

Assignment 3: CNN Cancer Detection Kaggle Mini-Project

Description

This project is a binary image classification problem. The goal of this project is to develop a convolutional neural network model that can accurately identify metastatic cancer patches in an image. The images are provided by the Kaggle Histopathologic Cancer Detection Competition and located at <https://www.kaggle.com/competitions/histopathologic-cancer-detection/data>. Multilayer convolutional neural networks will be developed, trained and validated. The best model will then be used to predict the labels on the test images.

Natural Language Processing (NLP)

NLP is a machine learning technique that seeks to understand and make sense of the human language in its different forms, text, speech, etc. NLP processes a series of words, text or images and attempts to analyze the input to produce the desired output.

The challenge in NLP lies in capturing the intended meaning of the input, given that the same input can have different meanings, i.e. different outputs. The trick lies in capturing the context of the input so the the correct output can be derived.

Data Summary

The data consists of training and test images with image ids provided as the filename. There are 220,025 training images and 57,458 test images. The train_labels.csv contains 220,025 rows that house the image id and assoiciated ground truth lables for the training images. The sample_submission.csv contains the image ids of the test images and sample ground truth labels. The labels are to be replaced with test results and submitted for assessment of the model.

```
In [1]: #Set Page Width to 100%
from IPython.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>"))
```

```
In [19]: #Load Required Resources
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
import seaborn as sns
import math
import time
import cv2
from sklearn import metrics
from sklearn.model_selection import train_test_split
```

```
import gc

import tensorflow as tf
from tensorflow.keras import models
from keras_preprocessing.image import ImageDataGenerator
from PIL import Image
from tensorflow.python.keras.layers import LSTM, Dense, Conv2D, MaxPooling2D, Dropout,
from tensorflow.python.keras.models import Sequential
from tensorflow.keras.layers import BatchNormalization
from keras.optimizers import Adam
```

```
In [3]: print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
        print(tf.__version__)
```

```
Num GPUs Available: 0
2.10.1
```

GPU Limitation :As noted above this project does not have GPU access. Some models and simulations were reduced in complexity based on actual run times.

```
In [20]: ## Import Data
        train_image_df = pd.read_csv('train/train_labels.csv')
        test_image_df = pd.read_csv("sample_submission.csv" )

        print(train_image_df.head(), '\n')
        print(train_image_df.info(), '\n')
        print(test_image_df.head(), '\n')
        print(test_image_df.info())
```

	id	label
0	f38a6374c348f90b587e046aac6079959adf3835	0
1	c18f2d887b7ae4f6742ee445113fa1aef383ed77	1
2	755db6279dae599ebb4d39a9123cce439965282d	0
3	bc3f0c64fb968ff4a8bd33af6971ecae77c75e08	0
4	068aba587a4950175d04c680d38943fd488d6a9d	0

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 220025 entries, 0 to 220024
Data columns (total 2 columns):
#   Column  Non-Null Count  Dtype
---  -
0    id      220025 non-null    object
1   label   220025 non-null    int64
dtypes: int64(1), object(1)
memory usage: 3.4+ MB
None
```

	id	label
0	0b2ea2a822ad23fdb1b5dd26653da899fbd2c0d5	0
1	95596b92e5066c5c52466c90b69ff089b39f2737	0
2	248e6738860e2ebcf6258cdc1f32f299e0c76914	0
3	2c35657e312966e9294eac6841726ff3a748febf	0
4	145782eb7caa1c516acbe2eda34d9a3f31c41fd6	0

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 57458 entries, 0 to 57457
Data columns (total 2 columns):
#   Column  Non-Null Count  Dtype
---  -
0    id      57458 non-null    object
1   label   57458 non-null    int64
dtypes: int64(1), object(1)
memory usage: 897.9+ KB
None
```

Data

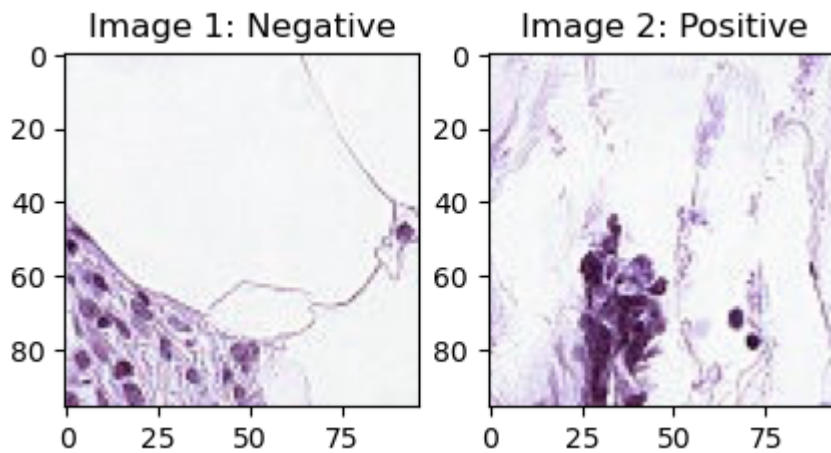
See Images 1 and 2 for examples of negative and positive instances, respectively. A brief review of the images, image ids and ground truth labels showed no anomolous cases. It is assumed that the provided data set is in proper order.

In [21]: *#Display Sample Images*

```
fig, ax = plt.subplots(1, 2, figsize = (5, 5))

ax[0].imshow(cv2.imread('train/' + train_image_df['id'][0] + '.tif'))
ax[0].set_title('Image 1: Negative')
ax[1].imshow(cv2.imread('train/' + train_image_df['id'][1] + '.tif'))
ax[1].set_title('Image 2: Positive')
```

Out[21]: Text(0.5, 1.0, 'Image 2: Positive')



EDA

As shown in Chart 1, 59.5% of the training examples are negative while 40.5% positive. This imbalance could result in biased training so the training set is rebalanced to a 50-50 split. Plot 2 shows the new distribution to be used as the training set. As noted above, a review of the images, image ids and labels revealed no anomalies. No additional data cleansing or adjustments are required.

```
In [22]: #Add tif file extension
train_image_df['id'] = train_image_df['id'].astype('str') + '.tif'
print(train_image_df.head())

test_image_df['id'] = test_image_df['id'].astype('str') + '.tif'
print(test_image_df.head())
print(test_image_df.info())
```

	id	label
0	f38a6374c348f90b587e046aac6079959adf3835.tif	0
1	c18f2d887b7ae4f6742ee445113fa1aef383ed77.tif	1
2	755db6279dae599ebb4d39a9123cce439965282d.tif	0
3	bc3f0c64fb968ff4a8bd33af6971ecae77c75e08.tif	0
4	068aba587a4950175d04c680d38943fd488d6a9d.tif	0

	id	label
0	0b2ea2a822ad23fdb1b5dd26653da899fbd2c0d5.tif	0
1	95596b92e5066c5c52466c90b69ff089b39f2737.tif	0
2	248e6738860e2ebcf6258cdc1f32f299e0c76914.tif	0
3	2c35657e312966e9294eac6841726ff3a748febf.tif	0
4	145782eb7caa1c516acbe2eda34d9a3f31c41fd6.tif	0

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 57458 entries, 0 to 57457
Data columns (total 2 columns):
#   Column  Non-Null Count  Dtype
---  -
0    id      57458 non-null    object
1    label   57458 non-null    int64
dtypes: int64(1), object(1)
memory usage: 897.9+ KB
None
```

```
In [23]: # Charts, data shape
```

```

plt.figure()
sns.countplot(data=train_image_df, x='label', palette=['#ff0000', "#008000"])
plt.title('Chart 1: Unbalanced Distribution of Target Labels')
plt.show()

# Rebalance and training arrays

#Remove 31% of negative images to balance dataset
train_image_df = train_image_df.drop(train_image_df[train_image_df['label'] == 0].sample(frac=0.31))

train_negative_df = train_image_df[train_image_df['label'] == 0]
print('Negative Train Samples: ', train_negative_df.shape)

