Rice Disease Detection

In [81]:
```
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
import tensorflow as tf

from tensorflow.keras.utils import to_categorical
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from tensorflow.python.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Dense, Bidirectional, LSTM, Reshape, Dropout, MultiHeadAttention
from sklearn.metrics import classification_report, log_loss, accuracy_score
from sklearn.model_selection import train_test_split
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, CSVLogger

import seaborn as sb
from sklearn.metrics import confusion_matrix
```

Allocate memory and environment to GPU

In [2]:
```
phy_devices = tf.config.experimental.list_physical_devices('GPU')
print(phy_devices)
if phy_devices:
    print("Memory allocation and computations pushed to GPU env")
    tf.config.experimental.set_memory_growth(phy_devices[0], True)
```

```
[PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
Memory allocation and computations pushed to GPU env
```

Data extraction and augmentation

In [3]:
```
#dataset path
dataset_dir = 'D:/Andrei/Andrei/Prog Applications/datasets'
dataset_name = '/Rice diseases exclusively'
dataset_dir = dataset_dir + dataset_name

#image details
size = (224, 224)
img_color_mode = 'rgb'
img_type = '.jpg'
```

In [86]:
```
class_names=[]
for file in os.listdir(dataset_dir):
    class_names+=[file]
print(class_names)
print(len(class_names))
```

```
['blast', 'blight', 'tungro']
3
```

In [105]:
```
N=[]
for i in range(len(class_names)):
    N+=[i]

normal_mapping=dict(zip(class_names,N))
reverse_mapping=dict(zip(N,class_names))

def mapper(value):
    return reverse_mapping[value]
```

In [117]:
```
# Append images to dataset var converted to 2d arrays
dataset = []
count=0
for name in class_names:
    path=os.path.join(dataset_dir,name)
    t=0
    for im in os.listdir(path):
        if im[-4:]==img_type:
            image=load_img(
                os.path.join(path,im),
                grayscale=False,
                color_mode=img_color_mode,
                target_size=size
            )
            image=img_to_array(image)
            image=image/255.0 #normalize
            dataset.append([image,count])
    count=count+1
```

In [118]:
```
data,labels0=zip(*dataset)
```

In [119]:
```
labels1=to_categorical(labels0)
data=np.array(data)
labels=np.array(labels1)
```

Data Splitting

In [228]:
```
# 60% training, 20% testing, 20% validation data split
dataset_size = len(dataset)
train_split_ratio = 0.80
test_split_ratio = 0.20

# getting the ratio of validation set from train set by using this formula
# this equates to somewhere close or near the 20% if extracted from the combined dataset
valid_split_ratio = (dataset_size * test_split_ratio) / (dataset_size * train_split_ratio)
```

In [230]:
```
# split training/validation dataset from testing dataset [80:20]
trainvalidx, testx, trainvalidy, testy = train_test_split(
    data,
    labels,
    test_size=test_split_ratio,
    random_state=27
)
```

In [232]:
```
# split training and validation dataset [60:20]
trainx, validx, trainy, validy = train_test_split(
    trainvalidx,
    trainvalidy,
    test_size=valid_split_ratio,
    random_state=27
)
```

In [246]:
```
print(f"Training data shape: {trainx.shape}")
print(f"Validation data shape: {validx.shape}")
print(f"Testing data shape: {testx.shape}")
print(f"Training images {round((train_split_ratio - (train_split_ratio * valid_split_ratio))* 100)}% : {trainx.s
print(f"Validation images {round(train_split_ratio*valid_split_ratio* 100) }% : {validx.shape[0]}")
print(f"Testing images {round(test_split_ratio * 100)}% : {testx.shape[0]}")
print("=" *30)
print(f"Total Images: {trainx.shape[0]+validx.shape[0]+testx.shape[0]}")
print(f"Classifications: {len(class_names)}, {class_names}")
```

```
Training data shape: (144, 224, 224, 3)
Validation data shape: (48, 224, 224, 3)
Testing data shape: (48, 224, 224, 3)
Training images 60% : 144
Validation images 20% : 48
Testing images 20% : 48
==============================
Total Images: 240
Classifications: 3, ['blast', 'blight', 'tungro']
```

Augmentation

In [56]:
```
datagen = ImageDataGenerator(
    horizontal_flip=True,
    vertical_flip=True,
    rotation_range=20,
    zoom_range=0.3,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.1,
    fill_mode="nearest"
)
```

Models

Custom Layers

In [328]:
```
def ReshapeLayer(x):
    shape = x.shape
    reshape = Reshape((shape[1],shape[2]*shape[3]))(x)
    return reshape

def BiLSTMLayer(x, neurons=128):
    # Tanh Activation provides access of the LSTM to the cuDNN which provides faster computation
    return Bidirectional(LSTM(neurons, activation='tanh', recurrent_dropout=0))(x)

def AttentionLayer(x, heads = 1, dim = 1, training = False):
    return MultiHeadAttention(num_heads=heads, key_dim=dim)(x, x, training=training)
```

In [329]:

```
def DenseBilstm(attention=False):
    cnn = tf.keras.applications.DenseNet201(
        input_shape=(size[0],size[1],3),
        include_top=False,
        weights='imagenet'
    )
    cnn.trainable = False

    #Model Sequence
    images = cnn.input
    x = cnn.output
    if attention:
        x = AttentionLayer(x, heads = 2, dim = 1, training = True)
    x = ReshapeLayer(x)
    x = BiLSTMLayer(x, 128)
    pred = Dense(3, activation='softmax')(x)

    model = tf.keras.Model(inputs=images, outputs=pred)
    model.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])

    return model
```

In [330]:
```
def MoBilstm(attention=False):
    cnn = tf.keras.applications.MobileNet(
        input_shape=(size[0],size[1],3),
        include_top=False,
        weights='imagenet'
    )
    cnn.trainable = False

    #Model Sequence
    images = cnn.input
    x = cnn.output
    if attention:
        x = AttentionLayer(x, heads = 2, dim = 1, training = True)
    x = ReshapeLayer(x)
    x = BiLSTMLayer(x, 128)
    pred = Dense(3, activation='softmax')(x)

    model = tf.keras.Model(inputs=images, outputs=pred)
    model.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
    return model
```

