation_94[0][0]']
batch_normalization_108 (Batch Normalization)	(None, 16, 16, 32)	128	['conv2d_128[0][0]']
activation_95 (Activation)	(None, 16, 16, 32)	0	['batch_normalization_108[0][0]']
conv2d_129 (Conv2D)	(None, 16, 16, 32)	9248	['activation_95[0][0]']
batch_normalization_109 (Batch Normalization)	(None, 16, 16, 32)	128	['conv2d_129[0][0]']
add_36 (Add)	(None, 16, 16, 32)	0	['activation_94[0][0]', 'batch_normalization_109[0][0]']
activation_96 (Activation)	(None, 16, 16, 32)	0	['add_36[0][0]']
conv2d_130 (Conv2D)	(None, 16, 16, 32)	9248	['activation_96[0][0]']
batch_normalization_110 (Batch Normalization)	(None, 16, 16, 32)	128	['conv2d_130[0][0]']
activation_97 (Activation)	(None, 16, 16, 32)	0	['batch_normalization_110[0][0]']
conv2d_131 (Conv2D)	(None, 16, 16, 32)	9248	['activation_97[0][0]']
batch_normalization_111 (Batch Normalization)	(None, 16, 16, 32)	128	['conv2d_131[0][0]']
add_37 (Add)	(None, 16, 16, 32)	0	['activation_96[0][0]', 'batch_normalization_111[0][0]']
activation_98 (Activation)	(None, 16, 16, 32)	0	['add_37[0][0]']
conv2d_132 (Conv2D)	(None, 8, 8, 64)	18496	['activation_98[0][0]']
batch_normalization_112 (Batch Normalization)	(None, 8, 8, 64)	256	['conv2d_132[0][0]']
activation_99 (Activation)	(None, 8, 8, 64)	0	['batch_normalization_112[0][0]']
conv2d_133 (Conv2D)	(None, 8, 8, 64)	36928	['activation_99[0][0]']
conv2d_134 (Conv2D)	(None, 8, 8, 64)	2112	['activation_98[0][0]']
batch_normalization_113 (Batch Normalization)	(None, 8, 8, 64)	256	['conv2d_133[0][0]']
add_38 (Add)	(None, 8, 8, 64)	0	['conv2d_134[0][0]', 'batch_normalization_113[0][0]']

activation_100 (Activation)	(None, 8, 8, 64)	0	['add_38[0][0]']
conv2d_135 (Conv2D)	(None, 8, 8, 64)	36928	['activation_100[0][0]']
batch_normalization_114 (Batch Normalization)	(None, 8, 8, 64)	256	['conv2d_135[0][0]']
activation_101 (Activation)	(None, 8, 8, 64)	0	['batch_normalization_114[0][0]']
conv2d_136 (Conv2D)	(None, 8, 8, 64)	36928	['activation_101[0][0]']
batch_normalization_115 (Batch Normalization)	(None, 8, 8, 64)	256	['conv2d_136[0][0]']
add_39 (Add)	(None, 8, 8, 64)	0	['activation_100[0][0]', 'batch_normalization_115[0][0]']
activation_102 (Activation)	(None, 8, 8, 64)	0	['add_39[0][0]']
conv2d_137 (Conv2D)	(None, 8, 8, 64)	36928	['activation_102[0][0]']
batch_normalization_116 (Batch Normalization)	(None, 8, 8, 64)	256	['conv2d_137[0][0]']
activation_103 (Activation)	(None, 8, 8, 64)	0	['batch_normalization_116[0][0]']
conv2d_138 (Conv2D)	(None, 8, 8, 64)	36928	['activation_103[0][0]']
batch_normalization_117 (Batch Normalization)	(None, 8, 8, 64)	256	['conv2d_138[0][0]']
add_40 (Add)	(None, 8, 8, 64)	0	['activation_102[0][0]', 'batch_normalization_117[0][0]']
activation_104 (Activation)	(None, 8, 8, 64)	0	['add_40[0][0]']
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average_pooling2d_3 (AveragePooling2D)	(None, 1, 1, 64)	0	['activation_104[0][0]']
flatten_3 (Flatten)	(None, 64)	0	['average_pooling2d_3[0][0]']
dense_3 (Dense)	(None, 10)	650	['flatten_3[0][0]']
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Figure 1: First Model Summary for cifar 10 dataset

For cifar10 dataset:

parameters of training:

learning rate = 1e-3,

epoch = 20,

batch size = 32

x_train.shape = (50000, 32, 32, 3)

loss function = categorical cross entropy, optimizer = Adam, metrics = accuracy

Training and validation accuracies in each epoch are given at Figure 2.

```

Epoch 1/20
1563/1563 [=====] - 835s 531ms/step - loss: 1.5529 - accuracy: 0.4937 - val_loss: 3.1442 - val_accuracy: 0.2933
Epoch 2/20
1563/1563 [=====] - 818s 523ms/step - loss: 1.1681 - accuracy: 0.6380 - val_loss: 1.4682 - val_accuracy: 0.5523
Epoch 3/20
1563/1563 [=====] - 824s 527ms/step - loss: 1.0089 - accuracy: 0.7035 - val_loss: 1.2021 - val_accuracy: 0.6481
Epoch 4/20
1563/1563 [=====] - 824s 527ms/step - loss: 0.9138 - accuracy: 0.7387 - val_loss: 1.0146 - val_accuracy: 0.7191
Epoch 5/20
1563/1563 [=====] - 826s 528ms/step - loss: 0.8540 - accuracy: 0.7631 - val_loss: 0.9753 - val_accuracy: 0.7320
Epoch 6/20
1563/1563 [=====] - 826s 529ms/step - loss: 0.8073 - accuracy: 0.7796 - val_loss: 0.8574 - val_accuracy: 0.7621
Epoch 7/20
1563/1563 [=====] - 826s 528ms/step - loss: 0.7788 - accuracy: 0.7904 - val_loss: 0.9595 - val_accuracy: 0.7397
Epoch 8/20
1563/1563 [=====] - 824s 527ms/step - loss: 0.7469 - accuracy: 0.8021 - val_loss: 0.8815 - val_accuracy: 0.7617
Epoch 9/20
1563/1563 [=====] - 821s 525ms/step - loss: 0.7228 - accuracy: 0.8111 - val_loss: 0.8488 - val_accuracy: 0.7677
Epoch 10/20
1563/1563 [=====] - 823s 526ms/step - loss: 0.7064 - accuracy: 0.8185 - val_loss: 0.9824 - val_accuracy: 0.7526
Epoch 11/20
1563/1563 [=====] - 825s 528ms/step - loss: 0.6912 - accuracy: 0.8254 - val_loss: 0.8126 - val_accuracy: 0.7858
Epoch 12/20
1563/1563 [=====] - 824s 527ms/step - loss: 0.6737 - accuracy: 0.8310 - val_loss: 1.0291 - val_accuracy: 0.7373
Epoch 13/20
1563/1563 [=====] - 824s 527ms/step - loss: 0.6587 - accuracy: 0.8376 - val_loss: 0.8008 - val_accuracy: 0.7938
Epoch 14/20
1563/1563 [=====] - 825s 528ms/step - loss: 0.6505 - accuracy: 0.8418 - val_loss: 0.8222 - val_accuracy: 0.7940

Epoch 15/20
1563/1563 [=====] - 826s 528ms/step - loss: 0.6401 - accuracy: 0.8460 - val_loss: 0.7224 - val_accuracy: 0.8213
Epoch 16/20
1563/1563 [=====] - 824s 527ms/step - loss: 0.6301 - accuracy: 0.8493 - val_loss: 0.9085 - val_accuracy: 0.7651
Epoch 17/20
1563/1563 [=====] - 798s 510ms/step - loss: 0.6211 - accuracy: 0.8515 - val_loss: 0.7345 - val_accuracy: 0.8171
Epoch 18/20
1563/1563 [=====] - 795s 508ms/step - loss: 0.6151 - accuracy: 0.8541 - val_loss: 0.8469 - val_accuracy: 0.7987
Epoch 19/20
1563/1563 [=====] - 793s 507ms/step - loss: 0.6098 - accuracy: 0.8560 - val_loss: 0.8154 - val_accuracy: 0.7970
Epoch 20/20
1563/1563 [=====] - 784s 502ms/step - loss: 0.6017 - accuracy: 0.8596 - val_loss: 0.7638 - val_accuracy: 0.8128
313/313 [=====] - 34s 107ms/step - loss: 0.7638 - accuracy: 0.8128