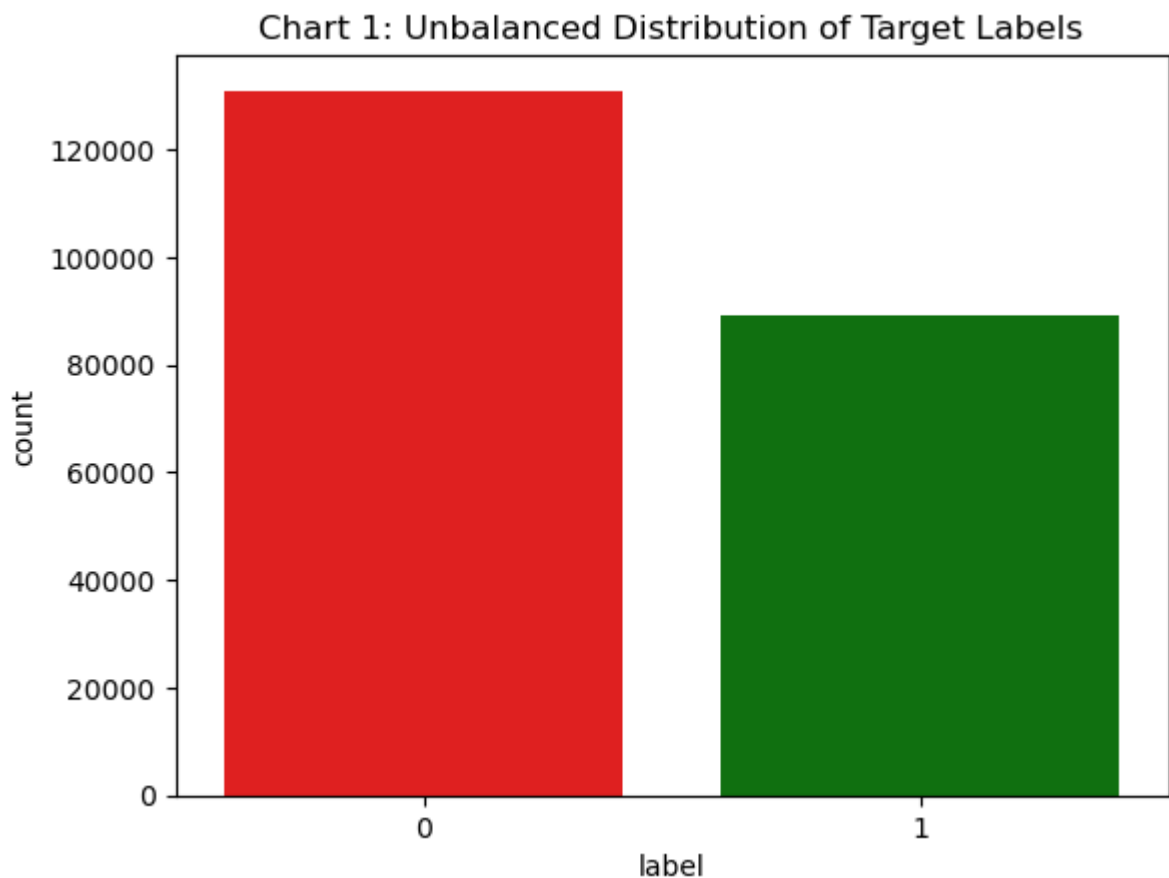
train_positive_df = train_image_df[train_image_df['label'] == 1]
print('Positive Train Samples: ', train_positive_df.shape)

#Convert to Numpy Array
train_image_id = train_image_df["id"].to_numpy()
test_image_id = test_image_df["id"].to_numpy()
train_image_label = train_image_df["label"].to_numpy()

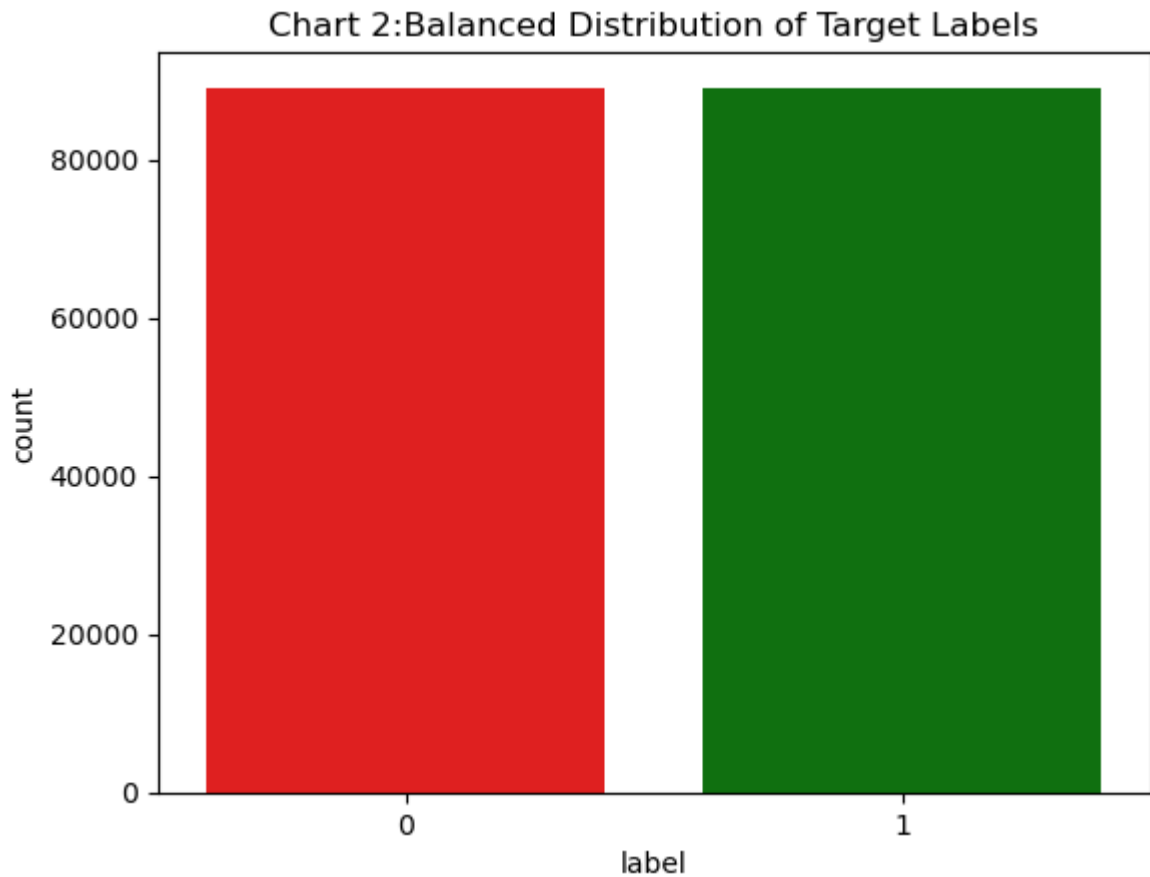
print('Train Image Id array shape: ', train_image_id.shape)
print('Test Image Id array shape: ', test_image_id.shape )

# Charts, new data shape
plt.figure()
sns.countplot(data=train_image_df, x='label', palette=['#ff0000', "#008000"])
plt.title('Chart 2: Balanced Distribution of Target Labels')
plt.show()

```



Negative Train Samples: (89017, 2)
Positive Train Samples: (89117, 2)
Train Image Id array shape: (178134,)
Test Image Id array shape: (57458,)



Approach

Based on the EDA the following approach will be deployed.

1. Establish train and test sets. 25,000 images of each classification.
2. Preprocess the data (scaling, normalization).
3. Compare two models where the Batch Normalization layers are in different positions.
Before and after the Activation layer (optimizer - adam, metric - accuracy).
4. Improve best model through hyperparameter tuning

Model Architecture

The core of the models will be the Convolutional layers. The Convolutional model is extremely adapt at processing images to various levels. Multiple Convolution layers (3) will be used in an effort to increase accuracy. The Convolutional layers are bracketed by Batch Normalization and Max pooling layers. These layers are added to improve both model performance and efficiency. Relu activation will be used in the first three Activation layers as this method is best suited for this type of analysis. A Dense layer is placed in front of the final Activation layer. The final Activation layer will use sigmoid activation for classification purposes.


```
class_mode="raw",
target_size=(32,32),
validation_steps=100)
```

```

      id  label
0  35a93e5612821c37670e70af150238932e20a942.tif      0
1  a3fa8742c25a40834271ecb40e23b28a323b27ff.tif      0
2  66bf34cfaa615793d2266e0668f0e81ba384f9a3.tif      0
3  a55f0f48559ed6328c6f666e6f32f8c4d13c52d9.tif      0
4  3e571e7b6cb092a08fb7d6592d54a7c5c47b8302.tif      0
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  -
 0    id      50000 non-null    object 
 1   label    50000 non-null    int64  
dtypes: int64(1), object(1)
memory usage: 781.4+ KB
None
Found 35000 validated image filenames.
Found 15000 validated image filenames.
Found 57458 validated image filenames.
```

Models

Batch Normalization Before Activation Layer

```
In [54]: #Before Model - two convolution layers, flatten layer, dense layer, batch normalization
number_of_epochs = 20

before_model = Sequential()

before_model.add(Conv2D(32, (3, 3), input_shape=(32, 32, 3)))

before_model.add(BatchNormalization())
before_model.add(Activation('relu'))

before_model.add(MaxPooling2D(pool_size=(3, 3)))
before_model.add(Conv2D(64, (3, 3)))

before_model.add(BatchNormalization())
before_model.add(Activation('relu'))

before_model.add(MaxPooling2D(pool_size=(3, 3)))
before_model.add(Flatten())
before_model.add(Dense(128))

before_model.add(BatchNormalization())
before_model.add(Activation('relu'))

before_model.add(Dense(1))
before_model.add(Activation('sigmoid'))

before_model.summary()

before_model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```



```
before_history = before_model.fit(generator_train_set,  
                                  epochs = number_of_epochs,  
                                  steps_per_epoch=(generator_train_set.n//generator_train_set.batch_  
validation_data = generator_validation_set,  
validation_steps=(generator_validation_set.n//generator_validation_  
  
before_model.save("before_model")
```

Model: "sequential_14"

Layer (type)	Output Shape	Param #
conv2d_33 (Conv2D)	(None, 30, 30, 32)	896
module_wrapper_47 (ModuleWra	(None, 30, 30, 32)	128
activation_61 (Activation)	(None, 30, 30, 32)	0
max_pooling2d_33 (MaxPooling	(None, 10, 10, 32)	0
conv2d_34 (Conv2D)	(None, 8, 8, 64)	18496
module_wrapper_48 (ModuleWra	(None, 8, 8, 64)	256
activation_62 (Activation)	(None, 8, 8, 64)	0
max_pooling2d_34 (MaxPooling	(None, 2, 2, 64)	0
flatten_14 (Flatten)	(None, 256)	0
dense_28 (Dense)	(None, 128)	32896
module_wrapper_49 (ModuleWra	(None, 128)	512
activation_63 (Activation)	(None, 128)	0
dense_29 (Dense)	(None, 1)	129
activation_64 (Activation)	(None, 1)	0
Total params: 53,313		
Trainable params: 52,865		
Non-trainable params: 448		