Training without Attention

In [292]:
```
# set early stopping criteria
pat = 5 # this is the number of epochs with no improvment after which the training will stop
early_stopping = EarlyStopping(monitor='val_loss', patience=pat, verbose=1, baseline=None)

# to save the history of models
csv_logger = CSVLogger(f'logs/{model_label}.log', separator=",", append=True)

# define the model checkpoint callback -> this will keep on saving the model as a physical file
def ModelCheckPointCB(model_label = 'mnet_bilstm_sample1', save_best_only=True):
    return ModelCheckpoint(
        f'model_checkpoints/{model_label}.h5',
        verbose=1, save_best_only=save_best_only
    )
```

In [293]:
```
model1 = DenseBilstm(attention = False)
model1.summary()
```

```
                                                                 conv5_block28_2_conv[0][0]
__________________________________________________________________________________________________
conv5_block29_0_bn (BatchNormal (None, 7, 7, 1792)   7168        conv5_block28_concat[0][0]
__________________________________________________________________________________________________
conv5_block29_0_relu (Activatio (None, 7, 7, 1792)   0           conv5_block29_0_bn[0][0]
__________________________________________________________________________________________________
conv5_block29_1_conv (Conv2D)   (None, 7, 7, 128)    229376      conv5_block29_0_relu[0][0]
__________________________________________________________________________________________________
conv5_block29_1_bn (BatchNormal (None, 7, 7, 128)    512         conv5_block29_1_conv[0][0]

__________________________________________________________________________________________________
conv5_block29_1_relu (Activatio (None, 7, 7, 128)    0           conv5_block29_1_bn[0][0]
__________________________________________________________________________________________________
conv5_block29_2_conv (Conv2D)   (None, 7, 7, 32)     36864       conv5_block29_1_relu[0][0]
__________________________________________________________________________________________________
conv5_block29_concat (Concatena (None, 7, 7, 1824)   0           conv5_block28_concat[0][0]
                                                                 conv5_block29_2_conv[0][0]
__________________________________________________________________________________________________
conv5_block30_0_bn (BatchNormal (None, 7, 7, 1824)   7296        conv5_block29_concat[0][0]
__________________________________________________________________________________________________
conv5_block30_0_relu (Activatio (None, 7, 7, 1824)   0           conv5_block30_0_bn[0][0]
```

In [294]:
```
# model 1, DenseBiLSTM_noAttention
model_label = "DenseBiLSTM_noAttention"
history1 = model1.fit(
        x = datagen.flow(trainx,trainy,batch_size=16),
        validation_data = ImageDataGenerator().flow(validx, validy, batch_size=16),
        batch_size=32,
        epochs=50,
        callbacks=[early_stopping, ModelCheckPointCB(model_label), csv_logger],
        verbose=1,
    )
```

```
Epoch 1/50
9/9 [==============================] - 24s 813ms/step - loss: 1.3505 - accuracy: 0.4444 - val_loss: 0.7303 -
val_accuracy: 0.7917

Epoch 00001: val_loss improved from inf to 0.73032, saving model to model_checkpoints\DenseBiLSTM_noAttentio
n.h5
Epoch 2/50
9/9 [==============================] - 2s 243ms/step - loss: 0.6594 - accuracy: 0.7917 - val_loss: 0.5965 -
val_accuracy: 0.7292

Epoch 00002: val_loss improved from 0.73032 to 0.59654, saving model to model_checkpoints\DenseBiLSTM_noAtte
ntion.h5
Epoch 3/50
9/9 [==============================] - 2s 242ms/step - loss: 0.4260 - accuracy: 0.8819 - val_loss: 0.5136 -
val_accuracy: 0.7917

Epoch 00003: val_loss improved from 0.59654 to 0.51364, saving model to model_checkpoints\DenseBiLSTM_noAtte
ntion.h5
Epoch 4/50
```

In [295]:
```
# model 2, MoBiLSTM_noAttention
model2 = MoBilstm(attention = False)
model2.summary()
```

```
conv_dw_10 (DepthwiseConv2D) (None, 14, 14, 512)       4608
_________________________________________________________________
conv_dw_10_bn (BatchNormaliz (None, 14, 14, 512)       2048
_________________________________________________________________
conv_dw_10_relu (ReLU)       (None, 14, 14, 512)       0
_________________________________________________________________
conv_pw_10 (Conv2D)          (None, 14, 14, 512)       262144
_________________________________________________________________
conv_pw_10_bn (BatchNormaliz (None, 14, 14, 512)       2048
_________________________________________________________________
conv_pw_10_relu (ReLU)       (None, 14, 14, 512)       0
_________________________________________________________________
conv_dw_11 (DepthwiseConv2D) (None, 14, 14, 512)       4608
_________________________________________________________________
conv_dw_11_bn (BatchNormaliz (None, 14, 14, 512)       2048
_________________________________________________________________
conv_dw_11_relu (ReLU)       (None, 14, 14, 512)       0
_________________________________________________________________
conv_pw_11 (Conv2D)          (None, 14, 14, 512)       262144
_________________________________________________________________
```

In [296]:
```
model_label2 = "MoBiLSTM_noAttention"
history2 = model2.fit(
        x = datagen.flow(trainx,trainy,batch_size=16),
        validation_data = ImageDataGenerator().flow(validx, validy, batch_size=16),
        batch_size=32,
        epochs=50,
        callbacks=[early_stopping, ModelCheckPointCB(model_label2), csv_logger],
        verbose=1,
    )
```

```
Epoch 1/50
9/9 [==============================] - 11s 759ms/step - loss: 1.7057 - accuracy: 0.3889 - val_loss: 0.9027 - v
al_accuracy: 0.5833

Epoch 00001: val_loss improved from inf to 0.90272, saving model to model_checkpoints\MoBiLSTM_noAttention.h5
Epoch 2/50
9/9 [==============================] - 2s 209ms/step - loss: 0.8633 - accuracy: 0.6319 - val_loss: 0.7984 - va
l_accuracy: 0.6458

Epoch 00002: val_loss improved from 0.90272 to 0.79837, saving model to model_checkpoints\MoBiLSTM_noAttentio
n.h5
Epoch 3/50
9/9 [==============================] - 2s 218ms/step - loss: 0.6618 - accuracy: 0.8194 - val_loss: 0.6443 - va
l_accuracy: 0.7500

Epoch 00003: val_loss improved from 0.79837 to 0.64431, saving model to model_checkpoints\MoBiLSTM_noAttentio
n.h5
Epoch 4/50
9/9 [==============================] - 2s 209ms/step - loss: 0.5248 - accuracy: 0.8333 - val_loss: 0.5711 - va
l_accuracy: 0.7708

Epoch 00004: val_loss improved from 0.64431 to 0.57110, saving model to model_checkpoints\MoBiLSTM_noAttentio
n.h5
Epoch 5/50
9/9 [==============================] - 2s 213ms/step - loss: 0.4484 - accuracy: 0.8681 - val_loss: 0.4898 - va
l_accuracy: 0.8333

Epoch 00005: val_loss improved from 0.57110 to 0.48980, saving model to model_checkpoints\MoBiLSTM_noAttentio
n.h5
Epoch 6/50
9/9 [==============================] - 2s 210ms/step - loss: 0.3982 - accuracy: 0.8819 - val_loss: 0.4411 - va
l_accuracy: 0.8542
```

