

Data Loading

```
In [1]: import tensorflow as tf
        from tensorflow.keras import models, layers
        import matplotlib.pyplot as plt
        import numpy as np
        import os
```

```
In [2]: IMAGE_SIZE = 224
        BATCH_SIZE = 32
        CHANNELS = 3
        EPOCHS = 30
```

```
In [3]: dataset = tf.keras.preprocessing.image_dataset_from_directory(
        'rice_leaf_disease_images',
        shuffle = True,
        image_size = (IMAGE_SIZE, IMAGE_SIZE),
        batch_size = BATCH_SIZE
    )
```

Found 7926 files belonging to 5 classes.

```
In [4]: class_names = dataset.class_names
        class_names
```

```
Out[4]: ['Bacterialblight', 'Blast', 'Brownspot', 'Healthy', 'Tungro']
```

```
In [5]: len(dataset) #186*32=5931
```

```
Out[5]: 248
```

```
In [6]: # One random batch of images
        for image_batch, label_batch in dataset.take(1):
            print(image_batch.shape)
            print(label_batch.numpy())
```

(32, 224, 224, 3)

[1 3 4 1 2 3 3 4 0 0 3 2 4 0 0 0 0 1 2 1 1 1 1 0 2 0 0 0 2 2 3 2]

```
In [7]: plt.figure(figsize=(10,10))
for image_batch, label_batch in dataset.take(1):
    print(image_batch.shape)
    print(label_batch.numpy())
    for i in range(12): #showing 12 images out of 32
        ax = plt.subplot(3,4,i+1)
        plt.imshow(image_batch[i].numpy().astype("uint8"))
        plt.title(class_names[label_batch[i]])
        plt.axis("off")
```

(32, 224, 224, 3)

[3 2 2 2 2 3 2 0 2 4 4 2 1 4 2 2 0 1 2 2 0 2 1 4 1 3 4 2 0 2 4 1]



```
In [8]: # (32=batch_size, 256, 256=image_size, 0 to 3=typesofdiseases)
# 0 - Bacterial Blight
# 1 - Blast
# 2 - Brownspot
# 3 - Tungro
```

```
In [9]: # Spitting dataset for training, validation and testing
# 80% for training 10% for validation and 10% for testing
def get_dataset_partitions_tf(ds, train_split=0.8, val_split=0.1, test_split=0.1):
    ds_size = len(ds)
    if shuffle:
        ds = ds.shuffle(ds_size, seed=12)
    train_size = int(train_split*ds_size)
    val_size = int(val_split*ds_size)

    train_ds = ds.take(train_size)
    val_ds = ds.skip(train_size).take(val_size)
    test_ds = ds.skip(train_size).skip(val_size)

    return train_ds, val_ds, test_ds
```

```
In [10]: train_ds, val_ds, test_ds = get_dataset_partitions_tf(dataset)
```

```
In [11]: # Catching and prefetching
train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
val_ds = val_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
test_ds = test_ds.cache().prefetch(buffer_size=tf.data.AUTOTUNE)
```

Preprocessing

```
In [12]: # Layer for resizing and rescaling
resize_and_rescale = tf.keras.Sequential([
    layers.experimental.preprocessing.Resizing(IMAGE_SIZE, IMAGE_SIZE),
    layers.experimental.preprocessing.Rescaling(1.0/255)
])
```

```
In [13]: # Data Augmentation
data_augmentation = tf.keras.Sequential([
    layers.experimental.preprocessing.RandomFlip("horizontal_and_vertical"),
    layers.experimental.preprocessing.RandomRotation(0.2)
])
```

VGG16

```
In [14]: from tensorflow.keras.applications.vgg16 import VGG16
```

```
In [15]: vgg16 = VGG16(input_shape=(IMAGE_SIZE, IMAGE_SIZE, CHANNELS), weights='imagenet',
```

```
In [16]: # Don't train existing weights
for layer in vgg16.layers:
    layer.trainable = False
```

```
In [17]: x = tf.keras.layers.Flatten()(vgg16.output)
```

```
In [18]: prediction = tf.keras.layers.Dense(len(class_names),activation='softmax')(x)
```

```
In [19]: model = tf.keras.Model(inputs=vgg16.input, outputs=prediction)
```

```
In [20]: model.summary()
```