Epoch 1/20

546/546 [=====] - 83s 151ms/step - loss: 0.4874 - accuracy: 0.7683 - val_loss: 0.5213 - val_accuracy: 0.7301

Epoch 2/20

546/546 [=====] - 93s 171ms/step - loss: 0.4383 - accuracy: 0.8002 - val_loss: 0.5845 - val_accuracy: 0.7227

Epoch 3/20

546/546 [=====] - 81s 148ms/step - loss: 0.4268 - accuracy: 0.8067 - val_loss: 0.4928 - val_accuracy: 0.7714

Epoch 4/20

546/546 [=====] - 84s 154ms/step - loss: 0.4205 - accuracy: 0.8099 - val_loss: 0.4599 - val_accuracy: 0.7872

Epoch 5/20

546/546 [=====] - 85s 157ms/step - loss: 0.4089 - accuracy: 0.8174 - val_loss: 0.5329 - val_accuracy: 0.7623

Epoch 6/20

546/546 [=====] - 77s 141ms/step - loss: 0.4075 - accuracy: 0.8167 - val_loss: 1.3158 - val_accuracy: 0.5690

Epoch 7/20

546/546 [=====] - 77s 142ms/step - loss: 0.4004 - accuracy: 0.8203 - val_loss: 1.1754 - val_accuracy: 0.5135

Epoch 8/20

546/546 [=====] - 144s 263ms/step - loss: 0.4031 - accuracy: 0.8168 - val_loss: 0.4541 - val_accuracy: 0.7892

Epoch 9/20
 546/546 [=====] - 93s 170ms/step - loss: 0.4022 - accuracy: 0.8221 - val_loss: 0.3894 - val_accuracy: 0.8247
 Epoch 10/20
 546/546 [=====] - 108s 198ms/step - loss: 0.3832 - accuracy: 0.8297 - val_loss: 0.4053 - val_accuracy: 0.8187
 Epoch 11/20
 546/546 [=====] - 114s 208ms/step - loss: 0.3813 - accuracy: 0.8308 - val_loss: 0.5363 - val_accuracy: 0.7361
 Epoch 12/20
 546/546 [=====] - 97s 177ms/step - loss: 0.3839 - accuracy: 0.8301 - val_loss: 0.5687 - val_accuracy: 0.7489
 Epoch 13/20
 546/546 [=====] - 81s 148ms/step - loss: 0.3824 - accuracy: 0.8318 - val_loss: 0.6038 - val_accuracy: 0.7202
 Epoch 14/20
 546/546 [=====] - 91s 166ms/step - loss: 0.3719 - accuracy: 0.8367 - val_loss: 0.4316 - val_accuracy: 0.7952
 Epoch 15/20
 546/546 [=====] - 81s 148ms/step - loss: 0.3687 - accuracy: 0.8353 - val_loss: 0.4084 - val_accuracy: 0.8160
 Epoch 16/20
 546/546 [=====] - 83s 153ms/step - loss: 0.3721 - accuracy: 0.8357 - val_loss: 0.6459 - val_accuracy: 0.6981
 Epoch 17/20
 546/546 [=====] - 73s 135ms/step - loss: 0.3587 - accuracy: 0.8425 - val_loss: 0.8854 - val_accuracy: 0.6485
 Epoch 18/20
 546/546 [=====] - 79s 145ms/step - loss: 0.3641 - accuracy: 0.8400 - val_loss: 0.4916 - val_accuracy: 0.7755
 Epoch 19/20
 546/546 [=====] - 77s 141ms/step - loss: 0.3587 - accuracy: 0.8448 - val_loss: 0.7193 - val_accuracy: 0.7123
 Epoch 20/20
 546/546 [=====] - 78s 144ms/step - loss: 0.3534 - accuracy: 0.8444 - val_loss: 0.5166 - val_accuracy: 0.7460
 INFO:tensorflow:Assets written to: before_model\assets

Batch Normalization After Activation Layer

```
In [55]: #Train models
#After Model - two convolution layers, flatten layer, dense layer, batch normalization
after_model = Sequential()

after_model.add(Conv2D(32, (3, 3), input_shape=(32, 32, 3)))

after_model.add(Activation('relu'))
after_model.add(BatchNormalization())

after_model.add(MaxPooling2D(pool_size=(3, 3)))
after_model.add(Conv2D(64, (3, 3)))

after_model.add(Activation('relu'))
after_model.add(BatchNormalization())

after_model.add(MaxPooling2D(pool_size=(3, 3)))
after_model.add(Flatten())
after_model.add(Dense(128))
```

```
after_model.add(Activation('relu'))
after_model.add(BatchNormalization())

after_model.add(Dense(1))
after_model.add(Activation('sigmoid'))

after_model.summary()

after_model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

after_history = after_model.fit(generator_train_set,
                                epochs = number_of_epochs,
                                steps_per_epoch=(generator_train_set.n//generator_train_set.batch_size),
                                validation_data = generator_validation_set,
                                validation_steps=(generator_validation_set.n//generator_validation_set.batch_size))

after_model.save("after_model")
```

Model: "sequential_15"

Layer (type)	Output Shape	Param #
conv2d_35 (Conv2D)	(None, 30, 30, 32)	896
activation_65 (Activation)	(None, 30, 30, 32)	0
module_wrapper_50 (ModuleWra	(None, 30, 30, 32)	128
max_pooling2d_35 (MaxPooling	(None, 10, 10, 32)	0
conv2d_36 (Conv2D)	(None, 8, 8, 64)	18496
activation_66 (Activation)	(None, 8, 8, 64)	0
module_wrapper_51 (ModuleWra	(None, 8, 8, 64)	256
max_pooling2d_36 (MaxPooling	(None, 2, 2, 64)	0
flatten_15 (Flatten)	(None, 256)	0
dense_30 (Dense)	(None, 128)	32896
activation_67 (Activation)	(None, 128)	0
module_wrapper_52 (ModuleWra	(None, 128)	512
dense_31 (Dense)	(None, 1)	129
activation_68 (Activation)	(None, 1)	0
Total params: 53,313		
Trainable params: 52,865		
Non-trainable params: 448		

Epoch 1/20

546/546 [=====] - 82s 149ms/step - loss: 0.5161 - accuracy: 0.7529 - val_loss: 0.6983 - val_accuracy: 0.6525

Epoch 2/20

546/546 [=====] - 85s 156ms/step - loss: 0.4799 - accuracy: 0.7731 - val_loss: 1.0931 - val_accuracy: 0.5390

Epoch 3/20

546/546 [=====] - 78s 142ms/step - loss: 0.4644 - accuracy: 0.7820 - val_loss: 0.4655 - val_accuracy: 0.7869

Epoch 4/20

546/546 [=====] - 89s 164ms/step - loss: 0.4564 - accuracy: 0.7892 - val_loss: 0.7704 - val_accuracy: 0.6044

Epoch 5/20

546/546 [=====] - 85s 155ms/step - loss: 0.4433 - accuracy: 0.7922 - val_loss: 0.6654 - val_accuracy: 0.6768

Epoch 6/20

546/546 [=====] - 87s 160ms/step - loss: 0.4414 - accuracy: 0.7986 - val_loss: 0.8334 - val_accuracy: 0.5504

Epoch 7/20

546/546 [=====] - 76s 139ms/step - loss: 0.4368 - accuracy: 0.8016 - val_loss: 0.5505 - val_accuracy: 0.7622

Epoch 8/20

546/546 [=====] - 77s 141ms/step - loss: 0.4319 - accuracy: 0.8027 - val_loss: 0.6268 - val_accuracy: 0.7430

```

Epoch 9/20
546/546 [=====] - 75s 138ms/step - loss: 0.4282 - accuracy:
0.8064 - val_loss: 0.6375 - val_accuracy: 0.6879
Epoch 10/20
546/546 [=====] - 76s 139ms/step - loss: 0.4251 - accuracy:
0.8090 - val_loss: 0.4326 - val_accuracy: 0.8049
Epoch 11/20
546/546 [=====] - 74s 135ms/step - loss: 0.4241 - accuracy:
0.8092 - val_loss: 2.4545 - val_accuracy: 0.4742
Epoch 12/20
546/546 [=====] - 77s 142ms/step - loss: 0.4160 - accuracy:
0.8135 - val_loss: 0.5557 - val_accuracy: 0.7512
Epoch 13/20
546/546 [=====] - 129s 237ms/step - loss: 0.4179 - accuracy:
0.8090 - val_loss: 1.2267 - val_accuracy: 0.5585
Epoch 14/20
546/546 [=====] - 226s 414ms/step - loss: 0.4105 - accuracy:
0.8147 - val_loss: 0.6451 - val_accuracy: 0.7112
Epoch 15/20
546/546 [=====] - 183s 335ms/step - loss: 0.4103 - accuracy:
0.8159 - val_loss: 0.5352 - val_accuracy: 0.7428
Epoch 16/20
546/546 [=====] - 168s 308ms/step - loss: 0.4104 - accuracy:
0.8141 - val_loss: 0.4273 - val_accuracy: 0.8064
Epoch 17/20
546/546 [=====] - 125s 230ms/step - loss: 0.4015 - accuracy:
0.8181 - val_loss: 0.4554 - val_accuracy: 0.8006
Epoch 18/20
546/546 [=====] - 77s 142ms/step - loss: 0.3934 - accuracy:
0.8271 - val_loss: 0.7176 - val_accuracy: 0.6309
Epoch 19/20
546/546 [=====] - 70s 129ms/step - loss: 0.3920 - accuracy:
0.8248 - val_loss: 1.1621 - val_accuracy: 0.5946
Epoch 20/20
546/546 [=====] - 71s 131ms/step - loss: 0.3988 - accuracy:
0.8206 - val_loss: 0.4312 - val_accuracy: 0.8072
INFO:tensorflow:Assets written to: after_model\assets