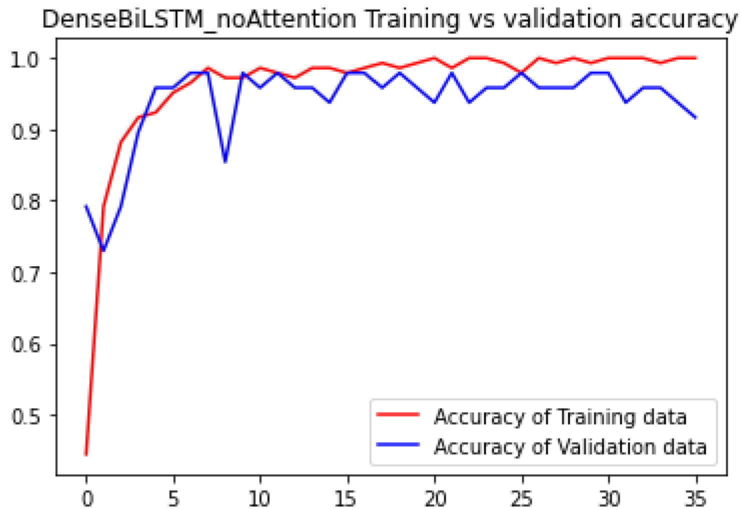
```
Epoch 00006: val_loss improved from 0.48980 to 0.44108, saving model to model_checkpoints\MoBiLSTM_noAttentio
n.h5
Epoch 7/50
9/9 [==============================] - 2s 227ms/step - loss: 0.3412 - accuracy: 0.9097 - val_loss: 0.4040 - va
l_accuracy: 0.8542

Epoch 00007: val_loss improved from 0.44108 to 0.40404, saving model to model_checkpoints\MoBiLSTM_noAttentio
n.h5
Epoch 8/50
9/9 [==============================] - 2s 213ms/step - loss: 0.3618 - accuracy: 0.8889 - val_loss: 0.4078 - va
l_accuracy: 0.8333

Epoch 00008: val_loss did not improve from 0.40404
Epoch 9/50
9/9 [==============================] - 2s 216ms/step - loss: 0.3003 - accuracy: 0.9375 - val_loss: 0.3654 - va
l_accuracy: 0.8542

Epoch 00009: val_loss improved from 0.40404 to 0.36537, saving model to model_checkpoints\MoBiLSTM_noAttentio
n.h5
Epoch 10/50
9/9 [==============================] - 2s 214ms/step - loss: 0.2160 - accuracy: 0.9514 - val_loss: 0.3782 - va
l_accuracy: 0.8750

Epoch 00010: val_loss did not improve from 0.36537
Epoch 11/50
9/9 [==============================] - 2s 213ms/step - loss: 0.2052 - accuracy: 0.9583 - val_loss: 0.3522 - va
l_accuracy: 0.8958

Epoch 00011: val_loss improved from 0.36537 to 0.35219, saving model to model_checkpoints\MoBiLSTM_noAttentio
n.h5
Epoch 12/50
9/9 [==============================] - 2s 214ms/step - loss: 0.1939 - accuracy: 0.9514 - val_loss: 0.3220 - va
l_accuracy: 0.8750

Epoch 00012: val_loss improved from 0.35219 to 0.32196, saving model to model_checkpoints\MoBiLSTM_noAttentio
n.h5
Epoch 13/50
9/9 [==============================] - 2s 213ms/step - loss: 0.1548 - accuracy: 0.9792 - val_loss: 0.2922 - va
l_accuracy: 0.8750

Epoch 00013: val_loss improved from 0.32196 to 0.29218, saving model to model_checkpoints\MoBiLSTM_noAttentio
n.h5
Epoch 14/50
```

```
9/9 [==============================] - 2s 221ms/step - loss: 0.1649 - accuracy: 0.9653 - val_loss: 0.3022 - va
l_accuracy: 0.8542

Epoch 00014: val_loss did not improve from 0.29218
Epoch 15/50
9/9 [==============================] - 2s 211ms/step - loss: 0.1752 - accuracy: 0.9375 - val_loss: 0.3327 - va
l_accuracy: 0.8750

Epoch 00015: val_loss did not improve from 0.29218
Epoch 16/50
9/9 [==============================] - 2s 214ms/step - loss: 0.1431 - accuracy: 0.9792 - val_loss: 0.4711 - va
l_accuracy: 0.7917

Epoch 00016: val_loss did not improve from 0.29218
Epoch 17/50
9/9 [==============================] - 2s 224ms/step - loss: 0.1399 - accuracy: 0.9514 - val_loss: 0.3517 - va
l_accuracy: 0.8750

Epoch 00017: val_loss did not improve from 0.29218
Epoch 18/50
9/9 [==============================] - 2s 220ms/step - loss: 0.1356 - accuracy: 0.9653 - val_loss: 0.3259 - va
l_accuracy: 0.8542

Epoch 00018: val_loss did not improve from 0.29218
Epoch 00018: early stopping
```

Data Presentation

In [297]:

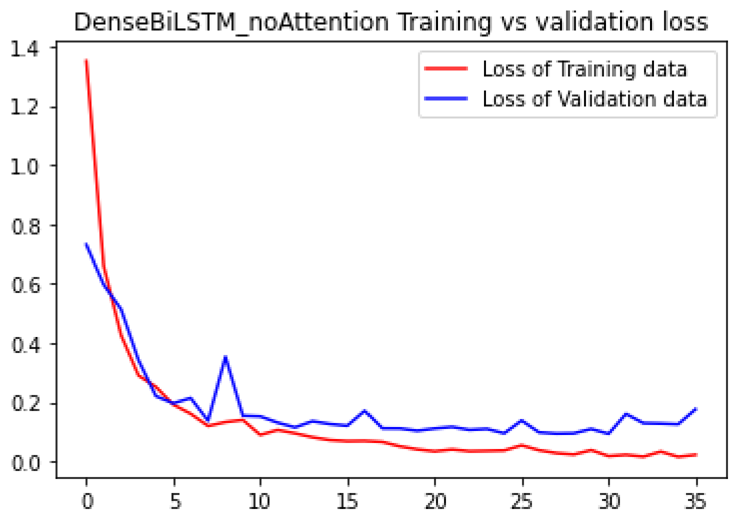
```
get_acc = history1.history['accuracy']
value_acc = history1.history['val_accuracy']
get_loss = history1.history['loss']
validation_loss = history1.history['val_loss']

epochs = range(len(get_acc))
plt.plot(epochs, get_acc, 'r', label='Accuracy of Training data')
plt.plot(epochs, value_acc, 'b', label='Accuracy of Validation data')
plt.title(f'{model_label} Training vs validation accuracy')
plt.legend(loc=0)
plt.figure()
plt.show()
```



```
<Figure size 432x288 with 0 Axes>
```

In [298]:

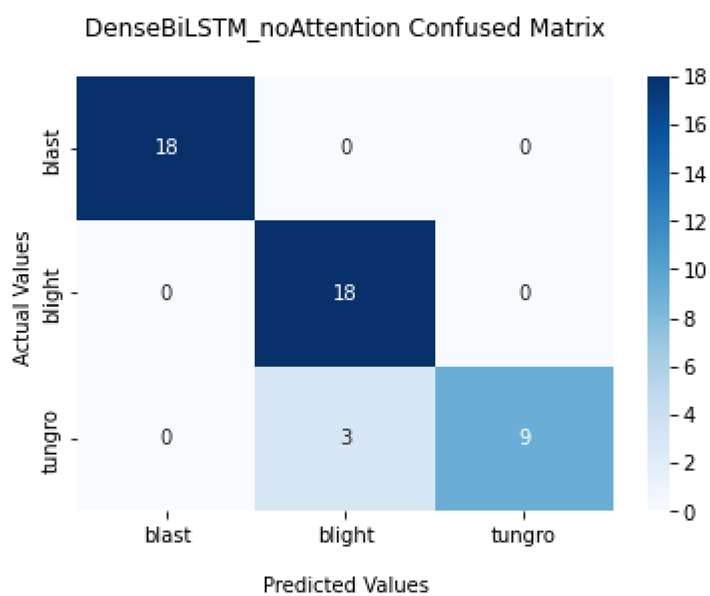
```
epochs = range(len(get_loss))
plt.plot(epochs, get_loss, 'r', label='Loss of Training data')
plt.plot(epochs, validation_loss, 'b', label='Loss of Validation data')
plt.title(f'{model_label} Training vs validation loss')
plt.legend(loc=0)
plt.figure()
plt.show()
```




```
<Figure size 432x288 with 0 Axes>
```

In [299]:
```
y_pred=model1.predict(testx)
pred=np.argmax(y_pred,axis=1)
ground = np.argmax(testy,axis=1)

conf_matrix = confusion_matrix(ground, pred)
ax = sb.heatmap(conf_matrix, annot=True, cmap='Blues')
ax.set_title(f'{model_label} Confused Matrix\n')
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ')
ax.xaxis.set_ticklabels(class_names)
ax.yaxis.set_ticklabels(class_names)
```

Out[299]:
```
[Text(0, 0.5, 'blast'), Text(0, 1.5, 'blight'), Text(0, 2.5, 'tungro')]
```



In [300]:
```
print(classification_report(ground,pred))
```

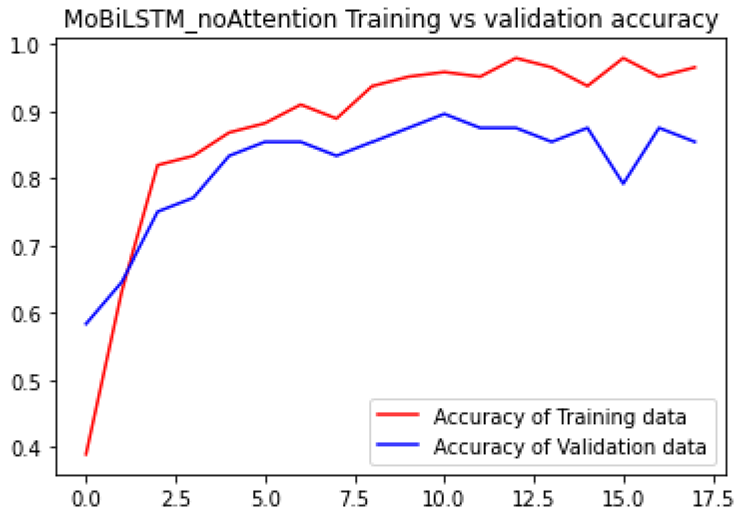
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        18
           1       0.86      1.00      0.92        18
           2       1.00      0.75      0.86        12

    accuracy                           0.94        48
   macro avg       0.95      0.92      0.93        48
weighted avg       0.95      0.94      0.94        48
```

In [302]:
```
model1.evaluate(x=ImageDataGenerator().flow(testx, testy, batch_size=32), verbose = 1)
```