```

Figure 2: Training and validation accuracies in each epoch

The test loss and test accuracy for this model are given in Figure 3:

```

Test loss: 0.9023741483688354
Test accuracy: 0.7856000065803528

```

Figure 3: test loss and accuracy of the model

The plot of validation and training accuracy for each epoch is given in Figure 4:

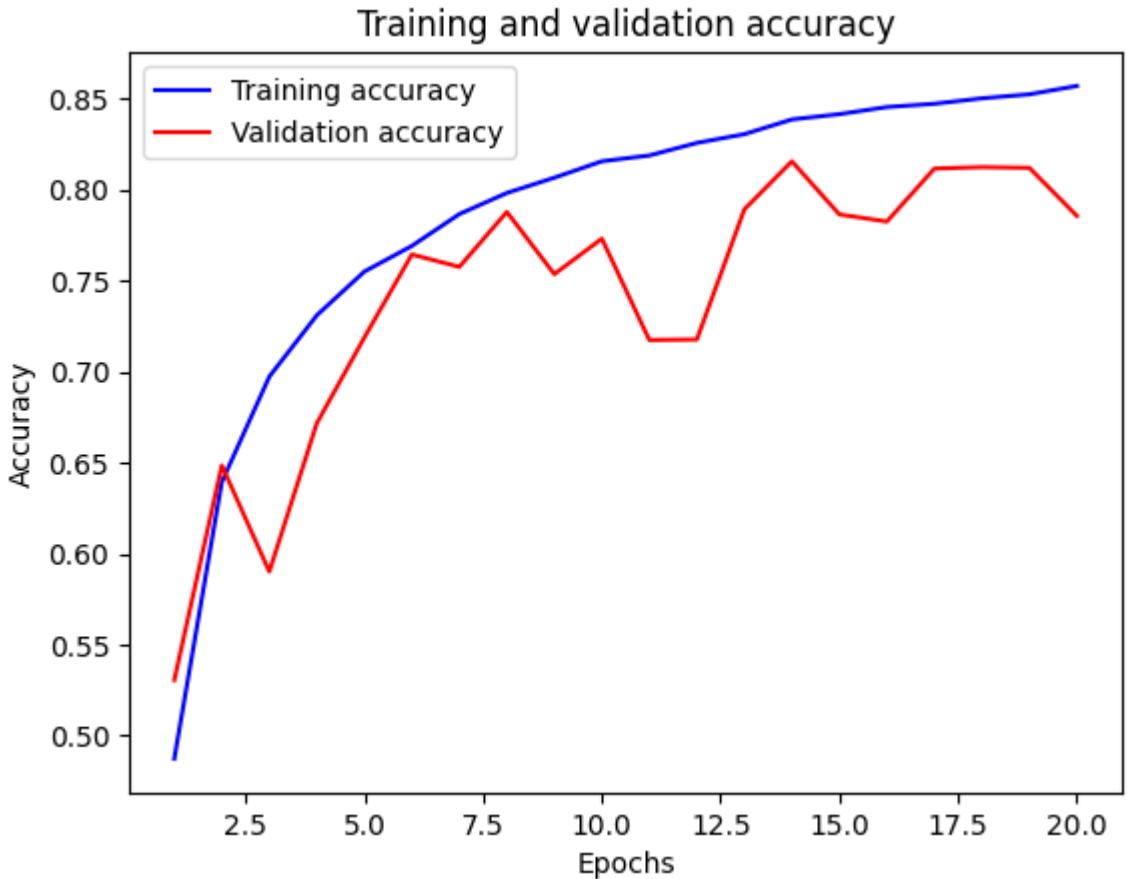


Figure 4: Validation and Training Accuracy

2. Discussion

As it can be observed the model for cifar10, there is no overfitting observed and the training and test accurices are good. Trying the model with optimizer sgd instead of Adam gives the following results in Figure 5;

```

Epoch 1/20
<ipython-input-10-898cdac8ad22>:50: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use
    model2.fit_generator(dataGen.flow(x_train, y_train, batch_size=batch_size),
1563/1563 [=====] - 67s 33ms/step - loss: 1.8475 - accuracy: 0.3780 - val_loss: 1.7610 - val_accuracy: 0.4155
Epoch 2/20
1563/1563 [=====] - 51s 33ms/step - loss: 1.5742 - accuracy: 0.4823 - val_loss: 1.5229 - val_accuracy: 0.5027
Epoch 3/20
1563/1563 [=====] - 50s 32ms/step - loss: 1.4513 - accuracy: 0.5300 - val_loss: 1.6667 - val_accuracy: 0.4643
Epoch 4/20
1563/1563 [=====] - 50s 32ms/step - loss: 1.3553 - accuracy: 0.5708 - val_loss: 1.4536 - val_accuracy: 0.5326
Epoch 5/20
1563/1563 [=====] - 50s 32ms/step - loss: 1.2750 - accuracy: 0.5989 - val_loss: 1.2358 - val_accuracy: 0.6087
Epoch 6/20
1563/1563 [=====] - 49s 31ms/step - loss: 1.2105 - accuracy: 0.6204 - val_loss: 1.3633 - val_accuracy: 0.5863
Epoch 7/20
1563/1563 [=====] - 50s 32ms/step - loss: 1.1590 - accuracy: 0.6409 - val_loss: 1.2024 - val_accuracy: 0.6313
Epoch 8/20
1563/1563 [=====] - 50s 32ms/step - loss: 1.1143 - accuracy: 0.6585 - val_loss: 1.4766 - val_accuracy: 0.5709
Epoch 9/20
1563/1563 [=====] - 49s 31ms/step - loss: 1.0744 - accuracy: 0.6712 - val_loss: 1.1519 - val_accuracy: 0.6562
Epoch 10/20
1563/1563 [=====] - 48s 31ms/step - loss: 1.0427 - accuracy: 0.6835 - val_loss: 1.2669 - val_accuracy: 0.6243
Epoch 11/20
1563/1563 [=====] - 48s 31ms/step - loss: 1.0013 - accuracy: 0.6989 - val_loss: 1.3094 - val_accuracy: 0.6113
Epoch 12/20
1563/1563 [=====] - 49s 31ms/step - loss: 0.9703 - accuracy: 0.7101 - val_loss: 1.1781 - val_accuracy: 0.6397
Epoch 13/20
1563/1563 [=====] - 50s 32ms/step - loss: 0.9415 - accuracy: 0.7196 - val_loss: 1.0044 - val_accuracy: 0.6990
Epoch 14/20
1563/1563 [=====] - 49s 31ms/step - loss: 0.9146 - accuracy: 0.7300 - val_loss: 1.1780 - val_accuracy: 0.6495
Epoch 15/20
1563/1563 [=====] - 49s 31ms/step - loss: 0.8931 - accuracy: 0.7387 - val_loss: 1.2694 - val_accuracy: 0.6357
Epoch 16/20