```

Model Comparison Results/Analysis

```

In [56]: #Before Model
before_model_accuracy = before_history.history['accuracy']
before_model_val_acc = before_history.history['val_accuracy']
before_model_loss = before_history.history['loss']
before_model_val_loss = before_history.history['val_loss']

before_epochs_range = range(number_of_epochs)

plt.figure(figsize=(10, 10))
plt.subplot(2, 2, 1)
plt.plot(before_epochs_range, before_model_accuracy, label='Training Accuracy')
plt.plot(before_epochs_range, before_model_val_acc, label='Validation Accuracy')
plt.legend(loc='lower right', fontsize = 8)
plt.title('Plot 1: Accuracy (Batch Normalization Before Activation)', fontsize = 10)

plt.subplot(2, 2, 2)
plt.plot(before_epochs_range, before_model_loss, label='Training Loss')
plt.plot(before_epochs_range, before_model_val_loss, label='Validation Loss')
plt.legend(loc='upper right', fontsize = 8)

```

```
plt.title('Plot 2: Loss (Batch Normalization Before Activation)', fontsize = 10)
plt.show()
```

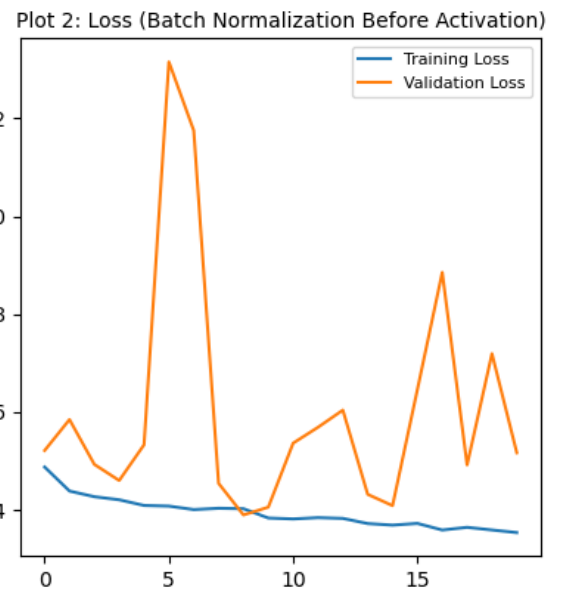
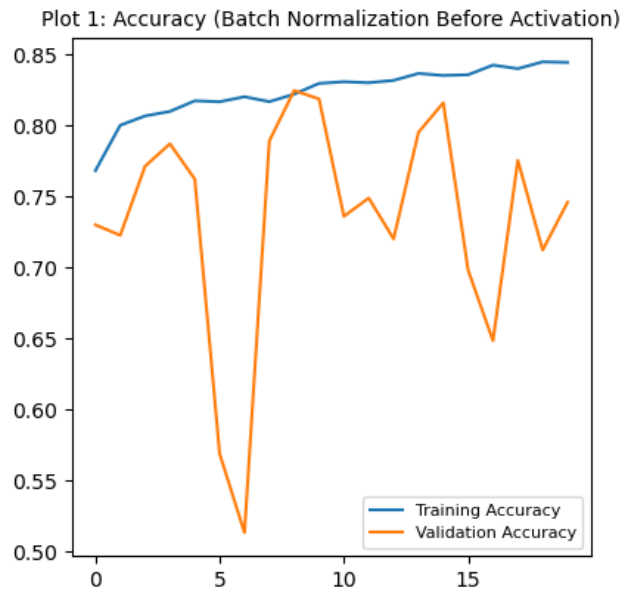
#After Model

```
after_model_accuracy = after_history.history['accuracy']
after_model_val_acc = after_history.history['val_accuracy']
after_model_loss = after_history.history['loss']
after_model_val_loss = after_history.history['val_loss']
```

```
after_epochs_range = range(number_of_epochs)
```

```
plt.figure(figsize=(10, 10))
plt.subplot(2, 2, 1)
plt.plot(after_epochs_range, after_model_accuracy, label='Training Accuracy')
plt.plot(after_epochs_range, after_model_val_acc, label='Validation Accuracy')
plt.legend(loc='lower right', fontsize = 8)
plt.title('Plot 3: Accuracy (Batch Normalization After Activation)', fontsize = 10)
```

```
plt.subplot(2, 2, 2)
plt.plot(after_epochs_range, after_model_loss, label='Training Loss')
plt.plot(after_epochs_range, after_model_val_loss, label='Validation Loss')
plt.legend(loc='upper left', fontsize = 8)
plt.title('Plot 4: Loss (Batch Normalization After Activation)', fontsize = 10)
plt.show()
```



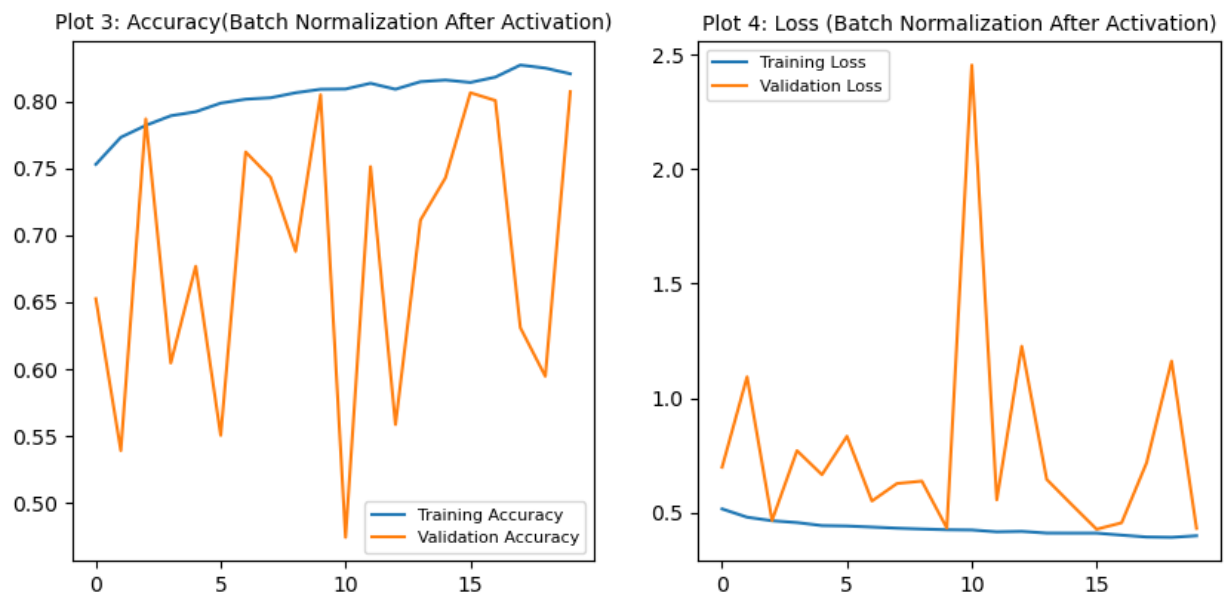


Table 1: Before and After Activation Layer vs Accuracy*

Model	Accuracy	Validation Accuracy
Before	.8444	.7460
After	.8206	.8070

Plots 1 thru 4 provide a view of the training accuracy and loss metrics between the models with the Batch Normalization layer before and after the activation layers.

Table 1 indicates that the before model has an accuracy of 84.44%, 2.36% better than the after model at 82.06%

However, when looking closely at the plots, at around the 10th epoch, the before model's training and validation accuracy begin to diverge, while the after model's accuracy trend continues to track and converge. This is an indication of potential overfitting in the before model.

The loss plots show a similar pattern with the training and validation loss diverging in the before model while the after model's losses track and continue to exhibit a converging pattern. Again, another indication of overfitting of the before model.

Taking these two observations together it appears that the before model is showing signs of overfitting while the after model is stable and continues to improve. The implication being that placing the Batch Normalization layer after the Activation layer aided in protecting the after model from overfitting. In the end analysis, given the marginal difference in accuracy between the models, and the fact the the before model shows signs of overfitting, the after model is deemed the better of the two.