```
2/2 [==============================] - 0s 146ms/step - loss: 0.1664 - accuracy: 0.9375
```

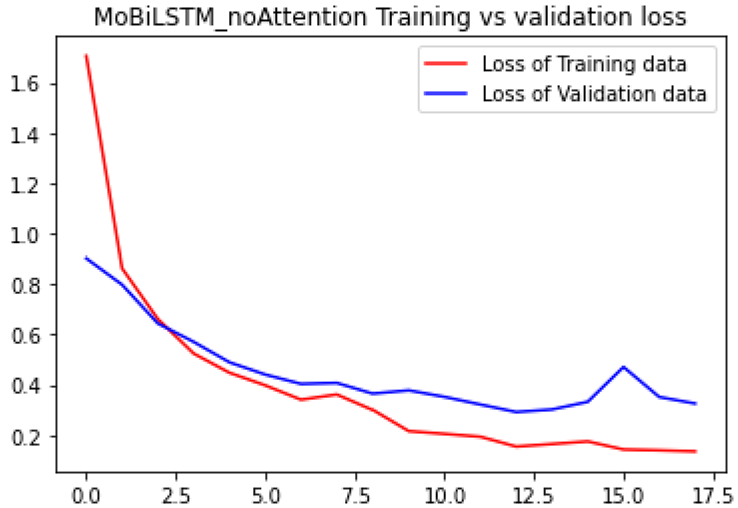
Out[302]:
```
[0.16636617481708527, 0.9375]
```

In [305]:
```
get_acc = history2.history['accuracy']
value_acc = history2.history['val_accuracy']
get_loss = history2.history['loss']
validation_loss = history2.history['val_loss']

epochs = range(len(get_acc))
plt.plot(epochs, get_acc, 'r', label='Accuracy of Training data')
plt.plot(epochs, value_acc, 'b', label='Accuracy of Validation data')
plt.title(f'{model_label2} Training vs validation accuracy')
plt.legend(loc=0)
plt.figure()
plt.show()
```




```
<Figure size 432x288 with 0 Axes>
```

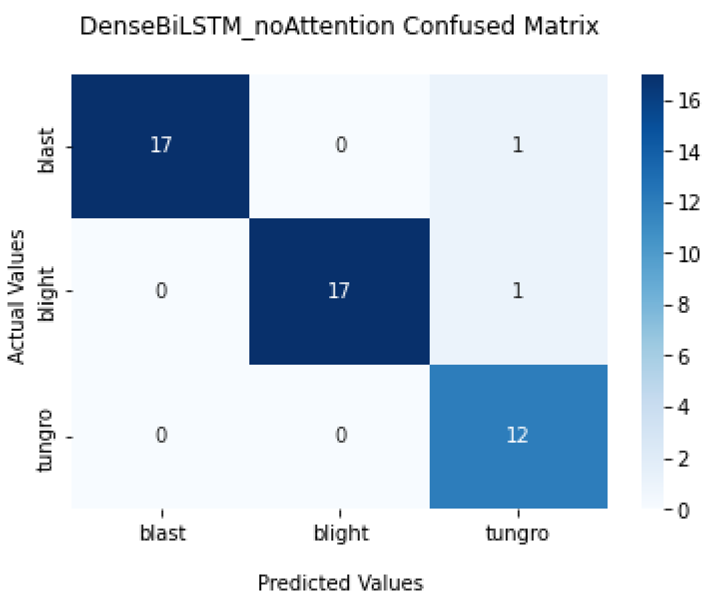
In [306]:
```
epochs = range(len(get_loss))
plt.plot(epochs, get_loss, 'r', label='Loss of Training data')
plt.plot(epochs, validation_loss, 'b', label='Loss of Validation data')
plt.title(f'{model_label2} Training vs validation loss')
plt.legend(loc=0)
plt.figure()
plt.show()
```




```
<Figure size 432x288 with 0 Axes>
```

In [307]:
```
y_pred=model2.predict(testx)
pred=np.argmax(y_pred,axis=1)
ground = np.argmax(testy,axis=1)

conf_matrix = confusion_matrix(ground, pred)
ax = sb.heatmap(conf_matrix, annot=True, cmap='Blues')
ax.set_title(f'{model_label} Confused Matrix\n')
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ')
ax.xaxis.set_ticklabels(class_names)
ax.yaxis.set_ticklabels(class_names)
```

Out[307]:
```
[Text(0, 0.5, 'blast'), Text(0, 1.5, 'blight'), Text(0, 2.5, 'tungro')]
```



In [308]:
```
print(classification_report(ground,pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.94      0.97        18
           1       1.00      0.94      0.97        18
           2       0.86      1.00      0.92        12

    accuracy                           0.96        48
   macro avg       0.95      0.96      0.96        48
weighted avg       0.96      0.96      0.96        48
```

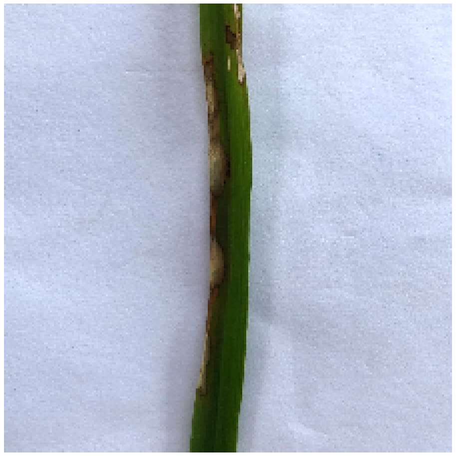
In [309]:
```
model2.evaluate(x=ImageDataGenerator().flow(testx, testy, batch_size=32), verbose = 1)
```

```
2/2 [==============================] - 0s 46ms/step - loss: 0.1961 - accuracy: 0.9583
```

Out[309]:
```
[0.19610244035720825, 0.9583333134651184]
```

In [310]:
```
image = load_img(f"{dataset_dir}/blight/IMG_1034.jpg",target_size=(224,224))
image
```

Out[310]:



In [311]:
```
image=img_to_array(image)
image=image/255.0
prediction_image=np.array(image)
prediction_image= np.expand_dims(image, axis=0)
```

In [312]:
```
prediction=model1.predict(prediction_image)
value=np.argmax(prediction)
move_name=mapper(value)
#print(prediction)
#print(value)
print("Prediction is {}.".format(move_name))
```

```
Prediction is blight.
```

In [313]:
```
prediction=model2.predict(prediction_image)
value=np.argmax(prediction)
move_name=mapper(value)
#print(prediction)
#print(value)
print("Prediction is {}.".format(move_name))
```

```
Prediction is blight.
```

Training with Attention

In [331]:
```
model1 = DenseBilstm(attention = True)
model1.summary()
```