Model: "model"

| Layer (type) | Output Shape | Param # |
|----------------------------------|-----------------------|---------|
| ===== | | |
| input_1 (InputLayer) | [(None, 224, 224, 3)] | 0 |
| block1_conv1 (Conv2D) | (None, 224, 224, 64) | 1792 |
| block1_conv2 (Conv2D) | (None, 224, 224, 64) | 36928 |
| block1_pool (MaxPooling2D) | (None, 112, 112, 64) | 0 |
| block2_conv1 (Conv2D) | (None, 112, 112, 128) | 73856 |
| block2_conv2 (Conv2D) | (None, 112, 112, 128) | 147584 |
| block2_pool (MaxPooling2D) | (None, 56, 56, 128) | 0 |
| block3_conv1 (Conv2D) | (None, 56, 56, 256) | 295168 |
| block3_conv2 (Conv2D) | (None, 56, 56, 256) | 590080 |
| block3_conv3 (Conv2D) | (None, 56, 56, 256) | 590080 |
| block3_pool (MaxPooling2D) | (None, 28, 28, 256) | 0 |
| block4_conv1 (Conv2D) | (None, 28, 28, 512) | 1180160 |
| block4_conv2 (Conv2D) | (None, 28, 28, 512) | 2359808 |
| block4_conv3 (Conv2D) | (None, 28, 28, 512) | 2359808 |
| block4_pool (MaxPooling2D) | (None, 14, 14, 512) | 0 |
| block5_conv1 (Conv2D) | (None, 14, 14, 512) | 2359808 |
| block5_conv2 (Conv2D) | (None, 14, 14, 512) | 2359808 |
| block5_conv3 (Conv2D) | (None, 14, 14, 512) | 2359808 |
| block5_pool (MaxPooling2D) | (None, 7, 7, 512) | 0 |
| flatten (Flatten) | (None, 25088) | 0 |
| dense (Dense) | (None, 5) | 125445 |
| ===== | | |
| Total params: 14,840,133 | | |
| Trainable params: 125,445 | | |
| Non-trainable params: 14,714,688 | | |

```
In [21]: model.compile(  
    optimizer='adam',  
    loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=False),  
    metrics=['accuracy'])
```

```
In [22]: logdir='logs'
```

```
In [23]: tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=logdir)
```

```
In [24]: history = model.fit(  
    train_ds,  
    epochs=EPOCHS,  
    batch_size=BATCH_SIZE,  
    verbose=1,  
    validation_data=val_ds,  
    callbacks=[tensorboard_callback]  
)
```

Epoch 1/30
198/198 [=====] - 1297s 6s/step - loss: 2.1488 - accuracy: 0.8927 - val_loss: 0.9133 - val_accuracy: 0.9531

Epoch 2/30
198/198 [=====] - 1165s 6s/step - loss: 0.5011 - accuracy: 0.9725 - val_loss: 0.6232 - val_accuracy: 0.9674

Epoch 3/30
198/198 [=====] - 1165s 6s/step - loss: 0.2833 - accuracy: 0.9831 - val_loss: 0.5731 - val_accuracy: 0.9740

Epoch 4/30
198/198 [=====] - 1537s 8s/step - loss: 0.2353 - accuracy: 0.9845 - val_loss: 0.5233 - val_accuracy: 0.9740

Epoch 5/30
198/198 [=====] - 1835s 9s/step - loss: 0.1392 - accuracy: 0.9908 - val_loss: 0.2885 - val_accuracy: 0.9818

Epoch 6/30
198/198 [=====] - 1708s 9s/step - loss: 0.1105 - accuracy: 0.9929 - val_loss: 0.3135 - val_accuracy: 0.9844

Epoch 7/30
198/198 [=====] - 1540s 8s/step - loss: 0.0832 - accuracy: 0.9949 - val_loss: 0.1527 - val_accuracy: 0.9961

