

```
In [ ]: import os
import numpy as np
import pandas as pd
from PIL import Image
import matplotlib.pyplot as plt
from tensorflow import keras
from keras import layers
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score,
```

Preprocess data and load data

Firstly I need to retrieve the labels from the jsonl file, then load the images into a numpy array. Then we connect the labels with the images and preprocess the data.

```
In [ ]: #read jsonl file
df = pd.read_json('./data/metadata.jsonl', lines=True)
df.head()
```

```
Out [ ]:
```

	file_name	text_prompt
0	train/sample_0.png	Low masking level
1	train/sample_1.png	Low masking level
2	train/sample_2.png	Low masking level
3	train/sample_3.png	Low masking level
4	train/sample_4.png	Low masking level

```
In [ ]: #convert text prompt to 0,1,2 instead of Low, Medium, High respectively
df['text_prompt'] = df['text_prompt'].map({'Low masking level': 0, 'Medium masking le
df.head()
```

```
Out [ ]:
```

	file_name	text_prompt
0	train/sample_0.png	0
1	train/sample_1.png	0
2	train/sample_2.png	0
3	train/sample_3.png	0
4	train/sample_4.png	0

```
In [ ]: #what is the distribution of the data
df['text_prompt'].value_counts()
```

```
Out [ ]: text_prompt
0      33333
1      33333
2      33333
Name: count, dtype: int64
```

```
In [ ]: labels = []
#read labels from jsonl file
for i in range(99999):
    labels.append(df['text_prompt'][i])

print(labels)
```

Here we do the preprocessing of the images reducing the size to 128x160 and also making sure the image is in grayscale. All the processed images are saved into a folder for future use, so we don't need to preprocess the images again.

```
In [ ]: #load png files

processed_folder = './data/processed/'
num_required_images = 99999

#check if the processed folder exists and has enough images
if os.path.exists(processed_folder) and len(os.listdir(processed_folder)) >= num_requ
    print('Processed folder exists and has enough images')
    images = []
    for i in range(num_required_images):
        print("Loading image", i)
        img = Image.open(os.path.join(processed_folder, 'sample_' + str(i) + '.png'))
        img = img.convert('L')
        img_array = np.array(img)
        images.append(img_array)
else:
    #process and save images
    print('Processing and saving images')
    images = []
    original_folder = './data/train/'
    for i in range(num_required_images):
        print("Processing image", i)
        filename = 'sample_' + str(i) + '.png'

        #create the processed folder if it doesn't exist
        if not os.path.exists(processed_folder):
            os.makedirs(processed_folder)

        #process the image
        img = Image.open(os.path.join(original_folder, filename))
        img = img.resize((128, 160))
        img = img.convert('L')
        img_array = np.array(img)

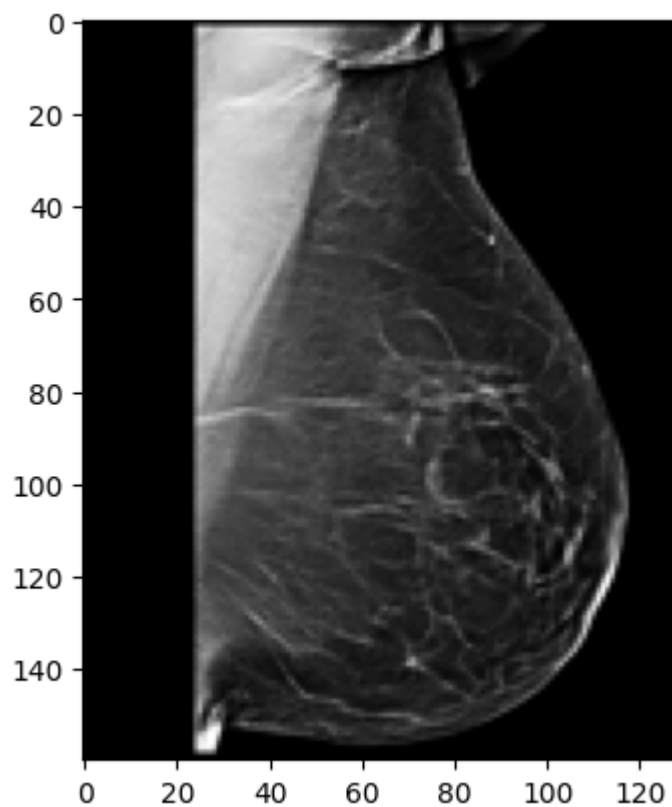
        #save the processed image
        img.save(os.path.join(processed_folder, filename))

        images.append(img_array)
```

```
In [ ]: print(images[0].shape)
#are the images loaded correctly?
plt.imshow(images[0], cmap='gray')
```

(160, 128)

```
Out[ ]: <matplotlib.image.AxesImage at 0x294ff4970>
```



Now a very important part is splitting the data into training, validation and test sets. We will use 60% of the data for training, 20% for validation and 20% for testing. To save memory we also delete the unused variables.

```
In [ ]: #initial split of the data 80% train, 20% test
X_train_temp, X_test, y_train_temp, y_test = train_test_split(images, labels, test_si

#further split the training data into 75% train, 25% validation
X_train, X_val, y_train, y_val = train_test_split(X_train_temp, y_train_temp, test_si

#clear unused variables for memory
del X_train_temp
del y_train_temp
del images
```

Building the base deep learning model

In the case that we have already built the model we will load it from the file, otherwise we will build the model and save it to a file.

```
In [ ]: #if modelV1.h5 exists, load it
try:
    modelV1 = keras.models.load_model('./models/modelV1.h5')
    print('Model loaded')
    print(modelV1.summary())
    print(modelV1.history)
    V1Created = True
except:
    V1Created = False
    print('Model not found')
```

```

2024-03-03 18:09:22.577014: I metal_plugin/src/device/metal_device.cc:1154] Metal device set to: Apple M1
2024-03-03 18:09:22.577336: I metal_plugin/src/device/metal_device.cc:296] systemMemory: 8.00 GB
2024-03-03 18:09:22.577713: I metal_plugin/src/device/metal_device.cc:313] maxCacheSize: 2.67 GB
2024-03-03 18:09:22.578160: I tensorflow/core/common_runtime/pluggable_device/pluggable_device_factory.cc:303] Could not identify NUMA node of platform GPU ID 0, defaulting to 0. Your kernel may not have been built with NUMA support.
2024-03-03 18:09:22.579061: I tensorflow/core/common_runtime/pluggable_device/pluggable_device_factory.cc:269] Created TensorFlow device (/job:localhost/replica:0/task:0/device:GPU:0 with 0 MB memory) -> physical PluggableDevice (device: 0, name: METAL, pci bus id: <undefined>)

```

Model loaded

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 160, 128, 1)]	0
conv2d (Conv2D)	(None, 158, 126, 16)	160
max_pooling2d (MaxPooling2D)	(None, 79, 63, 16)	0
flatten (Flatten)	(None, 79632)	0
dense (Dense)	(None, 3)	238899

Total params: 239059 (933.82 KB)

Trainable params: 239059 (933.82 KB)

Non-trainable params: 0 (0.00 Byte)

None

None

If we haven't built the model yet, we will build a simple deep learning model with 1 convolutional layer, a 2d max pooling layer, a flatten layer and 1 dense layer that is the classifier output using softmax. We will use the Adam optimizer and the categorical crossentropy loss function.

```

In [ ]: if not V1Created:
        inputs = keras.Input(shape=(160,128,1)) #resolution of images
        x = layers.Conv2D(16, 3, activation="relu")(inputs)
        x = layers.MaxPooling2D(pool_size=2)(x)
        x = layers.Flatten()(x)
        outputs = layers.Dense(3, activation="softmax")(x) #3 classes
        modelV1 = keras.Model(inputs=inputs, outputs=outputs)

```

```

In [ ]: modelV1.summary()
        print(modelV1.history)

```

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 160, 128, 1)]	0
conv2d (Conv2D)	(None, 158, 126, 16)	160
max_pooling2d (MaxPooling2D)	(None, 79, 63, 16)	0
flatten (Flatten)	(None, 79632)	0
dense (Dense)	(None, 3)	238899

=====
Total params: 239059 (933.82 KB)
Trainable params: 239059 (933.82 KB)
Non-trainable params: 0 (0.00 Byte)
=====

None

```
In [ ]: #compile model if not loaded
if not V1Created:
    #legacy is faster on mac m1 chip
    modelV1.compile(optimizer=keras.optimizers.legacy.Adam(learning_rate=0.001),
                    loss='sparse_categorical_crossentropy',
                    metrics=['accuracy'])
```

Now we will train the model using the training set and validate it using the validation set. We will also save the model to a file.

```
In [ ]: #train model if not loaded
if not V1Created:

    modelV1.fit(np.array(X_train), np.array(y_train), epochs=1, batch_size=16, valida
```

```
In [ ]: #save model if not loaded
if not V1Created:
    modelV1.save('./models/modelV1.h5')
```

Below we define a few functions to plot the training history and to evaluate the model using the test set.

```
In [ ]: #show graph of training loss and validation loss

def plot_loss_accuracy(modelCreated, model, modelName):
    if not modelCreated:
        history_dict = model.history.history
        loss_values = history_dict["loss"]
        val_loss_values = history_dict["val_loss"]
        epochs = range(1, len(loss_values) + 1)
        plt.plot(epochs, loss_values, "bo", label="Training loss")
        plt.plot(epochs, val_loss_values, "b", label="Validation loss")
        plt.title('Model loss')
        plt.ylabel('Loss')
        plt.xlabel('Epoch')
        plt.legend()
        plt.savefig('./models/' + modelName + '_loss.png')
        plt.show()
```

```

plt.clf()
plt.plot(epochs, history_dict['accuracy'], 'bo', label='Training accuracy')
plt.plot(epochs, history_dict['val_accuracy'], 'b', label='Validation accuracy')
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.savefig('./models/' + modelName + '_accuracy.png')
plt.show()

```

else:

```

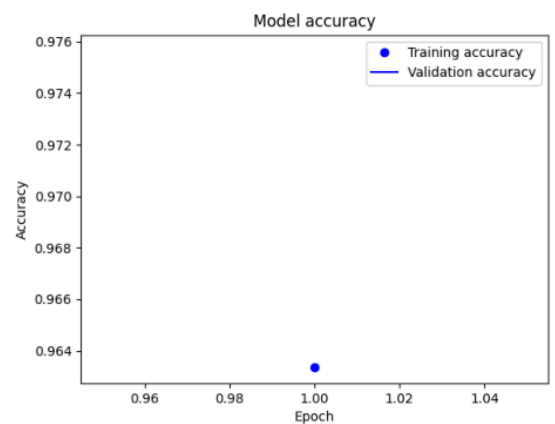
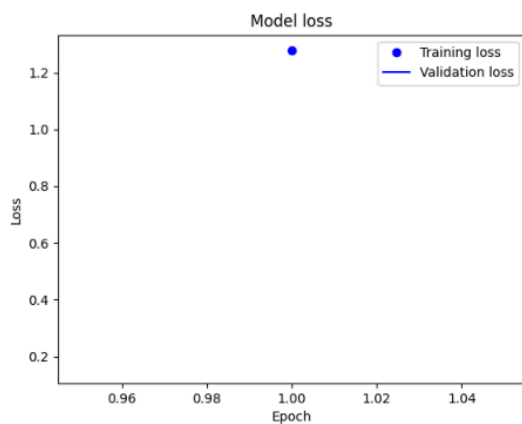
img1 = Image.open('./models/' + modelName + '_loss.png')
img2 = Image.open('./models/' + modelName + '_accuracy.png')
fig, ax = plt.subplots(1, 2, figsize=(15, 5))
fig.suptitle('Model loss and accuracy')
ax[0].imshow(img1)
ax[0].axis('off')

ax[1].imshow(img2)
ax[1].axis('off')

```

In []: `plot_loss_accuracy(V1Created, modelV1, 'modelV1')`

Model loss and accuracy



In []: `#evaluate model`

```

def evaluate_model(model, X_test, y_test, modelName):
    results = model.evaluate(np.array(X_test), np.array(y_test))

    #get predictions
    y_pred = model.predict(np.array(X_test))

    #convert probabilities to class labels
    y_pred = np.argmax(y_pred, axis=1)

    accuracy = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred, average='weighted')
    precision = precision_score(y_test, y_pred, average='weighted')
    recall = recall_score(y_test, y_pred, average='weighted')
    conf_matrix = confusion_matrix(y_test, y_pred)

    print("Results:", results)
    print("Accuracy:", accuracy)
    print("F1 Score:", f1)
    print("Precision:", precision)
    print("Recall:", recall)
    print("Confusion Matrix:\n", conf_matrix)

    #plot confusion matrix with numbers and labels

```

```

fig, ax = plt.subplots()
im = ax.imshow(conf_matrix)

ax.set_xticks(np.arange(3))
ax.set_yticks(np.arange(3))
ax.set_xticklabels(['Low', 'Medium', 'High'])
ax.set_yticklabels(['Low', 'Medium', 'High'])
ax.set_xlabel('Predicted')
ax.set_ylabel('True')

for i in range(3):
    for j in range(3):
        text = ax.text(j, i, conf_matrix[i, j], ha="center", va="center", color="

ax.set_title("Confusion Matrix")
fig.tight_layout()

plt.show()

#create a pandas series with the results
results = pd.Series([modelName ,accuracy, f1, precision, recall], index=['Model',
return results

```

```

In [ ]: modeV1_results = evaluate_model(modelV1, X_test, y_test, 'modelV1')
modeV1_results

```

2024-03-03 18:09:25.144292: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 11ms/step - loss: 0.1388 - accuracy: 0.9768

12/625 [.....] - ETA: 6s

2024-03-03 18:09:33.599095: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 5s 8ms/step

Results: [0.13882388174533844, 0.9768499732017517]

Accuracy: 0.97685

F1 Score: 0.9767627858890039

Precision: 0.9771766914265317

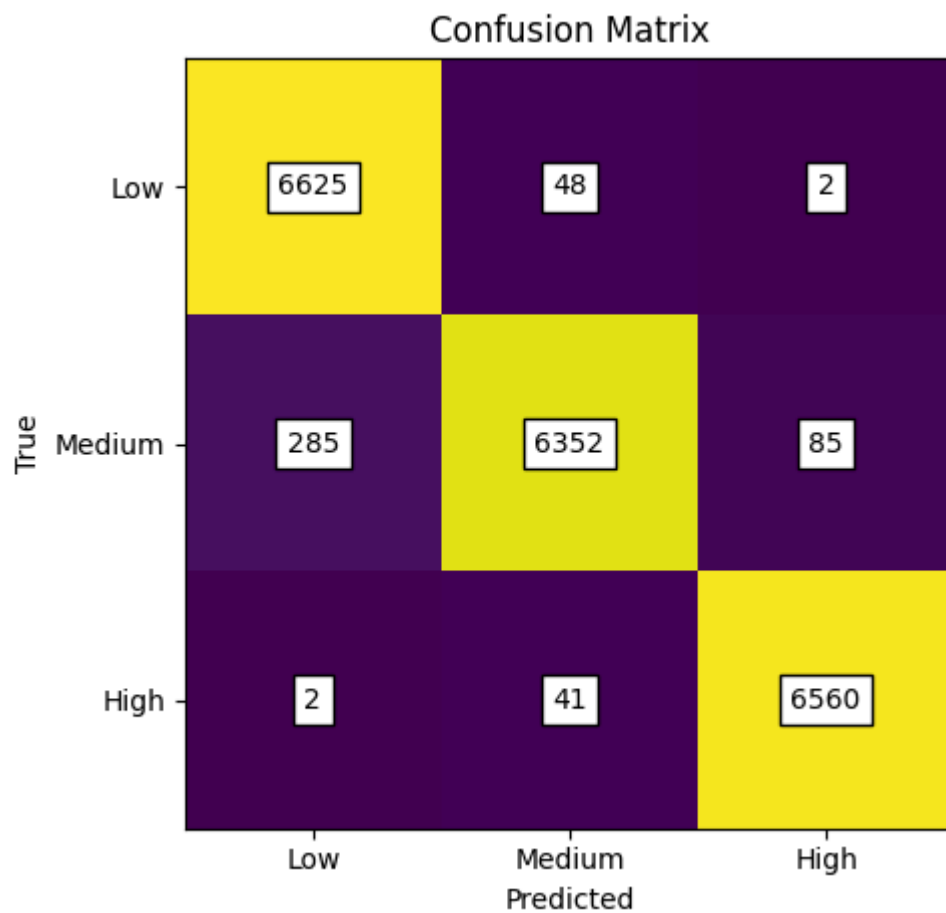
Recall: 0.97685

Confusion Matrix:

[[6625 48 2]

[285 6352 85]

[2 41 6560]]



```
Out[ ]: Model      modelV1
Accuracy    0.97685
F1 Score    0.976763
Precision   0.977177
Recall      0.97685
dtype: object
```

The first base model has already done an exceptional job, however there is still room for improvement. Which leads us to the next step.

Improving the model

We will attempt to find the best parameters for the model by adjusting the parameters values creating a model for each different value and testing the model. The results for each model will be saved and we shall compare the results to find the best model.

Values to tune:

- learning rate
- optimizer
- batch size
- epochs
- layers

Learning rate

```
In [ ]: #tuning different learning rates
#modelv1 uses adam optimizer, so it had a default learning rate of 0.001
#we will try learning rates of 0.1, 0.01, 0.0001
```



```

lr_df = pd.DataFrame(columns=['Learning Rate', 'Accuracy', 'F1 Score', 'Precision', 'Recall', 'Confusion Matrix'])
learning_rates = [0.1, 0.01, 0.001, 0.0001, 0.00001]

for rate in learning_rates:

    #try load already built model
    try:
        model_name = 'modelV1_lr_'+ str(rate)
        model = keras.models.load_model('./models/'+model_name+'.h5')
        print('Model loaded')
        modelCreated = True
    except:
        modelCreated = False
        print('Model not found')

    print("Learning Rate:", rate)

    if not modelCreated:
        #same model as modelV1, but with different learning rates
        inputs = keras.Input(shape=(160,128,1)) #resolution of images
        x = layers.Conv2D(16, 3, activation="relu")(inputs)
        x = layers.MaxPooling2D(pool_size=2)(x)
        x = layers.Flatten()(x)
        outputs = layers.Dense(3, activation="softmax")(x) #3 classes
        model = keras.Model(inputs=inputs, outputs=outputs)

        model.compile(optimizer=keras.optimizers.legacy.Adam(learning_rate=rate),
                      loss='sparse_categorical_crossentropy',
                      metrics=['accuracy'])
        model.fit(np.array(X_train), np.array(y_train), epochs=1, batch_size=16, validation_data=(X_test, y_test))

        model.save('./models/'+ model_name + '.h5')

    plot_loss_accuracy(modelCreated, model, model_name)
    results = evaluate_model(model, X_test, y_test, model_name)
    results['Learning Rate'] = rate
    lr_df.loc[len(lr_df.index)] = results

```

Model loaded

Learning Rate: 0.1

1/625 [.....] - ETA: 2:39 - loss: 1.1016 - accuracy: 0.3125

2024-03-03 18:09:40.617964: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 11ms/step - loss: 1.0990 - accuracy: 0.3361

9/625 [.....] - ETA: 9s

2024-03-03 18:09:48.726153: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 6s 9ms/step

Results: [1.0989689826965332, 0.3361000120639801]

Accuracy: 0.3361

F1 Score: 0.16909394506399222

Precision: 0.11296321000000001

Recall: 0.3361

Confusion Matrix:

```

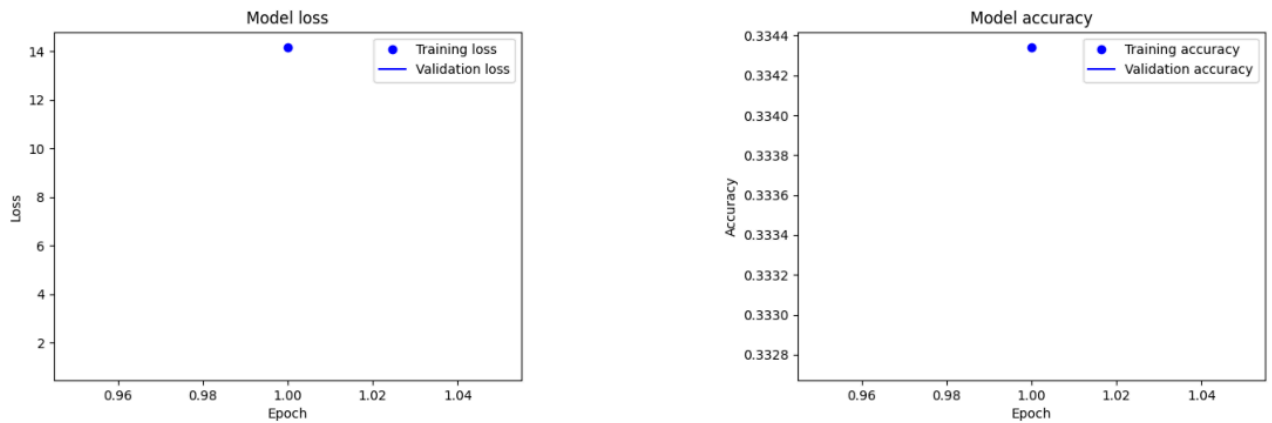
[[ 0 6675  0]
 [ 0 6722  0]
 [ 0 6603  0]]