```
conv5_block31_2_conv (Conv2D)   (None, 7, 7, 32)     36864       conv5_block31_1_relu[0][0]
__________________________________________________________________________________________________
conv5_block31_concat (Concatena (None, 7, 7, 1888)   0           conv5_block30_concat[0][0]
                                                                 conv5_block31_2_conv[0][0]
__________________________________________________________________________________________________
conv5_block32_0_bn (BatchNormal (None, 7, 7, 1888)   7552        conv5_block31_concat[0][0]
__________________________________________________________________________________________________
conv5_block32_0_relu (Activatio (None, 7, 7, 1888)   0           conv5_block32_0_bn[0][0]
__________________________________________________________________________________________________
conv5_block32_1_conv (Conv2D)   (None, 7, 7, 128)    241664      conv5_block32_0_relu[0][0]
__________________________________________________________________________________________________
conv5_block32_1_bn (BatchNormal (None, 7, 7, 128)    512         conv5_block32_1_conv[0][0]
__________________________________________________________________________________________________
conv5_block32_1_relu (Activatio (None, 7, 7, 128)    0           conv5_block32_1_bn[0][0]
__________________________________________________________________________________________________
conv5_block32_2_conv (Conv2D)   (None, 7, 7, 32)     36864       conv5_block32_1_relu[0][0]
__________________________________________________________________________________________________
conv5_block32_concat (Concatena (None, 7, 7, 1920)   0           conv5_block31_concat[0][0]
                                                                 conv5_block32_2_conv[0][0]
```

In [332]:

```
# model 1, DenseBiLSTM_Attention
model_label = "DenseBiLSTM_Attention"
history1 = model1.fit(
        x = datagen.flow(trainx,trainy,batch_size=16),
        validation_data = ImageDataGenerator().flow(validx, validy, batch_size=16),
        batch_size=32,
        epochs=50,
        callbacks=[early_stopping, ModelCheckPointCB(model_label), csv_logger],
        verbose=1,
    )
```

```
9/9 [==============================] - 2s 253ms/step - loss: 0.0799 - accuracy: 0.9722 - val_loss: 0.1545 -
val_accuracy: 0.9583

Epoch 00019: val_loss improved from 0.20733 to 0.15449, saving model to model_checkpoints\DenseBiLSTM_Attent
ion.h5
Epoch 20/50
9/9 [==============================] - 2s 256ms/step - loss: 0.0546 - accuracy: 0.9792 - val_loss: 0.3447 -
val_accuracy: 0.8958

Epoch 00020: val_loss did not improve from 0.15449
Epoch 21/50
9/9 [==============================] - 2s 254ms/step - loss: 0.0700 - accuracy: 0.9583 - val_loss: 0.3202 -
val_accuracy: 0.9583

Epoch 00021: val_loss did not improve from 0.15449
Epoch 22/50
9/9 [==============================] - 3s 272ms/step - loss: 0.1572 - accuracy: 0.9444 - val_loss: 0.3160 -
val_accuracy: 0.8958
```

In [ ]:

```
model2 = MoBilstm(attention = True)
model2.summary()
```

In [333]:
```
# model 2, DenseBiLSTM_Attention
model_label2 = "MoBiLSTM_Attention"
history2 = model2.fit(
        x = datagen.flow(trainx,trainy,batch_size=16),
        validation_data = ImageDataGenerator().flow(validx, validy, batch_size=16),
        batch_size=32,
        epochs=50,
        callbacks=[early_stopping, ModelCheckPointCB(model_label2), csv_logger],
        verbose=1,
    )
```

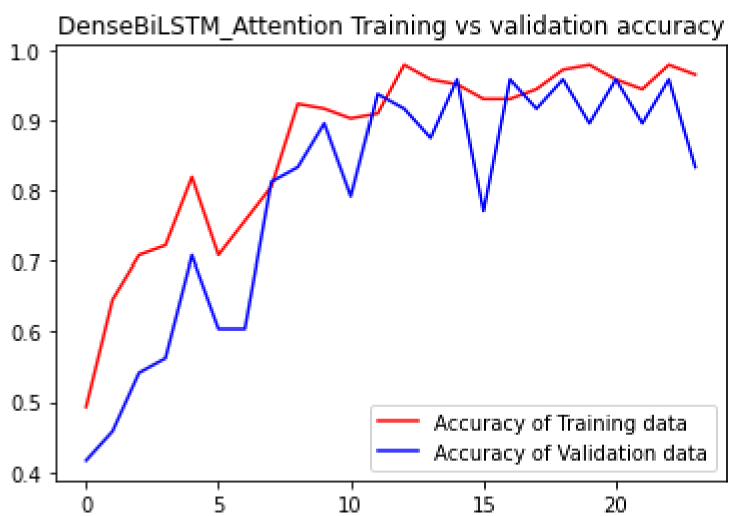
```
Epoch 1/50
9/9 [==============================] - 2s 228ms/step - loss: 0.2113 - accuracy: 0.9167 - val_loss: 0.3732 -
val_accuracy: 0.8542

Epoch 00001: val_loss improved from inf to 0.37319, saving model to model_checkpoints\MoBiLSTM_Attention.h5
Epoch 2/50
9/9 [==============================] - 2s 228ms/step - loss: 0.1329 - accuracy: 0.9514 - val_loss: 0.2458 -
val_accuracy: 0.8958

Epoch 00002: val_loss improved from 0.37319 to 0.24582, saving model to model_checkpoints\MoBiLSTM_Attentio
n.h5
Epoch 3/50
9/9 [==============================] - 2s 215ms/step - loss: 0.1284 - accuracy: 0.9583 - val_loss: 0.2903 -
val_accuracy: 0.8750

Epoch 00003: val_loss did not improve from 0.24582
Epoch 4/50
9/9 [==============================] - 2s 215ms/step - loss: 0.1183 - accuracy: 0.9722 - val_loss: 0.2886 -
val_accuracy: 0.8750

Epoch 00004: val_loss did not improve from 0.24582
Epoch 5/50
9/9 [==============================] - 2s 220ms/step - loss: 0.1452 - accuracy: 0.9444 - val_loss: 0.3040 -
val_accuracy: 0.8958

Epoch 00005: val_loss did not improve from 0.24582
Epoch 6/50
9/9 [==============================] - 2s 215ms/step - loss: 0.2006 - accuracy: 0.9306 - val_loss: 0.3005 -
val_accuracy: 0.8750

Epoch 00006: val_loss did not improve from 0.24582
```

```
Epoch 7/50
9/9 [==============================] - 2s 211ms/step - loss: 0.1505 - accuracy: 0.9653 - val_loss: 0.2739 -
val_accuracy: 0.8958