```

```

Epoch 15/20
1563/1563 [=====] - 49s 31ms/step - loss: 0.8931 - accuracy: 0.7387 - val_loss: 1.2694 - val_accuracy: 0.6357
Epoch 16/20
1563/1563 [=====] - 49s 31ms/step - loss: 0.8692 - accuracy: 0.7455 - val_loss: 1.1327 - val_accuracy: 0.6811
Epoch 17/20
1563/1563 [=====] - 49s 31ms/step - loss: 0.8471 - accuracy: 0.7550 - val_loss: 1.0730 - val_accuracy: 0.6982
Epoch 18/20
1563/1563 [=====] - 56s 36ms/step - loss: 0.8252 - accuracy: 0.7606 - val_loss: 0.9042 - val_accuracy: 0.7297
Epoch 19/20
1563/1563 [=====] - 57s 36ms/step - loss: 0.8083 - accuracy: 0.7677 - val_loss: 1.0221 - val_accuracy: 0.7159
Epoch 20/20
1563/1563 [=====] - 55s 35ms/step - loss: 0.7867 - accuracy: 0.7763 - val_loss: 0.9325 - val_accuracy: 0.7354
313/313 [=====] - 2s 5ms/step - loss: 0.9325 - accuracy: 0.7354
Test loss: 0.9325338006019592
Test accuracy: 0.7354000210762024

```

Figure 5: Training and validation accuracy at each epoch for optimizer sgd

As it can be seen the adam optimizer works better than sgd for this model. This might be due the the deep nature of this neural network. Now in the following I have tried the optimizer adam and increased the depth of the network by using n = 4 instead n = 3. It resulted as follows;

input_2 (InputLayer)	[(None, 32, 32, 3)]	0	[]
conv2d_21 (Conv2D)	(None, 32, 32, 16)	448	['input_2[0][0]']
batch_normalization_19 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_21[0][0]']
activation_19 (Activation)	(None, 32, 32, 16)	0	['batch_normalization_19[0][0]']
conv2d_22 (Conv2D)	(None, 32, 32, 16)	2320	['activation_19[0][0]']
batch_normalization_20 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_22[0][0]']
activation_20 (Activation)	(None, 32, 32, 16)	0	['batch_normalization_20[0][0]']
conv2d_23 (Conv2D)	(None, 32, 32, 16)	2320	['activation_20[0][0]']
batch_normalization_21 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_23[0][0]']
add_9 (Add)	(None, 32, 32, 16)	0	['activation_19[0][0]', 'batch_normalization_21[0][0]']
activation_21 (Activation)	(None, 32, 32, 16)	0	['add_9[0][0]']
conv2d_24 (Conv2D)	(None, 32, 32, 16)	2320	['activation_21[0][0]']
batch_normalization_22 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_24[0][0]']

conv2d_24 (Conv2D)	(None, 32, 32, 16)	2320	['activation_21[0][0]']
batch_normalization_22 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_24[0][0]']
activation_22 (Activation)	(None, 32, 32, 16)	0	['batch_normalization_22[0][0]']
conv2d_25 (Conv2D)	(None, 32, 32, 16)	2320	['activation_22[0][0]']
batch_normalization_23 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_25[0][0]']
add_10 (Add)	(None, 32, 32, 16)	0	['activation_21[0][0]', 'batch_normalization_23[0][0]']
activation_23 (Activation)	(None, 32, 32, 16)	0	['add_10[0][0]']
conv2d_26 (Conv2D)	(None, 32, 32, 16)	2320	['activation_23[0][0]']
batch_normalization_24 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_26[0][0]']
activation_24 (Activation)	(None, 32, 32, 16)	0	['batch_normalization_24[0][0]']
conv2d_27 (Conv2D)	(None, 32, 32, 16)	2320	['activation_24[0][0]']
batch_normalization_25 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_27[0][0]']
add_11 (Add)	(None, 32, 32, 16)	0	['activation_23[0][0]', 'batch_normalization_25[0][0]']
activation_25 (Activation)	(None, 32, 32, 16)	0	['add_11[0][0]']
conv2d_28 (Conv2D)	(None, 32, 32, 16)	2320	['activation_25[0][0]']
batch_normalization_26 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_28[0][0]']
activation_26 (Activation)	(None, 32, 32, 16)	0	['batch_normalization_26[0][0]']
conv2d_29 (Conv2D)	(None, 32, 32, 16)	2320	['activation_26[0][0]']
batch_normalization_27 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_29[0][0]']
add_12 (Add)	(None, 32, 32, 16)	0	['activation_25[0][0]', 'batch_normalization_27[0][0]']
activation_27 (Activation)	(None, 32, 32, 16)	0	['add_12[0][0]']
conv2d_30 (Conv2D)	(None, 16, 16, 32)	4640	['activation_27[0][0]']
batch_normalization_28 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_30[0][0]']
activation_28 (Activation)	(None, 16, 16, 32)	0	['batch_normalization_28[0][0]']

conv2d_31 (Conv2D)	(None, 16, 16, 32)	9248	['activation_28[0][0]']
conv2d_32 (Conv2D)	(None, 16, 16, 32)	544	['activation_27[0][0]']
batch_normalization_29 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_31[0][0]']
add_13 (Add)	(None, 16, 16, 32)	0	['conv2d_32[0][0]', 'batch_normalization_29[0][0]']
activation_29 (Activation)	(None, 16, 16, 32)	0	['add_13[0][0]']
conv2d_33 (Conv2D)	(None, 16, 16, 32)	9248	['activation_29[0][0]']
batch_normalization_30 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_33[0][0]']
activation_30 (Activation)	(None, 16, 16, 32)	0	['batch_normalization_30[0][0]']
conv2d_34 (Conv2D)	(None, 16, 16, 32)	9248	['activation_30[0][0]']
batch_normalization_31 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_34[0][0]']
add_14 (Add)	(None, 16, 16, 32)	0	['activation_29[0][0]', 'batch_normalization_31[0][0]']
activation_31 (Activation)	(None, 16, 16, 32)	0	['add_14[0][0]']
conv2d_35 (Conv2D)	(None, 16, 16, 32)	9248	['activation_31[0][0]']
batch_normalization_32 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_35[0][0]']
activation_32 (Activation)	(None, 16, 16, 32)	0	['batch_normalization_32[0][0]']
conv2d_36 (Conv2D)	(None, 16, 16, 32)	9248	['activation_32[0][0]']
batch_normalization_33 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_36[0][0]']
add_15 (Add)	(None, 16, 16, 32)	0	['activation_31[0][0]', 'batch_normalization_33[0][0]']
activation_33 (Activation)	(None, 16, 16, 32)	0	['add_15[0][0]']
conv2d_37 (Conv2D)	(None, 16, 16, 32)	9248	['activation_33[0][0]']
batch_normalization_34 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_37[0][0]']
activation_34 (Activation)	(None, 16, 16, 32)	0	['batch_normalization_34[0][0]']
conv2d_38 (Conv2D)	(None, 16, 16, 32)	9248	['activation_34[0][0]']
batch_normalization_35 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_38[0][0]']