Epoch 8/30
198/198 [=====] - 1485s 8s/step - loss: 0.0733 - accuracy: 0.9945 - val_loss: 0.4575 - val_accuracy: 0.9896

Epoch 9/30
198/198 [=====] - 1524s 8s/step - loss: 0.1739 - accuracy: 0.9910 - val_loss: 0.8641 - val_accuracy: 0.9766

Epoch 10/30
198/198 [=====] - 1855s 9s/step - loss: 0.2123 - accuracy: 0.9910 - val_loss: 0.2036 - val_accuracy: 0.9870

Epoch 11/30
198/198 [=====] - 1853s 9s/step - loss: 0.1116 - accuracy: 0.9954 - val_loss: 0.2666 - val_accuracy: 0.9870

Epoch 12/30
198/198 [=====] - 1598s 8s/step - loss: 0.0638 - accuracy: 0.9965 - val_loss: 0.0793 - val_accuracy: 0.9961

Epoch 13/30
198/198 [=====] - 1499s 8s/step - loss: 0.0664 - accuracy: 0.9970 - val_loss: 0.3193 - val_accuracy: 0.9870

Epoch 14/30
198/198 [=====] - 1472s 7s/step - loss: 0.1434 - accuracy: 0.9938 - val_loss: 0.3297 - val_accuracy: 0.9922

Epoch 15/30
198/198 [=====] - 1641s 8s/step - loss: 0.1278 - accuracy: 0.9940 - val_loss: 0.3938 - val_accuracy: 0.9844

Epoch 16/30
198/198 [=====] - 1681s 8s/step - loss: 0.1026 - accuracy: 0.9967 - val_loss: 0.4645 - val_accuracy: 0.9896

Epoch 17/30
198/198 [=====] - 1873s 9s/step - loss: 0.1097 - accuracy: 0.9965 - val_loss: 0.4900 - val_accuracy: 0.9883

Epoch 18/30
198/198 [=====] - 2206s 11s/step - loss: 0.1961 - accuracy: 0.9930 - val_loss: 0.5340 - val_accuracy: 0.9857

Epoch 19/30
198/198 [=====] - 2054s 10s/step - loss: 0.1214 - accuracy: 0.9957 - val_loss: 0.5983 - val_accuracy: 0.9883


```

Epoch 20/30
198/198 [=====] - 1938s 10s/step - loss: 0.0378 - ac
curacy: 0.9983 - val_loss: 0.2611 - val_accuracy: 0.9935
Epoch 21/30
198/198 [=====] - 1825s 9s/step - loss: 0.0396 - acc
uracy: 0.9976 - val_loss: 0.5703 - val_accuracy: 0.9909
Epoch 22/30
198/198 [=====] - 1985s 10s/step - loss: 0.0782 - ac
curacy: 0.9972 - val_loss: 0.1955 - val_accuracy: 0.9935
Epoch 23/30
198/198 [=====] - 2211s 11s/step - loss: 0.1338 - ac
curacy: 0.9949 - val_loss: 0.2378 - val_accuracy: 0.9948
Epoch 24/30
198/198 [=====] - 2061s 10s/step - loss: 0.0613 - ac
curacy: 0.9968 - val_loss: 0.5224 - val_accuracy: 0.9909
Epoch 25/30
198/198 [=====] - 2059s 10s/step - loss: 0.0330 - ac
curacy: 0.9984 - val_loss: 0.4245 - val_accuracy: 0.9922
Epoch 26/30
198/198 [=====] - 2036s 10s/step - loss: 0.0119 - ac
curacy: 0.9992 - val_loss: 0.3353 - val_accuracy: 0.9935
Epoch 27/30
198/198 [=====] - 1834s 9s/step - loss: 0.0674 - acc
uracy: 0.9979 - val_loss: 0.3629 - val_accuracy: 0.9935
Epoch 28/30
198/198 [=====] - 2236s 11s/step - loss: 0.2007 - ac
curacy: 0.9959 - val_loss: 0.1345 - val_accuracy: 0.9922
Epoch 29/30
198/198 [=====] - 1763s 9s/step - loss: 0.0714 - acc
uracy: 0.9979 - val_loss: 0.7482 - val_accuracy: 0.9857
Epoch 30/30
198/198 [=====] - 1819s 9s/step - loss: 0.0484 - acc
uracy: 0.9978 - val_loss: 0.4536 - val_accuracy: 0.9935