Epoch 00007: val_loss did not improve from 0.24582
Epoch 00007: early stopping
```

Data Presentation

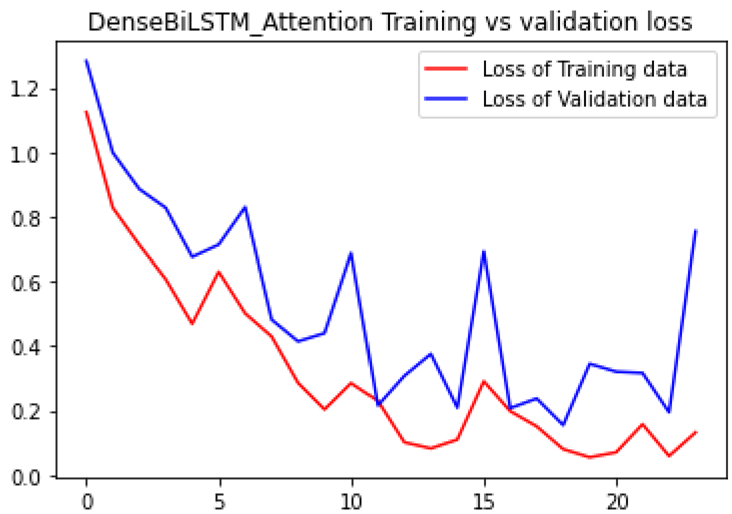
In [334]:

```python
get_acc = history1.history['accuracy']
value_acc = history1.history['val_accuracy']
get_loss = history1.history['loss']
validation_loss = history1.history['val_loss']

epochs = range(len(get_acc))
plt.plot(epochs, get_acc, 'r', label='Accuracy of Training data')
plt.plot(epochs, value_acc, 'b', label='Accuracy of Validation data')
plt.title(f'{model_label} Training vs validation accuracy')
plt.legend(loc=0)
plt.figure()
plt.show()
```




```
<Figure size 432x288 with 0 Axes>
```

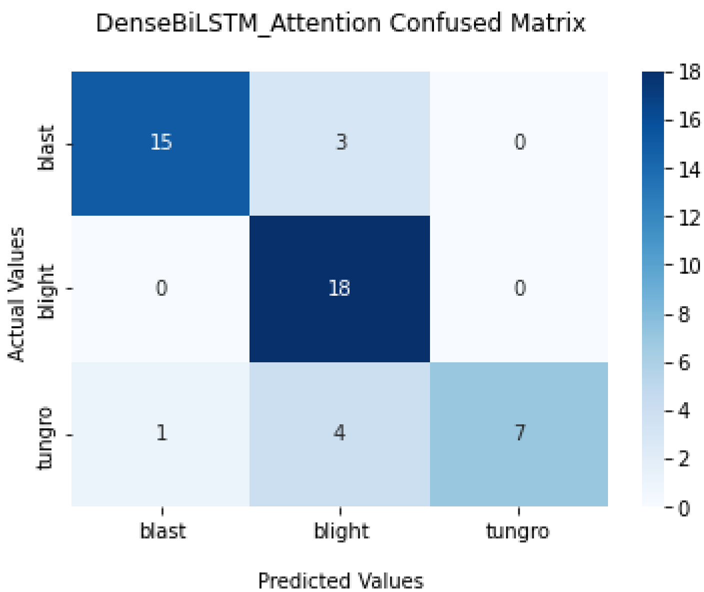
In [335]:
```
epochs = range(len(get_loss))
plt.plot(epochs, get_loss, 'r', label='Loss of Training data')
plt.plot(epochs, validation_loss, 'b', label='Loss of Validation data')
plt.title(f'{model_label} Training vs validation loss')
plt.legend(loc=0)
plt.figure()
plt.show()
```




```
<Figure size 432x288 with 0 Axes>
```

In [336]:
```
y_pred=model1.predict(testx)
pred=np.argmax(y_pred,axis=1)
ground = np.argmax(testy,axis=1)

conf_matrix = confusion_matrix(ground, pred)
ax = sb.heatmap(conf_matrix, annot=True, cmap='Blues')
ax.set_title(f'{model_label} Confused Matrix\n')
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ')
ax.xaxis.set_ticklabels(class_names)
ax.yaxis.set_ticklabels(class_names)
```

Out[336]:
```
[Text(0, 0.5, 'blast'), Text(0, 1.5, 'blight'), Text(0, 2.5, 'tungro')]
```



In [337]:
```
print(classification_report(ground,pred))
```

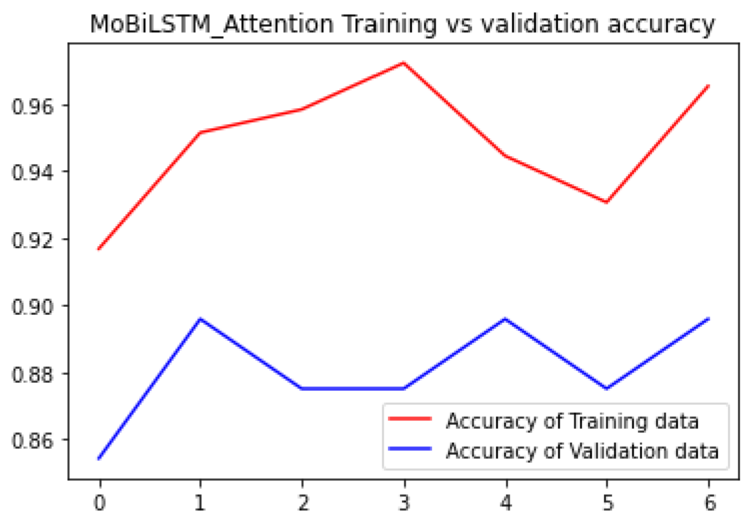
```
              precision    recall  f1-score   support

           0       0.94      0.83      0.88        18
           1       0.72      1.00      0.84        18
           2       1.00      0.58      0.74        12

    accuracy                           0.83        48
   macro avg       0.89      0.81      0.82        48
weighted avg       0.87      0.83      0.83        48
```

In [338]:
```
model1.evaluate(x=ImageDataGenerator().flow(testx, testy, batch_size=32), verbose = 1)
```