add_16 (Add)	(None, 16, 16, 32)	0	['activation_33[0][0]', 'batch_normalization_35[0][0]']
activation_35 (Activation)	(None, 16, 16, 32)	0	['add_16[0][0]']
conv2d_39 (Conv2D)	(None, 8, 8, 64)	18496	['activation_35[0][0]']
batch_normalization_36 (BatchN ormalization)	(None, 8, 8, 64)	256	['conv2d_39[0][0]']
activation_36 (Activation)	(None, 8, 8, 64)	0	['batch_normalization_36[0][0]']
conv2d_40 (Conv2D)	(None, 8, 8, 64)	36928	['activation_36[0][0]']
conv2d_41 (Conv2D)	(None, 8, 8, 64)	2112	['activation_35[0][0]']
batch_normalization_37 (BatchN ormalization)	(None, 8, 8, 64)	256	['conv2d_40[0][0]']
add_17 (Add)	(None, 8, 8, 64)	0	['conv2d_41[0][0]', 'batch_normalization_37[0][0]']
activation_37 (Activation)	(None, 8, 8, 64)	0	['add_17[0][0]']
conv2d_42 (Conv2D)	(None, 8, 8, 64)	36928	['activation_37[0][0]']
batch_normalization_38 (BatchN ormalization)	(None, 8, 8, 64)	256	['conv2d_42[0][0]']
activation_38 (Activation)	(None, 8, 8, 64)	0	['batch_normalization_38[0][0]']
conv2d_43 (Conv2D)	(None, 8, 8, 64)	36928	['activation_38[0][0]']
batch_normalization_39 (BatchN ormalization)	(None, 8, 8, 64)	256	['conv2d_43[0][0]']
add_18 (Add)	(None, 8, 8, 64)	0	['activation_37[0][0]', 'batch_normalization_39[0][0]']
activation_39 (Activation)	(None, 8, 8, 64)	0	['add_18[0][0]']
conv2d_44 (Conv2D)	(None, 8, 8, 64)	36928	['activation_39[0][0]']
batch_normalization_40 (BatchN ormalization)	(None, 8, 8, 64)	256	['conv2d_44[0][0]']
activation_40 (Activation)	(None, 8, 8, 64)	0	['batch_normalization_40[0][0]']
conv2d_45 (Conv2D)	(None, 8, 8, 64)	36928	['activation_40[0][0]']
batch_normalization_41 (BatchN ormalization)	(None, 8, 8, 64)	256	['conv2d_45[0][0]']
add_19 (Add)	(None, 8, 8, 64)	0	['activation_39[0][0]', 'batch_normalization_41[0][0]']
activation_41 (Activation)	(None, 8, 8, 64)	0	['add_19[0][0]']
conv2d_46 (Conv2D)	(None, 8, 8, 64)	36928	['activation_41[0][0]']
batch_normalization_42 (BatchN ormalization)	(None, 8, 8, 64)	256	['conv2d_46[0][0]']
activation_42 (Activation)	(None, 8, 8, 64)	0	['batch_normalization_42[0][0]']

```

activation_42 (Activation)      (None, 8, 8, 64)    0      ['batch_normalization_42[0][0]']
conv2d_47 (Conv2D)            (None, 8, 8, 64)    36928   ['activation_42[0][0]']
batch_normalization_43 (BatchN (None, 8, 8, 64)    256    ['conv2d_47[0][0]']
ormalization)
add_20 (Add)                 (None, 8, 8, 64)    0      ['activation_41[0][0]', 'batch_normalization_43[0][0]']
activation_43 (Activation)    (None, 8, 8, 64)    0      ['add_20[0][0]']
average_pooling2d_1 (AveragePo (None, 1, 1, 64)    0      ['activation_43[0][0]']
oling2D)
flatten_1 (Flatten)          (None, 64)        0      ['average_pooling2d_1[0][0]']
dense_1 (Dense)              (None, 10)       650    ['flatten_1[0][0]']

=====
Total params: 372,330
Trainable params: 370,506
Non-trainable params: 1,824

```

Figure 6: Model summary with n = 4

This model gave the accuracy plots as such:

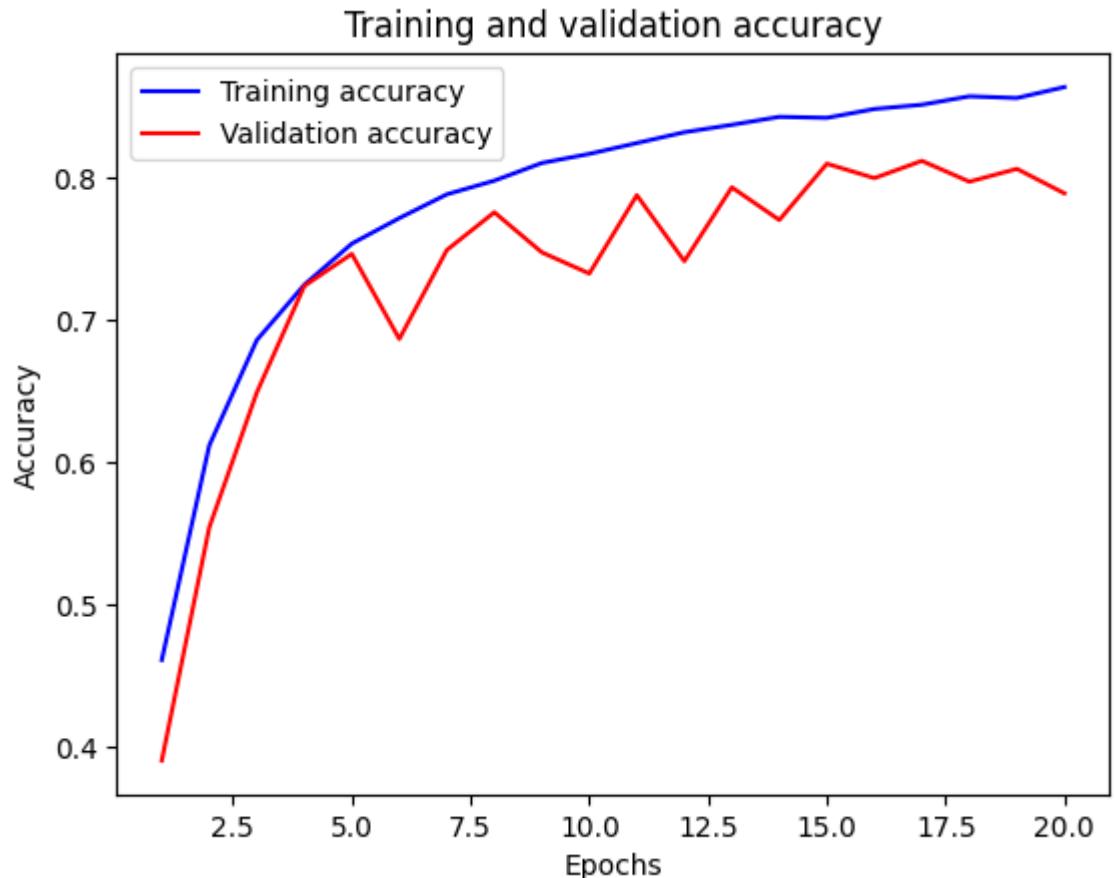


Figure 7: Training and validation accuracy

Test accuracy for this model is 0.7888000011444092

As it can be observed that the model with $n = 4$, the model with more depth has better accuracy. The optimizer used for this model is adam and the other parameters are the same. Since resnet models have shortcuts the training is fast and lets deeper models train and outcome overall good accuracies.

3. Experimental Results for cifar100 dataset

The model summary for Resnet20 is given in the figure below; the only difference with the model used for cifar 10 dataset is the output layer having 100 nodes instead of 10.

Layer (type)	Output Shape	Param #	Connected to
<hr/>			
input_2 (InputLayer)	[None, 32, 32, 3]	0	[]
conv2d_21 (Conv2D)	(None, 32, 32, 16)	448	['input_2[0][0]']
batch_normalization_19 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_21[0][0]']
activation_19 (Activation)	(None, 32, 32, 16)	0	['batch_normalization_19[0][0]']
conv2d_22 (Conv2D)	(None, 32, 32, 16)	2320	['activation_19[0][0]']
batch_normalization_20 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_22[0][0]']
activation_20 (Activation)	(None, 32, 32, 16)	0	['batch_normalization_20[0][0]']
conv2d_23 (Conv2D)	(None, 32, 32, 16)	2320	['activation_20[0][0]']
batch_normalization_21 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_23[0][0]']
add_9 (Add)	(None, 32, 32, 16)	0	['activation_19[0][0]', 'batch_normalization_21[0][0]']
activation_21 (Activation)	(None, 32, 32, 16)	0	['add_9[0][0]']
conv2d_24 (Conv2D)	(None, 32, 32, 16)	2320	['activation_21[0][0]']