```

```

In [25]: scores = model.evaluate(test_ds)
         scores

```

```

26/26 [=====] - 304s 7s/step - loss: 0.4968 - accura
cy: 0.9940

```

```

Out[25]: [0.49677610397338867, 0.9939903616905212]

```

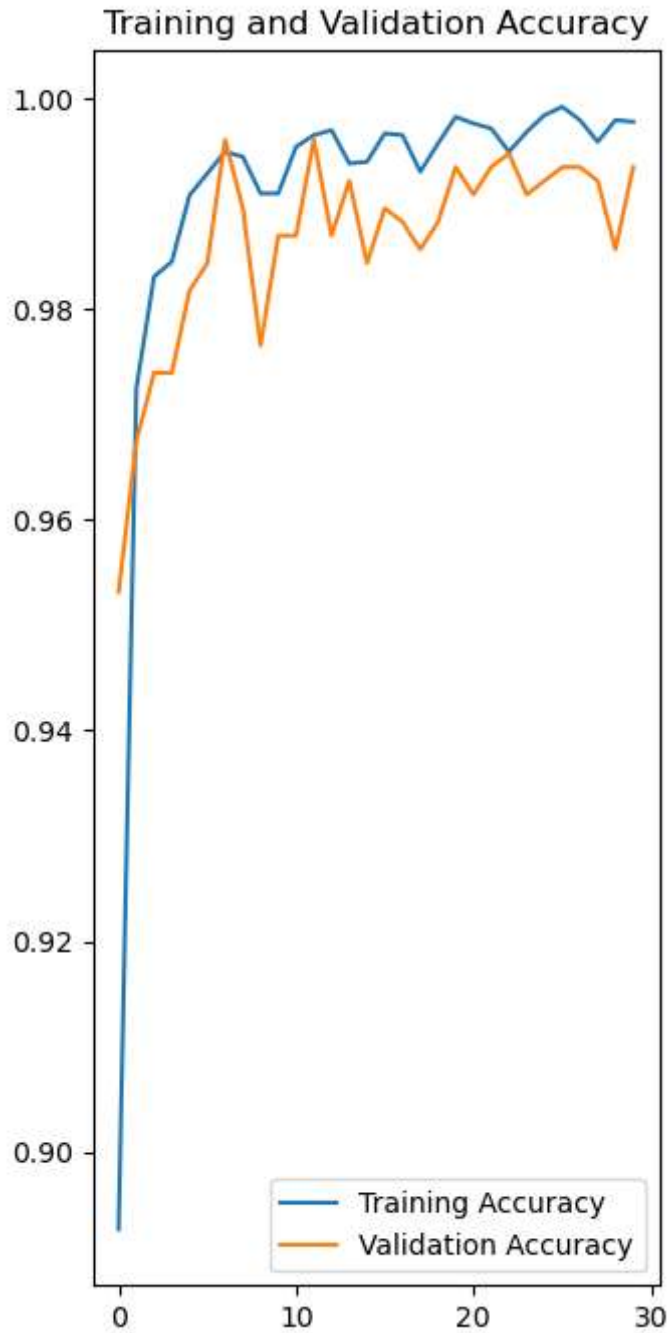
```

In [26]: acc = history.history['accuracy']
         val_acc = history.history['val_accuracy']
         loss = history.history['loss']
         val_loss = history.history['val_loss']

```

```
In [27]: plt.figure(figsize=(8,8))
plt.subplot(1,2,1)
plt.plot(range(EPOCHS), acc, label='Training Accuracy')
plt.plot(range(EPOCHS), val_acc, label='Validation Accuracy')
plt.legend(loc = 'lower right')
plt.title('Training and Validation Accuracy')
```