```
2/2 [==============================] - 0s 145ms/step - loss: 0.9462 - accuracy: 0.8333
```

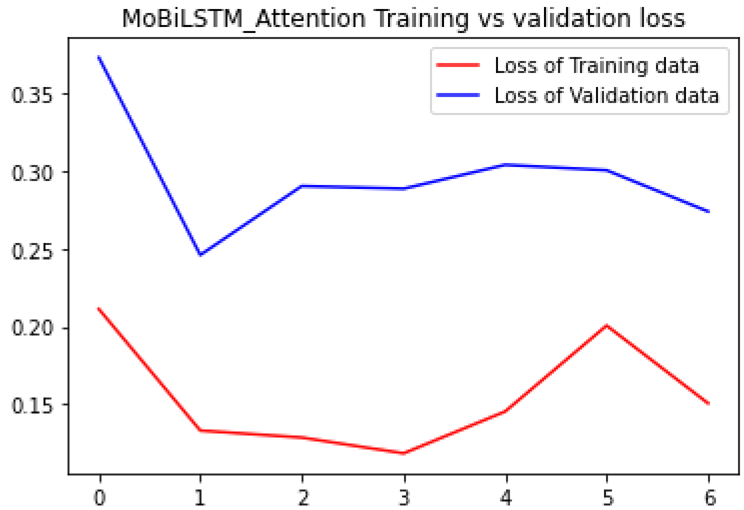
Out[338]:
```
[0.9461714625358582, 0.8333333134651184]
```

In [339]:
```
get_acc = history2.history['accuracy']
value_acc = history2.history['val_accuracy']
get_loss = history2.history['loss']
validation_loss = history2.history['val_loss']

epochs = range(len(get_acc))
plt.plot(epochs, get_acc, 'r', label='Accuracy of Training data')
plt.plot(epochs, value_acc, 'b', label='Accuracy of Validation data')
plt.title(f'{model_label2} Training vs validation accuracy')
plt.legend(loc=0)
plt.figure()
plt.show()
```




```
<Figure size 432x288 with 0 Axes>
```

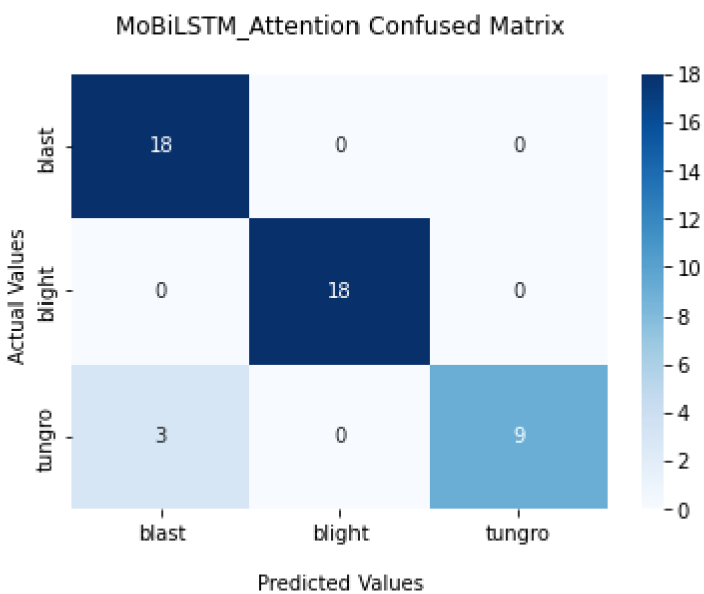
In [340]:
```
epochs = range(len(get_loss))
plt.plot(epochs, get_loss, 'r', label='Loss of Training data')
plt.plot(epochs, validation_loss, 'b', label='Loss of Validation data')
plt.title(f'{model_label2} Training vs validation loss')
plt.legend(loc=0)
plt.figure()
plt.show()
```




```
<Figure size 432x288 with 0 Axes>
```

In [342]:
```
y_pred=model2.predict(testx)
pred=np.argmax(y_pred,axis=1)
ground = np.argmax(testy,axis=1)

conf_matrix = confusion_matrix(ground, pred)
ax = sb.heatmap(conf_matrix, annot=True, cmap='Blues')
ax.set_title(f'{model_label2} Confused Matrix\n')
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ')
ax.xaxis.set_ticklabels(class_names)
ax.yaxis.set_ticklabels(class_names)
```

Out[342]:
```
[Text(0, 0.5, 'blast'), Text(0, 1.5, 'blight'), Text(0, 2.5, 'tungro')]
```



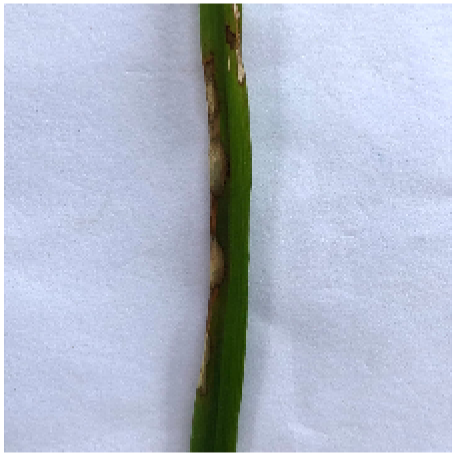
In [343]:
```
model2.evaluate(x=ImageDataGenerator().flow(testx, testy, batch_size=32), verbose = 1)
```

```
2/2 [==============================] - 0s 44ms/step - loss: 0.1735 - accuracy: 0.9375
```

Out[343]:
```
[0.1735318899154663, 0.9375]
```

In [344]:
```
image = load_img(f"{dataset_dir}/blight/IMG_1034.jpg",target_size=(224,224))
image
```

Out[344]:



In [345]:
```
image=img_to_array(image)
image=image/255.0
prediction_image=np.array(image)
prediction_image= np.expand_dims(image, axis=0)
```

In [346]:
```
prediction=model1.predict(prediction_image)
value=np.argmax(prediction)
move_name=mapper(value)
#print(prediction)
#print(value)
print("Prediction is {}.".format(move_name))
```

```
Prediction is blight.
```

In [347]:
```
prediction=model2.predict(prediction_image)
value=np.argmax(prediction)
move_name=mapper(value)
#print(prediction)
#print(value)
print("Prediction is {}.".format(move_name))
```

```
Prediction is blight.
```