batch_normalization_22 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_24[0][0]']
activation_22 (Activation)	(None, 32, 32, 16)	0	['batch_normalization_22[0][0]']
conv2d_25 (Conv2D)	(None, 32, 32, 16)	2320	['activation_22[0][0]']
batch_normalization_23 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_25[0][0]']
add_10 (Add)	(None, 32, 32, 16)	0	['activation_21[0][0]', 'batch_normalization_23[0][0]']
activation_23 (Activation)	(None, 32, 32, 16)	0	['add_10[0][0]']
conv2d_26 (Conv2D)	(None, 32, 32, 16)	2320	['activation_23[0][0]']
batch_normalization_24 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_26[0][0]']
activation_24 (Activation)	(None, 32, 32, 16)	0	['batch_normalization_24[0][0]']
conv2d_27 (Conv2D)	(None, 32, 32, 16)	2320	['activation_24[0][0]']
batch_normalization_25 (BatchN ormalization)	(None, 32, 32, 16)	64	['conv2d_27[0][0]']
add_11 (Add)	(None, 32, 32, 16)	0	['activation_23[0][0]', 'batch_normalization_25[0][0]']
activation_25 (Activation)	(None, 32, 32, 16)	0	['add_11[0][0]']
conv2d_28 (Conv2D)	(None, 16, 16, 32)	4640	['activation_25[0][0]']
batch_normalization_26 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_28[0][0]']
activation_26 (Activation)	(None, 16, 16, 32)	0	['batch_normalization_26[0][0]']
conv2d_29 (Conv2D)	(None, 16, 16, 32)	9248	['activation_26[0][0]']
conv2d_30 (Conv2D)	(None, 16, 16, 32)	544	['activation_25[0][0]']
batch_normalization_27 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_29[0][0]']
add_12 (Add)	(None, 16, 16, 32)	0	['conv2d_30[0][0]', 'batch_normalization_27[0][0]']
activation_27 (Activation)	(None, 16, 16, 32)	0	['add_12[0][0]']
conv2d_31 (Conv2D)	(None, 16, 16, 32)	9248	['activation_27[0][0]']
batch_normalization_28 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_31[0][0]']
activation_28 (Activation)	(None, 16, 16, 32)	0	['batch_normalization_28[0][0]']
conv2d_32 (Conv2D)	(None, 16, 16, 32)	9248	['activation_28[0][0]']
batch_normalization_29 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_32[0][0]']

add_13 (Add)	(None, 16, 16, 32)	0	['activation_27[0][0]', 'batch_normalization_29[0][0]']
activation_29 (Activation)	(None, 16, 16, 32)	0	['add_13[0][0]']
conv2d_33 (Conv2D)	(None, 16, 16, 32)	9248	['activation_29[0][0]']
batch_normalization_30 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_33[0][0]']
activation_30 (Activation)	(None, 16, 16, 32)	0	['batch_normalization_30[0][0]']
conv2d_34 (Conv2D)	(None, 16, 16, 32)	9248	['activation_30[0][0]']
batch_normalization_31 (BatchN ormalization)	(None, 16, 16, 32)	128	['conv2d_34[0][0]']
add_14 (Add)	(None, 16, 16, 32)	0	['activation_29[0][0]', 'batch_normalization_31[0][0]']
activation_31 (Activation)	(None, 16, 16, 32)	0	['add_14[0][0]']
conv2d_35 (Conv2D)	(None, 8, 8, 64)	18496	['activation_31[0][0]']
batch_normalization_32 (BatchN ormalization)	(None, 8, 8, 64)	256	['conv2d_35[0][0]']
activation_32 (Activation)	(None, 8, 8, 64)	0	['batch_normalization_32[0][0]']
conv2d_36 (Conv2D)	(None, 8, 8, 64)	36928	['activation_32[0][0]']
conv2d_37 (Conv2D)	(None, 8, 8, 64)	2112	['activation_31[0][0]']
batch_normalization_33 (BatchN ormalization)	(None, 8, 8, 64)	256	['conv2d_36[0][0]']
add_15 (Add)	(None, 8, 8, 64)	0	['conv2d_37[0][0]', 'batch_normalization_33[0][0]']
activation_33 (Activation)	(None, 8, 8, 64)	0	['add_15[0][0]']
conv2d_38 (Conv2D)	(None, 8, 8, 64)	36928	['activation_33[0][0]']
batch_normalization_34 (BatchN ormalization)	(None, 8, 8, 64)	256	['conv2d_38[0][0]']
activation_34 (Activation)	(None, 8, 8, 64)	0	['batch_normalization_34[0][0]']
conv2d_39 (Conv2D)	(None, 8, 8, 64)	36928	['activation_34[0][0]']
batch_normalization_35 (BatchN ormalization)	(None, 8, 8, 64)	256	['conv2d_39[0][0]']
add_16 (Add)	(None, 8, 8, 64)	0	['activation_33[0][0]', 'batch_normalization_35[0][0]']
activation_35 (Activation)	(None, 8, 8, 64)	0	['add_16[0][0]']
conv2d_40 (Conv2D)	(None, 8, 8, 64)	36928	['activation_35[0][0]']
batch_normalization_36 (BatchN ormalization)	(None, 8, 8, 64)	256	['conv2d_40[0][0]']
activation_36 (Activation)	(None, 8, 8, 64)	0	['batch_normalization_36[0][0]']

<code>conv2d_41 (Conv2D)</code>	<code>(None, 8, 8, 64)</code>	36928	<code>['activation_36[0][0]']</code>
<code>batch_normalization_37 (BatchN ormalization)</code>	<code>(None, 8, 8, 64)</code>	256	<code>['conv2d_41[0][0]']</code>
<code>add_17 (Add)</code>	<code>(None, 8, 8, 64)</code>	0	<code>['activation_35[0][0]', 'batch_normalization_37[0][0]']</code>
<code>activation_37 (Activation)</code>	<code>(None, 8, 8, 64)</code>	0	<code>['add_17[0][0]']</code>
<code>average_pooling2d_1 (AveragePo oling2D)</code>	<code>(None, 1, 1, 64)</code>	0	<code>['activation_37[0][0]']</code>
<code>flatten_1 (Flatten)</code>	<code>(None, 64)</code>	0	<code>['average_pooling2d_1[0][0]']</code>
<code>dense_1 (Dense)</code>	<code>(None, 100)</code>	6500	<code>['flatten_1[0][0]']</code>
<hr/>			
<code>Total params: 280,292</code>			
<code>Trainable params: 278,916</code>			
<code>Non-trainable params: 1,376</code>			

Figure 8: Model summary for cifar 100 dataset

The training parameters of this model is:

parameters of training:

learning rate = 1e-3,

epoch = 20,

batch size = 32

`x_train.shape = (50000,32,32,3)`

loss function = categorical cross entropy, optimizer = Adam, metrics = accuracy

Training and validation accuracy plot in each epoch are given at Figure 9.