```

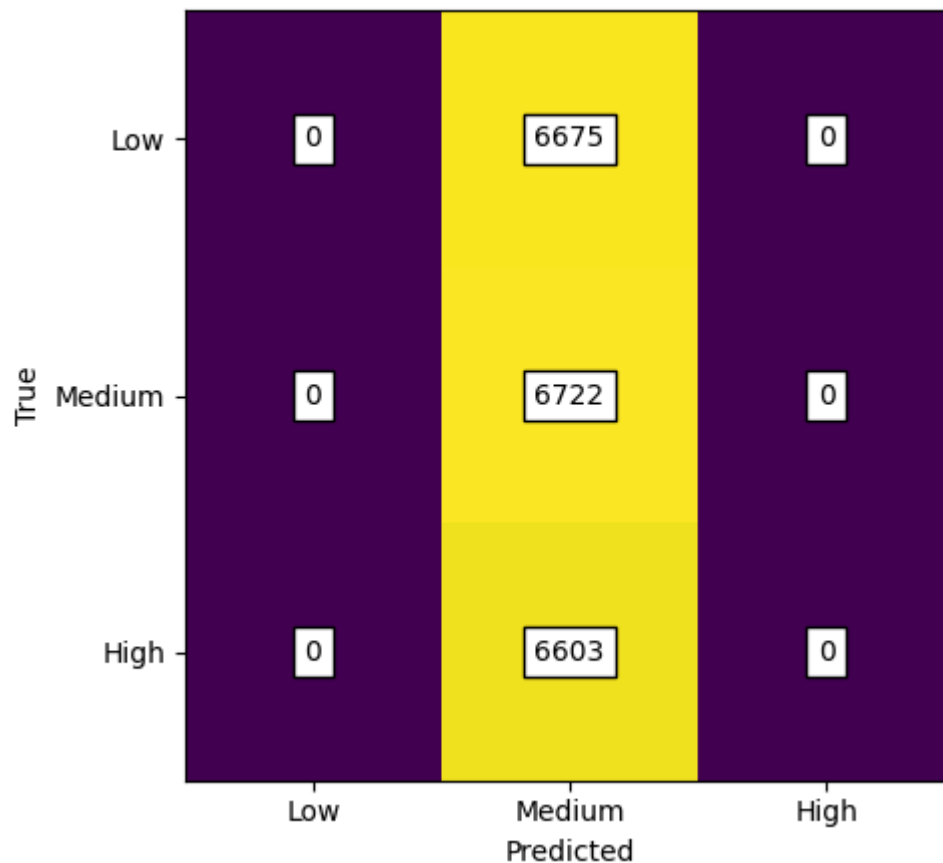
```
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1497: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Model loss and accuracy



Confusion Matrix



Model loaded

Learning Rate: 0.01

4/625 [.....] - ETA: 11s - loss: 0.3479 - accuracy: 0.8594

```
2024-03-03 18:09:55.861604: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
```

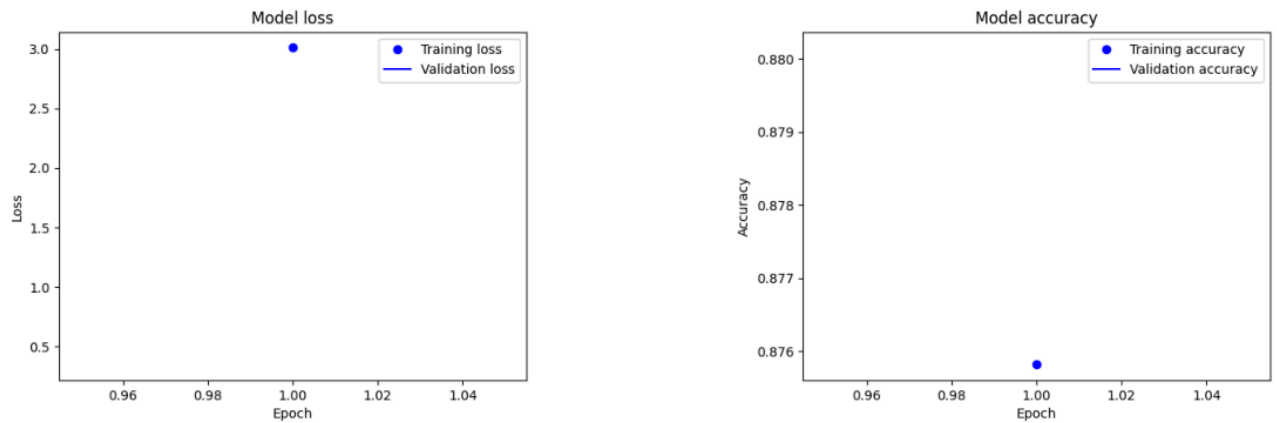
625/625 [=====] - 7s 11ms/step - loss: 0.3327 - accuracy: 0.8837

1/625 [.....] - ETA: 2:12

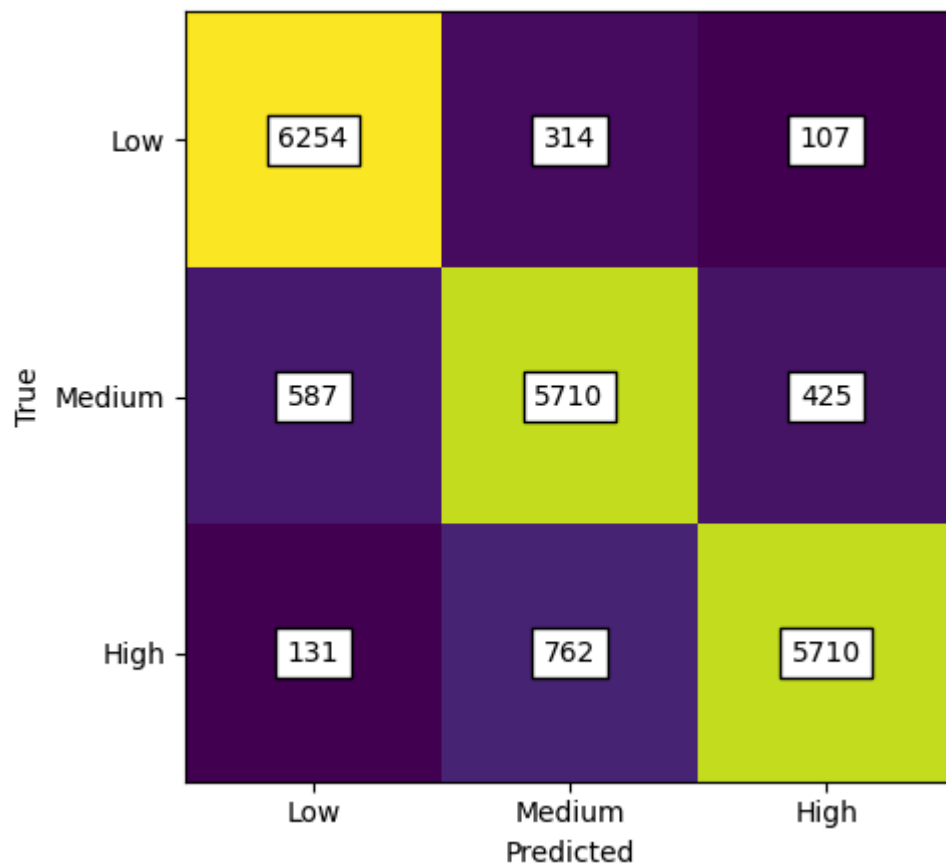
```
2024-03-03 18:10:03.845696: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
```

625/625 [=====] – 5s 8ms/step
 Results: [0.3326594829559326, 0.8837000131607056]
 Accuracy: 0.8837
 F1 Score: 0.883565805812315
 Precision: 0.8841983153762792
 Recall: 0.8837
 Confusion Matrix:
 [[6254 314 107]
 [587 5710 425]
 [131 762 5710]]

Model loss and accuracy



Confusion Matrix



Model loaded

Learning Rate: 0.001

5/625 [.....] – ETA: 9s – loss: 0.4963 – accuracy: 0.9563

2024-03-03 18:10:10.858600: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] – 9s 14ms/step – loss: 0.2774 – accuracy: 0.9675

9/625 [.....] – ETA: 9s

2024-03-03 18:10:20.649848: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 11ms/step

Results: [0.27738699316978455, 0.9674500226974487]

Accuracy: 0.96745

F1 Score: 0.9675297730913924

Precision: 0.969107979028746

Recall: 0.96745

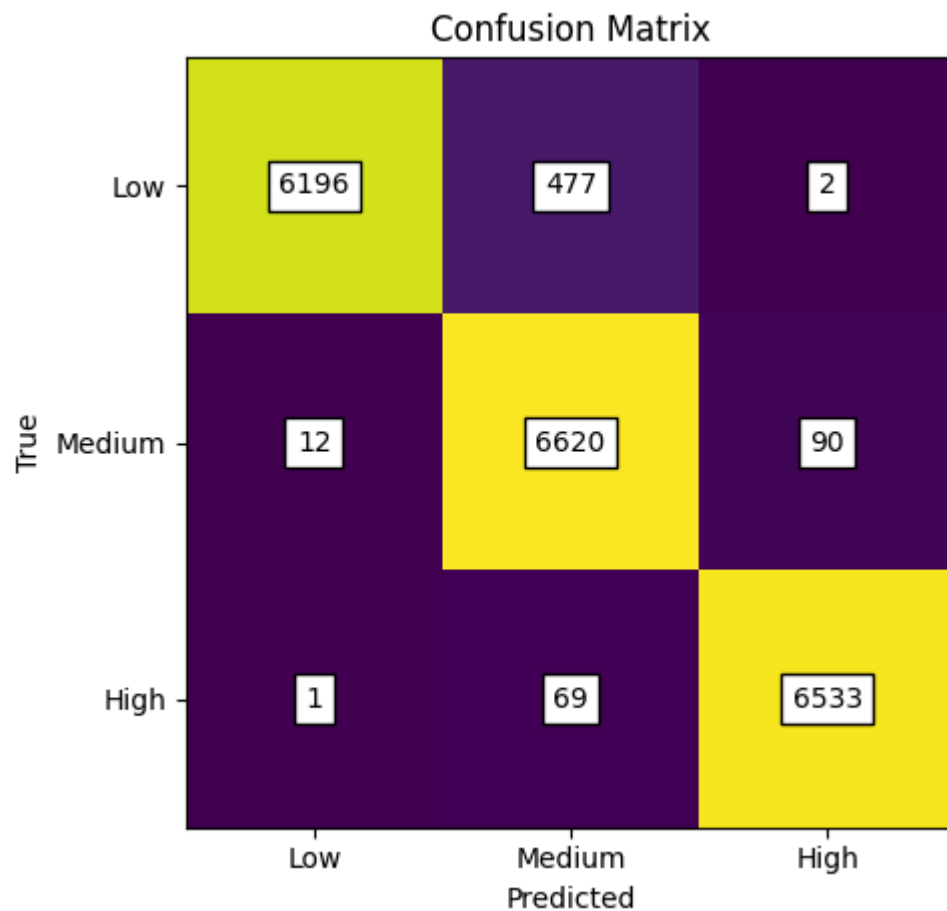
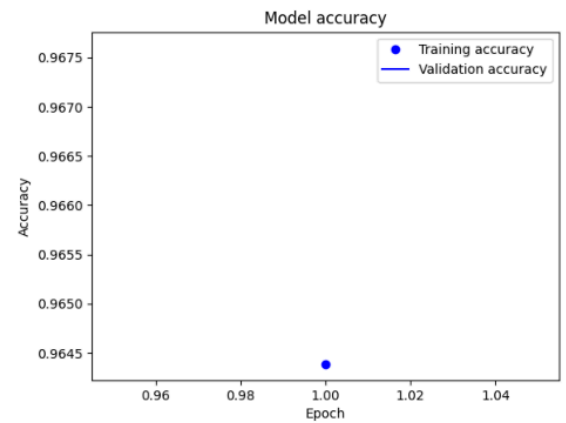
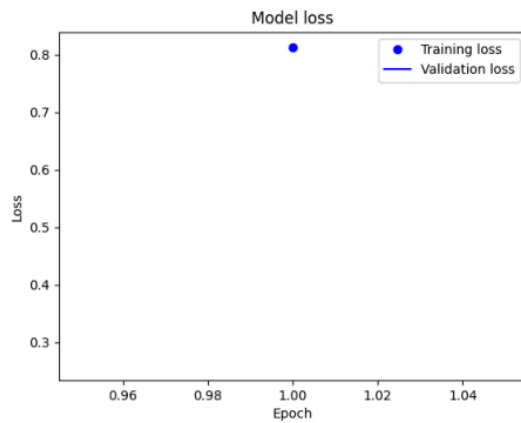
Confusion Matrix:

[[6196 477 2]

[12 6620 90]

[1 69 6533]]

Model loss and accuracy



Model loaded

Learning Rate: 0.0001

1/625 [.....] - ETA: 2:26 - loss: 0.1616 - accuracy: 0.9688

2024-03-03 18:10:29.106757: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 9s 14ms/step - loss: 0.1435 - accuracy: 0.9825

8/625 [.....] - ETA: 11s

2024-03-03 18:10:39.064325: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 11ms/step

Results: [0.14349274337291718, 0.982450008392334]

Accuracy: 0.98245

F1 Score: 0.9824009056758656

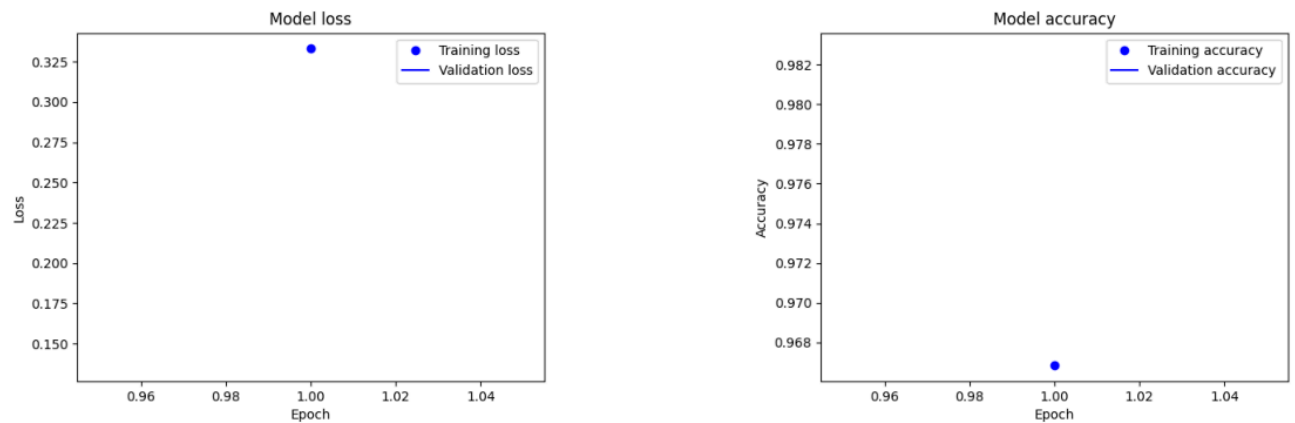
Precision: 0.9825064814648422

Recall: 0.98245

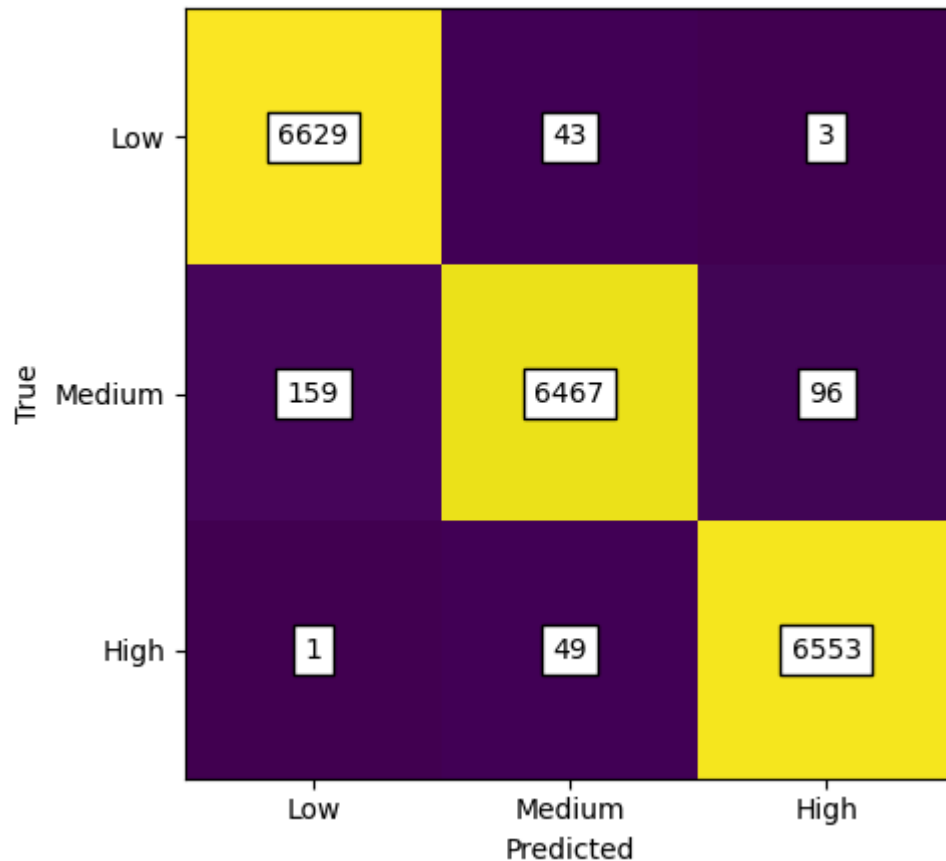
Confusion Matrix:

```
[[6629  43   3]
 [ 159 6467  96]
 [   1  49 6553]]
```

Model loss and accuracy



Confusion Matrix



Model loaded

Learning Rate: 1e-05

4/625 [.....] - ETA: 14s - loss: 0.0381 - accuracy: 0.9844

2024-03-03 18:10:47.405423: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 9s 14ms/step - loss: 0.2740 - accuracy: 0.9609

8/625 [.....] - ETA: 10s

2024-03-03 18:10:57.690376: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 11ms/step

Results: [0.2740277349948883, 0.9609000086784363]

Accuracy: 0.9609

F1 Score: 0.960660090874092

Precision: 0.9625574620649122

Recall: 0.9609

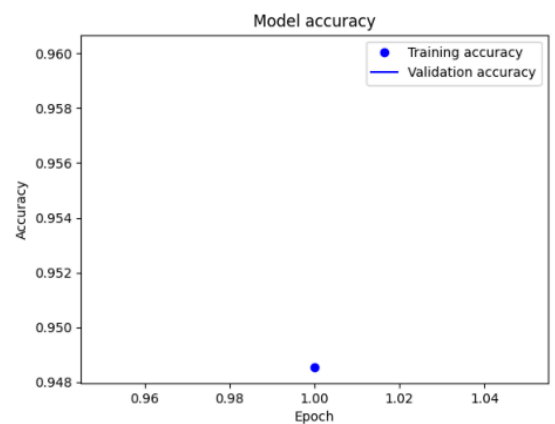
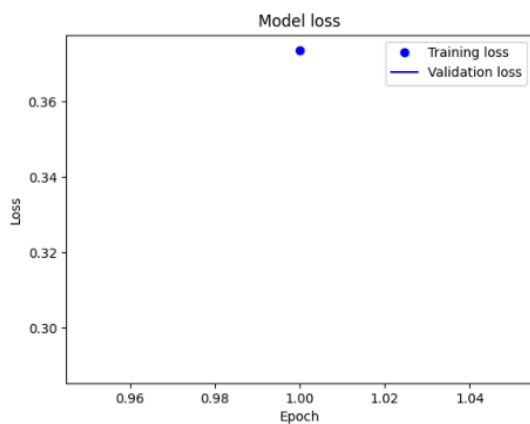
Confusion Matrix:

[[6649 26 0]

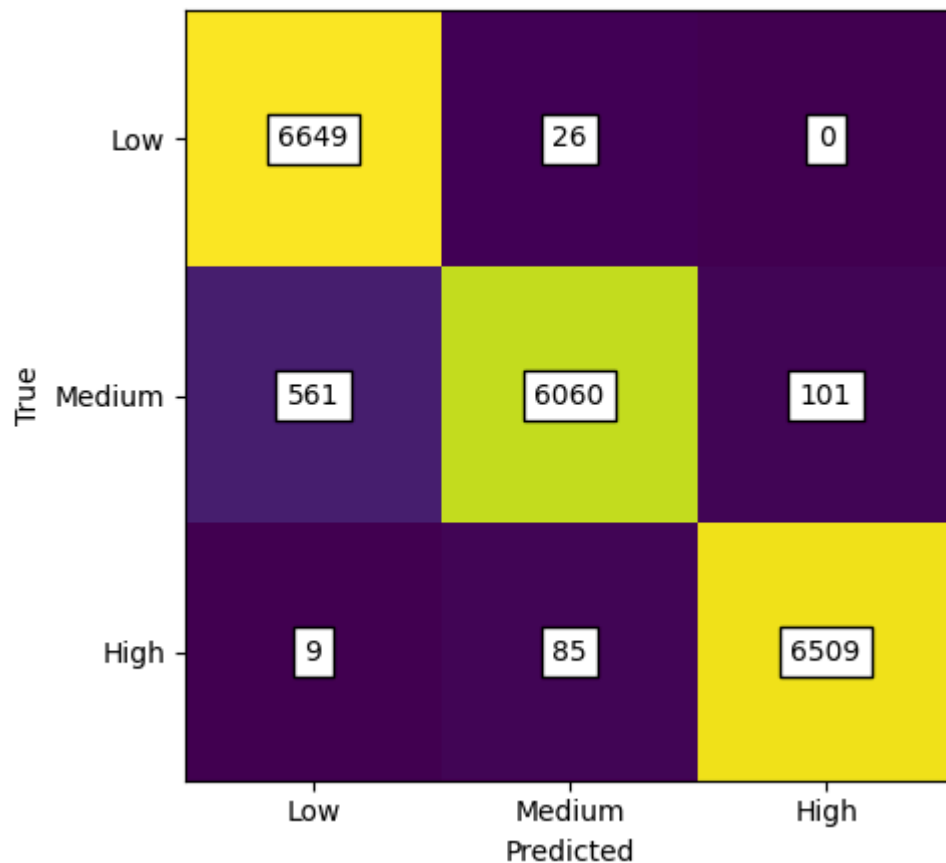
[561 6060 101]

[9 85 6509]]

Model loss and accuracy



Confusion Matrix