Test Submission


```
In [ ]: print(test_image_df)

print(test_image_df.head())
print(test_image_df.info())

test_results = before_model.predict(generator_test_set, batch_size = (generator_test_
print(test_results)
test_results

#3500/3500 [=====] - 108s 19ms/step
```

```
In [ ]: #Generate submission file
test_submission = np.where(test_results <= 0.5, 0, 1)

final_submission = np.transpose(test_submission)[0]
final_final_submission = pd.DataFrame()
final_submission['id'] = test_image_df['id'].apply(lambda x: x.split('.')[0])
final_submission['label'] = test_submission
final_submission.head()

final_submission.to_csv('submission.csv', index=False)
```

Hyperparameter Tuning

Momentum on the Batch Normalization Layers will be varied and the impact on accuracy assessed.

```
In [39]: mv2 = [.99, .75, .50, .25]
history = []

for m in mv2:
    before_model = Sequential()

    before_model.add(Conv2D(32, (3, 3), input_shape=(32, 32, 3)))
    before_model.add(BatchNormalization(momentum = m))
    before_model.add(Activation('relu'))
    before_model.add(MaxPooling2D(pool_size=(3, 3)))

    before_model.add(Conv2D(64, (3, 3)))
    before_model.add(BatchNormalization(momentum = m))
    before_model.add(Activation('relu'))
    before_model.add(MaxPooling2D(pool_size=(3, 3)))

    before_model.add(Flatten())
    before_model.add(Dense(128))
    before_model.add(BatchNormalization(momentum = m))
    before_model.add(Activation('relu'))

    before_model.add(Dense(1))
    before_model.add(Activation('sigmoid'))

    before_model.summary()

    before_model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accu
```

```
number_of_epochs = 20

tune_history = before_model.fit(generator_train_set,
                                epochs = number_of_epochs,
                                steps_per_epoch=(generator_train_set.n//generator_train_set.batch_size),
                                validation_data = generator_validation_set,
                                validation_steps=(generator_validation_set.n//generator_validation_set.batch_size))

print('Momentum: ', m)
print('History: ', tune_history.history)
history.append(tune_history.history)
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv2d_10 (Conv2D)	(None, 30, 30, 32)	896
module_wrapper_15 (ModuleWra	(None, 30, 30, 32)	128
activation_20 (Activation)	(None, 30, 30, 32)	0
max_pooling2d_10 (MaxPooling	(None, 10, 10, 32)	0
conv2d_11 (Conv2D)	(None, 8, 8, 64)	18496
module_wrapper_16 (ModuleWra	(None, 8, 8, 64)	256
activation_21 (Activation)	(None, 8, 8, 64)	0
max_pooling2d_11 (MaxPooling	(None, 2, 2, 64)	0
flatten_5 (Flatten)	(None, 256)	0
dense_10 (Dense)	(None, 128)	32896
module_wrapper_17 (ModuleWra	(None, 128)	512
activation_22 (Activation)	(None, 128)	0
dense_11 (Dense)	(None, 1)	129
activation_23 (Activation)	(None, 1)	0
Total params: 53,313		
Trainable params: 52,865		
Non-trainable params: 448		

Epoch 1/20

546/546 [=====] - 312s 567ms/step - loss: 0.4850 - accuracy: 0.7683 - val_loss: 1.0514 - val_accuracy: 0.5354

Epoch 2/20

546/546 [=====] - 248s 456ms/step - loss: 0.4522 - accuracy: 0.7924 - val_loss: 0.7236 - val_accuracy: 0.6920

Epoch 3/20

546/546 [=====] - 123s 225ms/step - loss: 0.4332 - accuracy: 0.8035 - val_loss: 0.4410 - val_accuracy: 0.7863

Epoch 4/20

546/546 [=====] - 175s 321ms/step - loss: 0.4219 - accuracy: 0.8085 - val_loss: 1.3560 - val_accuracy: 0.6011

Epoch 5/20

546/546 [=====] - 152s 278ms/step - loss: 0.4178 - accuracy: 0.8110 - val_loss: 0.3918 - val_accuracy: 0.8206

Epoch 6/20

546/546 [=====] - 265s 485ms/step - loss: 0.4045 - accuracy: 0.8192 - val_loss: 0.4177 - val_accuracy: 0.8064

Epoch 7/20

546/546 [=====] - 196s 359ms/step - loss: 0.3994 - accuracy: 0.8185 - val_loss: 0.5115 - val_accuracy: 0.7640

Epoch 8/20

546/546 [=====] - 126s 231ms/step - loss: 0.4000 - accuracy: 0.8226 - val_loss: 0.4740 - val_accuracy: 0.7631

Epoch 9/20
546/546 [=====] - 107s 196ms/step - loss: 0.3916 - accuracy: 0.8250 - val_loss: 0.4882 - val_accuracy: 0.7515
Epoch 10/20
546/546 [=====] - 116s 213ms/step - loss: 0.3861 - accuracy: 0.8279 - val_loss: 0.5286 - val_accuracy: 0.7489
Epoch 11/20
546/546 [=====] - 97s 179ms/step - loss: 0.3860 - accuracy: 0.8280 - val_loss: 0.9395 - val_accuracy: 0.6245
Epoch 12/20
546/546 [=====] - 115s 210ms/step - loss: 0.3784 - accuracy: 0.8328 - val_loss: 0.4330 - val_accuracy: 0.8098
Epoch 13/20
546/546 [=====] - 96s 176ms/step - loss: 0.3804 - accuracy: 0.8304 - val_loss: 0.5197 - val_accuracy: 0.7423
Epoch 14/20
546/546 [=====] - 113s 207ms/step - loss: 0.3748 - accuracy: 0.8372 - val_loss: 0.8836 - val_accuracy: 0.5774
Epoch 15/20
546/546 [=====] - 104s 191ms/step - loss: 0.3692 - accuracy: 0.8372 - val_loss: 1.0588 - val_accuracy: 0.5222
Epoch 16/20
546/546 [=====] - 121s 221ms/step - loss: 0.3689 - accuracy: 0.8401 - val_loss: 0.6488 - val_accuracy: 0.7425
Epoch 17/20
546/546 [=====] - 121s 223ms/step - loss: 0.3624 - accuracy: 0.8398 - val_loss: 0.4285 - val_accuracy: 0.8122
Epoch 18/20
546/546 [=====] - 121s 222ms/step - loss: 0.3588 - accuracy: 0.8439 - val_loss: 0.4089 - val_accuracy: 0.8095
Epoch 19/20
546/546 [=====] - 113s 208ms/step - loss: 0.3576 - accuracy: 0.8444 - val_loss: 0.5920 - val_accuracy: 0.7465
Epoch 20/20
546/546 [=====] - 113s 208ms/step - loss: 0.3602 - accuracy: 0.8405 - val_loss: 0.6725 - val_accuracy: 0.6893
Momentum: 0.99
History: {'loss': [0.4849769175052643, 0.4521576464176178, 0.4332250654697418, 0.42190587520599365, 0.41779088973999023, 0.4045145511627197, 0.39940616488456726, 0.4000301659107208, 0.39164865016937256, 0.38612380623817444, 0.386012464761734, 0.37836119532585144, 0.3803672790527344, 0.3748093247413635, 0.3691815435886383, 0.36885130405426025, 0.3624342978000641, 0.3588135242462158, 0.3576175272464752, 0.36024102568626404], 'accuracy': [0.7682661414146423, 0.7923534512519836, 0.8034814596176147, 0.8084936141967773, 0.8109825849533081, 0.8191964030265808, 0.8184837102890015, 0.8226304650306702, 0.8249542117118835, 0.8278960585594177, 0.8279889822006226, 0.8327609896659851, 0.8303939700126648, 0.8372252583503723, 0.8371506929397583, 0.8400869965553284, 0.8397846817970276, 0.8438644409179688, 0.8444228172302246, 0.8404876589775085], 'val_loss': [1.0514280796051025, 0.7236369252204895, 0.4410248100757599, 1.3560363054275513, 0.39180848002433777, 0.4176807701587677, 0.511466920375824, 0.4740268290042877, 0.4882241487503052, 0.5286386013031006, 0.939549446105957, 0.4330059885978699, 0.5196740031242371, 0.8835945725440979, 1.0587953329086304, 0.6488038897514343, 0.4284641146659851, 0.4088684618473053, 0.5919619202613831, 0.672546923160553], 'val_accuracy': [0.5353899598121643, 0.6919786334037781, 0.7863247990608215, 0.6010695099830627, 0.820646345615387, 0.8064171075820923, 0.7640224099159241, 0.7631015777587891, 0.7514690160751343, 0.7489304542541504, 0.624465823173523, 0.8097593784332275, 0.7422542572021484, 0.5774064064025879, 0.5221688151359558, 0.7425133585929871, 0.8122329115867615, 0.8094919919967651, 0.7465277910232544, 0.6893048286437988]}