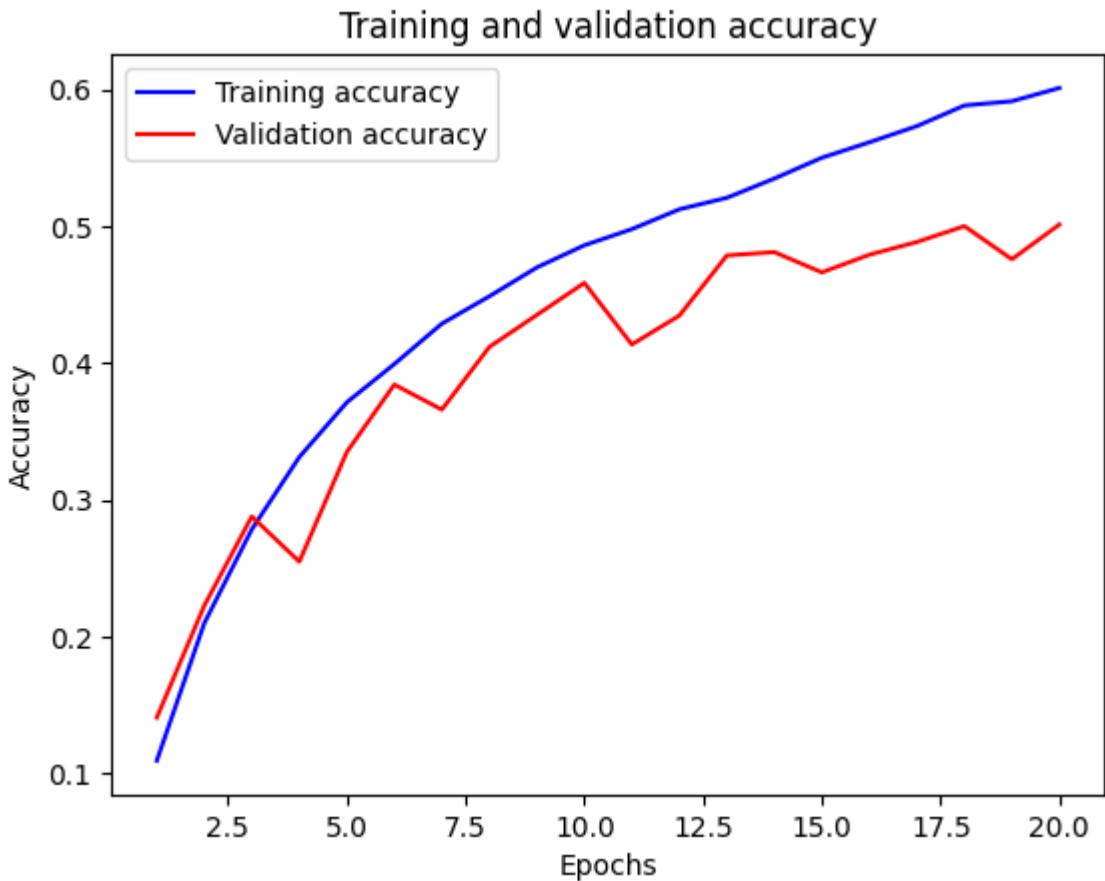


Figure 9 : The plot of train and test accuracy

4. Discussion for cifar-100 dataset

As it can be observed from the plot there is no over fitting observed in these 20 epochs.

The training time was significantly longer since there is 100 classes instead of 10. Comparing with the CNN modules used in the previous assignments resnets give much better results with not very significant training time differences.

5. Resnet50 vs model constructed for cifar 10 dataset

In this section the accuracy results for pre-trained Resnet50 and the 2 models with $n = 3$ and $n = 4$ are compared for cifar10 dataset.

Due to training time and since the network is deeper I set epoch to 5, the rest of the training parameters are the same.

The model summary for Resnet50 is given in the below figure;

Model: "model_1"				
Layer (type)	Output Shape	Param #	Connected to	
input_1 (InputLayer)	[(None, 32, 32, 3)]	0	[]	
conv1_pad (ZeroPadding2D)	(None, 38, 38, 3)	0	['input_1[0][0]']	
conv1_conv (Conv2D)	(None, 16, 16, 64)	9472	['conv1_pad[0][0]']	
conv1_bn (BatchNormalization)	(None, 16, 16, 64)	256	['conv1_conv[0][0]']	
conv1_relu (Activation)	(None, 16, 16, 64)	0	['conv1_bn[0][0]']	
pool1_pad (ZeroPadding2D)	(None, 18, 18, 64)	0	['conv1_relu[0][0]']	
pool1_pool (MaxPooling2D)	(None, 8, 8, 64)	0	['pool1_pad[0][0]']	
conv2_block1_1_conv (Conv2D)	(None, 8, 8, 64)	4160	['pool1_pool[0][0]']	
conv2_block1_1_bn (BatchNormal ization)	(None, 8, 8, 64)	256	['conv2_block1_1_conv[0][0]']	
conv2_block1_1_relu (Activatio n)	(None, 8, 8, 64)	0	['conv2_block1_1_bn[0][0]']	
conv2_block1_2_conv (Conv2D)	(None, 8, 8, 64)	36928	['conv2_block1_1_relu[0][0]']	
conv2_block1_2_bn (BatchNormal ization)	(None, 8, 8, 64)	256	['conv2_block1_2_conv[0][0]']	
conv2_block1_2_relu (Activatio n)	(None, 8, 8, 64)	0	['conv2_block1_2_bn[0][0]']	
conv2_block1_0_conv (Conv2D)	(None, 8, 8, 256)	16640	['pool1_pool[0][0]']	
conv2_block1_3_conv (Conv2D)	(None, 8, 8, 256)	16640	['conv2_block1_2_relu[0][0]']	
conv2_block1_0_bn (BatchNormal ization)	(None, 8, 8, 256)	1024	['conv2_block1_0_conv[0][0]']	
conv2_block1_3_bn (BatchNormal ization)	(None, 8, 8, 256)	1024	['conv2_block1_3_conv[0][0]']	
conv2_block1_add (Add)	(None, 8, 8, 256)	0	['conv2_block1_0_bn[0][0]', 'conv2_block1_3_bn[0][0]']	
conv2_block1_out (Activation)	(None, 8, 8, 256)	0	['conv2_block1_add[0][0]']	
conv2_block2_1_conv (Conv2D)	(None, 8, 8, 64)	16448	['conv2_block1_out[0][0]']	
conv2_block2_1_bn (BatchNormal ization)	(None, 8, 8, 64)	256	['conv2_block2_1_conv[0][0]']	
conv2_block2_1_relu (Activatio n)	(None, 8, 8, 64)	0	['conv2_block2_1_bn[0][0]']	
conv2_block2_2_conv (Conv2D)	(None, 8, 8, 64)	36928	['conv2_block2_1_relu[0][0]']	
conv2_block2_2_bn (BatchNormal ization)	(None, 8, 8, 64)	256	['conv2_block2_2_conv[0][0]']	
conv2_block2_2_relu (Activatio n)	(None, 8, 8, 64)	0	['conv2_block2_2_bn[0][0]']	
conv2_block2_3_conv (Conv2D)	(None, 8, 8, 256)	16640	['conv2_block2_2_relu[0][0]']	