```
In [ ]: #show the table results for each learning rate
lr_df
```

```
Out [ ]:
```

	Learning Rate	Accuracy	F1 Score	Precision	Recall
0	0.1	0.3361	0.169094	0.112963	0.3361
1	0.01	0.8837	0.883566	0.884198	0.8837
2	0.001	0.96745	0.96753	0.969108	0.96745
3	0.0001	0.98245	0.982401	0.982506	0.98245
4	0.00001	0.9609	0.96066	0.962557	0.9609

```
In [ ]: #draw line graphs for learning rate vs acc, f1, prec, recall
fig, axs = plt.subplots(2, 2, figsize=(15, 10))
fig.suptitle('Learning Rate vs Metrics')

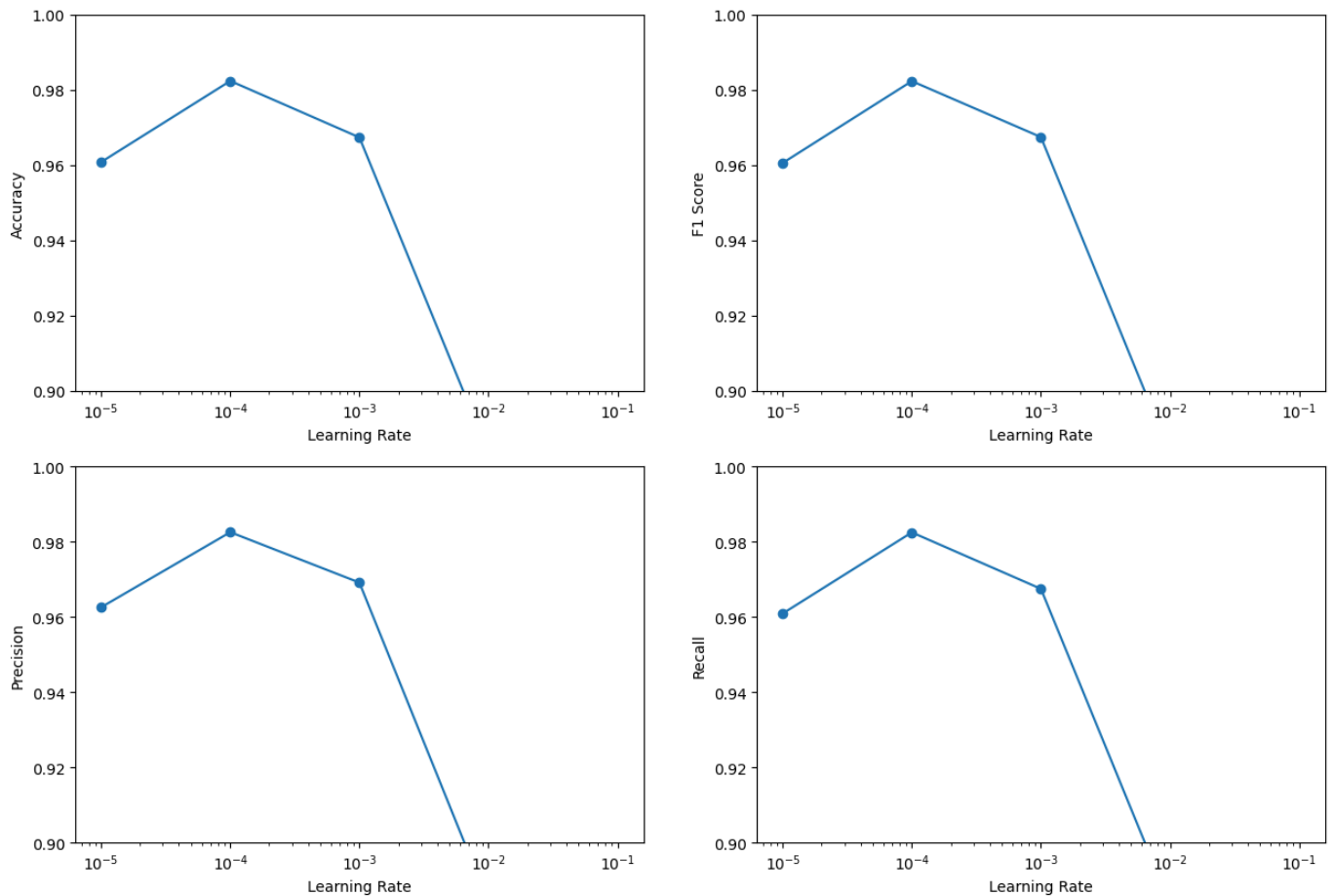
axs[0,0].plot(lr_df['Learning Rate'], lr_df['Accuracy'], label='Accuracy', marker='o')
axs[0,0].set_xscale('log')
axs[0,0].set_xlabel('Learning Rate')
axs[0,0].set_ylabel('Accuracy')
axs[0,0].set_ylim(0.9, 1)

axs[0,1].plot(lr_df['Learning Rate'], lr_df['F1 Score'], label='F1 Score', marker='o')
axs[0,1].set_xscale('log')
axs[0,1].set_xlabel('Learning Rate')
axs[0,1].set_ylabel('F1 Score')
axs[0,1].set_ylim(0.9, 1)

axs[1,0].plot(lr_df['Learning Rate'], lr_df['Precision'], label='Precision', marker='o')
axs[1,0].set_xscale('log')
axs[1,0].set_xlabel('Learning Rate')
axs[1,0].set_ylabel('Precision')
axs[1,0].set_ylim(0.9, 1)

axs[1,1].plot(lr_df['Learning Rate'], lr_df['Recall'], label='Recall', marker='o')
axs[1,1].set_xscale('log')
axs[1,1].set_xlabel('Learning Rate')
axs[1,1].set_ylabel('Recall')
axs[1,1].set_ylim(0.9, 1)

plt.show()
```



From these results it seems quiet clear that 0.0001 is the best learning rate for the model and I shall move on using this rate.

Optimizer

In []: *#tuning different optimizers*

```
opt_df = pd.DataFrame(columns=['Optimizers', 'Accuracy', 'F1 Score', 'Precision', 'Re
optimizers = {
    'sgd': keras.optimizers.legacy.SGD(learning_rate=0.0001),
    'rmsprop': keras.optimizers.legacy.RMSprop(learning_rate=0.0001),
    'adagrad': keras.optimizers.legacy.Adagrad(learning_rate=0.0001),
    'adam': keras.optimizers.legacy.Adam(learning_rate=0.0001),
}

for name, optimizer in optimizers.items():

    #try load already built model
    try:
        model_name = 'modelV1_opt_'+ str(name)
        model = keras.models.load_model('./models/'+model_name+'.h5')
        print('Model loaded')
        modelCreated = True
    except:
        modelCreated = False
        print('Model not found')

    print("OPTIMIZER:", name)

    if not modelCreated:
```



```

inputs = keras.Input(shape=(160,128,1)) #resolution of images
x = layers.Conv2D(16, 3, activation="relu")(inputs)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Flatten()(x)
outputs = layers.Dense(3, activation="softmax")(x) #3 classes
model = keras.Model(inputs=inputs, outputs=outputs)

model.compile(optimizer=optimizer,
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
model.fit(np.array(X_train), np.array(y_train), epochs=1, batch_size=16, vali

model.save('./models/'+ model_name + '.h5')

plot_loss_accuracy(modelCreated, model, model_name)
results = evaluate_model(model, X_test, y_test, model_name)
results['Optimizers'] = name
opt_df.loc[len(opt_df.index)] = results

```

Model loaded

OPTIMIZER: sgd

6/625 [.....] - ETA: 6s - loss: 0.0768 - accuracy: 0.9740

2024-03-03 18:11:07.676993: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 10ms/step - loss: 0.0702 - accuracy: 0.9810

23/625 [>.....] - ETA: 4s

2024-03-03 18:11:14.766806: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 5s 8ms/step

Results: [0.07020875811576843, 0.9810000061988831]

Accuracy: 0.981

F1 Score: 0.9809848120648418

Precision: 0.9809909501979848

Recall: 0.981

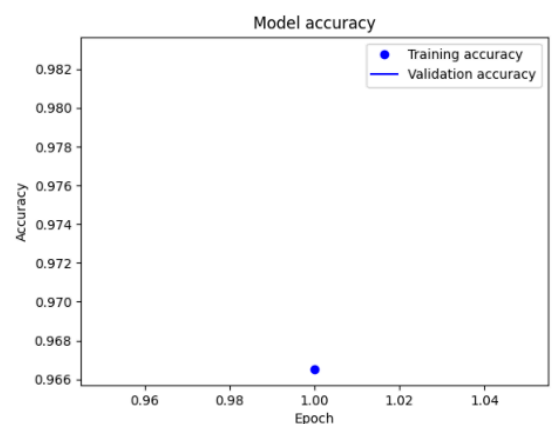
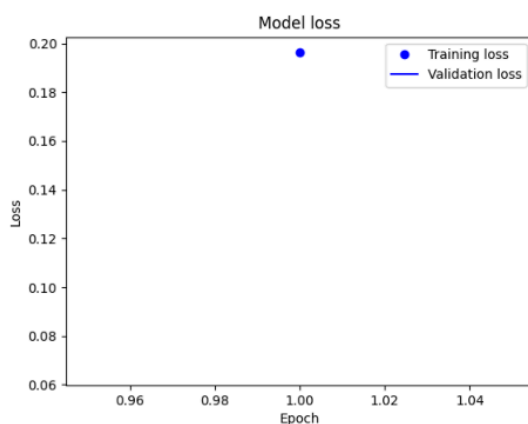
Confusion Matrix:

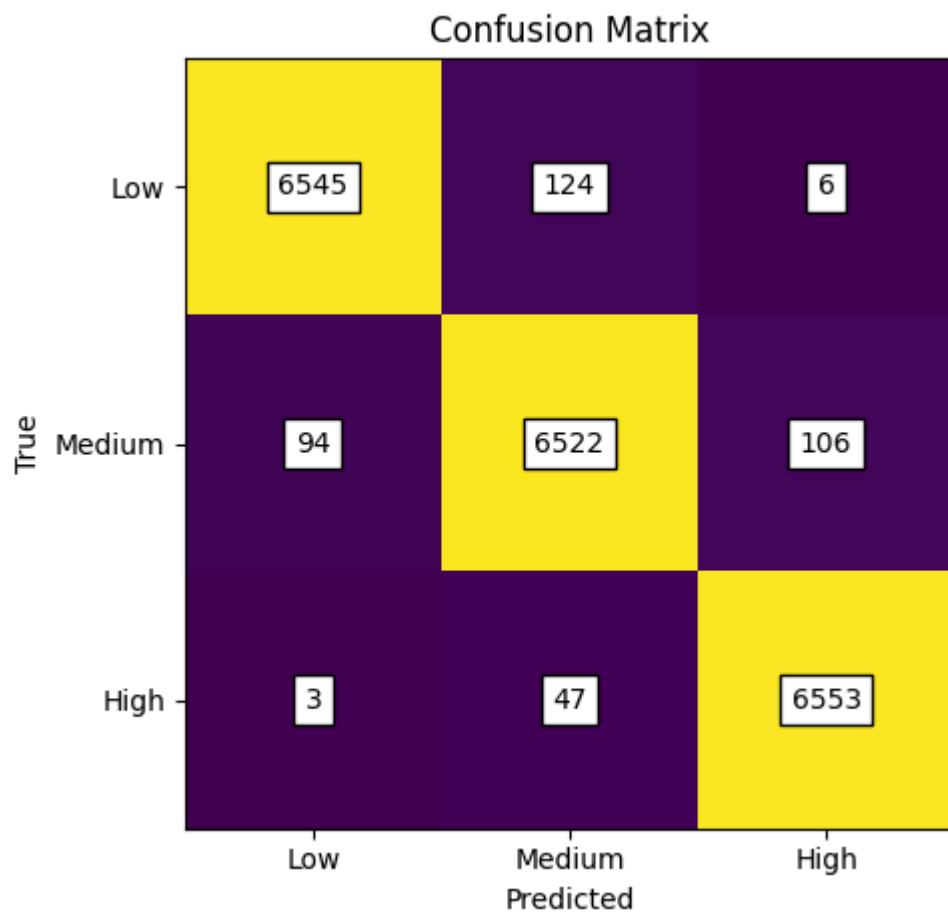
```

[[6545 124   6]
 [ 94 6522 106]
 [  3  47 6553]]

```

Model loss and accuracy





Model loaded

OPTIMIZER: rmsprop

2024-03-03 18:11:21.830581: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 10ms/step - loss: 0.3749 - accuracy: 0.9675

9/625 [.....] - ETA: 10s

2024-03-03 18:11:29.802985: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 5s 8ms/step

Results: [0.37493258714675903, 0.9675499796867371]

Accuracy: 0.96755

F1 Score: 0.9676600869968636

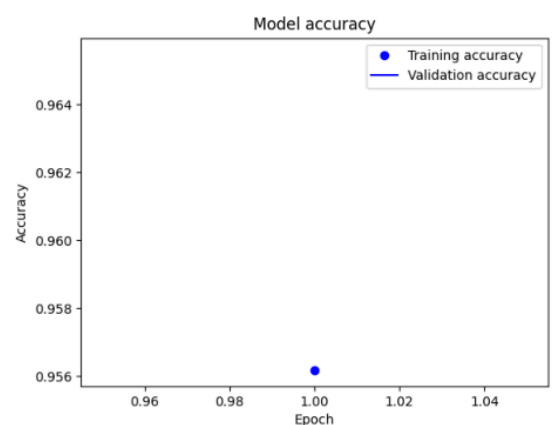
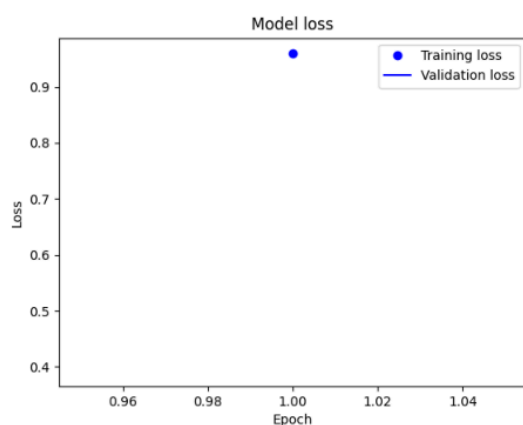
Precision: 0.9695250291234244

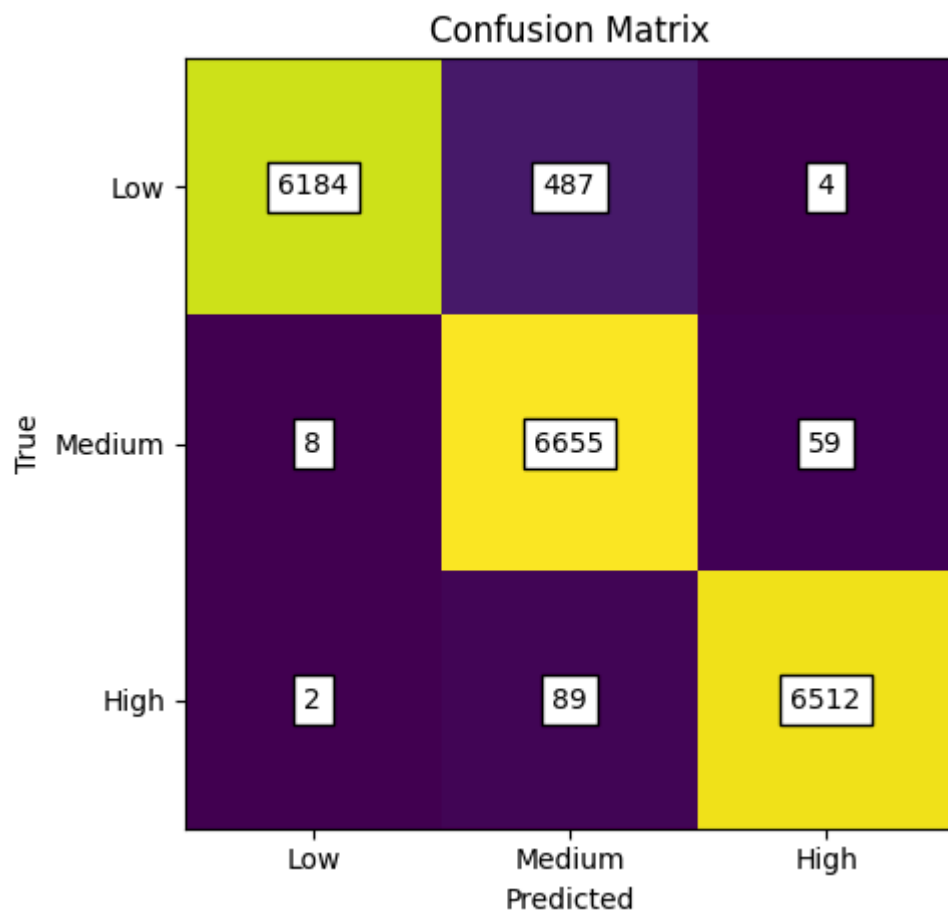
Recall: 0.96755

Confusion Matrix:

```
[[6184 487  4]
 [  8 6655 59]
 [  2  89 6512]]
```

Model loss and accuracy





Model loaded

OPTIMIZER: adagrad

5/625 [.....] - ETA: 8s - loss: 0.4961 - accuracy: 0.9500

2024-03-03 18:11:37.745855: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 10ms/step - loss: 0.3245 - accuracy: 0.9557

14/625 [.....] - ETA: 5s

2024-03-03 18:11:46.115668: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 6s 9ms/step

Results: [0.3244965970516205, 0.9556999802589417]

Accuracy: 0.9557

F1 Score: 0.9557476707835761

Precision: 0.9558896519085218

Recall: 0.9557

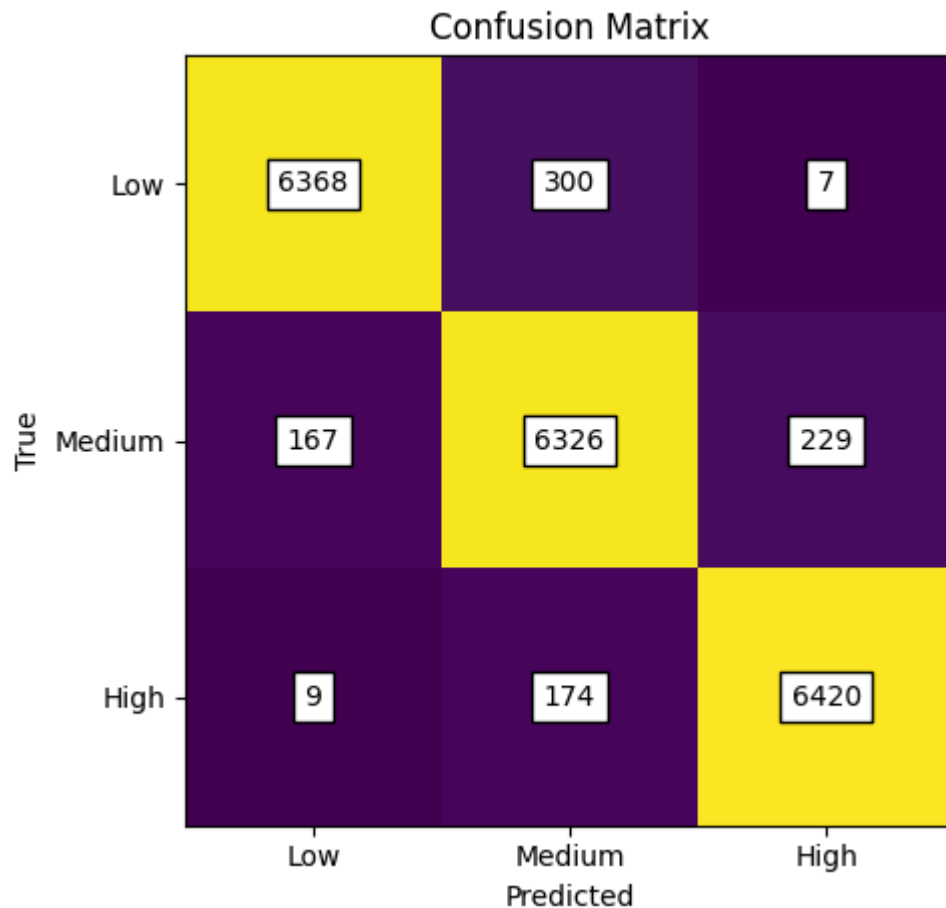
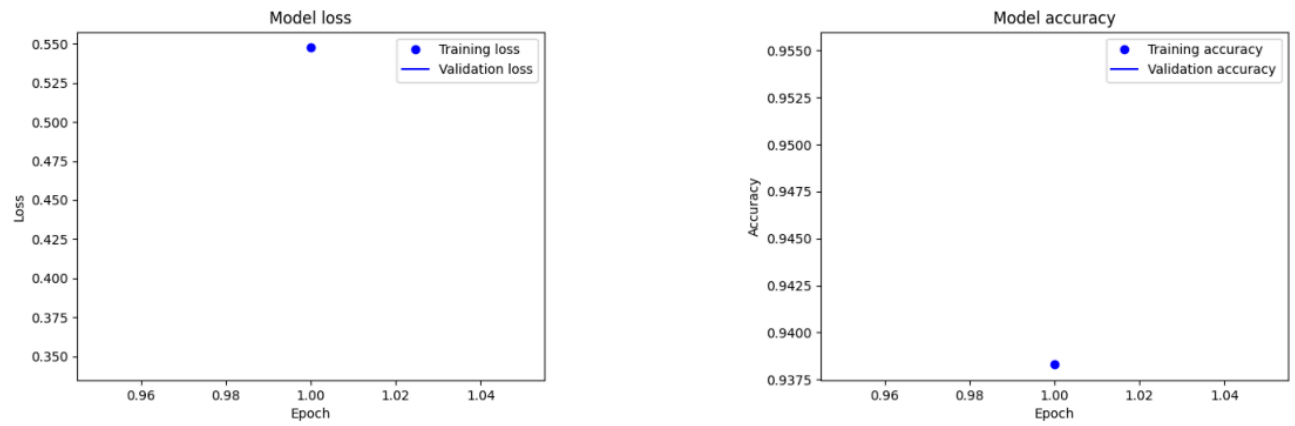
Confusion Matrix:

[[6368 300 7]

[167 6326 229]

[9 174 6420]]

Model loss and accuracy



Model loaded

OPTIMIZER: adam

2024-03-03 18:11:53.730862: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 10ms/step - loss: 0.1794 - accuracy: 0.9834

6/625 [.....] - ETA: 14s

2024-03-03 18:12:01.791543: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 11ms/step

Results: [0.17939729988574982, 0.9834499955177307]

Accuracy: 0.98345

F1 Score: 0.9835018962696649

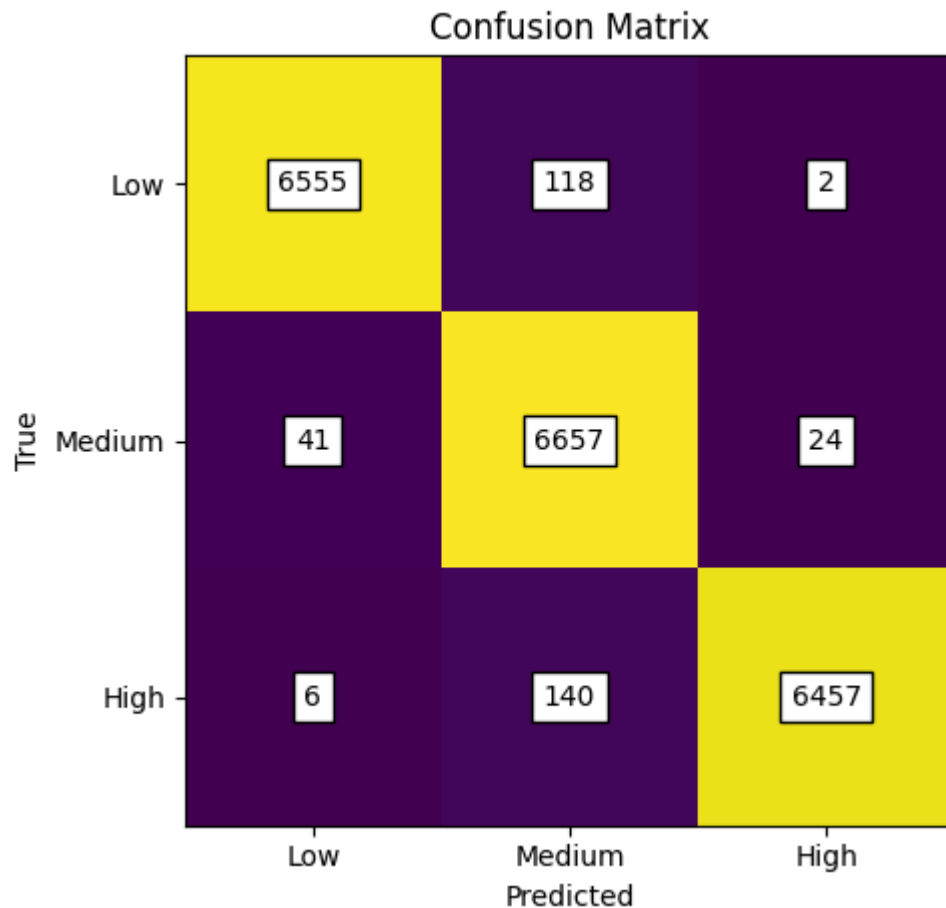
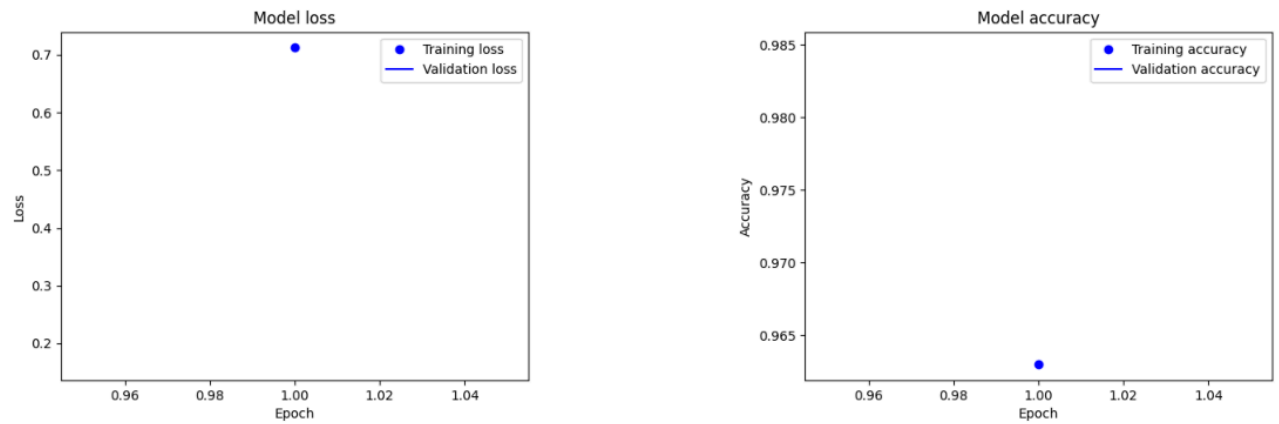
Precision: 0.9837599958999846

Recall: 0.98345

Confusion Matrix:

```
[[6555 118  2]
 [ 41 6657 24]
 [  6 140 6457]]
```

Model loss and accuracy



In []: opt_df

Out []:

	Optimizers	Accuracy	F1 Score	Precision	Recall
0	sgd	0.981	0.980985	0.980991	0.981
1	rmsprop	0.96755	0.96766	0.969525	0.96755
2	adagrad	0.9557	0.955748	0.95589	0.9557
3	adam	0.98345	0.983502	0.98376	0.98345

```
In [ ]: fig, axs = plt.subplots(2, 2, figsize=(15, 10))
fig.suptitle('Optimizers vs Metrics')

axs[0,0].bar(opt_df['Optimizers'], opt_df['Accuracy'], label='Accuracy')
axs[0,0].set_xlabel('Optimizers')
axs[0,0].set_ylabel('Accuracy')
axs[0,0].set_ylim(0.9, 1.0)
```

```

axs[0,1].bar(opt_df['Optimizers'], opt_df['F1 Score'], label='F1 Score')
axs[0,1].set_xlabel('Optimizers')
axs[0,1].set_ylabel('F1 Score')
axs[0,1].set_ylim(0.9, 1.0)

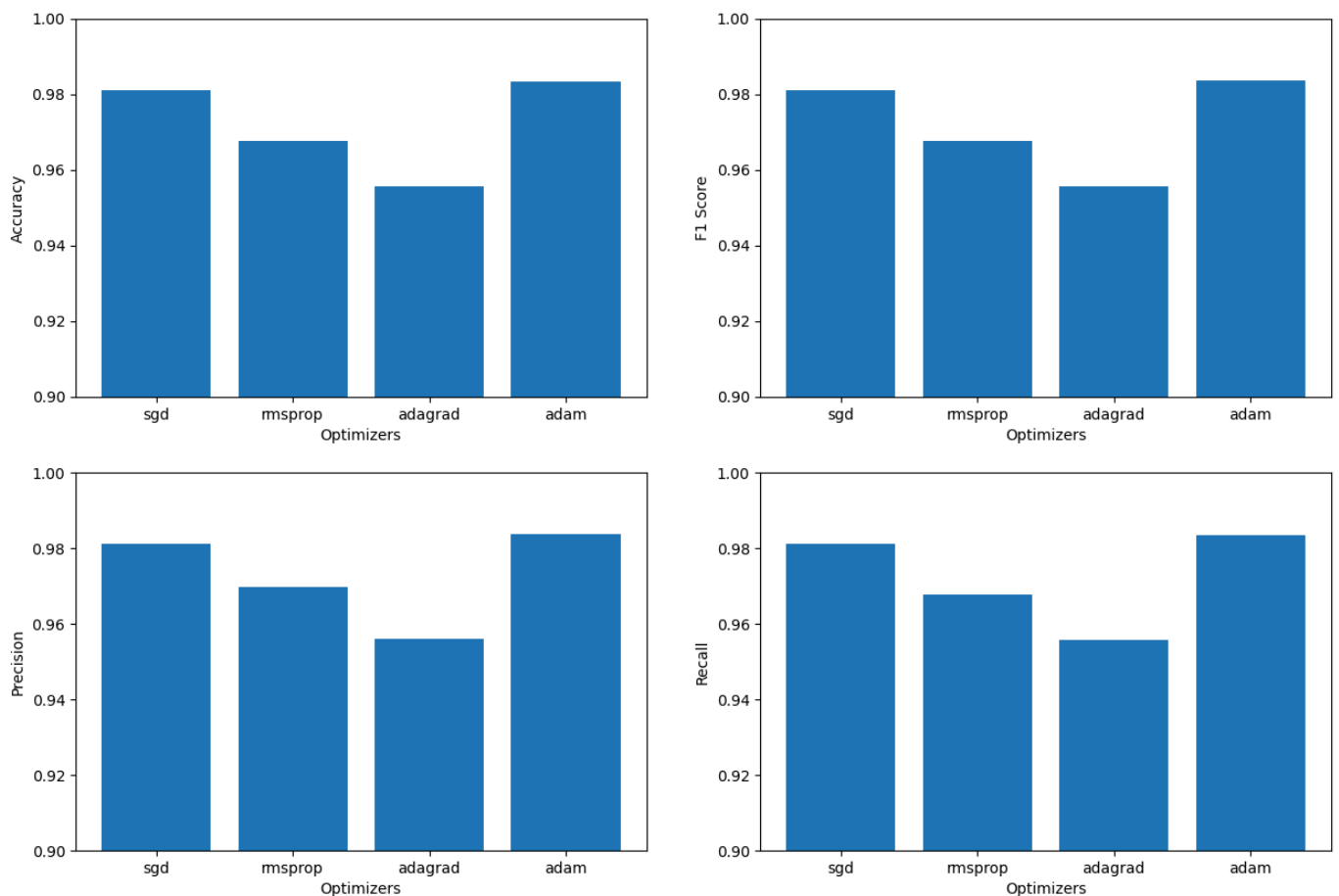
axs[1,0].bar(opt_df['Optimizers'], opt_df['Precision'], label='Precision')
axs[1,0].set_xlabel('Optimizers')
axs[1,0].set_ylabel('Precision')
axs[1,0].set_ylim(0.9, 1.0)

axs[1,1].bar(opt_df['Optimizers'], opt_df['Recall'], label='Recall')
axs[1,1].set_xlabel('Optimizers')
axs[1,1].set_ylabel('Recall')
axs[1,1].set_ylim(0.9, 1.0)

```

Out[]: (0.9, 1.0)

Optimizers vs Metrics



After testing all the optimiser both sgd and adam seem to be the best optimisers for the model. Although adam seems to be slightly better than sgd, I shall move on using adam.

Batch size

In []: *#tuning different batch sizes*

```

batch_df = pd.DataFrame(columns=['Batch Size', 'Accuracy', 'F1 Score', 'Precision', 'Recall'])
batch_sizes = [8, 16, 32, 64]

```

```

for batch_size in batch_sizes:

    #try load already built model
    try:
        model_name = 'modelV1_batch_'+ str(batch_size)
        model = keras.models.load_model('./models/'+model_name+'.h5')
        print('Model loaded')
        modelCreated = True
    except:
        modelCreated = False
        print('Model not found')

    print("Batch Size:", batch_size)

    if not modelCreated:
        inputs = keras.Input(shape=(160,128,1)) #resolution of images
        x = layers.Conv2D(16, 3, activation="relu")(inputs)
        x = layers.MaxPooling2D(pool_size=2)(x)
        x = layers.Flatten()(x)
        outputs = layers.Dense(3, activation="softmax")(x) #3 classes
        model = keras.Model(inputs=inputs, outputs=outputs)

        model.compile(optimizer=keras.optimizers.legacy.Adam(learning_rate=0.0001),
                        loss='sparse_categorical_crossentropy',
                        metrics=['accuracy'])
        model.fit(np.array(X_train), np.array(y_train), epochs=1, batch_size=batch_si

        model.save('./models/'+ model_name + '.h5')

    plot_loss_accuracy(modelCreated, model, model_name)
    results = evaluate_model(model, X_test, y_test, model_name)
    results['Batch Size'] = batch_size
    batch_df.loc[len(batch_df.index)] = results

```

Model loaded

Batch Size: 8

3/625 [.....] - ETA: 16s - loss: 0.9733 - accuracy: 0.9271

2024-03-03 18:12:10.640954: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 9s 14ms/step - loss: 0.4173 - accuracy: 0.9545

3/625 [.....] - ETA: 28s

2024-03-03 18:12:20.743437: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 11ms/step

Results: [0.4173380732536316, 0.9544500112533569]

Accuracy: 0.95445

F1 Score: 0.9546448033459637

Precision: 0.9587804952310373

Recall: 0.95445

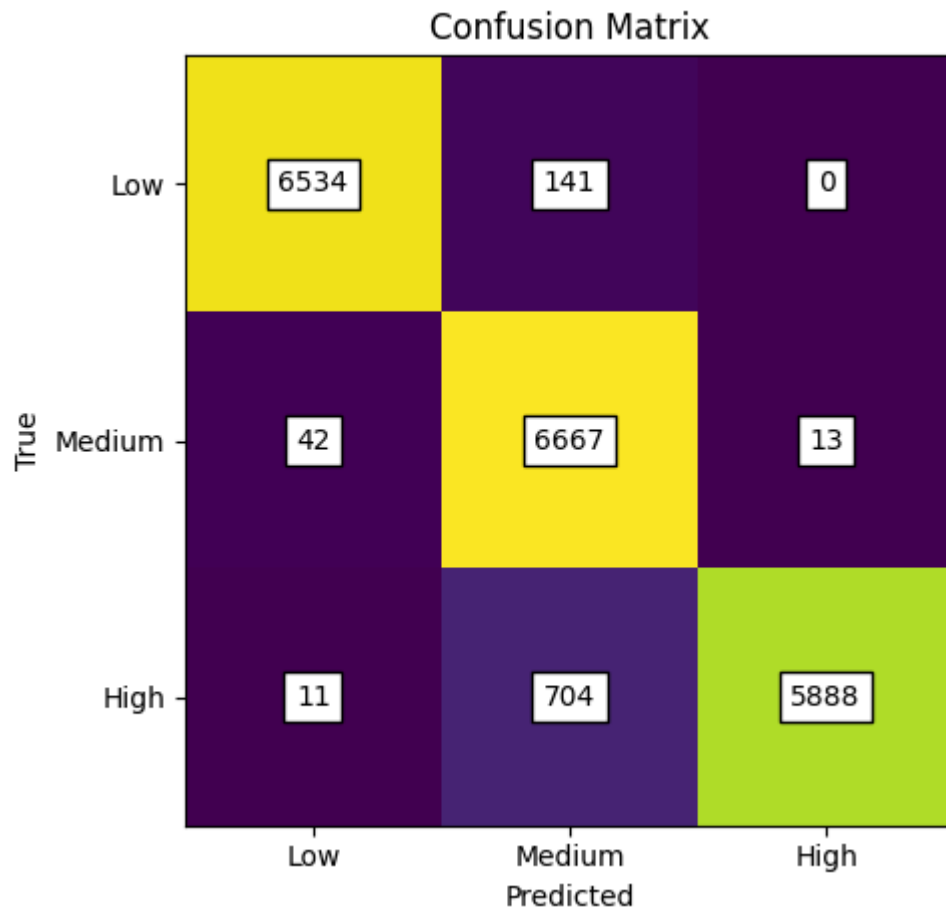
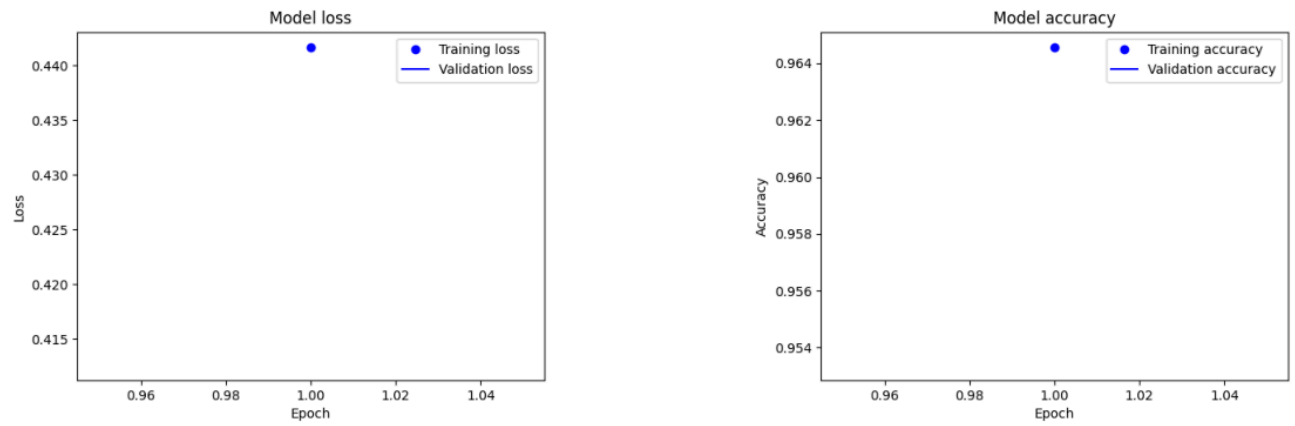
Confusion Matrix:

```
[[6534  141    0]
```

```
[  42 6667   13]
```

```
[  11  704 5888]]
```

Model loss and accuracy



Model loaded

Batch Size: 16

2024-03-03 18:12:30.311034: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 15s 23ms/step - loss: 0.2471 - accuracy: 0.9730

6/625 [.....] - ETA: 7s

2024-03-03 18:12:46.746385: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 8s 13ms/step

Results: [0.24707791209220886, 0.9730499982833862]

Accuracy: 0.97305

F1 Score: 0.9731786857494813

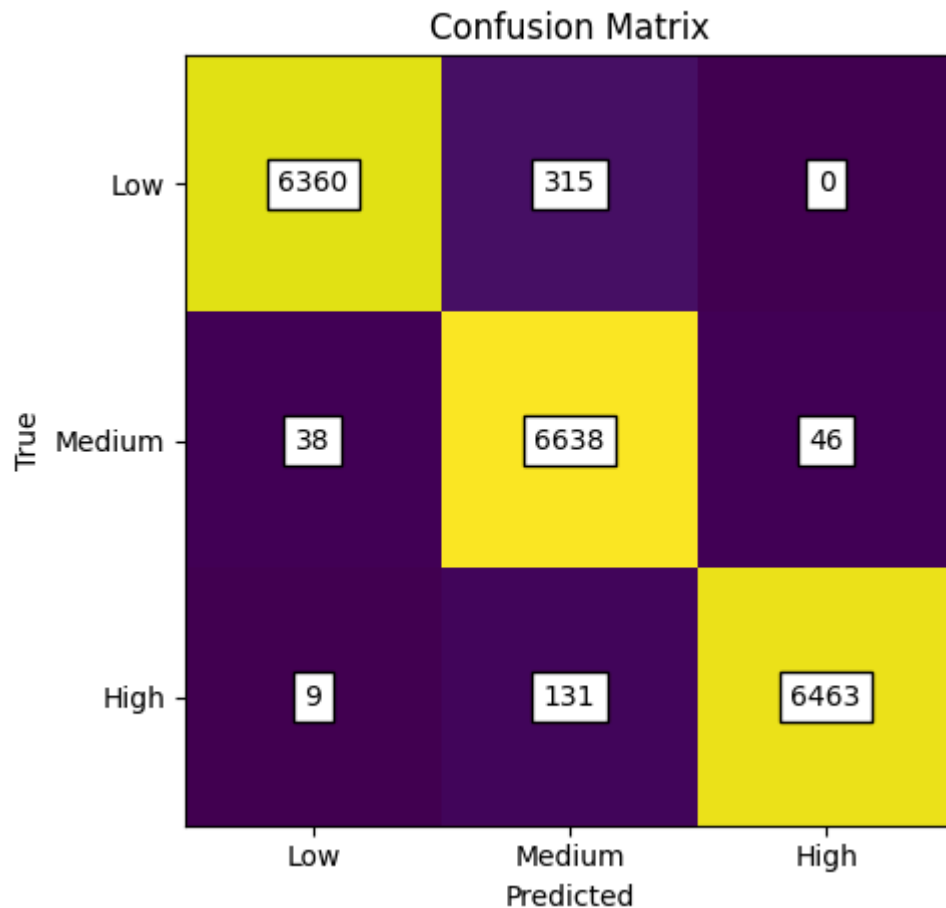
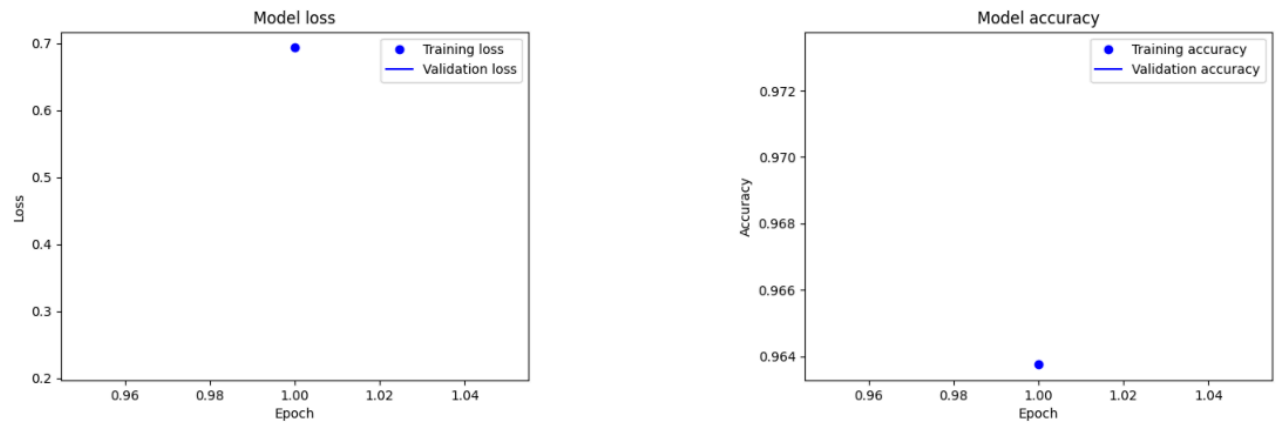
Precision: 0.9740580396408756

Recall: 0.97305

Confusion Matrix:

```
[[6360 315  0]
 [ 38 6638 46]
 [  9 131 6463]]
```


Model loss and accuracy



Model loaded
Batch Size: 32

2024-03-03 18:12:56.609466: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
625/625 [=====] - 10s 15ms/step - loss: 0.1468 - accuracy: 0.9853

15/625 [.....] - ETA: 4s

2024-03-03 18:13:06.890360: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 5s 9ms/step

Results: [0.14678354561328888, 0.9853000044822693]

Accuracy: 0.9853

F1 Score: 0.985323196396591

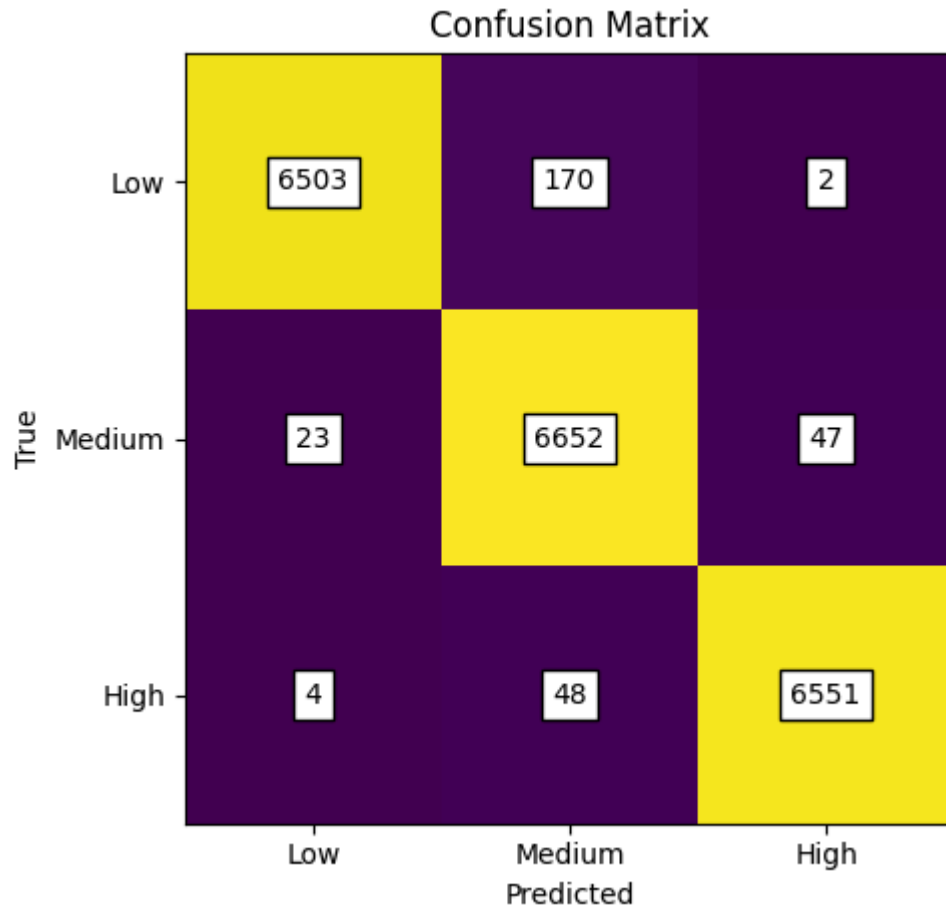
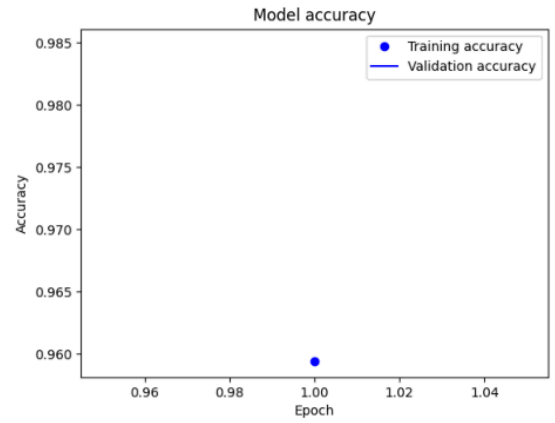
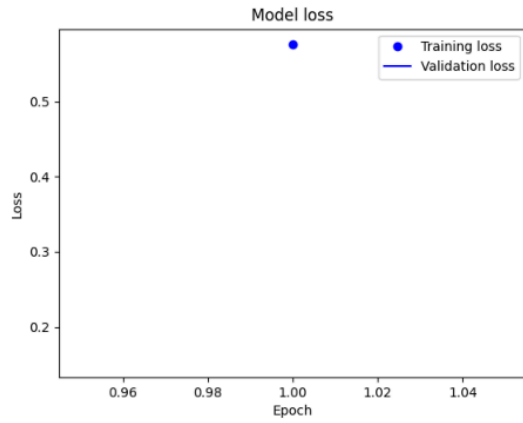
Precision: 0.9855037273840304

Recall: 0.9853

Confusion Matrix:

```
[[6503 170  2]
 [ 23 6652 47]
 [  4  48 6551]]
```

Model loss and accuracy



Model loaded
Batch Size: 64

2024-03-03 18:13:14.785529: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
625/625 [=====] - 7s 10ms/step - loss: 0.4720 - accuracy: 0.9643

21/625 [>.....] - ETA: 4s

2024-03-03 18:13:23.458896: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
625/625 [=====] - 5s 7ms/step

Results: [0.47198939323425293, 0.9643499851226807]

Accuracy: 0.96435

F1 Score: 0.9646704601681986

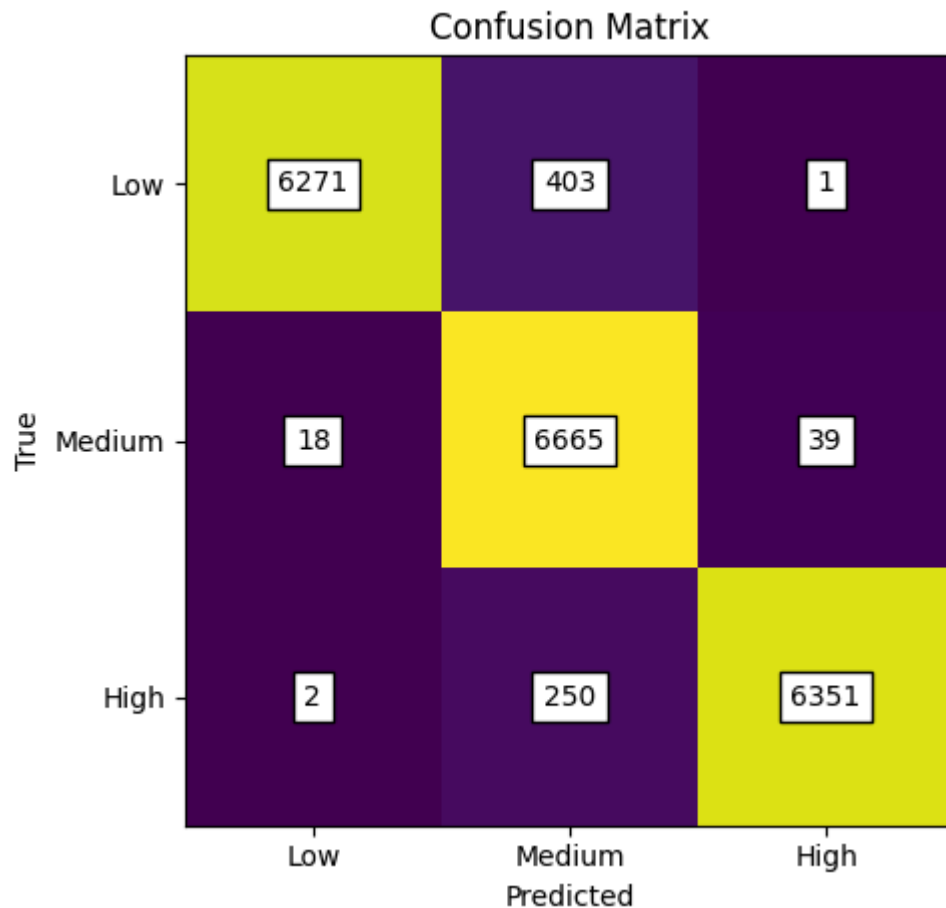
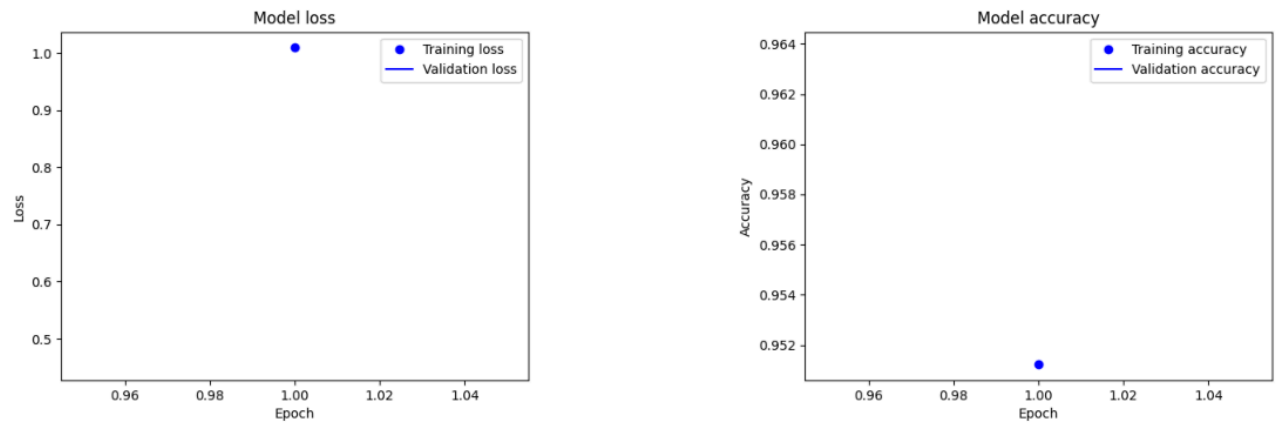
Precision: 0.9668817316365499

Recall: 0.96435

Confusion Matrix:

```
[[6271 403 1]
 [ 18 6665 39]
 [ 2 250 6351]]
```

Model loss and accuracy



```
In [ ]: fig, axs = plt.subplots(2, 2, figsize=(15, 10))
fig.suptitle('Batch Size vs Metrics')

axs[0,0].plot(batch_df['Batch Size'], batch_df['Accuracy'], label='Accuracy', marker='o')
axs[0,0].set_xlabel('Batch Size')
axs[0,0].set_ylabel('Accuracy')
axs[0,0].set_ylim(0.9, 1.0)

axs[0,1].plot(batch_df['Batch Size'], batch_df['F1 Score'], label='F1 Score', marker='o')
axs[0,1].set_xlabel('Batch Size')
axs[0,1].set_ylabel('F1 Score')
axs[0,1].set_ylim(0.9, 1.0)

axs[1,0].plot(batch_df['Batch Size'], batch_df['Precision'], label='Precision', marker='o')
axs[1,0].set_xlabel('Batch Size')
axs[1,0].set_ylabel('Precision')
axs[1,0].set_ylim(0.9, 1.0)

axs[1,1].plot(batch_df['Batch Size'], batch_df['Recall'], label='Recall', marker='o')
```

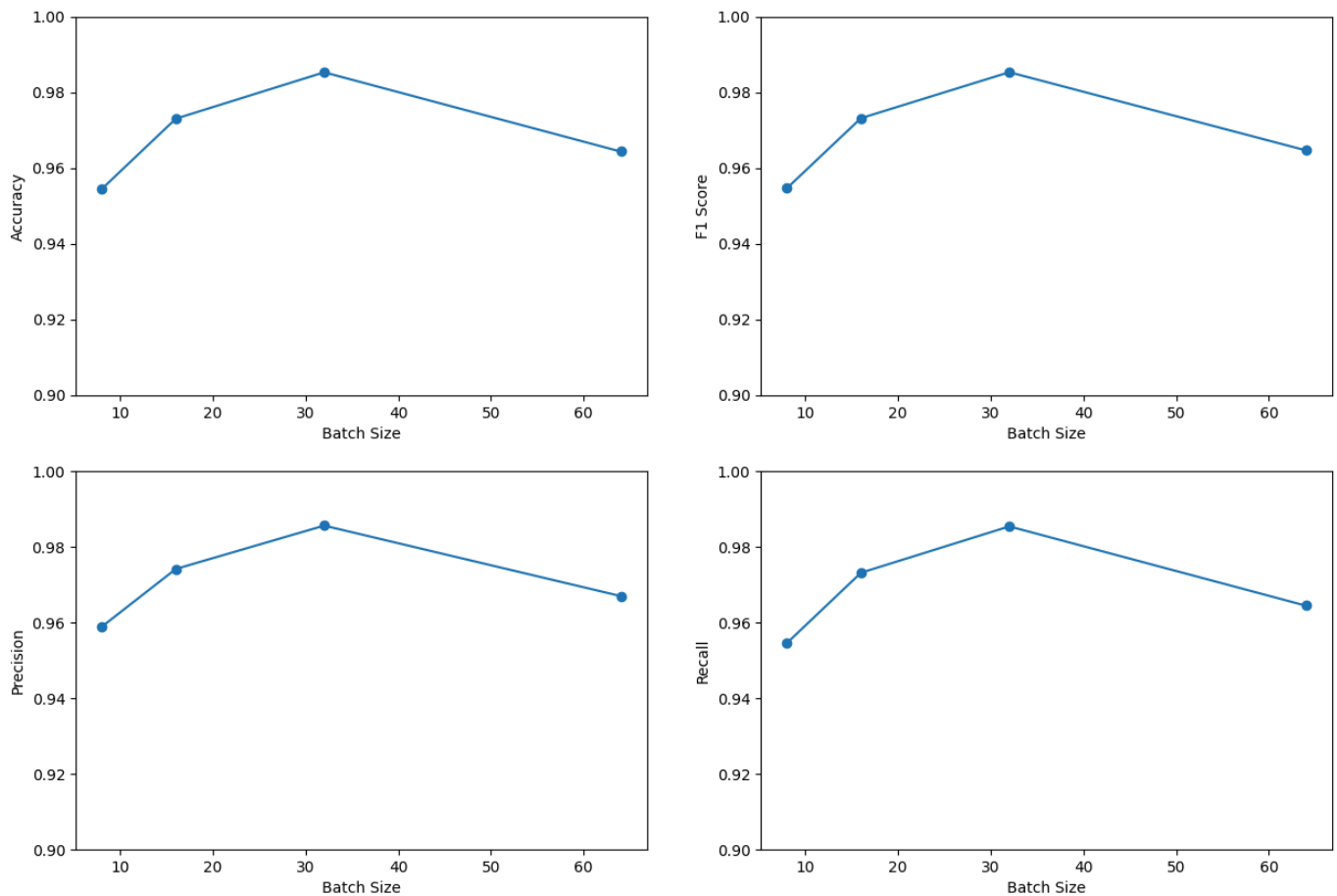
```

axs[1,1].set_xlabel('Batch Size')
axs[1,1].set_ylabel('Recall')
axs[1,1].set_ylim(0.9, 1.0)

```

Out[]: (0.9, 1.0)

Batch Size vs Metrics



These results show a lovely graph showing that the optimal batch size for this model and the data is 32 and anything above or below this value will result in a decrease in the model's performance.

Epochs

```

In [ ]: epoch_df = pd.DataFrame(columns=['Epochs', 'Accuracy', 'F1 Score', 'Precision', 'Recall'])
epochs = [1, 5, 10, 20]

for epoch in epochs:

    #try load already built model
    try:
        model_name = 'modelV1_epoch_'+ str(epoch)
        model = keras.models.load_model('./models/'+model_name+'.h5')
        print('Model loaded')
        modelCreated = True
    except:
        modelCreated = False
        print('Model not found')

    print("Epochs:", epoch)

    if not modelCreated:
        inputs = keras.Input(shape=(160,128,1)) #resolution of images
        x = layers.Conv2D(16, 3, activation="relu")(inputs)

```

```

x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Flatten()(x)
outputs = layers.Dense(3, activation="softmax")(x) #3 classes
model = keras.Model(inputs=inputs, outputs=outputs)

model.compile(optimizer=keras.optimizers.legacy.Adam(learning_rate=0.0001),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
model.fit(np.array(X_train), np.array(y_train), epochs=epoch, batch_size=32,

model.save('./models/'+ model_name + '.h5')

plot_loss_accuracy(modelCreated, model, model_name)
results = evaluate_model(model, X_test, y_test, model_name)
results['Epochs'] = epoch
epoch_df.loc[len(epoch_df.index)] = results

```

Model loaded

Epochs: 1

6/625 [.....] - ETA: 6s - loss: 0.3647 - accuracy: 0.9844

2024-03-03 18:13:30.886547: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 11ms/step - loss: 0.2899 - accuracy: 0.9791

23/625 [>.....] - ETA: 4s

2024-03-03 18:13:39.790837: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 5s 7ms/step

Results: [0.2898976802825928, 0.9790999889373779]

Accuracy: 0.9791

F1 Score: 0.9791914141384966

Precision: 0.979720156505092

Recall: 0.9791

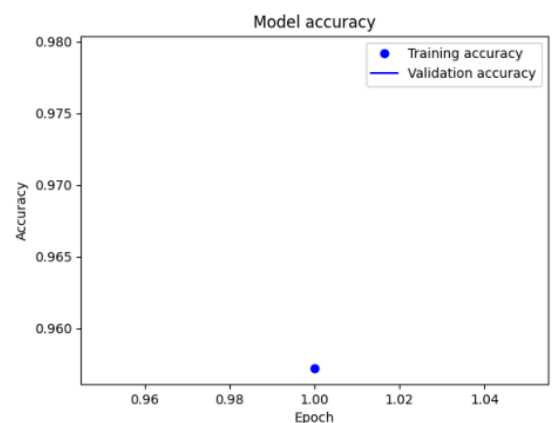
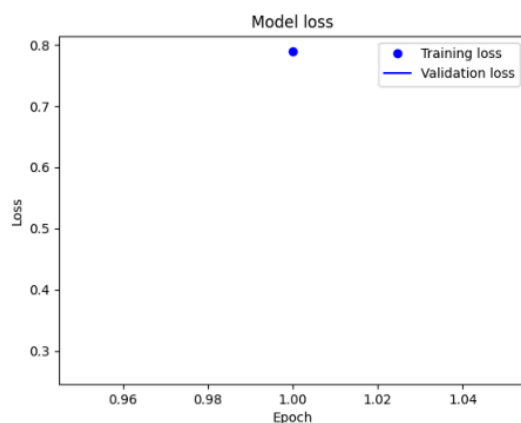
Confusion Matrix:

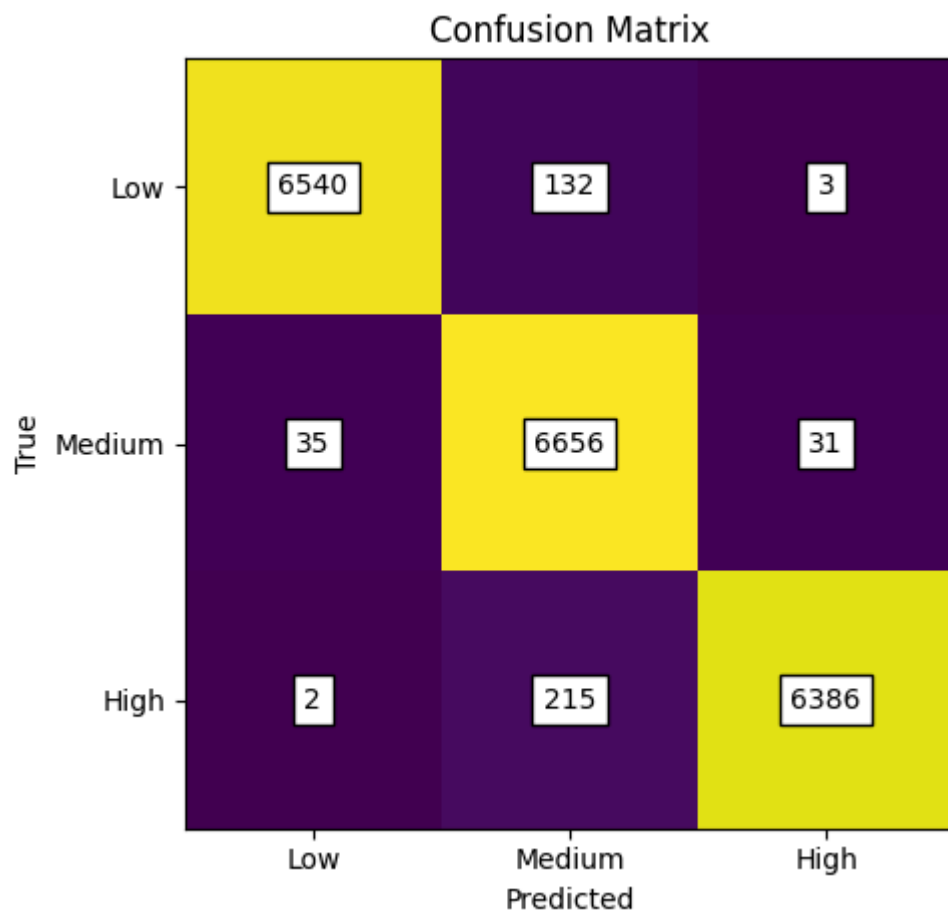
```