Model: "sequential_6"

Layer (type)	Output Shape	Param #
--------------	--------------	---------

=====		
conv2d_12 (Conv2D)	(None, 30, 30, 32)	896
<hr/>		
module_wrapper_18 (ModuleWra	(None, 30, 30, 32)	128
<hr/>		
activation_24 (Activation)	(None, 30, 30, 32)	0
<hr/>		
max_pooling2d_12 (MaxPooling	(None, 10, 10, 32)	0
<hr/>		
conv2d_13 (Conv2D)	(None, 8, 8, 64)	18496
<hr/>		
module_wrapper_19 (ModuleWra	(None, 8, 8, 64)	256
<hr/>		
activation_25 (Activation)	(None, 8, 8, 64)	0
<hr/>		
max_pooling2d_13 (MaxPooling	(None, 2, 2, 64)	0
<hr/>		
flatten_6 (Flatten)	(None, 256)	0
<hr/>		
dense_12 (Dense)	(None, 128)	32896
<hr/>		
module_wrapper_20 (ModuleWra	(None, 128)	512
<hr/>		
activation_26 (Activation)	(None, 128)	0
<hr/>		
dense_13 (Dense)	(None, 1)	129
<hr/>		
activation_27 (Activation)	(None, 1)	0
<hr/>		
=====		
Total params: 53,313		
Trainable params: 52,865		
Non-trainable params: 448		

Epoch 1/20

546/546 [=====] - 116s 211ms/step - loss: 0.4919 - accuracy: 0.7659 - val_loss: 0.5644 - val_accuracy: 0.7285

Epoch 2/20

546/546 [=====] - 107s 197ms/step - loss: 0.4530 - accuracy: 0.7923 - val_loss: 0.5167 - val_accuracy: 0.7654

Epoch 3/20

546/546 [=====] - 96s 176ms/step - loss: 0.4406 - accuracy: 0.7970 - val_loss: 0.5783 - val_accuracy: 0.7190

Epoch 4/20

546/546 [=====] - 106s 195ms/step - loss: 0.4201 - accuracy: 0.8094 - val_loss: 0.4414 - val_accuracy: 0.7971

Epoch 5/20

546/546 [=====] - 95s 174ms/step - loss: 0.4116 - accuracy: 0.8178 - val_loss: 0.3914 - val_accuracy: 0.8268

Epoch 6/20

546/546 [=====] - 105s 193ms/step - loss: 0.4132 - accuracy: 0.8136 - val_loss: 0.6397 - val_accuracy: 0.6877

Epoch 7/20

546/546 [=====] - 92s 168ms/step - loss: 0.4006 - accuracy: 0.8197 - val_loss: 0.5008 - val_accuracy: 0.7718

Epoch 8/20

546/546 [=====] - 103s 189ms/step - loss: 0.4020 - accuracy: 0.8211 - val_loss: 0.6255 - val_accuracy: 0.7083

Epoch 9/20

546/546 [=====] - 90s 164ms/step - loss: 0.3875 - accuracy: 0.8275 - val_loss: 0.4052 - val_accuracy: 0.8228

Epoch 10/20
546/546 [=====] - 102s 187ms/step - loss: 0.3901 - accuracy: 0.8257 - val_loss: 0.3849 - val_accuracy: 0.8253
Epoch 11/20
546/546 [=====] - 90s 166ms/step - loss: 0.3813 - accuracy: 0.8335 - val_loss: 0.3837 - val_accuracy: 0.8317
Epoch 12/20
546/546 [=====] - 105s 193ms/step - loss: 0.3825 - accuracy: 0.8285 - val_loss: 0.3756 - val_accuracy: 0.8306
Epoch 13/20
546/546 [=====] - 92s 170ms/step - loss: 0.3671 - accuracy: 0.8401 - val_loss: 0.5295 - val_accuracy: 0.7519
Epoch 14/20
546/546 [=====] - 104s 190ms/step - loss: 0.3829 - accuracy: 0.8311 - val_loss: 0.5657 - val_accuracy: 0.7541
Epoch 15/20
546/546 [=====] - 91s 166ms/step - loss: 0.3727 - accuracy: 0.8365 - val_loss: 0.4875 - val_accuracy: 0.7963
Epoch 16/20
546/546 [=====] - 109s 199ms/step - loss: 0.3683 - accuracy: 0.8366 - val_loss: 0.3829 - val_accuracy: 0.8318
Epoch 17/20
546/546 [=====] - 102s 187ms/step - loss: 0.3620 - accuracy: 0.8413 - val_loss: 0.3756 - val_accuracy: 0.8313
Epoch 18/20
546/546 [=====] - 108s 197ms/step - loss: 0.3586 - accuracy: 0.8414 - val_loss: 0.3940 - val_accuracy: 0.8277
Epoch 19/20
546/546 [=====] - 109s 200ms/step - loss: 0.3627 - accuracy: 0.8406 - val_loss: 0.3477 - val_accuracy: 0.8536
Epoch 20/20
546/546 [=====] - 116s 212ms/step - loss: 0.3566 - accuracy: 0.8423 - val_loss: 0.3610 - val_accuracy: 0.8469
Momentum: 0.75
History: {'loss': [0.491936594247818, 0.4529515504837036, 0.44059401750564575, 0.42005667090415955, 0.41160765290260315, 0.41323259472846985, 0.40060049295425415, 0.4019608199596405, 0.3874862492084503, 0.3901159465312958, 0.38133299350738525, 0.38254237174987793, 0.3670882284641266, 0.3828747868537903, 0.372717946767807, 0.36830881237983704, 0.3619937300682068, 0.35858792066574097, 0.3626682758331299, 0.3566318452358246], 'accuracy': [0.7659184336662292, 0.7922962307929993, 0.7969537377357483, 0.8094093203544617, 0.8177965879440308, 0.8136447072029114, 0.819686233997345, 0.8210851550102234, 0.8274736404418945, 0.8257211446762085, 0.8335433006286621, 0.828468382358551, 0.8400710225105286, 0.8311011791229248, 0.8364635705947876, 0.8365957140922546, 0.8413307666778564, 0.8414033651351929, 0.8405863642692566, 0.8422619104385376], 'val_loss': [0.5643996000289917, 0.5167384147644043, 0.5783010125160217, 0.4413726329803467, 0.39136797189712524, 0.639728844165802, 0.5008347034454346, 0.6255342364311218, 0.405185729265213, 0.3849208354949951, 0.3837343156337738, 0.3756384551525116, 0.5295457243919373, 0.5656939744949341, 0.4875234365463257, 0.3828989863395691, 0.3756312131881714, 0.3940175473690033, 0.3477363884449005, 0.3609672486782074], 'val_accuracy': [0.7284989356994629, 0.7653743028640747, 0.7190170884132385, 0.7970588207244873, 0.8267895579338074, 0.6877005100250244, 0.7717681527137756, 0.7082887887954712, 0.8227831125259399, 0.8252673745155334, 0.8317307829856873, 0.8306149840354919, 0.7518696784973145, 0.7541443705558777, 0.796340823173523, 0.831818163394928, 0.8313301205635071, 0.8276737928390503, 0.8536324501037598, 0.8469251394271851]}

Model: "sequential_7"

Layer (type)	Output Shape	Param #
conv2d_14 (Conv2D)	(None, 30, 30, 32)	896

module_wrapper_21 (ModuleWra	(None, 30, 30, 32)	128
activation_28 (Activation)	(None, 30, 30, 32)	0
max_pooling2d_14 (MaxPooling	(None, 10, 10, 32)	0
conv2d_15 (Conv2D)	(None, 8, 8, 64)	18496
module_wrapper_22 (ModuleWra	(None, 8, 8, 64)	256
activation_29 (Activation)	(None, 8, 8, 64)	0
max_pooling2d_15 (MaxPooling	(None, 2, 2, 64)	0
flatten_7 (Flatten)	(None, 256)	0
dense_14 (Dense)	(None, 128)	32896
module_wrapper_23 (ModuleWra	(None, 128)	512
activation_30 (Activation)	(None, 128)	0
dense_15 (Dense)	(None, 1)	129
activation_31 (Activation)	(None, 1)	0
=====		
Total params: 53,313		
Trainable params: 52,865		
Non-trainable params: 448		