conv2_block2_3_bn (BatchNormal ization)	(None, 8, 8, 256)	1024	['conv2_block2_3_conv[0][0]']
conv2_block2_add (Add)	(None, 8, 8, 256)	0	['conv2_block1_out[0][0]', 'conv2_block2_3_bn[0][0]']
conv2_block2_out (Activation)	(None, 8, 8, 256)	0	['conv2_block2_add[0][0]']
conv2_block3_1_conv (Conv2D)	(None, 8, 8, 64)	16448	['conv2_block2_out[0][0]']
conv2_block3_1_bn (BatchNormal ization)	(None, 8, 8, 64)	256	['conv2_block3_1_conv[0][0]']
conv2_block3_1_relu (Activatio n)	(None, 8, 8, 64)	0	['conv2_block3_1_bn[0][0]']
conv2_block3_2_conv (Conv2D)	(None, 8, 8, 64)	36928	['conv2_block3_1_relu[0][0]']
conv2_block3_2_bn (BatchNormal ization)	(None, 8, 8, 64)	256	['conv2_block3_2_conv[0][0]']
conv2_block3_2_relu (Activatio n)	(None, 8, 8, 64)	0	['conv2_block3_2_bn[0][0]']
conv2_block3_3_conv (Conv2D)	(None, 8, 8, 256)	16640	['conv2_block3_2_relu[0][0]']
conv2_block3_3_bn (BatchNormal ization)	(None, 8, 8, 256)	1024	['conv2_block3_3_conv[0][0]']
conv2_block3_add (Add)	(None, 8, 8, 256)	0	['conv2_block2_out[0][0]', 'conv2_block3_3_bn[0][0]']
conv2_block3_out (Activation)	(None, 8, 8, 256)	0	['conv2_block3_add[0][0]']
conv3_block1_1_conv (Conv2D)	(None, 4, 4, 128)	32896	['conv2_block3_out[0][0]']
conv3_block1_1_bn (BatchNormal ization)	(None, 4, 4, 128)	512	['conv3_block1_1_conv[0][0]']
conv3_block1_1_relu (Activatio n)	(None, 4, 4, 128)	0	['conv3_block1_1_bn[0][0]']
conv3_block1_2_conv (Conv2D)	(None, 4, 4, 128)	147584	['conv3_block1_1_relu[0][0]']
conv3_block1_2_bn (BatchNormal ization)	(None, 4, 4, 128)	512	['conv3_block1_2_conv[0][0]']
conv3_block1_2_relu (Activatio n)	(None, 4, 4, 128)	0	['conv3_block1_2_bn[0][0]']
conv3_block1_0_conv (Conv2D)	(None, 4, 4, 512)	131584	['conv2_block3_out[0][0]']
conv3_block1_3_conv (Conv2D)	(None, 4, 4, 512)	66048	['conv3_block1_2_relu[0][0]']
conv3_block1_0_bn (BatchNormal ization)	(None, 4, 4, 512)	2048	['conv3_block1_0_conv[0][0]']
conv3_block1_3_bn (BatchNormal ization)	(None, 4, 4, 512)	2048	['conv3_block1_3_conv[0][0]']
conv3_block1_add (Add)	(None, 4, 4, 512)	0	['conv3_block1_0_bn[0][0]', 'conv3_block1_3_bn[0][0]']
conv3_block1_out (Activation)	(None, 4, 4, 512)	0	['conv3_block1_add[0][0]']

conv3_block2_1_conv (Conv2D) (None, 4, 4, 128)	65664	['conv3_block1_out[0][0]']
conv3_block2_1_bn (BatchNormal (None, 4, 4, 128) ization)	512	['conv3_block2_1_conv[0][0]']
conv3_block2_1_relu (Activatio n) (None, 4, 4, 128)	0	['conv3_block2_1_bn[0][0]']
conv3_block2_2_conv (Conv2D) (None, 4, 4, 128)	147584	['conv3_block2_1_relu[0][0]']
conv3_block2_2_bn (BatchNormal (None, 4, 4, 128) ization)	512	['conv3_block2_2_conv[0][0]']
conv3_block2_2_relu (Activatio n) (None, 4, 4, 128)	0	['conv3_block2_2_bn[0][0]']
conv3_block2_3_conv (Conv2D) (None, 4, 4, 512)	66048	['conv3_block2_2_relu[0][0]']
conv3_block2_3_bn (BatchNormal (None, 4, 4, 512) ization)	2048	['conv3_block2_3_conv[0][0]']
conv3_block2_add (Add) (None, 4, 4, 512)	0	['conv3_block1_out[0][0]', 'conv3_block2_3_bn[0][0]']
conv3_block2_out (Activation) (None, 4, 4, 512)	0	['conv3_block2_add[0][0]']
conv3_block3_1_conv (Conv2D) (None, 4, 4, 128)	65664	['conv3_block2_out[0][0]']
conv3_block3_1_bn (BatchNormal (None, 4, 4, 128) ization)	512	['conv3_block3_1_conv[0][0]']
conv3_block3_1_relu (Activatio n) (None, 4, 4, 128)	0	['conv3_block3_1_bn[0][0]']
conv3_block3_2_conv (Conv2D) (None, 4, 4, 128)	147584	['conv3_block3_1_relu[0][0]']
conv3_block3_2_bn (BatchNormal (None, 4, 4, 128) ization)	512	['conv3_block3_2_conv[0][0]']
conv3_block3_2_relu (Activatio n) (None, 4, 4, 128)	0	['conv3_block3_2_bn[0][0]']
conv3_block3_3_conv (Conv2D) (None, 4, 4, 512)	66048	['conv3_block3_2_relu[0][0]']
conv3_block3_3_bn (BatchNormal (None, 4, 4, 512) ization)	2048	['conv3_block3_3_conv[0][0]']
conv3_block3_add (Add) (None, 4, 4, 512)	0	['conv3_block2_out[0][0]', 'conv3_block3_3_bn[0][0]']
conv3_block3_out (Activation) (None, 4, 4, 512)	0	['conv3_block3_add[0][0]']
conv3_block4_1_conv (Conv2D) (None, 4, 4, 128)	65664	['conv3_block3_out[0][0]']
conv3_block4_1_bn (BatchNormal (None, 4, 4, 128) ization)	512	['conv3_block4_1_conv[0][0]']
conv3_block4_1_relu (Activatio n) (None, 4, 4, 128)	0	['conv3_block4_1_bn[0][0]']
conv3_block4_2_conv (Conv2D) (None, 4, 4, 128)	147584	['conv3_block4_1_relu[0][0]']
conv3_block4_2_bn (BatchNormal (None, 4, 4, 128) ization)	512	['conv3_block4_2_conv[0][0]']
conv3_block4_2_relu (Activatio n) (None, 4, 4, 128)	0	['conv3_block4_2_bn[0][0]']

conv3_block4_3_conv (Conv2D) (None, 4, 4, 512)	66048	['conv3_block4_2_relu[0][0]']
conv3_block4_3_bn (BatchNormal (None, 4, 4, 512) ization)	2048	['conv3_block4_3_conv[0][0]']
conv3_block4_add (Add) (None, 4, 4, 512)	0	['conv3_block3_out[0][0]', 'conv3_block4_3_bn[0][0]']
conv3_block4_out (Activation) (None, 4, 4, 512)	0	['conv3_block4_add[0][0]']
conv4_block1_1_conv (Conv2D) (None, 2, 2, 256)	131328	['conv3_block4_out[0][0]']
conv4_block1_1_bn (BatchNormal (None, 2, 2, 256) ization)	1024	['conv4_block1_1_conv[0][0]']
conv4_block1_1_relu (Activatio (None, 2, 2, 256) n)	0	['conv4_block1_1_bn[0][0]']
conv4_block1_2_conv (Conv2D) (None, 2, 2, 256)	590080	['conv4_block1_1_relu[0][0]']
conv4_block1_2_bn (BatchNormal (None, 2, 2, 256) ization)	1024	['conv4_block1_2_conv[0][0]']
conv4_block1_2_relu (Activatio (None, 2, 2, 256) n)	0	['conv4_block1_2_bn[0][0]']
conv4_block1_0_conv (Conv2D) (None, 2, 2, 1024)	525312	['conv3_block4_out[0][0]']
conv4_block1_3_conv (Conv2D) (None, 2, 2, 1024)	263168	['conv4_block1_2_relu[0][0]']
conv4_block1_0_bn (BatchNormal (None, 2, 2, 1024)	4096	['conv4_block1_0_conv[0][0]']
conv4_block1_3_bn (BatchNormal (None, 2, 2, 1024) ization)	4096	['conv4_block1_3_conv[0][0]']
conv4_block1_add (Add) (None, 2, 2, 1024)	0	['conv4_block1_0_bn[0][0]', 'conv4_block1_3_bn[0][0]']
conv4_block1_out (Activation) (None, 2, 2, 1024)	0	['conv4_block1_add[0][0]']
conv4_block2_1_conv (Conv2D) (None, 2, 2, 256)	262400	['conv4_block1_out[0][0]']
conv4_block2_1_bn (BatchNormal (None, 2, 2, 256) ization)	1024	['conv4_block2_1_conv[0][0]']
conv4_block2_1_relu (Activatio (None, 2, 2, 256) n)	0	['conv4_block2_1_bn[0][0]']
conv4_block2_2_conv (Conv2D) (None, 2, 2, 256)	590080	['conv4_block2_1_relu[0][0]']
conv4_block2_2_bn (BatchNormal (None, 2, 2, 256) ization)	1024	['conv4_block2_2_conv[0][0]']
conv4_block2_2_relu (Activatio (None, 2, 2, 256) n)	0	['conv4_block2_2_bn[0][0]']
conv4_block2_3_conv (Conv2D) (None, 2, 2, 1024)	263168	['conv4_block2_2_relu[0][0]']
conv4_block2_3_bn (BatchNormal (None, 2, 2, 1024) ization)	4096	['conv4_block2_3_conv[0][0]']
conv4_block2_add (Add) (None, 2, 2, 1024)	0	['conv4_block1_out[0][0]', 'conv4_block2_3_bn[0][0]']
conv4_block2_out (Activation) (None, 2, 2, 1024)	0	['conv4_block2 add[0][0]']