[[6540  132   3]
 [  35 6656  31]
 [   2  215 6386]]

```

Model loss and accuracy





Model loaded

Epochs: 5

6/625 [.....] - ETA: 7s - loss: 0.3617 - accuracy: 0.9740

2024-03-03 18:13:46.140667: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 11ms/step - loss: 0.1070 - accuracy: 0.9917

9/625 [.....] - ETA: 10s

2024-03-03 18:13:54.265499: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 6s 10ms/step

Results: [0.10703562200069427, 0.9916999936103821]

Accuracy: 0.9917

F1 Score: 0.991695817317054

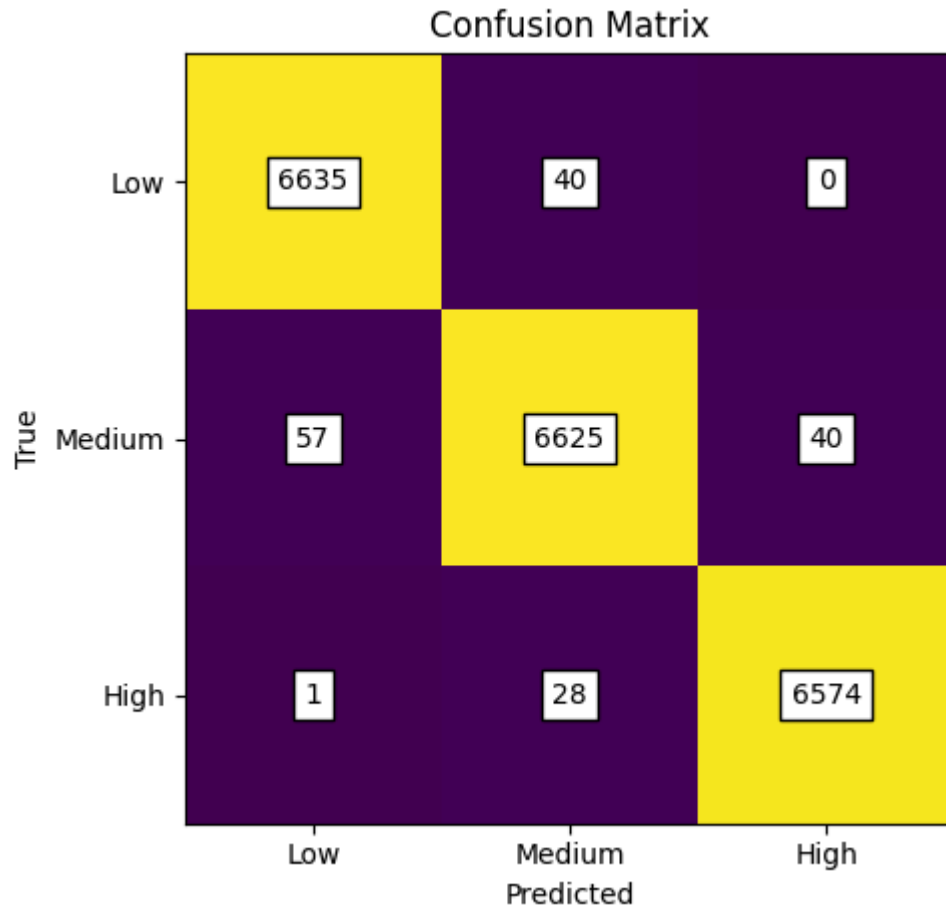
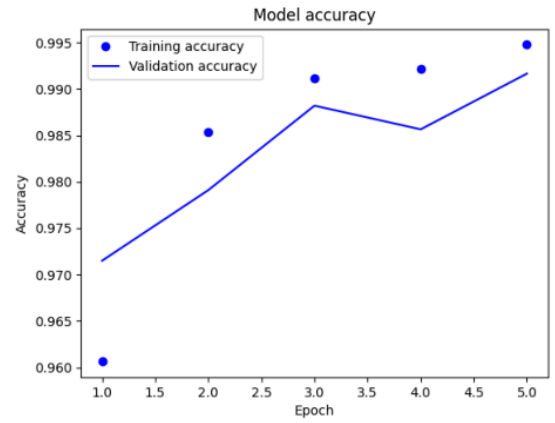
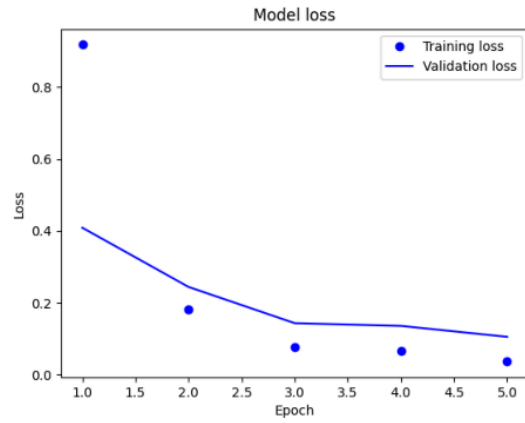
Precision: 0.9916963936614269

Recall: 0.9917

Confusion Matrix:

```
[[6635  40   0]
 [ 57 6625  40]
 [  1  28 6574]]
```

Model loss and accuracy



Model loaded

Epochs: 10

4/625 [.....] - ETA: 10s - loss: 0.7481 - accuracy: 0.9688

2024-03-03 18:14:01.915800: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

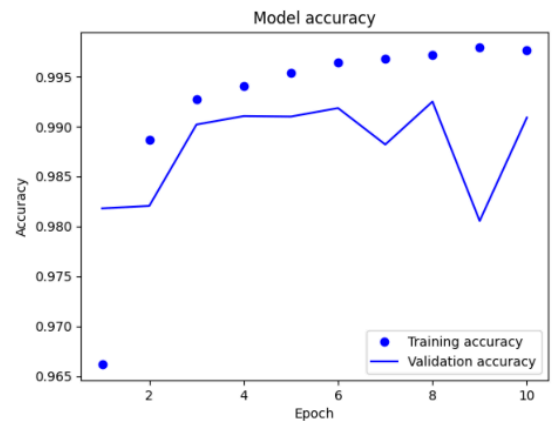
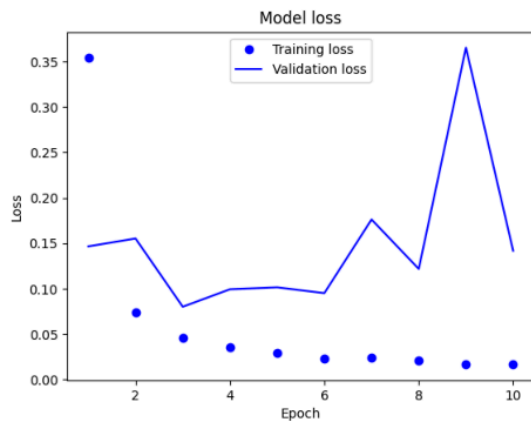
625/625 [=====] - 9s 14ms/step - loss: 0.1525 - accuracy: 0.9893

1/625 [.....] - ETA: 2:38

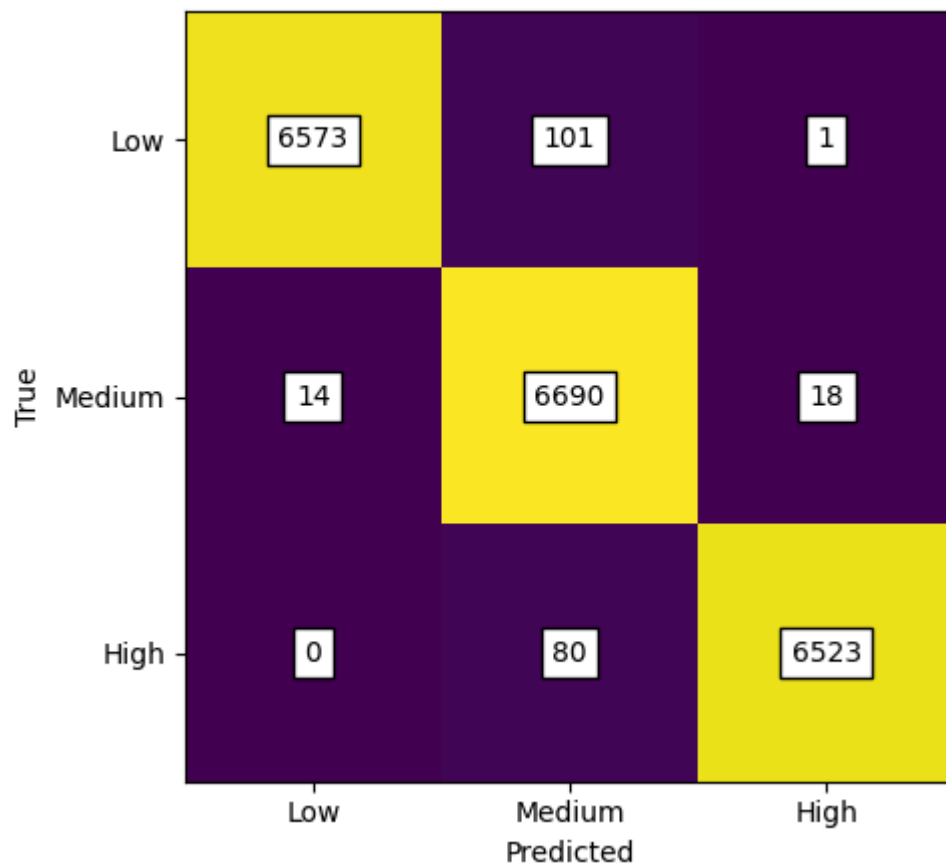
2024-03-03 18:14:12.144460: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 8s 12ms/step
 Results: [0.15249274671077728, 0.989300012588501]
 Accuracy: 0.9893
 F1 Score: 0.989327641811542
 Precision: 0.9894780424642031
 Recall: 0.9893
 Confusion Matrix:
 [[6573 101 1]
 [14 6690 18]
 [0 80 6523]]

Model loss and accuracy



Confusion Matrix



Model loaded
 Epochs: 20

2024-03-03 18:14:21.969614: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
 625/625 [=====] - 10s 15ms/step - loss: 0.1365 - accuracy: 0.9914
 4/625 [.....] - ETA: 11s
 2024-03-03 18:14:32.462518: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 7s 11ms/step

Results: [0.13652931153774261, 0.9914000034332275]

Accuracy: 0.9914

F1 Score: 0.991394451725914

Precision: 0.9913957017914836

Recall: 0.9914

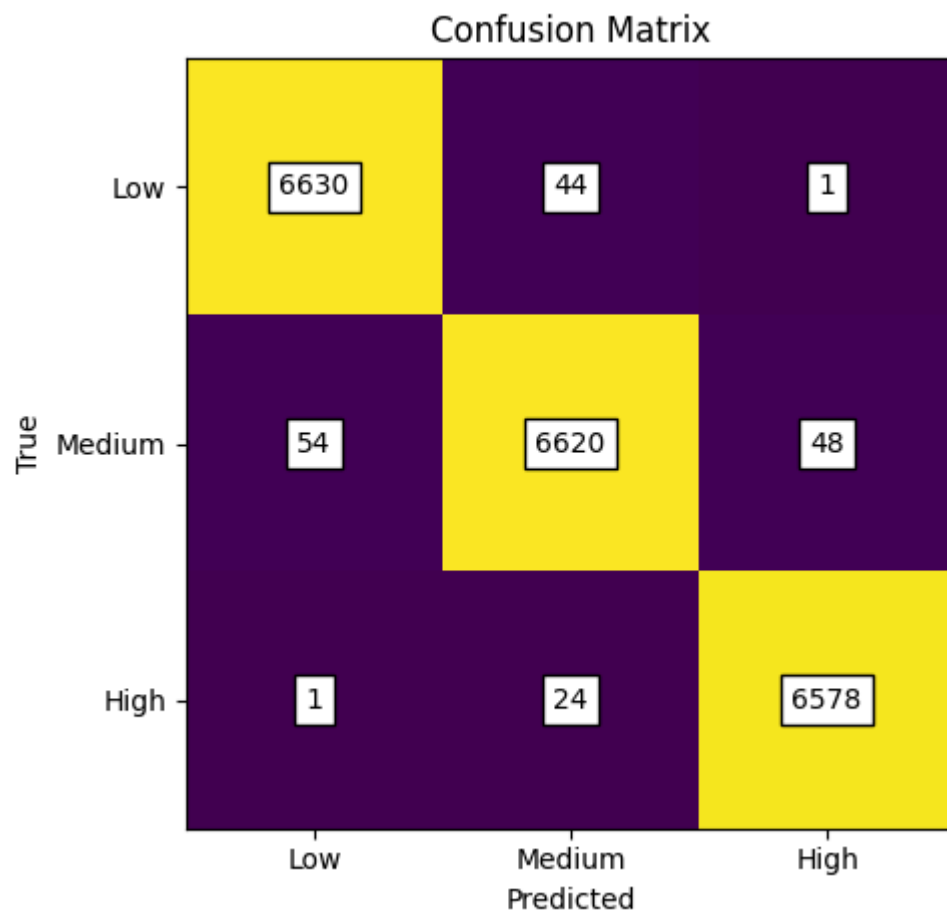
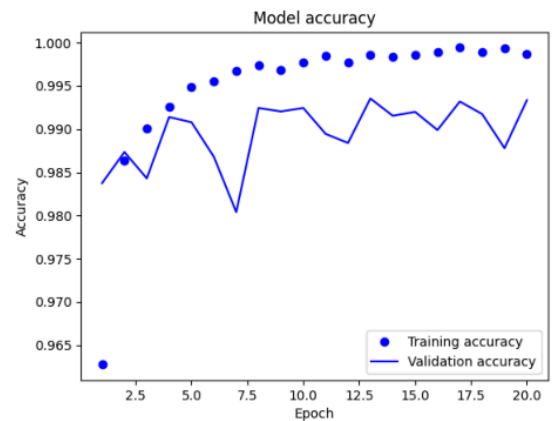
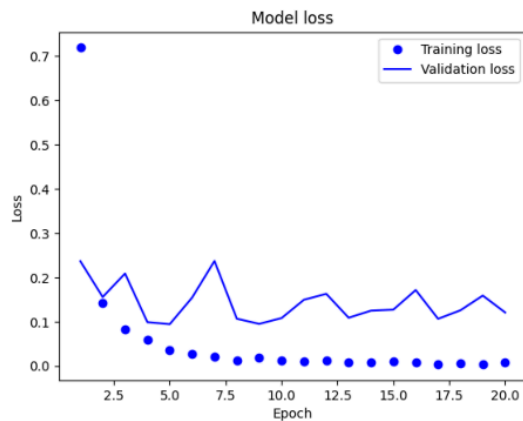
Confusion Matrix:

```
[[6630  44   1]
```

```
 [ 54 6620  48]
```

```
 [  1  24 6578]]
```

Model loss and accuracy



```
In [ ]: #plot line graphs for epochs vs acc, f1, prec, recall
fig, axs = plt.subplots(2, 2, figsize=(15, 10))
fig.suptitle('Epochs vs Metrics')

axs[0,0].plot(epoch_df['Epochs'], epoch_df['Accuracy'], label='Accuracy', marker='o')
axs[0,0].set_xlabel('Epochs')
axs[0,0].set_ylabel('Accuracy')
axs[0,0].set_ylim(0.95, 1.0)
```

```

axs[0,1].plot(epoch_df['Epochs'], epoch_df['F1 Score'], label='F1 Score', marker='o')
axs[0,1].set_xlabel('Epochs')
axs[0,1].set_ylabel('F1 Score')
axs[0,1].set_ylim(0.95, 1.0)

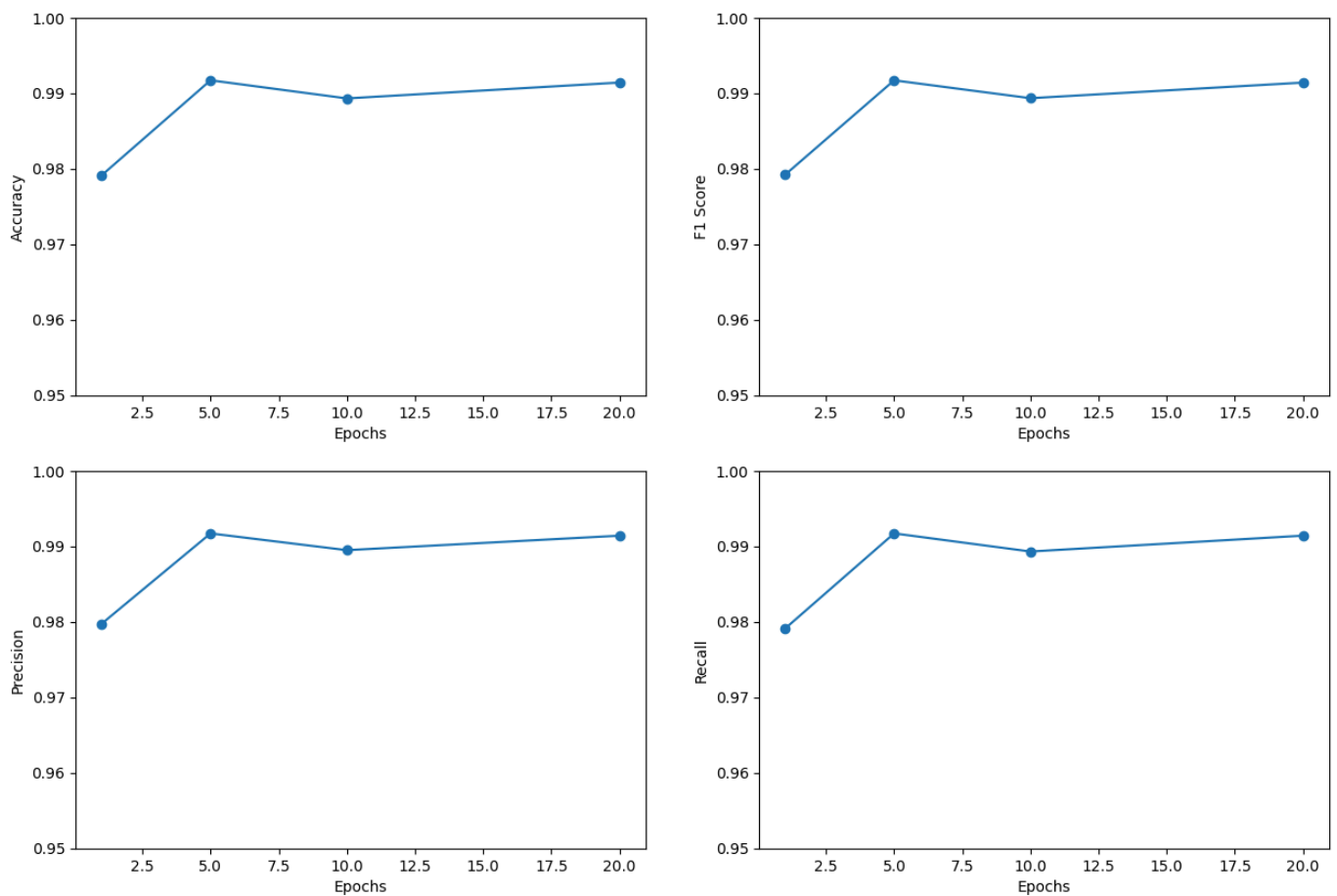
axs[1,0].plot(epoch_df['Epochs'], epoch_df['Precision'], label='Precision', marker='o')
axs[1,0].set_xlabel('Epochs')
axs[1,0].set_ylabel('Precision')
axs[1,0].set_ylim(0.95, 1.0)

axs[1,1].plot(epoch_df['Epochs'], epoch_df['Recall'], label='Recall', marker='o')
axs[1,1].set_xlabel('Epochs')
axs[1,1].set_ylabel('Recall')
axs[1,1].set_ylim(0.95, 1.0)

```

Out[]: (0.95, 1.0)

Epochs vs Metrics



These results are not as clear as the previous ones, since from 5 epochs and above the model's performance is very similar. However, upon looking at the training history of the model, it seems that the model is overfitting after 5 epochs, since after 5 epochs the validation accuracy begins plateauing and not improving. Therefore, I shall move on using 5 epochs to avoid overfitting.

Layers

```

In [ ]: #tuning for best amount of layers
layers_df = pd.DataFrame(columns=['Layer Config', 'Accuracy', 'F1 Score', 'Precision']
layers_to_test = [
    {'conv_layers': 1, 'dense_layers': 1},
    {'conv_layers': 2, 'dense_layers': 1},
    {'conv_layers': 1, 'dense_layers': 2},

```

```

    {'conv_layers': 2, 'dense_layers': 2},
]

for layer_config in layers_to_test:
    num_conv_layers = layer_config['conv_layers']
    num_dense_layers = layer_config['dense_layers']

    layer_config_name = str(num_conv_layers) + ' Conv Layers, ' + str(num_dense_layers)
    #try load already built model
    try:
        model_name = 'modelV1_'+str(num_conv_layers)+'conv_'+ str(num_dense_layers)+''
        model = keras.models.load_model('./models/'+model_name+'.h5')
        print('Model loaded')
        modelCreated = True
    except:
        modelCreated = False
        print('Model not found')

    print("Layer Config:", layer_config_name)

    if not modelCreated:
        #same model as modelV1, but with different learning rates
        inputs = keras.Input(shape=(160,128,1)) #resolution of images
        x = inputs

        #add the convolutional layers
        for _ in range(num_conv_layers):
            x = layers.Conv2D(16, 3, activation="relu")(x)
            x = layers.MaxPooling2D(pool_size=2)(x)

        x = layers.Flatten()(x)