Out[27]: Text(0.5, 1.0, 'Training and Validation Accuracy')



```
In [28]: def predict(model, img):  
    img_array = tf.keras.preprocessing.image.img_to_array(images[i].numpy())  
    img_array = tf.expand_dims(img_array, 0)  
  
    prediction = model.predict(img_array)  
  
    prediction_class = class_names[np.argmax(prediction[0])]  
    confidence = round(100 * (np.max(prediction[0])),2)  
  
    return prediction_class, confidence
```

```
In [29]: plt.figure(figsize=(15,15))
for images, labels in test_ds.take(2):
    for i in range(9):
        ax = plt.subplot(3,3,i+1)
        plt.imshow(images[i].numpy().astype('uint8'))

        predicted_class, confidence = predict(model, images[i].numpy())
        actual_class = class_names[labels[i]]
        plt.title(f'predicted: {predicted_class},\n confidence: {confidence},
        plt.axis("off")
```

```
1/1 [=====] - 1s 1s/step
1/1 [=====] - 0s 259ms/step
1/1 [=====] - 0s 221ms/step
1/1 [=====] - 0s 309ms/step
1/1 [=====] - 0s 263ms/step
1/1 [=====] - 0s 251ms/step
1/1 [=====] - 0s 253ms/step
1/1 [=====] - 0s 338ms/step
1/1 [=====] - 0s 254ms/step
1/1 [=====] - 0s 310ms/step
1/1 [=====] - 0s 242ms/step
1/1 [=====] - 0s 267ms/step
1/1 [=====] - 0s 281ms/step
1/1 [=====] - 0s 264ms/step
1/1 [=====] - 0s 283ms/step
1/1 [=====] - 0s 254ms/step
1/1 [=====] - 0s 278ms/step
1/1 [=====] - 0s 251ms/step
```

predicted: Tungro,
confidence: 100.0,
Actual: Tungro



predicted: Brownspot,
confidence: 100.0,
Actual: Brownspot



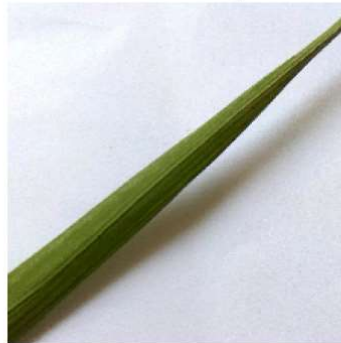
predicted: Blast,
confidence: 100.0,
Actual: Blast



predicted: Bacterialblight,
confidence: 100.0,
Actual: Bacterialblight



predicted: Healthy,
confidence: 100.0,
Actual: Healthy



predicted: Blast,
confidence: 100.0,
Actual: Blast



predicted: Blast,
confidence: 100.0,
Actual: Blast



predicted: Tungro,
confidence: 100.0,
Actual: Tungro



predicted: Brownspot,
confidence: 100.0,
Actual: Brownspot



```
In [33]: # Saving the model
model_version = max([int(i) for i in os.listdir("new_models") + [0]])+1
model.save(f'new_models\{model_version}')
```

WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op while saving (showing 5 of 14). These functions will not be directly callable after loading.

INFO:tensorflow:Assets written to: new_models\6\assets

INFO:tensorflow:Assets written to: new_models\6\assets

In []:

```
In [34]: new_model = tf.keras.models.load_model('new_models/6')

# Check its architecture
new_model.summary()
```