conv4_block3_1_conv (Conv2D) (None, 2, 2, 256)	262400	['conv4_block2_out[0][0]']
conv4_block3_1_bn (BatchNormal ization) (None, 2, 2, 256)	1024	['conv4_block3_1_conv[0][0]']
conv4_block3_1_relu (Activatio n) (None, 2, 2, 256)	0	['conv4_block3_1_bn[0][0]']
conv4_block3_2_conv (Conv2D) (None, 2, 2, 256)	590080	['conv4_block3_1_relu[0][0]']
conv4_block3_2_bn (BatchNormal ization) (None, 2, 2, 256)	1024	['conv4_block3_2_conv[0][0]']
conv4_block3_2_relu (Activatio n) (None, 2, 2, 256)	0	['conv4_block3_2_bn[0][0]']
conv4_block3_3_conv (Conv2D) (None, 2, 2, 1024)	263168	['conv4_block3_2_relu[0][0]']
conv4_block3_3_bn (BatchNormal ization) (None, 2, 2, 1024)	4096	['conv4_block3_3_conv[0][0]']
conv4_block3_add (Add) (None, 2, 2, 1024)	0	['conv4_block2_out[0][0]', 'conv4_block3_3_bn[0][0]']
conv4_block3_out (Activation) (None, 2, 2, 1024)	0	['conv4_block3_add[0][0]']
conv4_block4_1_conv (Conv2D) (None, 2, 2, 256)	262400	['conv4_block3_out[0][0]']
conv4_block4_1_bn (BatchNormal ization) (None, 2, 2, 256)	1024	['conv4_block4_1_conv[0][0]']
conv4_block4_1_relu (Activatio n) (None, 2, 2, 256)	0	['conv4_block4_1_bn[0][0]']
conv4_block4_2_conv (Conv2D) (None, 2, 2, 256)	590080	['conv4_block4_1_relu[0][0]']
conv4_block4_2_bn (BatchNormal ization) (None, 2, 2, 256)	1024	['conv4_block4_2_conv[0][0]']
conv4_block4_2_bn (BatchNormal ization) (None, 2, 2, 256)	1024	['conv4_block4_2_conv[0][0]']
conv4_block4_2_relu (Activatio n) (None, 2, 2, 256)	0	['conv4_block4_2_bn[0][0]']
conv4_block4_3_conv (Conv2D) (None, 2, 2, 1024)	263168	['conv4_block4_2_relu[0][0]']
conv4_block4_3_bn (BatchNormal ization) (None, 2, 2, 1024)	4096	['conv4_block4_3_conv[0][0]']
conv4_block4_add (Add) (None, 2, 2, 1024)	0	['conv4_block3_out[0][0]', 'conv4_block4_3_bn[0][0]']
conv4_block4_out (Activation) (None, 2, 2, 1024)	0	['conv4_block4_add[0][0]']
conv4_block5_1_conv (Conv2D) (None, 2, 2, 256)	262400	['conv4_block4_out[0][0]']
conv4_block5_1_bn (BatchNormal ization) (None, 2, 2, 256)	1024	['conv4_block5_1_conv[0][0]']
conv4_block5_1_relu (Activatio n) (None, 2, 2, 256)	0	['conv4_block5_1_bn[0][0]']

Figure 10: Resnet50 model summary for cifar-10 dataset

The resulting accuracy plot it gives is in the following figure.

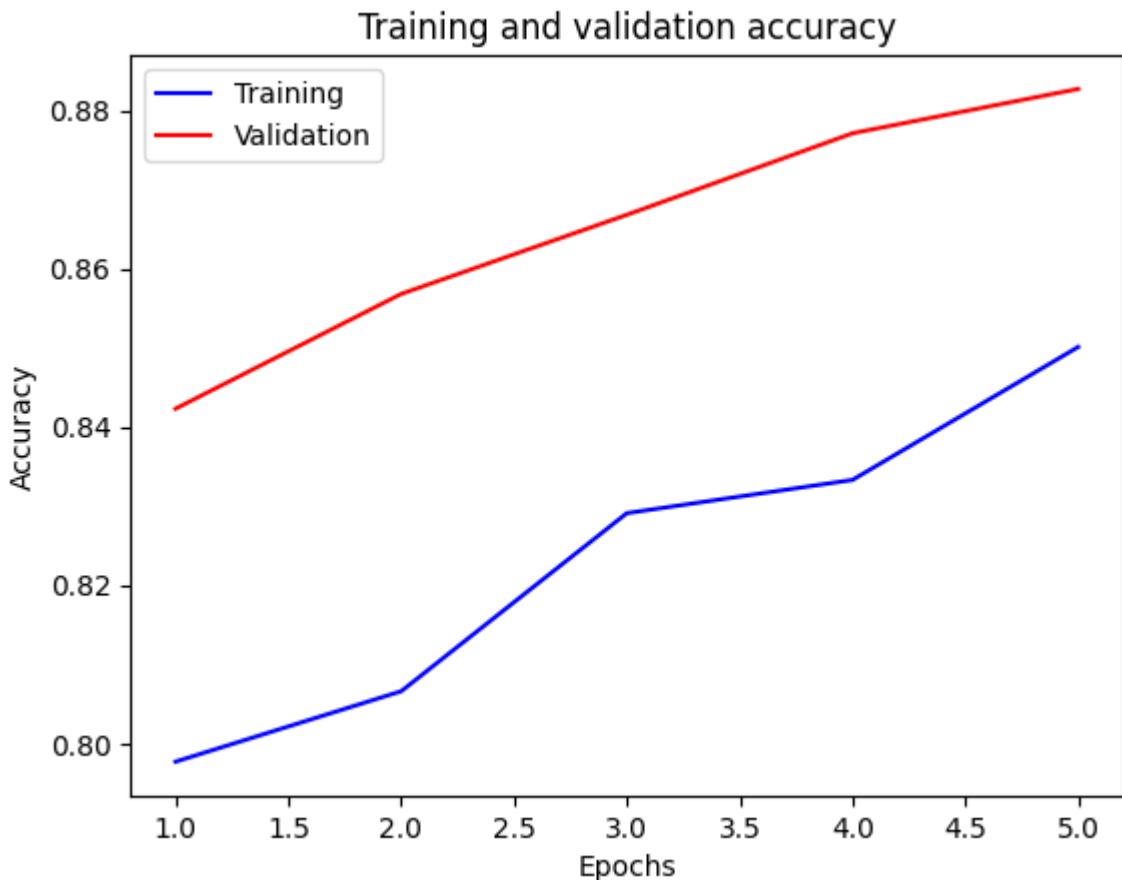


Figure 11: Resnet50 accuracy plot for cifar 10 dataset

The table shows the difference in accuracies for each model.

	Resnet50	Resnet20, n = 3	Resnet with n = 4
test accuracies	0.882764834833 449	0.7354000210762 024	0.7888000011444 092

The best accuracy is acquired from Resnet50, which has the most depth among the Resnets trained. hence allows more complex features to be learned and represented.