        #add the dense layers
        for _ in range(num_dense_layers - 1): #subtract 1 since we already have a de
            x = layers.Dense(32, activation="relu")(x)

        outputs = layers.Dense(3, activation="softmax")(x) #3 classes
        model = keras.Model(inputs=inputs, outputs=outputs)

        model.compile(optimizer=keras.optimizers.legacy.Adam(learning_rate=0.0001),
                      loss='sparse_categorical_crossentropy',
                      metrics=['accuracy'])
        model.fit(np.array(X_train), np.array(y_train), epochs=5, batch_size=32, vali

        model.save('./models/'+ model_name + '.h5')

    plot_loss_accuracy(modelCreated, model, model_name)
    results = evaluate_model(model, X_test, y_test, model_name)
    layer_config_name = str(num_conv_layers) + 'CL ' + str(num_dense_layers) + 'DL'
    results['Layer Config'] = layer_config_name
    layers_df.loc[len(layers_df.index)] = results

```

Model loaded

Layer Config: 1 Conv Layers, 1 Dense Layers

4/625 [.....] - ETA: 11s - loss: 0.2836 - accuracy: 0.9844

2024-03-03 18:14:41.543000: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

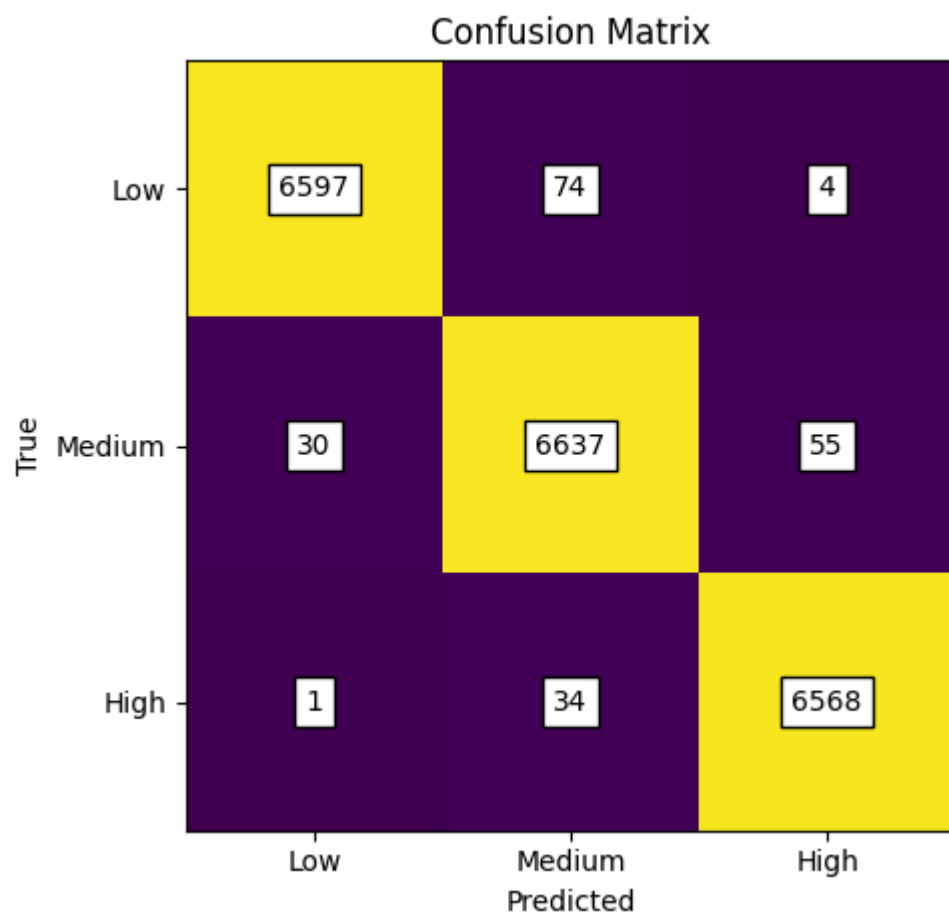
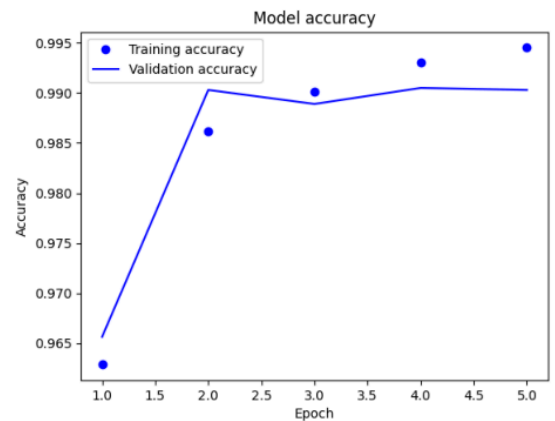
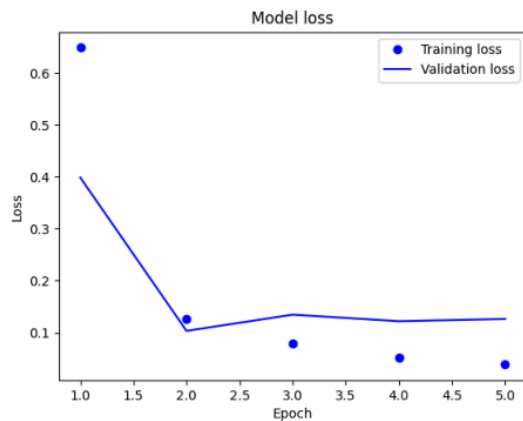
625/625 [=====] - 9s 14ms/step - loss: 0.1337 - accuracy: 0.9901

1/625 [.....] - ETA: 2:33

2024-03-03 18:14:51.817286: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] – 7s 11ms/step
 Results: [0.13368579745292664, 0.9901000261306763]
 Accuracy: 0.9901
 F1 Score: 0.990102876024772
 Precision: 0.9901181059577124
 Recall: 0.9901
 Confusion Matrix:
 [[6597 74 4]
 [30 6637 55]
 [1 34 6568]]

Model loss and accuracy

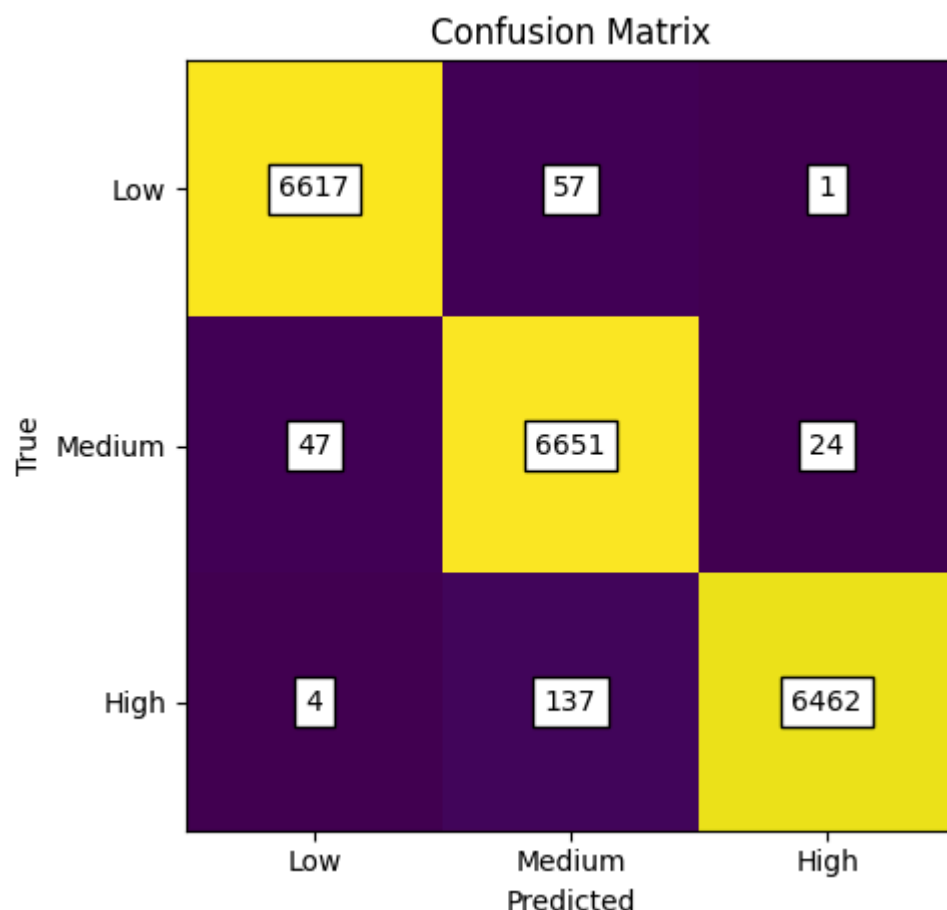
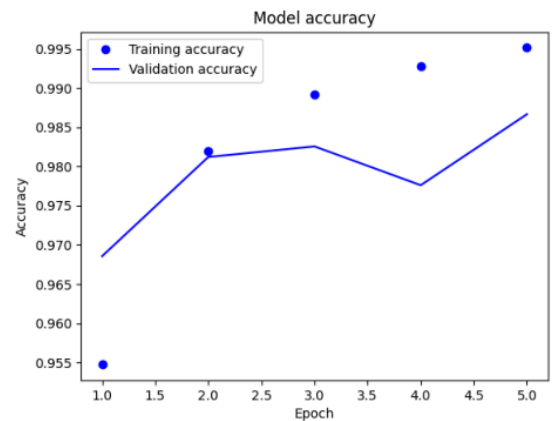
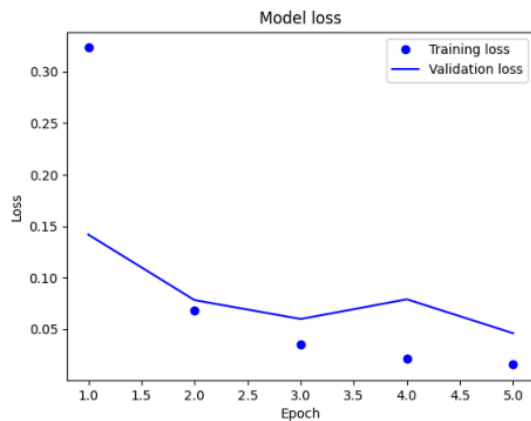


Model loaded
 Layer Config: 2 Conv Layers, 1 Dense Layers

2024-03-03 18:15:00.716793: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
 625/625 [=====] – 11s 16ms/step – loss: 0.0454 – accuracy: 0.9865
 6/625 [.....] – ETA: 16s
 2024-03-03 18:15:12.337887: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] – 9s 14ms/step
 Results: [0.04540864750742912, 0.9865000247955322]
 Accuracy: 0.9865
 F1 Score: 0.9865218572670048
 Precision: 0.9866492730488097
 Recall: 0.9865
 Confusion Matrix:
 [[6617 57 1]
 [47 6651 24]
 [4 137 6462]]

Model loss and accuracy

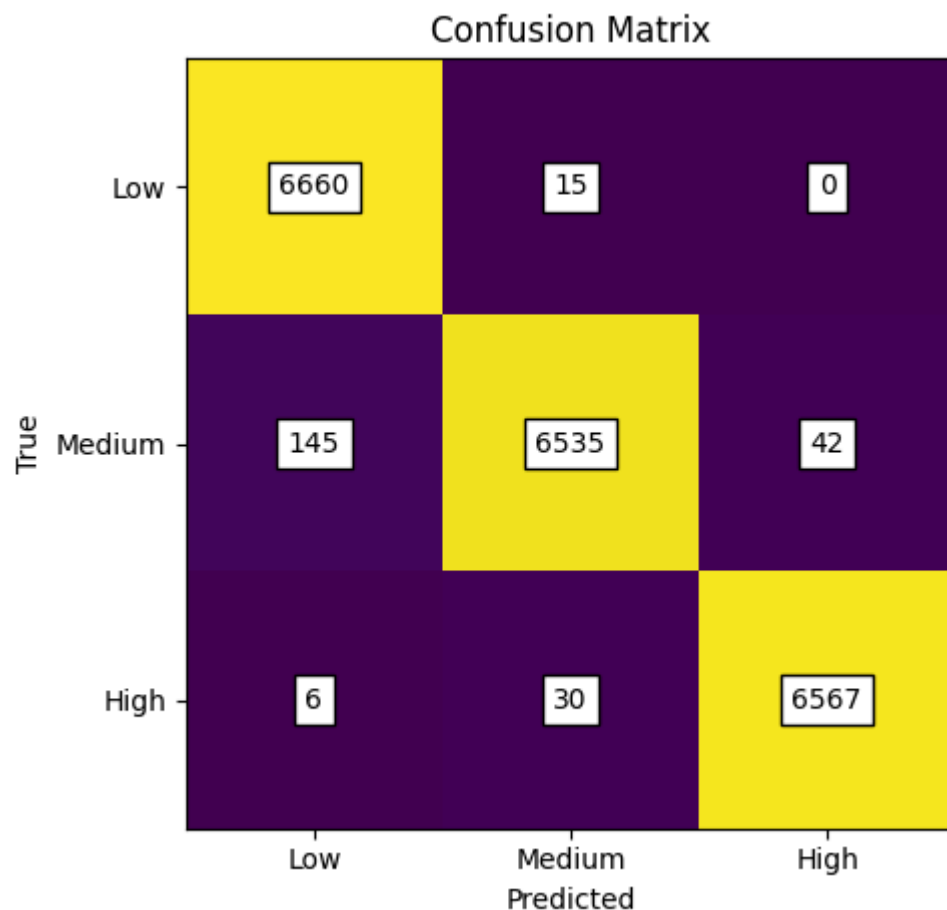
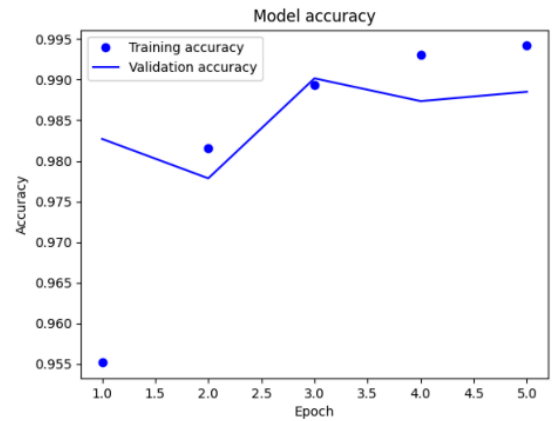
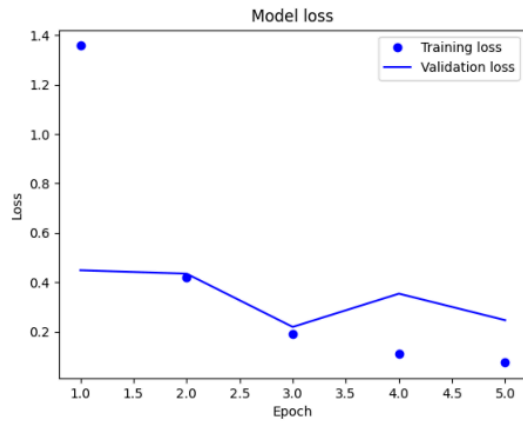


Model loaded
 Layer Config: 1 Conv Layers, 2 Dense Layers

2024-03-03 18:15:22.896378: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
 625/625 [=====] – 11s 17ms/step – loss: 0.2577 – accuracy: 0.9881
 5/625 [.....] – ETA: 21s
 2024-03-03 18:15:35.152461: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] – 9s 15ms/step
 Results: [0.2576688230037689, 0.988099992275238]
 Accuracy: 0.9881
 F1 Score: 0.9880808208654004
 Precision: 0.9882041063899354
 Recall: 0.9881
 Confusion Matrix:
 [[6660 15 0]
 [145 6535 42]
 [6 30 6567]]

Model loss and accuracy



Model loaded

Layer Config: 2 Conv Layers, 2 Dense Layers

5/625 [.....] – ETA: 8s – loss: 0.1588 – accuracy: 0.9750

2024-03-03 18:15:47.081388: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] – 8s 13ms/step – loss: 0.1443 – accuracy: 0.9880

6/625 [.....] – ETA: 15s

```
2024-03-03 18:15:56.653524: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
```

```
625/625 [=====] - 6s 10ms/step
```

```
Results: [0.1443140059709549, 0.9879500269889832]
```

```
Accuracy: 0.98795
```

```
F1 Score: 0.9879628216502099
```

```
Precision: 0.9880058514204385
```

```
Recall: 0.98795
```

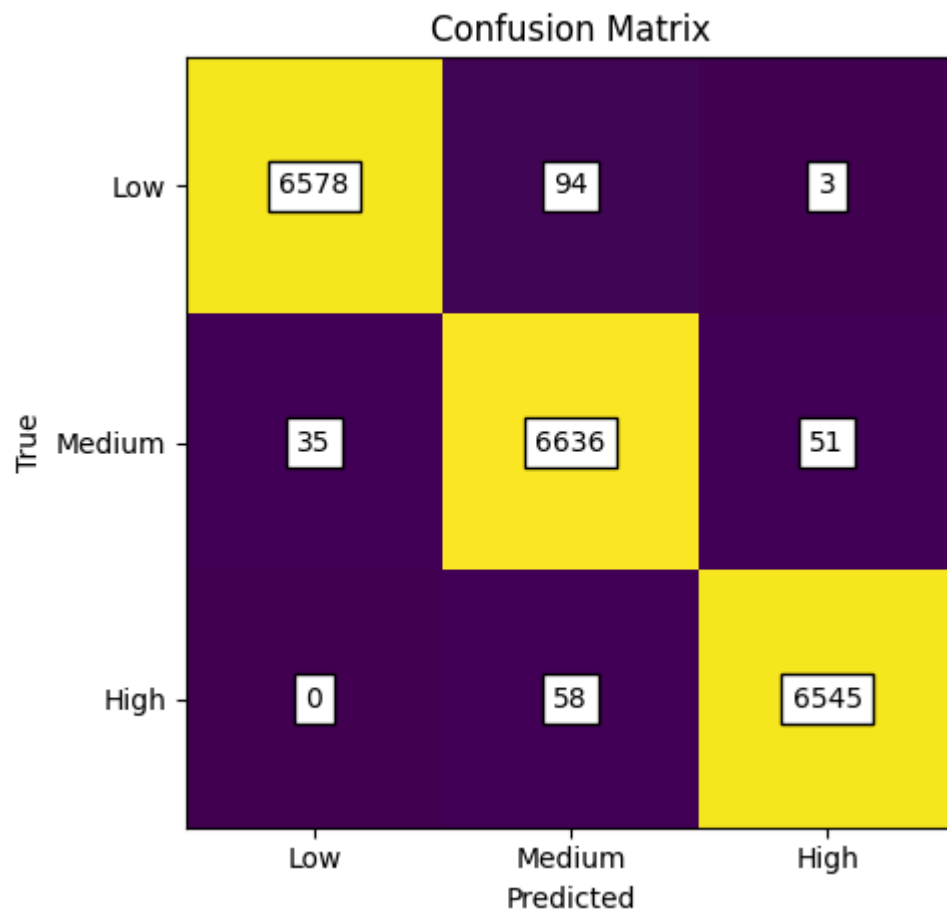
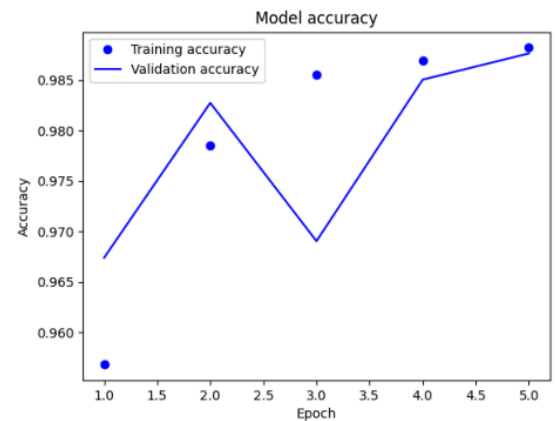
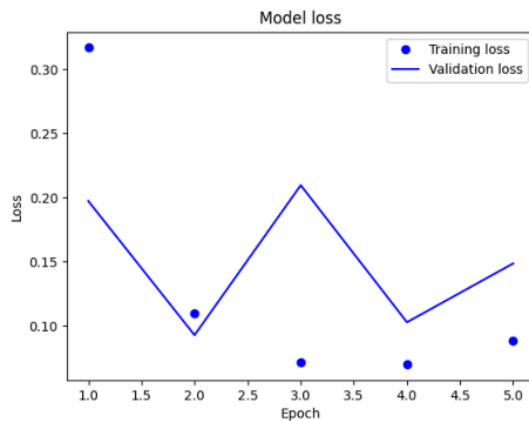
```
Confusion Matrix:
```

```
[[6578  94   3]
```

```
 [ 35 6636  51]
```

```
 [  0  58 6545]]
```

Model loss and accuracy



```
In [ ]: #plot bar graphs for layer config vs acc, f1, prec, recall
fig, axs = plt.subplots(2, 2, figsize=(15, 10))
fig.suptitle('Layer Config vs Metrics')

axs[0,0].bar(layers_df['Layer Config'], layers_df['Accuracy'], label='Accuracy')
axs[0,0].set_xlabel('Layer Config')
```

```

axs[0,0].set_ylabel('Accuracy')
axs[0,0].set_ylim(0.98, 1.0)

axs[0,1].bar(layers_df['Layer Config'], layers_df['F1 Score'], label='F1 Score')
axs[0,1].set_xlabel('Layer Config')
axs[0,1].set_ylabel('F1 Score')
axs[0,1].set_ylim(0.98, 1.0)

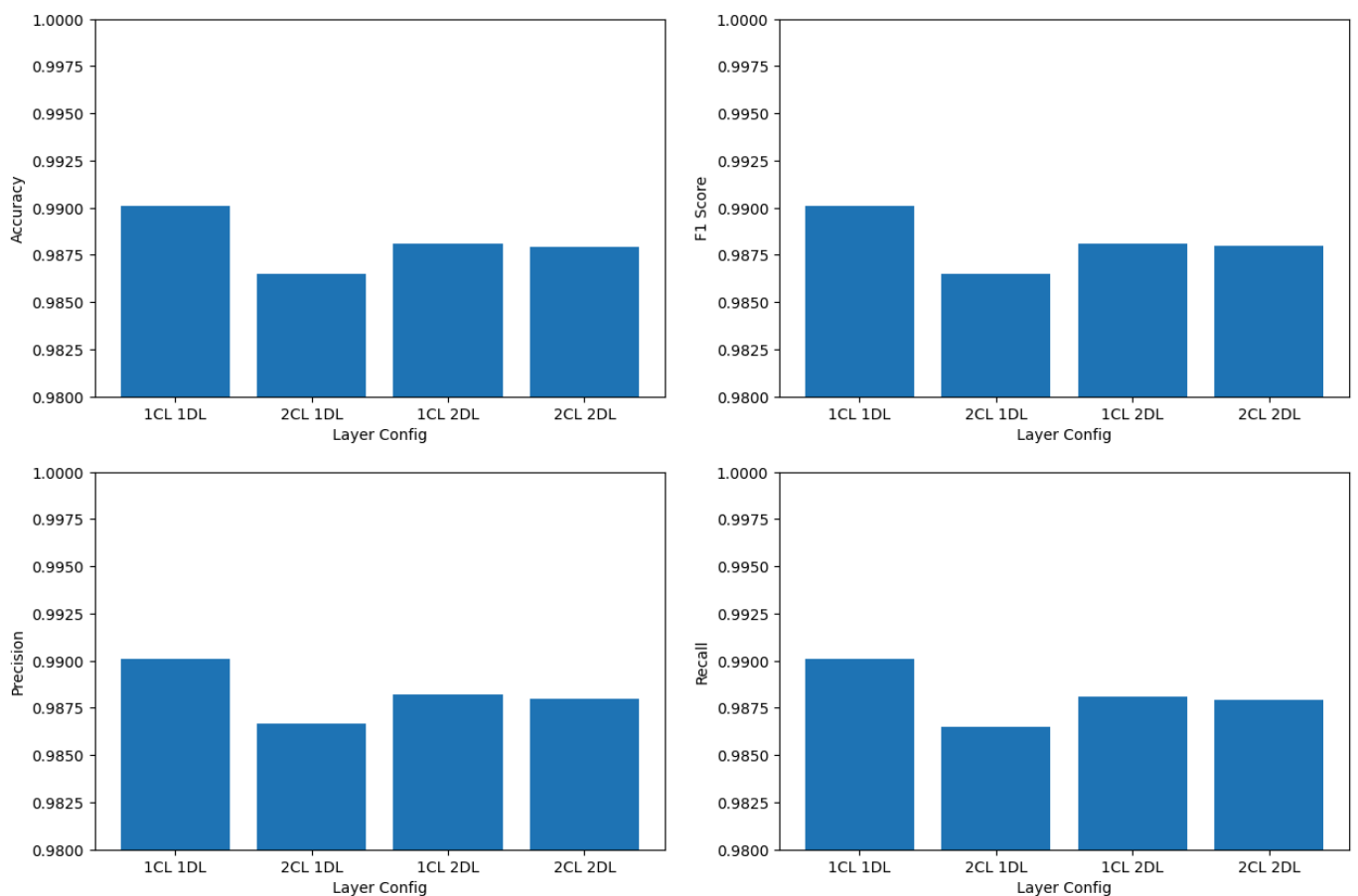
axs[1,0].bar(layers_df['Layer Config'], layers_df['Precision'], label='Precision')
axs[1,0].set_xlabel('Layer Config')
axs[1,0].set_ylabel('Precision')
axs[1,0].set_ylim(0.98, 1.0)

axs[1,1].bar(layers_df['Layer Config'], layers_df['Recall'], label='Recall')
axs[1,1].set_xlabel('Layer Config')
axs[1,1].set_ylabel('Recall')
axs[1,1].set_ylim(0.98, 1.0)

```

Out[]: (0.98, 1.0)

Layer Config vs Metrics



From these results it definitely seems quite clear that the best out of the tested layer configurations is 1 Convolutional Layer and 1 Dense Layer. This seems to be the best model.

Final Model

After all the testing and tuning, the best model seems to be the one with the following parameters:

- Learning rate: 0.0001
- Optimizer: Adam
- Batch size: 32

- Epochs: 5
- Layers: 1 Convolutional Layer and 1 Dense Layer

We shall save this model and use it to evaluate the test set.

```
In [ ]: #save the lclld as the best model if it doesn't exist
if not os.path.exists('./models/best_model.h5'):
    best_model = keras.models.load_model('./models/modelV1_1conv_1dense.h5')
    best_model.save('./models/best_model.h5')
else:
    best_model = keras.models.load_model('./models/best_model.h5')
```

Evaluating the model against a pretrained VGG16 model

As a final evaluation, I will compare the model I have built with a pretrained VGG16 model. I will load the VGG16 model and train it using the training set and validate it using the validation set. I will also save the model to a file.

However the VGG16 model does not take the same input shape as the model I have built, so I will need to preprocess the data again where we include the RGB values and resize the images to 224x224. Due to memory limitations on my machine, I will only use 6000 images for the training set, 2000 images for the validation set and 2000 images for the test set.

```
In [ ]: #VGG Only takes rgb images and images of size 224x224, so we need to load the images
images_rgb = []
num_required_images = 99999
processed_folder = './data/processed/'
for i in range(num_required_images):
    print("Loading image", i)
    img = Image.open(os.path.join(processed_folder, 'sample_' + str(i) + '.png'))
    img = img.convert('RGB')
    #resize the image to 224x224 because VGG16 only takes that size
    img = img.resize((224, 224))
    img_array = np.array(img)
    images_rgb.append(img_array)
```

```
In [ ]: #only use 10000 images for VGG16 due to memory issues so split the data again
throw_away_x, X_reduced, throw_away_y, y_reduced = train_test_split(images_rgb, labels,
                              test_size=0.2, random_state=42)

del throw_away_x
del throw_away_y
del images_rgb
#now split the data into 80% train, 20% test
X_train_temp_vgg, X_test_vgg, y_train_temp_vgg, y_test_vgg = train_test_split(X_reduced, y_reduced,
                                      test_size=0.2, random_state=42)

#further split the training data into 75% train, 25% validation
X_train_vgg, X_val_vgg, y_train_vgg, y_val_vgg = train_test_split(X_train_temp_vgg, y_train_temp_vgg,
                                                                    test_size=0.25, random_state=42)

del X_train_temp_vgg
del y_train_temp_vgg
```

```
In [ ]: #first check if the model exists
try:
    modelVGG = keras.models.load_model('./models/modelVGG16.h5')
    print('Model loaded')
    modelVGGCreated = True
```

```
except:
    modelVGCCreated = False
    print('Model not found')
```

Model loaded

Now we can compile the VGG16 model and train it using the training set and validate it using the validation set. We will also save the model to a file.

Finally we will evaluate the model using the test sets and compare the results with the model I have built.

```
In [ ]: if not modelVGCCreated:
        from keras.applications import VGG16

        #load pre-trained VGG16 model
        vgg16 = VGG16(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

        for layer in vgg16.layers:
            layer.trainable = False

        #add custom layers
        x = layers.Flatten()(vgg16.output)
        x = layers.Dense(1024, activation='relu')(x)
        x = layers.Dropout(0.2)(x)
        predictions = layers.Dense(3, activation='softmax')(x)

        modelVGG = keras.Model(vgg16.input, predictions)
```

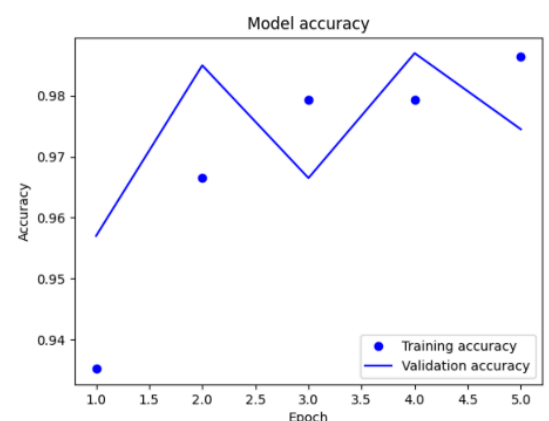
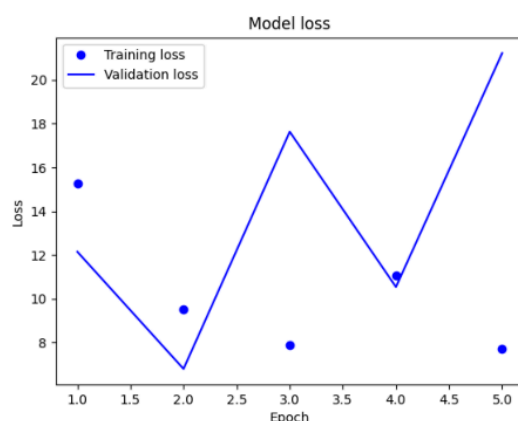
```
In [ ]: if not modelVGCCreated:
        #compile the model
        modelVGG.compile(optimizer='adam',
                        loss='sparse_categorical_crossentropy',
                        metrics=['accuracy'])
```

```
In [ ]: if not modelVGCCreated:
        #train the model
        modelVGG.fit(np.array(X_train_vgg), np.array(y_train_vgg), epochs=5, batch_size=4

        #save the model
        modelVGG.save('./models/modelVGG16.h5')
```

```
In [ ]: #plot the loss and accuracy graphs
plot_loss_accuracy(modelVGCCreated, modelVGG, 'modelVGG16')
```

Model loss and accuracy



```
In [ ]: #evaluate the model
vgg_results = evaluate_model(modelVGG, X_test_vgg, y_test_vgg, 'modelVGG16')
vgg_results
```

```
2024-03-03 18:18:41.316180: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
```

```
63/63 [=====] - 81s 1s/step - loss: 14.5549 - accuracy: 0.9775
```

```
2024-03-03 18:20:03.036861: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
```

```
63/63 [=====] - 69s 1s/step
```

```
Results: [14.55486011505127, 0.9775000214576721]
```

```
Accuracy: 0.9775
```

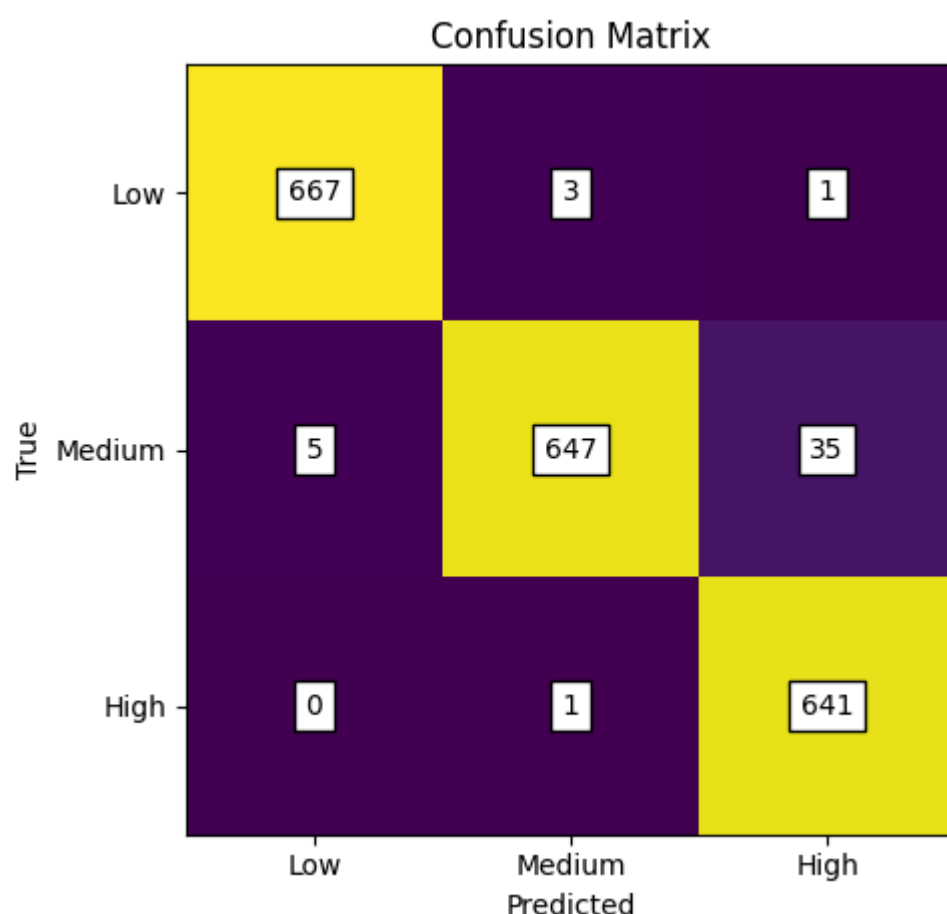
```
F1 Score: 0.9774511623274429
```

```
Precision: 0.9783236972306552
```

```
Recall: 0.9775
```

```
Confusion Matrix:
```

```
[[667  3  1]
 [  5 647 35]
 [  0  1 641]]
```



```
Out[ ]: Model      modelVGG16
Accuracy      0.9775
F1 Score      0.977451
Precision     0.978324
Recall        0.9775
dtype: object
```

```
In [ ]: #evaluate the best model
best_model_results = evaluate_model(best_model, X_test, y_test, 'best_model')
```

```
4/625 [.....] - ETA: 10s - loss: 0.2836 - accuracy: 0.9844
```

```
2024-03-03 18:21:15.567914: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
```

625/625 [=====] - 7s 11ms/step - loss: 0.1337 - accuracy: 0.9901

12/625 [.....] - ETA: 6s

2024-03-03 18:21:23.633450: I tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.

625/625 [=====] - 6s 9ms/step

Results: [0.13368579745292664, 0.9901000261306763]

Accuracy: 0.9901

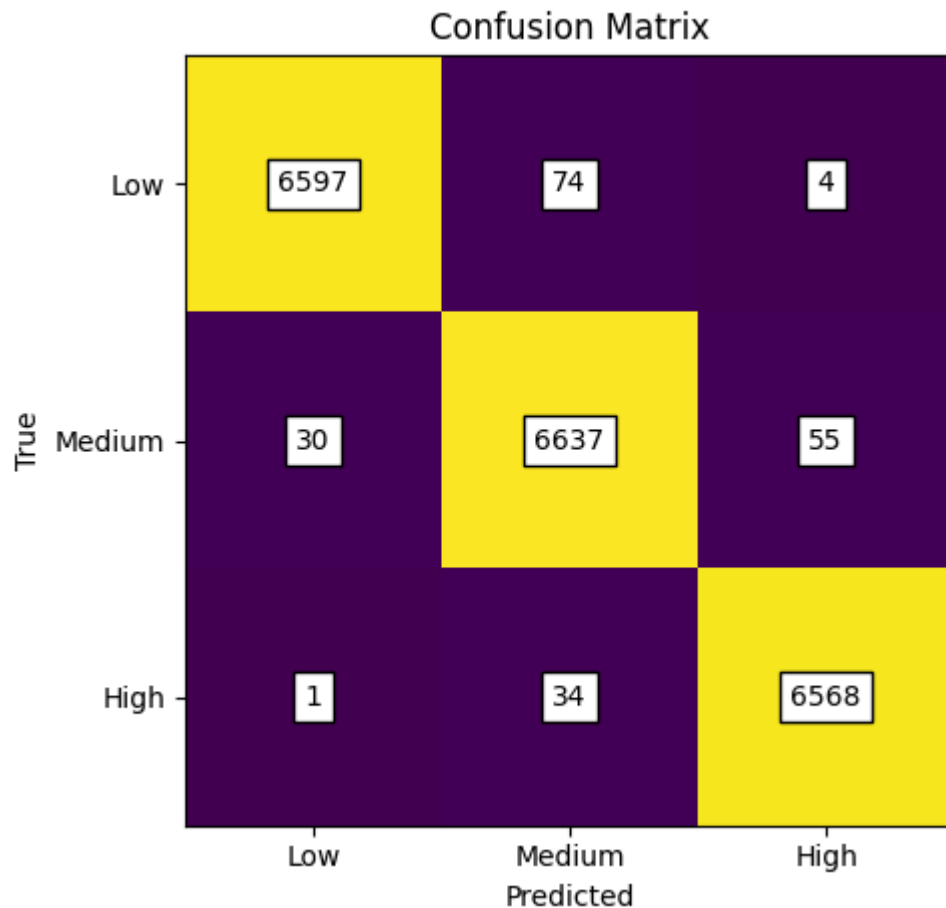
F1 Score: 0.990102876024772

Precision: 0.9901181059577124

Recall: 0.9901

Confusion Matrix:

```
[[6597  74   4]
 [ 30 6637  55]
 [  1  34 6568]]
```



```
In [ ]: #plot the best models evaluation results against the vgg16 model
results_df = pd.DataFrame(columns=['Model', 'Accuracy', 'F1 Score', 'Precision', 'Recall'])
results_df.loc[len(results_df.index)] = best_model_results
results_df.loc[len(results_df.index)] = vgg_results

fig, axs = plt.subplots(2, 2, figsize=(15, 10))
fig.suptitle('Model Comparison')

axs[0,0].bar(results_df['Model'], results_df['Accuracy'], label='Accuracy')
axs[0,0].set_xlabel('Model')
axs[0,0].set_ylabel('Accuracy')
axs[0,0].set_ylim(0.95, 1.0)

axs[0,1].bar(results_df['Model'], results_df['F1 Score'], label='F1 Score')
axs[0,1].set_xlabel('Model')
axs[0,1].set_ylabel('F1 Score')
axs[0,1].set_ylim(0.95, 1.0)

axs[1,0].bar(results_df['Model'], results_df['Precision'], label='Precision')
```

```

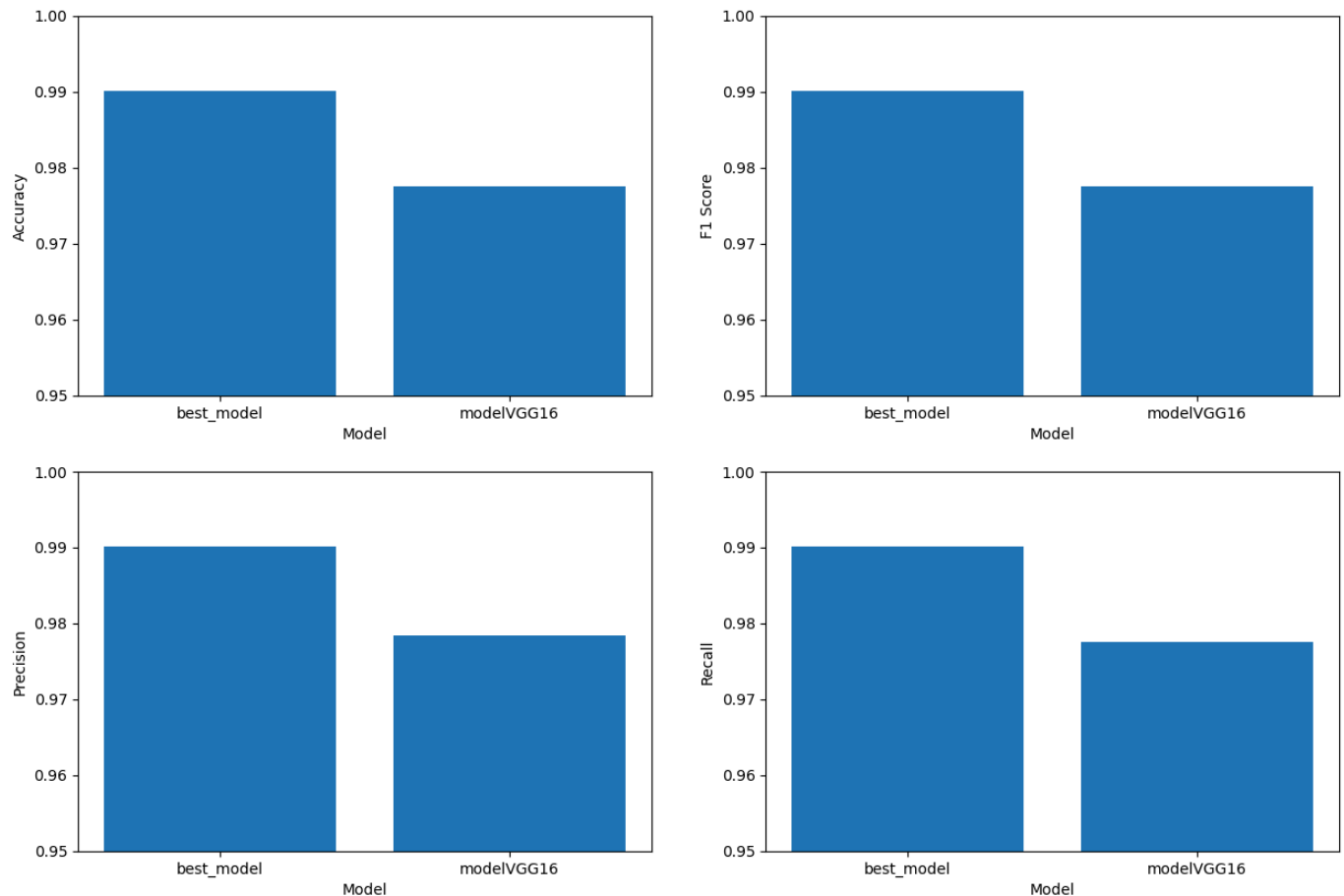
axs[1,0].set_xlabel('Model')
axs[1,0].set_ylabel('Precision')
axs[1,0].set_ylim(0.95, 1.0)

axs[1,1].bar(results_df['Model'], results_df['Recall'], label='Recall')
axs[1,1].set_xlabel('Model')
axs[1,1].set_ylabel('Recall')
axs[1,1].set_ylim(0.95, 1.0)

```

Out[]: (0.95, 1.0)

Model Comparison



The custom built model has done exceptionally well in beating out the VGG16 model, where the custom built model has an accuracy, f1 score, precision and recall all at about 0.99 and the VGG16 model shortly behind with all around 0.97. This is a great result and shows that the custom built model is a great model for this dataset.

Conclusion

In conclusion, the project has successfully developed and evaluated a deep learning model for classifying masking levels in mammograms, contributing to the field of medical image analysis. The implementation of a convolutional neural network (CNN) allowed for accurate and efficient classification of breast tissue density, aiding in the early detection of breast cancer.