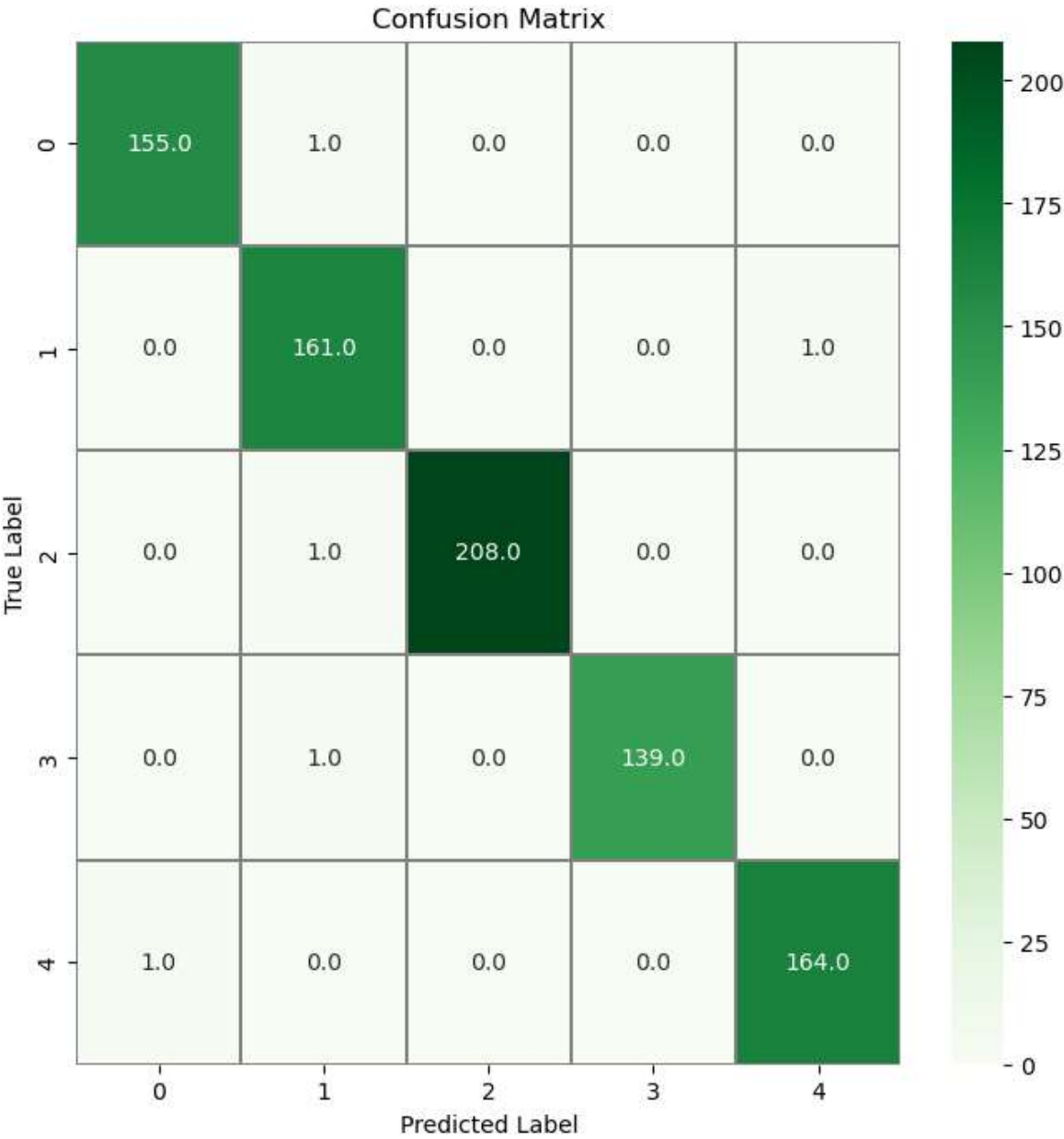
Model: "model"