```

Epoch 1/20
546/546 [=====] - 100s 181ms/step - loss: 0.4783 - accuracy:
0.7747 - val_loss: 0.4534 - val_accuracy: 0.7905
Epoch 2/20
546/546 [=====] - 108s 199ms/step - loss: 0.4430 - accuracy:
0.7969 - val_loss: 0.4436 - val_accuracy: 0.7955
Epoch 3/20
546/546 [=====] - 179s 328ms/step - loss: 0.4254 - accuracy:
0.8059 - val_loss: 0.4087 - val_accuracy: 0.8145
Epoch 4/20
546/546 [=====] - 270s 495ms/step - loss: 0.4230 - accuracy:
0.8078 - val_loss: 0.4225 - val_accuracy: 0.8075
Epoch 5/20
546/546 [=====] - 152s 279ms/step - loss: 0.4093 - accuracy:
0.8149 - val_loss: 0.4600 - val_accuracy: 0.7768
Epoch 6/20
546/546 [=====] - 151s 276ms/step - loss: 0.4120 - accuracy:
0.8132 - val_loss: 0.3939 - val_accuracy: 0.8207
Epoch 7/20
546/546 [=====] - 82s 150ms/step - loss: 0.4052 - accuracy:
0.8162 - val_loss: 0.4195 - val_accuracy: 0.8124
Epoch 8/20
546/546 [=====] - 80s 147ms/step - loss: 0.4048 - accuracy:
0.8174 - val_loss: 0.4297 - val_accuracy: 0.7983
Epoch 9/20
546/546 [=====] - 76s 140ms/step - loss: 0.3873 - accuracy:
0.8247 - val_loss: 0.4254 - val_accuracy: 0.8061
Epoch 10/20
546/546 [=====] - 82s 150ms/step - loss: 0.3910 - accuracy:
0.8277 - val_loss: 0.3852 - val_accuracy: 0.8333

```

Epoch 11/20
546/546 [=====] - 75s 137ms/step - loss: 0.3797 - accuracy: 0.8310 - val_loss: 0.3611 - val_accuracy: 0.8451
Epoch 12/20
546/546 [=====] - 78s 143ms/step - loss: 0.3891 - accuracy: 0.8263 - val_loss: 0.3924 - val_accuracy: 0.8223
Epoch 13/20
546/546 [=====] - 81s 148ms/step - loss: 0.3823 - accuracy: 0.8278 - val_loss: 0.4996 - val_accuracy: 0.7730
Epoch 14/20
546/546 [=====] - 86s 158ms/step - loss: 0.3770 - accuracy: 0.8325 - val_loss: 0.3968 - val_accuracy: 0.8247
Epoch 15/20
546/546 [=====] - 87s 159ms/step - loss: 0.3695 - accuracy: 0.8376 - val_loss: 0.3887 - val_accuracy: 0.8360
Epoch 16/20
546/546 [=====] - 85s 156ms/step - loss: 0.3650 - accuracy: 0.8393 - val_loss: 0.3647 - val_accuracy: 0.8382
Epoch 17/20
546/546 [=====] - 82s 150ms/step - loss: 0.3595 - accuracy: 0.8436 - val_loss: 0.4219 - val_accuracy: 0.8070
Epoch 18/20
546/546 [=====] - 97s 179ms/step - loss: 0.3588 - accuracy: 0.8438 - val_loss: 0.3786 - val_accuracy: 0.8293
Epoch 19/20
546/546 [=====] - 96s 177ms/step - loss: 0.3543 - accuracy: 0.8470 - val_loss: 0.3733 - val_accuracy: 0.8415
Epoch 20/20
546/546 [=====] - 104s 191ms/step - loss: 0.3508 - accuracy: 0.8494 - val_loss: 0.3790 - val_accuracy: 0.8341
Momentum: 0.5
History: {'loss': [0.4782549738883972, 0.44297072291374207, 0.42543235421180725, 0.4230184555053711, 0.40933364629745483, 0.4120127856731415, 0.4052249491214752, 0.40475207567214966, 0.38731464743614197, 0.39102041721343994, 0.3796846568584442, 0.38907477259635925, 0.3822660446166992, 0.37701615691185, 0.36950573325157166, 0.3649819493293762, 0.3595219552516937, 0.35878658294677734, 0.35427695512771606, 0.35083621740341187], 'accuracy': [0.7747365832328796, 0.7969322204589844, 0.8058863878250122, 0.8078067898750305, 0.8148763179779053, 0.8131868243217468, 0.8161932826042175, 0.8173649311065674, 0.8247251510620117, 0.8277243375778198, 0.8310238122940063, 0.8262934684753418, 0.8278172016143799, 0.8325320482254028, 0.8375515341758728, 0.8392857313156128, 0.8435639142990112, 0.84375, 0.8469995260238647, 0.8493589758872986], 'val_loss': [0.45343253016471863, 0.4435521364212036, 0.4087141752243042, 0.4224659502506256, 0.4600066840648651, 0.3938656747341156, 0.419475793838501, 0.42965251207351685, 0.4254249036312103, 0.38515013456344604, 0.3611338436603546, 0.3924413025379181, 0.4995637536048889, 0.396753191947937, 0.38871046900749207, 0.3647327125072479, 0.4219432771205902, 0.378569632768631, 0.3733358383178711, 0.3789542615413666], 'val_accuracy': [0.7904647588729858, 0.7954545617103577, 0.8145031929016113, 0.8074866533279419, 0.7768429517745972, 0.8207219243049622, 0.8123664259910583, 0.7982620596885681, 0.8060897588729858, 0.8332887887954712, 0.8450854420661926, 0.8223261833190918, 0.7729700803756714, 0.8247326016426086, 0.8360042572021484, 0.8382353186607361, 0.8070245981216431, 0.8292780518531799, 0.8414797186851501, 0.8340908885002136]}

Model: "sequential_8"

Layer (type)	Output Shape	Param #
=====		
conv2d_16 (Conv2D)	(None, 30, 30, 32)	896
=====		
module_wrapper_24 (ModuleWra	(None, 30, 30, 32)	128
=====		
activation_32 (Activation)	(None, 30, 30, 32)	0

max_pooling2d_16 (MaxPooling (None, 10, 10, 32)	0
conv2d_17 (Conv2D) (None, 8, 8, 64)	18496
module_wrapper_25 (ModuleWra (None, 8, 8, 64)	256
activation_33 (Activation) (None, 8, 8, 64)	0
max_pooling2d_17 (MaxPooling (None, 2, 2, 64)	0
flatten_8 (Flatten) (None, 256)	0
dense_16 (Dense) (None, 128)	32896
module_wrapper_26 (ModuleWra (None, 128)	512
activation_34 (Activation) (None, 128)	0
dense_17 (Dense) (None, 1)	129
activation_35 (Activation) (None, 1)	0
=====	
Total params: 53,313	
Trainable params: 52,865	
Non-trainable params: 448	

Epoch 1/20

546/546 [=====] - 102s 185ms/step - loss: 0.4946 - accuracy: 0.7656 - val_loss: 0.4714 - val_accuracy: 0.7804

Epoch 2/20

546/546 [=====] - 124s 227ms/step - loss: 0.4540 - accuracy: 0.7895 - val_loss: 0.4138 - val_accuracy: 0.8099

Epoch 3/20

546/546 [=====] - 94s 172ms/step - loss: 0.4432 - accuracy: 0.7977 - val_loss: 0.4295 - val_accuracy: 0.8010

Epoch 4/20

546/546 [=====] - 94s 172ms/step - loss: 0.4223 - accuracy: 0.8088 - val_loss: 0.4107 - val_accuracy: 0.8045

Epoch 5/20

546/546 [=====] - 89s 163ms/step - loss: 0.4161 - accuracy: 0.8120 - val_loss: 0.3846 - val_accuracy: 0.8291

Epoch 6/20

546/546 [=====] - 102s 186ms/step - loss: 0.4104 - accuracy: 0.8149 - val_loss: 0.3833 - val_accuracy: 0.8345

Epoch 7/20

546/546 [=====] - 120s 220ms/step - loss: 0.3966 - accuracy: 0.8230 - val_loss: 0.4058 - val_accuracy: 0.8185

Epoch 8/20

546/546 [=====] - 134s 245ms/step - loss: 0.4013 - accuracy: 0.8206 - val_loss: 0.3910 - val_accuracy: 0.8274

Epoch 9/20

546/546 [=====] - 134s 247ms/step - loss: 0.3927 - accuracy: 0.8220 - val_loss: 0.3886 - val_accuracy: 0.8288

Epoch 10/20

546/546 [=====] - 134s 245ms/step - loss: 0.3934 - accuracy: 0.8242 - val_loss: 0.4313 - val_accuracy: 0.7984

Epoch 11/20

546/546 [=====] - 129s 237ms/step - loss: 0.3858 - accuracy: 0.8299 - val_loss: 0.3734 - val_accuracy: 0.8331

```

Epoch 12/20
546/546 [=====] - 115s 210ms/step - loss: 0.3871 - accuracy:
0.8283 - val_loss: 0.3963 - val_accuracy: 0.8198
Epoch 13/20
546/546 [=====] - 104s 191ms/step - loss: 0.3827 - accuracy:
0.8300 - val_loss: 0.3971 - val_accuracy: 0.8196
Epoch 14/20
546/546 [=====] - 106s 194ms/step - loss: 0.3773 - accuracy:
0.8333 - val_loss: 0.4257 - val_accuracy: 0.8032
Epoch 15/20
546/546 [=====] - 104s 191ms/step - loss: 0.3748 - accuracy:
0.8334 - val_loss: 0.3680 - val_accuracy: 0.8412
Epoch 16/20
546/546 [=====] - 105s 193ms/step - loss: 0.3683 - accuracy:
0.8389 - val_loss: 0.3726 - val_accuracy: 0.8320
Epoch 17/20
546/546 [=====] - 102s 186ms/step - loss: 0.3604 - accuracy:
0.8428 - val_loss: 0.3852 - val_accuracy: 0.8301
Epoch 18/20
546/546 [=====] - 105s 192ms/step - loss: 0.3644 - accuracy:
0.8396 - val_loss: 0.3531 - val_accuracy: 0.8479
Epoch 19/20
546/546 [=====] - 107s 196ms/step - loss: 0.3625 - accuracy:
0.8414 - val_loss: 0.3528 - val_accuracy: 0.8471
Epoch 20/20
546/546 [=====] - 140s 256ms/step - loss: 0.3511 - accuracy:
0.8432 - val_loss: 0.3590 - val_accuracy: 0.8436
Momentum: 0.25
History: {'loss': [0.49455761909484863, 0.45400887727737427, 0.4431801736354828, 0.4
2225244641304016, 0.41612425446510315, 0.4103754758834839, 0.39658114314079285, 0.401
31276845932007, 0.392747163772583, 0.39335402846336365, 0.38575831055641174, 0.387124
240398407, 0.3826524615287781, 0.3773442804813385, 0.3748388886451721, 0.368334293365
4785, 0.3604435622692108, 0.36442652344703674, 0.3624778091907501, 0.351147383451461
8], 'accuracy': [0.765632152557373, 0.7895489931106567, 0.7976981401443481, 0.8087797
76096344, 0.8120132684707642, 0.8149038553237915, 0.823007345199585, 0.82062727212905
88, 0.8220338821411133, 0.8242330551147461, 0.8299358487129211, 0.8282967209815979,
0.8299931287765503, 0.8333333134651184, 0.8334287405014038, 0.838942289352417, 0.8427
622318267822, 0.8395718932151794, 0.84144526720047, 0.8432348966598511], 'val_loss':
[0.47139647603034973, 0.41383710503578186, 0.4294649362564087, 0.41069862246513367,
0.38461852073669434, 0.38328418135643005, 0.4058365821838379, 0.3909931778907776, 0.3
885525166988373, 0.43133559823036194, 0.37339961528778076, 0.3963363766670227, 0.3970
6292748451233, 0.4257175922393799, 0.3679625988006592, 0.3725605607032776, 0.38522690
534591675, 0.35314831137657166, 0.3528195023536682, 0.3589937388896942], 'val_accurac
y': [0.7804487347602844, 0.8098930716514587, 0.8010149598121643, 0.8045454621315002,
0.8290598392486572, 0.8344919681549072, 0.8185096383094788, 0.8274064064025879, 0.828
7927508354187, 0.7983956933021545, 0.8330662250518799, 0.8197860717773438, 0.81957799
19624329, 0.8032085299491882, 0.8412126302719116, 0.8319518566131592, 0.8301281929016
113, 0.8478609919548035, 0.8470886945724487, 0.8435828685760498]}

```

Hyperparameter Tuning Results / Analysis

In [44]: `tune_epochs_range = range(number_of_epochs)`