| Layer (type) | Output Shape | Param # |
|----------------------------------|-----------------------|---------|
| ===== | | |
| input_1 (InputLayer) | [(None, 224, 224, 3)] | 0 |
| block1_conv1 (Conv2D) | (None, 224, 224, 64) | 1792 |
| block1_conv2 (Conv2D) | (None, 224, 224, 64) | 36928 |
| block1_pool (MaxPooling2D) | (None, 112, 112, 64) | 0 |
| block2_conv1 (Conv2D) | (None, 112, 112, 128) | 73856 |
| block2_conv2 (Conv2D) | (None, 112, 112, 128) | 147584 |
| block2_pool (MaxPooling2D) | (None, 56, 56, 128) | 0 |
| block3_conv1 (Conv2D) | (None, 56, 56, 256) | 295168 |
| block3_conv2 (Conv2D) | (None, 56, 56, 256) | 590080 |
| block3_conv3 (Conv2D) | (None, 56, 56, 256) | 590080 |
| block3_pool (MaxPooling2D) | (None, 28, 28, 256) | 0 |
| block4_conv1 (Conv2D) | (None, 28, 28, 512) | 1180160 |
| block4_conv2 (Conv2D) | (None, 28, 28, 512) | 2359808 |
| block4_conv3 (Conv2D) | (None, 28, 28, 512) | 2359808 |
| block4_pool (MaxPooling2D) | (None, 14, 14, 512) | 0 |
| block5_conv1 (Conv2D) | (None, 14, 14, 512) | 2359808 |
| block5_conv2 (Conv2D) | (None, 14, 14, 512) | 2359808 |
| block5_conv3 (Conv2D) | (None, 14, 14, 512) | 2359808 |
| block5_pool (MaxPooling2D) | (None, 7, 7, 512) | 0 |
| flatten (Flatten) | (None, 25088) | 0 |
| dense (Dense) | (None, 5) | 125445 |
| ===== | | |
| Total params: 14,840,133 | | |
| Trainable params: 125,445 | | |
| Non-trainable params: 14,714,688 | | |

```
In [35]: from sklearn.metrics import confusion_matrix , classification_report
```

```
In [36]: # confusion matrix
import seaborn as sns
# Predict the values from the validation dataset
Y_pred = new_model.predict(test_ds)
# Convert predictions classes to one hot vectors
Y_pred_classes = np.argmax(Y_pred,axis = 1)
# Convert validation observations to one hot vectors
Y_true = tf.concat([y for x, y in test_ds], axis=0)
# compute the confusion matrix
confusion_mtx = confusion_matrix(Y_true, Y_pred_classes)
# plot the confusion matrix
f,ax = plt.subplots(figsize=(8, 8))
sns.heatmap(confusion_mtx, annot=True, linewidths=0.01,cmap="Greens",linecolor
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()
```

26/26 [=====] - 207s 8s/step



```
In [37]: print(classification_report(Y_true, Y_pred_classes, target_names=class_names))
```

| | precision | recall | f1-score | support |
|-----------------|-----------|--------|----------|---------|
| Bacterialblight | 0.99 | 0.99 | 0.99 | 156 |
| Blast | 0.98 | 0.99 | 0.99 | 162 |
| Brownspot | 1.00 | 1.00 | 1.00 | 209 |
| Healthy | 1.00 | 0.99 | 1.00 | 140 |
| Tungro | 0.99 | 0.99 | 0.99 | 165 |
| accuracy | | | 0.99 | 832 |
| macro avg | 0.99 | 0.99 | 0.99 | 832 |
| weighted avg | 0.99 | 0.99 | 0.99 | 832 |

In []:

In []:

```
In [38]: import numpy as np
import cv2
```

```
In [57]: img_path = cv2.imread(os.path.join('Testing Images', 'bb.jpg'))
img_path = cv2.cvtColor(img_path, cv2.COLOR_BGR2RGB)
plt.imshow(img_path)
```

Out[57]: <matplotlib.image.AxesImage at 0x2f08251cb20>



```
In [58]: img = cv2.resize(img_path, (224, 224))
img = np.reshape(img, [1, 224, 224, 3])
```

```
In [59]: pred = new_model.predict(img)
```

1/1 [=====] - 0s 384ms/step

```
In [60]: pred
```

Out[60]: array([[1.000000e+00, 1.783569e-24, 0.000000e+00, 0.000000e+00, 0.000000e+00]], dtype=float32)

```
In [61]: prediction_class = class_names[np.argmax(pred)]  
prediction_class
```

```
Out[61]: 'Bacterialblight'
```

```
In [ ]:
```

```
In [ ]:
```