```

plt.figure(figsize=(10, 10))
plt.subplot(2, 2, 1)
plt.plot(tune_epochs_range, history[0]['accuracy'], label='Momentum = .99')
plt.plot(tune_epochs_range, history[1]['accuracy'], label='Momentum = .75')
plt.plot(tune_epochs_range, history[2]['accuracy'], label='Momentum = .50')
plt.plot(tune_epochs_range, history[3]['accuracy'], label='Momentum = .25')

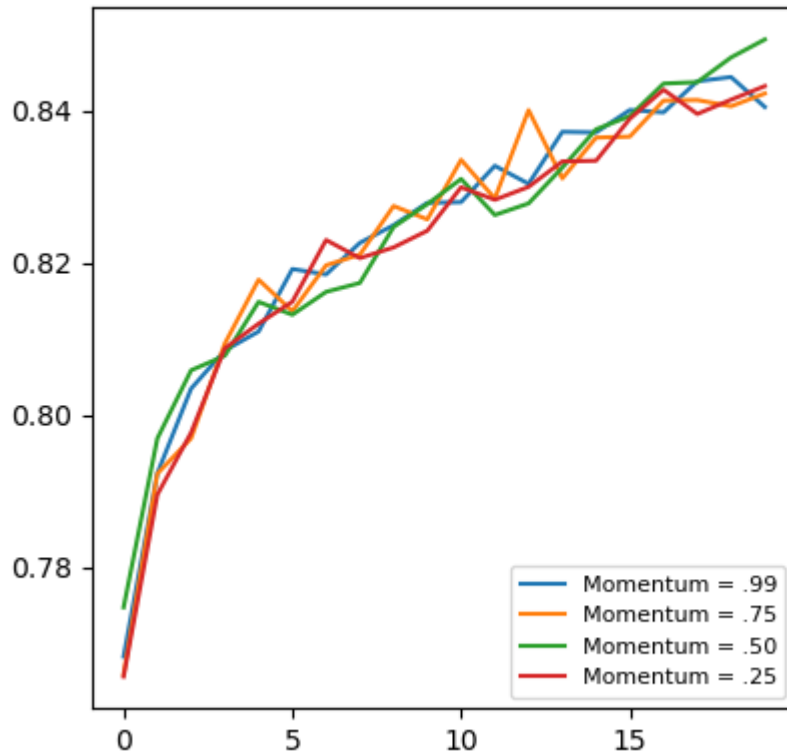
```

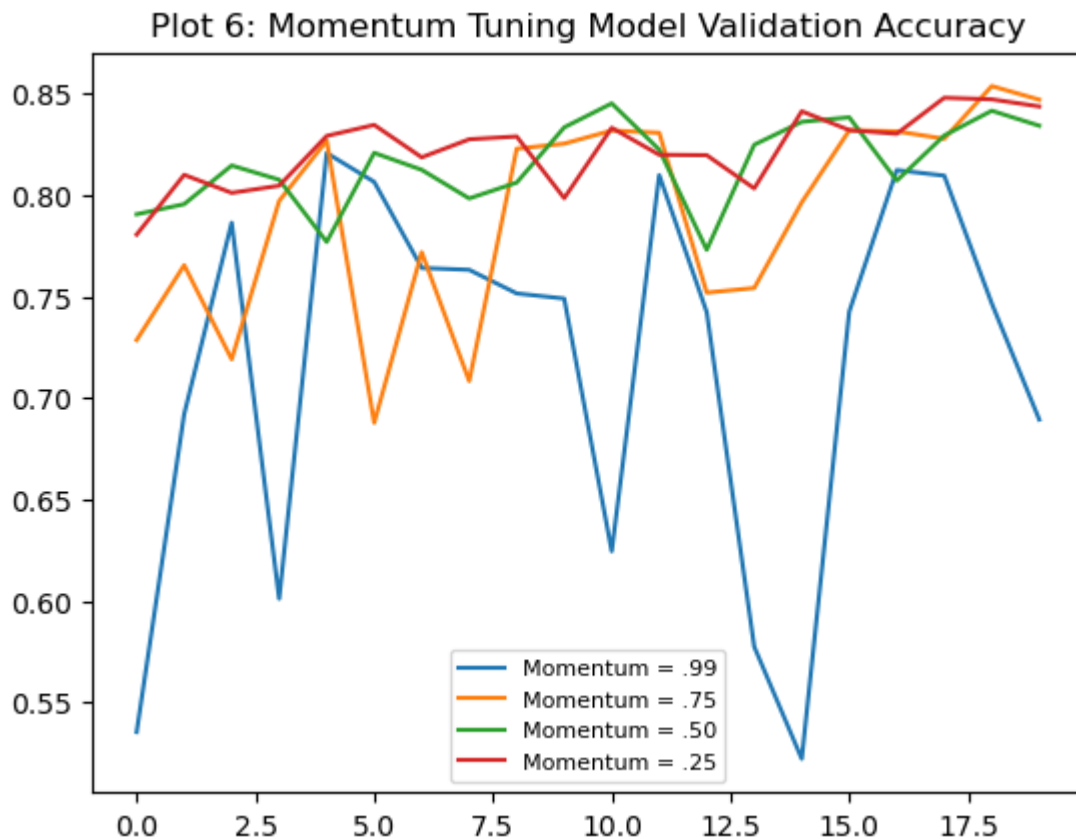
```

plt.legend(loc='lower right', fontsize=8)
plt.title('Plot 5: Momentum Tuning Model Training Accuracy')
plt.show()
#plt.subplot(2, 2, 2)
plt.plot(tune_epochs_range, history[0]['val_accuracy'], label='Momentum = .99')
plt.plot(tune_epochs_range, history[1]['val_accuracy'], label='Momentum = .75')
plt.plot(tune_epochs_range, history[2]['val_accuracy'], label='Momentum = .50')
plt.plot(tune_epochs_range, history[3]['val_accuracy'], label='Momentum = .25')
plt.legend(loc='lower center', fontsize=8)
plt.title('Plot 6: Momentum Tuning Model Validation Accuracy')
plt.show()

```

Plot 5: Momentum Tuning Model Training Accuracy





Accuracy Comparison / Analysis

Table 2: Momentum vs Accuracy

Momentum	Accuracy	Validation Accuracy
.99	.8409	.7505
.75	.8375	.8374
.50	.8431	.8449
.25	.8379	.8389

As can be seen in Plot 5 and Table 2, 'Momentum vs Accuracy', all 4 momentum levels reach similar levels of accuracy. Model 3, momentum = .5, performed best with an accuracy of 84.31%. The worst performer was Model 2, momentum = .75, with accuracy of 83.75%. When comparing models strictly from an accuracy perspective there is no appreciable difference between models. The best and worst performers were separated by only .56%, essentially no difference.

However, it's how the models got there that is interesting. Plot 5 shows that Model 4, momentum = .25, exhibited the least amount of variability through its trajectory. On the other hand, Model 1, momentum = .99, varied wildly throughout its path. This is not unexpected as the larger momentum model would be expected to 'bounce' more than the lower momentum models.

Plot 6, Validation Accuracy, more clearly details how the higher momentums impact the loss trajectory. As expected, as the momentum of the models decreased, so did the variation in the

loss path.

Given the marginal difference in accuracy in conjunction with the variation in the accuracy trajectories, the data shows that working with a lower momentum provides a more stable model in terms of accuracy and loss. Model 4, momentum = .25 is the preferred model.

Conclusion

Model Comparison

Over 15 epochs, comparisons of the before and after models showed marginal accuracy and loss differences. The before model performed slightly better with its final accuracy 2.38% better at 84.44%, then the after model at 80.20%.

However as outlined above, the before model began to show signs of overfitting at around the 10th epoch, while the after model did not. Based on the analysis and discussion above, the conclusion is that placing the Batch Normalization layer after the Activation layer proved to be beneficial. Given the marginal difference in performance and the overfitting protection in the after model, the after model is deemed the better of the two.

Hyperparameter Tuning

Hyperparameter tuning, varying the momentum parameter, provided some insight into how momentum impacted the model's performance. The total difference in performance across the four different momentum values resulted in a maximum accuracy difference of .56%. The middle two momentum values (.75 and .50) resulted in a .56% difference in accuracy.

When considering that the accuracies and accuracy trajectories are essentially identical, the deciding factor comes down to the variability in the accuracy paths. Given that Model 4, momentum of .25, exhibited the least amount of variability, Model 4 is considered the most stable and therefore deemed the best model of the four.

In []: