

```

import datetime
cur_date=datetime.datetime.now()
print("current date and time",cur_date)

current date and time 2024-02-18 17:58:14.706974

from tensorflow.keras.preprocessing.image import img_to_array
from tensorflow.keras.applications import MobileNet
from tensorflow.keras.layers import AveragePooling2D
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Input
from tensorflow.keras.models import Model
from keras.models import Sequential

from sklearn.preprocessing import MultiLabelBinarizer
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report

import matplotlib.pyplot as plt
import numpy as np
import random
import cv2
import os
import h5py

from imutils import paths

imagePaths = sorted(list(paths.list_images("F:\\Paper6_vit+cnn\\
Groundnut_Leaf_dataset\\train1")))
#F:\\Paper6_vit+cnn\\Groundnut_Leaf_dataset\\train1
#D:\\G_Dataset_final\\Train
# random shuffle
random.seed(42)
random.shuffle(imagePaths)

data = []
labels = []
image_dims = (224, 224, 3)# 212 for xception model

for imagePath in imagePaths:
    image = cv2.imread(imagePath)
    image = cv2.resize(image, (image_dims[1], image_dims[0]))
    image = img_to_array(image)
    data.append(image)
    l = label = imagePath.split(os.path.sep)[-2].split("_")
    labels.append(l)

data = np.array(data, dtype="float") / 255.0
labels = np.array(labels)

```

```

print("{} images ({:.2f}MB)".format(len(imagePaths), data.nbytes /
(1024 * 1000.0)))

7910 images (9302.16MB)

data = np.array(data)
label = np.array(labels)
print(data.shape)

(7910, 224, 224, 3)

mlb = MultiLabelBinarizer()
labels = mlb.fit_transform(labels)
# total 4 labels
print("class labels:")
for (i, label) in enumerate(mlb.classes_):
    print("{} . {}".format(i + 1, label))

class labels:
1. ELS
2. ER
3. HL
4. LLS
5. ND
6. RUST

trainX, testX, trainY, testY = train_test_split(data, labels,
test_size=0.45) # (0.20)

from keras.applications import MobileNet #InceptionResNetV2
NASNetMobile InceptionV3 VGG19
inc=MobileNet(input_shape=(224,224,3),weights='imagenet',include_top=False)

for i in inc.layers:
    i.trainable=False

from tensorflow.keras import layers
x=Flatten()(inc.output)
#x=layers.Dropout(0.2)(x)

pred=Dense(6,activation='softmax')(x)

from keras.models import Model
model=Model(inputs=inc.input,outputs=pred)

model.summary()

Model: "model"

```

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

input_1 (InputLayer)	[(None, 224, 224, 3)]	0
conv1 (Conv2D)	(None, 112, 112, 32)	864
conv1_bn (BatchNormalizatio n)	(None, 112, 112, 32)	128
conv1_relu (ReLU)	(None, 112, 112, 32)	0
conv_dw_1 (DepthwiseConv2D)	(None, 112, 112, 32)	288
conv_dw_1_bn (BatchNormaliz ation)	(None, 112, 112, 32)	128
conv_dw_1_relu (ReLU)	(None, 112, 112, 32)	0
conv_pw_1 (Conv2D)	(None, 112, 112, 64)	2048
conv_pw_1_bn (BatchNormaliz ation)	(None, 112, 112, 64)	256
conv_pw_1_relu (ReLU)	(None, 112, 112, 64)	0
conv_pad_2 (ZeroPadding2D)	(None, 113, 113, 64)	0
conv_dw_2 (DepthwiseConv2D)	(None, 56, 56, 64)	576
conv_dw_2_bn (BatchNormaliz ation)	(None, 56, 56, 64)	256
conv_dw_2_relu (ReLU)	(None, 56, 56, 64)	0
conv_pw_2 (Conv2D)	(None, 56, 56, 128)	8192
conv_pw_2_bn (BatchNormaliz ation)	(None, 56, 56, 128)	512
conv_pw_2_relu (ReLU)	(None, 56, 56, 128)	0
conv_dw_3 (DepthwiseConv2D)	(None, 56, 56, 128)	1152
conv_dw_3_bn (BatchNormaliz ation)	(None, 56, 56, 128)	512
conv_dw_3_relu (ReLU)	(None, 56, 56, 128)	0
conv_pw_3 (Conv2D)	(None, 56, 56, 128)	16384
conv_pw_3_bn (BatchNormaliz	(None, 56, 56, 128)	512

ation)

conv\_pw\_3\_relu (ReLU) (None, 56, 56, 128) 0

conv\_pad\_4 (ZeroPadding2D) (None, 57, 57, 128) 0

conv\_dw\_4 (DepthwiseConv2D) (None, 28, 28, 128) 1152

conv\_dw\_4\_bn (BatchNormaliz  
ation) (None, 28, 28, 128) 512

conv\_dw\_4\_relu (ReLU) (None, 28, 28, 128) 0

conv\_pw\_4 (Conv2D) (None, 28, 28, 256) 32768

conv\_pw\_4\_bn (BatchNormaliz  
ation) (None, 28, 28, 256) 1024

conv\_pw\_4\_relu (ReLU) (None, 28, 28, 256) 0

conv\_dw\_5 (DepthwiseConv2D) (None, 28, 28, 256) 2304

conv\_dw\_5\_bn (BatchNormaliz  
ation) (None, 28, 28, 256) 1024

conv\_dw\_5\_relu (ReLU) (None, 28, 28, 256) 0

conv\_pw\_5 (Conv2D) (None, 28, 28, 256) 65536

conv\_pw\_5\_bn (BatchNormaliz  
ation) (None, 28, 28, 256) 1024

conv\_pw\_5\_relu (ReLU) (None, 28, 28, 256) 0

conv\_pad\_6 (ZeroPadding2D) (None, 29, 29, 256) 0

conv\_dw\_6 (DepthwiseConv2D) (None, 14, 14, 256) 2304

conv\_dw\_6\_bn (BatchNormaliz  
ation) (None, 14, 14, 256) 1024

conv\_dw\_6\_relu (ReLU) (None, 14, 14, 256) 0

conv\_pw\_6 (Conv2D) (None, 14, 14, 512) 131072

conv\_pw\_6\_bn (BatchNormaliz  
ation) (None, 14, 14, 512) 2048

conv\_pw\_6\_relu (ReLU) (None, 14, 14, 512) 0

conv_dw_7 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_7_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_dw_7_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_7 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_7_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_pw_7_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_8 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_8_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_dw_8_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_8 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_8_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_pw_8_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_9 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_9_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_dw_9_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_9 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_9_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_pw_9_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_10 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_10_bn (BatchNormalization)	(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 (BatchNormalization)	(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 (BatchNormalization)	(None, 14, 14, 512)	2048
conv_dw_11_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_11 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_11_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_pw_11_relu (ReLU)	(None, 14, 14, 512)	0
conv_pad_12 (ZeroPadding2D)	(None, 15, 15, 512)	0
conv_dw_12 (DepthwiseConv2D)	(None, 7, 7, 512)	4608
conv_dw_12_bn (BatchNormalization)	(None, 7, 7, 512)	2048
conv_dw_12_relu (ReLU)	(None, 7, 7, 512)	0
conv_pw_12 (Conv2D)	(None, 7, 7, 1024)	524288
conv_pw_12_bn (BatchNormalization)	(None, 7, 7, 1024)	4096
conv_pw_12_relu (ReLU)	(None, 7, 7, 1024)	0
conv_dw_13 (DepthwiseConv2D)	(None, 7, 7, 1024)	9216
conv_dw_13_bn (BatchNormalization)	(None, 7, 7, 1024)	4096
conv_dw_13_relu (ReLU)	(None, 7, 7, 1024)	0

conv_pw_13 (Conv2D)	(None, 7, 7, 1024)	1048576
conv_pw_13_bn (Batch Normalization)	(None, 7, 7, 1024)	4096
conv_pw_13_relu (ReLU)	(None, 7, 7, 1024)	0
flatten (Flatten)	(None, 50176)	0
dense (Dense)	(None, 6)	301062

```
=====
Total params: 3,529,926
Trainable params: 301,062
Non-trainable params: 3,228,864
=====
```

```
from tensorflow import keras
opt = keras.optimizers.Adam(learning_rate=0.001)
model.compile(optimizer=opt, loss='categorical_crossentropy', metrics=['accuracy'])
#model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
history=model.fit(trainX, trainY,
                  batch_size=16,
                  epochs=10,
                  verbose=1,
                  validation_data=(testX, testY))
```

```
Epoch 1/10
272/272 [=====] - 103s 375ms/step - loss: 1.8610 - accuracy: 0.8285 - val_loss: 0.9048 - val_accuracy: 0.9270
Epoch 2/10
272/272 [=====] - 99s 365ms/step - loss: 0.3354 - accuracy: 0.9646 - val_loss: 0.9264 - val_accuracy: 0.9219
Epoch 3/10
272/272 [=====] - 101s 370ms/step - loss: 0.3731 - accuracy: 0.9655 - val_loss: 1.0201 - val_accuracy: 0.9449
Epoch 4/10
272/272 [=====] - 100s 368ms/step - loss: 0.4369 - accuracy: 0.9694 - val_loss: 1.3725 - val_accuracy: 0.9365
Epoch 5/10
272/272 [=====] - 100s 367ms/step - loss: 0.2205 - accuracy: 0.9857 - val_loss: 1.8999 - val_accuracy: 0.9135
Epoch 6/10
272/272 [=====] - 100s 367ms/step - loss: 0.2275 - accuracy: 0.9828 - val_loss: 1.2530 - val_accuracy: 0.9458
Epoch 7/10
272/272 [=====] - 101s 373ms/step - loss:
```

```
0.1672 - accuracy: 0.9894 - val_loss: 1.0155 - val_accuracy: 0.9508
Epoch 8/10
272/272 [=====] - 101s 371ms/step - loss:
0.1538 - accuracy: 0.9908 - val_loss: 3.0135 - val_accuracy: 0.9129
Epoch 9/10
272/272 [=====] - 102s 374ms/step - loss:
0.2772 - accuracy: 0.9855 - val_loss: 1.1140 - val_accuracy: 0.9551
Epoch 10/10
272/272 [=====] - 100s 370ms/step - loss:
0.1629 - accuracy: 0.9908 - val_loss: 2.0874 - val_accuracy: 0.9272
```

```
print("[INF0] evaluating network...")
predIdxs = model.predict(testX, batch_size=16)

# for each image in the testing set we need to find the index of the
# label with corresponding largest predicted probability
predIdxs = np.argmax(predIdxs, axis=1)

# show a nicely formatted classification report
print(classification_report(testY.argmax(axis=1),
predIdxs,target_names=mlb.classes_))
```

```
[INF0] evaluating network...
223/223 [=====] - 55s 243ms/step
```

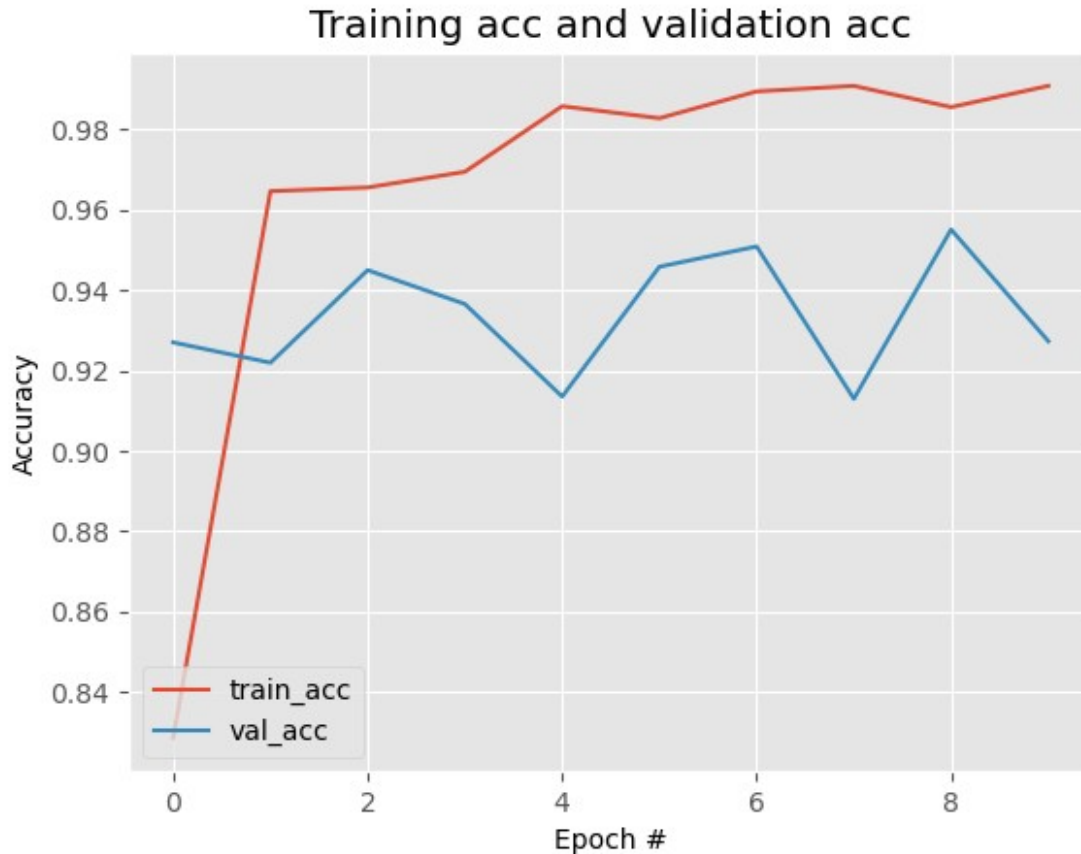
	precision	recall	f1-score	support
ELS	0.97	0.72	0.83	592
ER	1.00	0.96	0.98	478
HL	0.94	0.95	0.95	677
LLS	0.83	0.96	0.89	655
ND	0.89	0.97	0.93	557
RUST	0.99	1.00	0.99	601
accuracy			0.93	3560
macro avg	0.94	0.93	0.93	3560
weighted avg	0.93	0.93	0.93	3560

```
N = 10
plt.style.use("ggplot")
plt.figure()
#plt.plot(np.arange(0, N), H.history["loss"], label="train_loss")
#plt.plot(np.arange(0, N), H.history["val_loss"], label="val_loss")
plt.plot(np.arange(0, N), history.history["accuracy"],
label="train_acc")
plt.plot(np.arange(0, N), history.history["val_accuracy"],
label="val_acc")
plt.title("Training acc and validation acc")
plt.xlabel("Epoch #")
```



```
plt.ylabel("Accuracy")
plt.legend(loc="lower left")

<matplotlib.legend.Legend at 0x210c2fee4a0>
```



```
N = 10
plt.style.use("ggplot")
plt.figure()
plt.plot(np.arange(0, N), history.history["loss"], label="train_loss")
plt.plot(np.arange(0, N), history.history["val_loss"],
label="val_loss")
#plt.plot(np.arange(0, N), H.history["accuracy"], label="train_acc")
#plt.plot(np.arange(0, N), H.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and validation loss")
plt.xlabel("Epoch #")
plt.ylabel("Loss")
plt.legend(loc="lower left")

<matplotlib.legend.Legend at 0x210c38a8b20>
```



```
from sklearn.metrics import confusion_matrix
print(confusion_matrix(testY.argmax(axis=1), predIdxs))
```

```
[[426   0  23 120  21   2]
 [  0 461   0   9   5   3]
 [  1   0 646   0  30   0]
 [ 10   0   3 628  10   4]
 [  1   0  14   0 542   0]
 [  0   2   0   1   0 598]]
```

*#Import the necessary libraries*

```
import numpy as np
```

```
from sklearn.metrics import confusion_matrix
```

```
import seaborn as sns
```

```
import matplotlib.pyplot as plt
```

```
plt.figure(figsize=(6, 6))
```

*#compute the confusion matrix.*

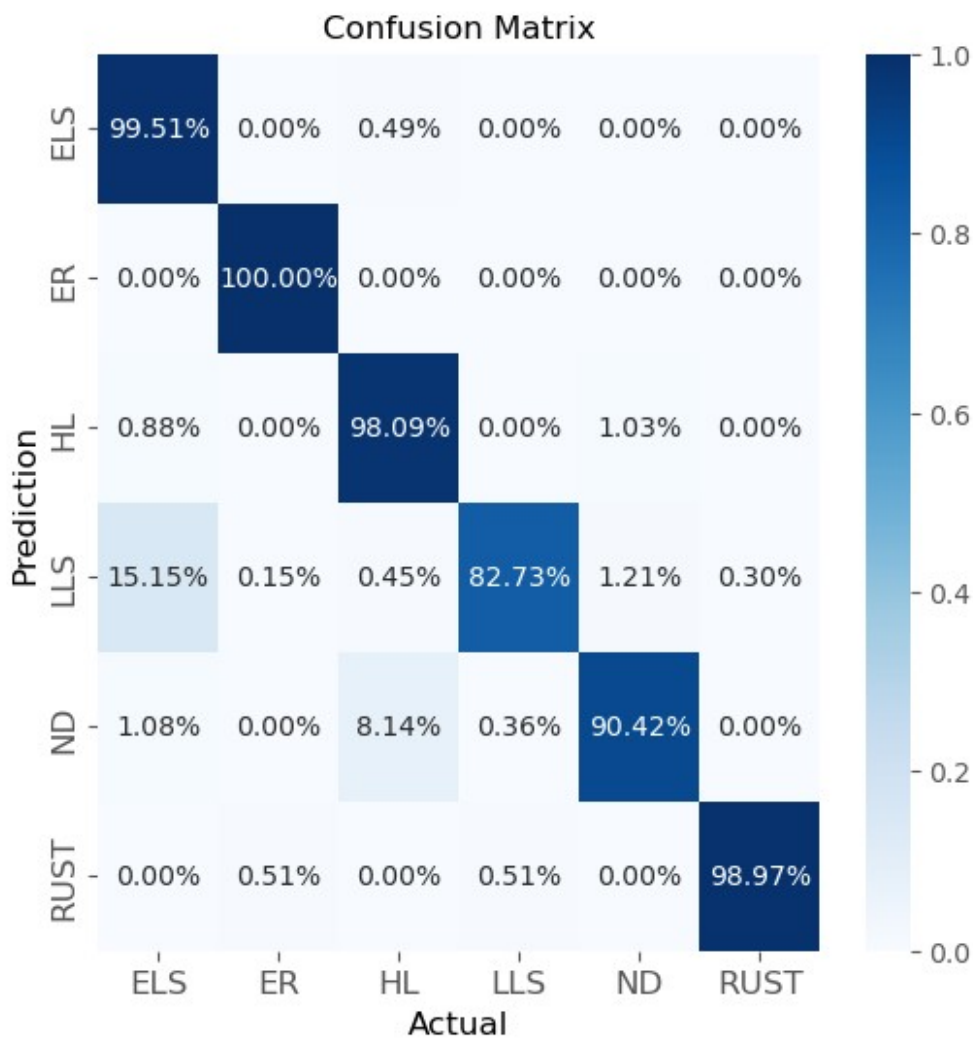
```
#cm = confusion_matrix(testY.argmax(axis=1), predIdxs)
```

```
cm=np.array([[612,0,3,0,0,0],
             [0,468,0,0,0,0],
             [6,0,667,0,7,0],
```

```

[100,1,3,546,8,2],
[6,0,45,2,500,0],
[0,3,0,3,0, 578]])
#Plot the confusion matrix.
sns.heatmap(cm/np.sum(cm,axis=1).reshape(-
1,1),cmap='Blues',annot=True,fmt='.2%',xticklabels=['ELS','ER','HL','L
LS','ND','RUST'],yticklabels=['ELS','ER','HL','LLS','ND','RUST'])
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.ylabel('Prediction',fontsize=12)
plt.xlabel('Actual',fontsize=12)
plt.title('Confusion Matrix',fontsize=12)
#plt.savefig('F:/paper_3_code_files_final/results/results1/mobilenet_C
M.jpg',dpi=600)
plt.show()

```



```

from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
precision_score(testY.argmax(axis=1), predIdxs, average='micro')

0.927247191011236

recall = recall_score(testY.argmax(axis=1), predIdxs, average='micro')
print('recall=', recall)

recall= 0.927247191011236

from sklearn.metrics import f1_score
f1_score(testY.argmax(axis=1), predIdxs, average='micro')

0.927247191011236

from sklearn.metrics import matthews_corrcoef
from sklearn.metrics import balanced_accuracy_score
a=matthews_corrcoef(testY.argmax(axis=1), predIdxs)
b=balanced_accuracy_score(testY.argmax(axis=1), predIdxs)
print(a)
print(b)

0.914045809949668
0.9275160755508924

from sklearn.manifold import TSNE
# Extract the features from the last layer of the CNN
features = model.predict(trainX)
# Reduce the dimensionality of the features using t-SNE
tsne = TSNE(n_components=2, perplexity=30.0, early_exaggeration=12.0,
learning_rate=200.0, n_iter=1000, n_iter_without_progress=300,
min_grad_norm=1e-07, metric='euclidean', metric_params=None,
init='pca', verbose=0, random_state=None, method='barnes_hut',
angle=0.5, n_jobs=None)
features_embedded = tsne.fit_transform(features)

136/136 [=====] - 66s 482ms/step

# Plot the results
ax=plt.axes()
ax.set_facecolor("white")
plt.scatter(features_embedded[:, 0], features_embedded[:, 1], c=
trainY.argmax(axis=1))
#plt.axis('off')
#plt.savefig('F:/Paper6_vit+cnn/results/P6_Xception_TSNE.pdf', dpi=600)
#plt.savefig('F:/Paper6_vit+cnn/results/updated_results/P6_Xception_TS
NE.png', dpi=600)
#plt.legend()
plt.grid(False)

plt.show()

```



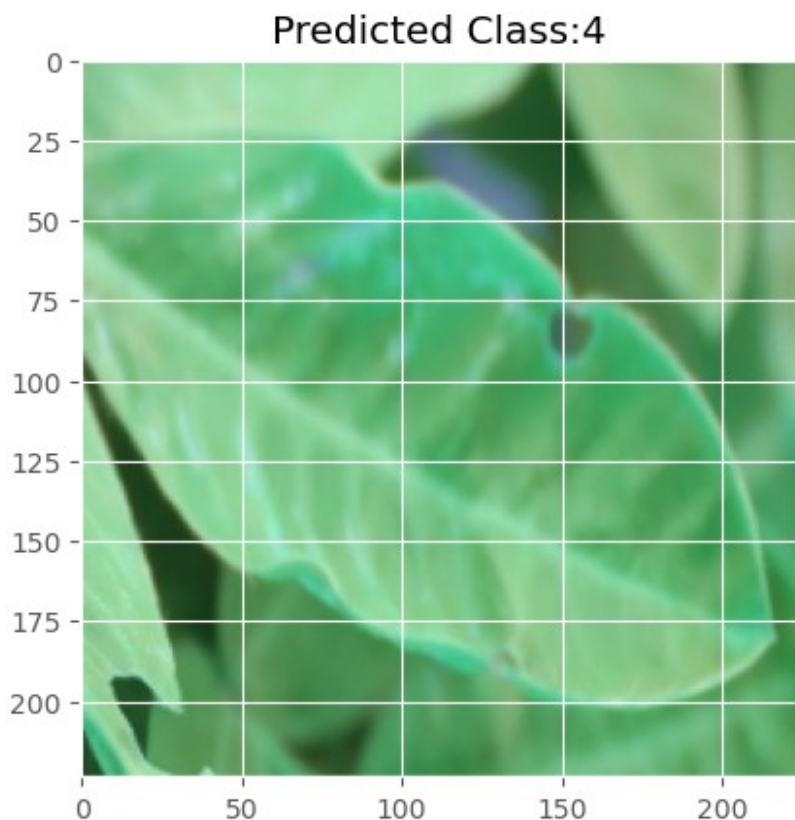
```
import lime
from lime import lime_image

# Choose an image from the test set for explanation
image_index = 20
img = testX[image_index]
img_array = np.expand_dims(img, axis=0)

# Make predictions
predictions = model.predict(img_array)
predicted_class = np.argmax(predictions)

# Display the original image and predictions
plt.imshow(img.reshape(224, 224, 3))
plt.title(f'Predicted Class:{predicted_class}')
plt.show()

1/1 [=====] - 0s 73ms/step
```



```
# Create a LIME explainer for image classification
explainer = lime_image.LimeImageExplainer()

# Explain predictions
explanation = explainer.explain_instance(img_array[0], model.predict,
top_labels=1, hide_color=0, num_samples=1000)

{"model_id":"5af440789aa44dbd8bdd78c37aa5c399","version_major":2,"version_minor":0}

1/1 [=====] - 0s 157ms/step
1/1 [=====] - 0s 159ms/step
1/1 [=====] - 0s 174ms/step
1/1 [=====] - 0s 218ms/step
1/1 [=====] - 0s 167ms/step
1/1 [=====] - 0s 172ms/step
1/1 [=====] - 0s 156ms/step
1/1 [=====] - 0s 203ms/step
1/1 [=====] - 0s 231ms/step
1/1 [=====] - 0s 183ms/step
1/1 [=====] - 0s 200ms/step
1/1 [=====] - 0s 146ms/step
1/1 [=====] - 0s 231ms/step
1/1 [=====] - 0s 156ms/step
```

1/1	[=====]	- 0s 138ms/step
1/1	[=====]	- 0s 135ms/step
1/1	[=====]	- 0s 175ms/step
1/1	[=====]	- 0s 159ms/step
1/1	[=====]	- 0s 152ms/step
1/1	[=====]	- 0s 158ms/step
1/1	[=====]	- 0s 168ms/step
1/1	[=====]	- 0s 156ms/step
1/1	[=====]	- 0s 140ms/step
1/1	[=====]	- 0s 142ms/step
1/1	[=====]	- 0s 156ms/step
1/1	[=====]	- 0s 167ms/step
1/1	[=====]	- 0s 159ms/step
1/1	[=====]	- 0s 137ms/step
1/1	[=====]	- 0s 159ms/step
1/1	[=====]	- 0s 170ms/step
1/1	[=====]	- 0s 172ms/step
1/1	[=====]	- 0s 148ms/step
1/1	[=====]	- 0s 153ms/step
1/1	[=====]	- 0s 145ms/step
1/1	[=====]	- 0s 156ms/step
1/1	[=====]	- 0s 137ms/step
1/1	[=====]	- 0s 144ms/step
1/1	[=====]	- 0s 150ms/step
1/1	[=====]	- 0s 156ms/step
1/1	[=====]	- 0s 187ms/step
1/1	[=====]	- 0s 142ms/step
1/1	[=====]	- 0s 139ms/step
1/1	[=====]	- 0s 153ms/step
1/1	[=====]	- 0s 172ms/step
1/1	[=====]	- 0s 149ms/step
1/1	[=====]	- 0s 138ms/step
1/1	[=====]	- 0s 145ms/step
1/1	[=====]	- 0s 158ms/step
1/1	[=====]	- 0s 144ms/step
1/1	[=====]	- 0s 140ms/step
1/1	[=====]	- 0s 130ms/step
1/1	[=====]	- 0s 144ms/step
1/1	[=====]	- 0s 156ms/step
1/1	[=====]	- 0s 145ms/step
1/1	[=====]	- 0s 134ms/step
1/1	[=====]	- 0s 145ms/step
1/1	[=====]	- 0s 139ms/step
1/1	[=====]	- 0s 156ms/step
1/1	[=====]	- 0s 149ms/step
1/1	[=====]	- 0s 142ms/step
1/1	[=====]	- 0s 146ms/step
1/1	[=====]	- 0s 154ms/step
1/1	[=====]	- 0s 141ms/step

```

1/1 [=====] - 0s 144ms/step
1/1 [=====] - 0s 140ms/step
1/1 [=====] - 0s 147ms/step
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1/1 [=====] - 0s 140ms/step
1/1 [=====] - 0s 156ms/step
1/1 [=====] - 0s 140ms/step
1/1 [=====] - 0s 130ms/step
1/1 [=====] - 0s 129ms/step
1/1 [=====] - 0s 152ms/step
1/1 [=====] - 0s 142ms/step
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1/1 [=====] - 0s 143ms/step
1/1 [=====] - 0s 143ms/step
1/1 [=====] - 0s 144ms/step

```

*# explain predictions*

```

explanation=explainer.explain_instance(img_array[0],model.predict,top_
labels=1,hide_color=0,num_samples=1000)

```

```

{"model_id":"38e09d9565ef41299869c41a966823ce","version_major":2,"vers
ion_minor":0}

```

```

1/1 [=====] - 0s 141ms/step
1/1 [=====] - 0s 156ms/step
1/1 [=====] - 0s 150ms/step
1/1 [=====] - 0s 146ms/step
1/1 [=====] - 0s 141ms/step

```



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1/1 [=====] - 0s 158ms/step
1/1 [=====] - 0s 161ms/step
1/1 [=====] - 0s 167ms/step
1/1 [=====] - 0s 201ms/step
1/1 [=====] - 0s 220ms/step
1/1 [=====] - 0s 186ms/step
1/1 [=====] - 0s 202ms/step
1/1 [=====] - 0s 185ms/step
1/1 [=====] - 0s 197ms/step
1/1 [=====] - 0s 160ms/step
1/1 [=====] - 0s 143ms/step
1/1 [=====] - 0s 140ms/step
1/1 [=====] - 0s 135ms/step
1/1 [=====] - 0s 156ms/step
1/1 [=====] - 0s 132ms/step
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1/1 [=====] - 0s 146ms/step
1/1 [=====] - 0s 138ms/step
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1/1 [=====] - 0s 141ms/step
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1/1 [=====] - 0s 155ms/step
1/1 [=====] - 0s 151ms/step
1/1 [=====] - 0s 139ms/step

```

```

#visualise LIME explanations with cv2.polylines

```

```

temp,mask=explanation.get_image_and_mask(explanation.top_labels[0],
positive_only=False,num_features=5,hide_rest=False)

```

```

#convert temp to uint8 for cv2.polylines
temp=(temp/2+0.5*mask[:, :, np.newaxis])*255
temp=temp.astype(np.uint8)

#find contours in the mask
contours, _=cv2.findContours(mask.astype(np.uint8), cv2.RETR_EXTERNAL, cv
2.CHAIN_APPROX_SIMPLE)

#Draw contours on the image
cv2.polylines(temp, contours, isClosed=False, color=(0, 255, 0), thickness=2
)

array([[ [ 66,  98,  73],
        [ 66,  98,  73],
        [ 66,  97,  72],
        ...,
        [249, 213, 184],
        [  0, 255,  0],
        [  0, 255,  0]],

       [[ [ 66,  97,  72],
        [ 66,  97,  72],
        [ 66,  97,  72],
        ...,
        [249, 213, 185],
        [  0, 255,  0],
        [  0, 255,  0]],

       [[ [ 66,  97,  72],
        [ 66,  97,  72],
        [ 66,  97,  72],
        ...,
        [249, 214, 185],
        [  0, 255,  0],
        [  0, 255,  0]],

       ...,

       [[ [ 11,  33,  16],
        [ 13,  33,  17],
        [ 17,  37,  20],
        ...,
        [249, 213, 180],
        [249, 212, 180],
        [249, 212, 180]],

       [[ [ 13,  32,  16],
        [ 15,  34,  18],
        [ 17,  36,  19],
        ...,

```

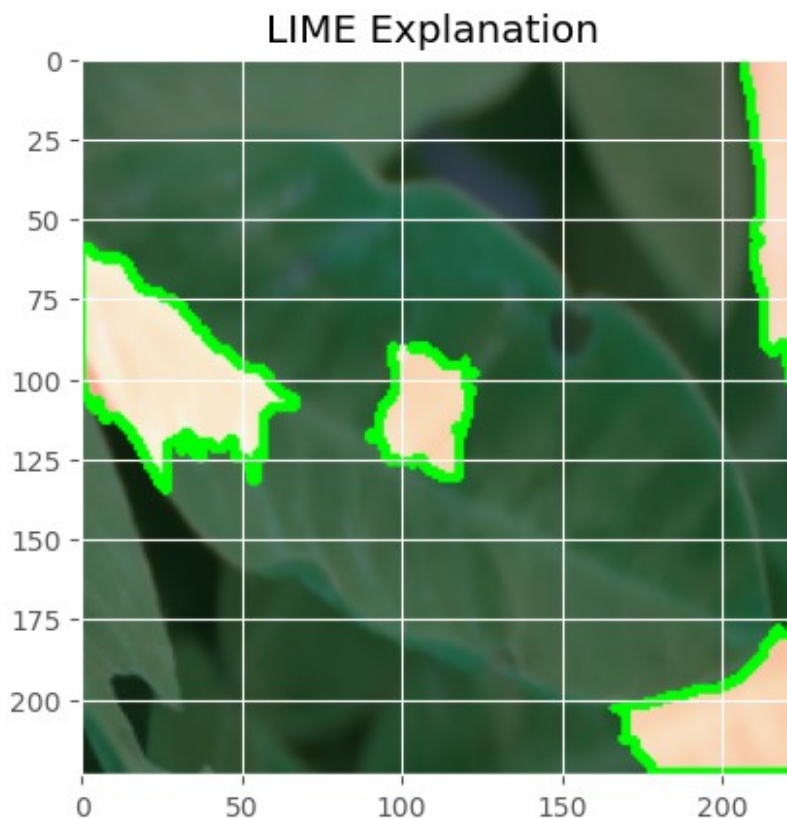
```

    [ 0, 255, 0],
    [ 0, 255, 0],
    [ 0, 255, 0]],

    [[ 16, 33, 17],
     [ 15, 33, 17],
     [ 17, 36, 19],
     ...,
     [ 0, 255, 0],
     [ 0, 255, 0],
     [ 0, 255, 0]]], dtype=uint8)

#display the image
plt.imshow(temp)
plt.title('LIME Explanation ')
#plt.savefig('F:/Paper6_vit+cnn/results/P6_proposed_lime1.jpg',dpi=600
)
plt.show()

```



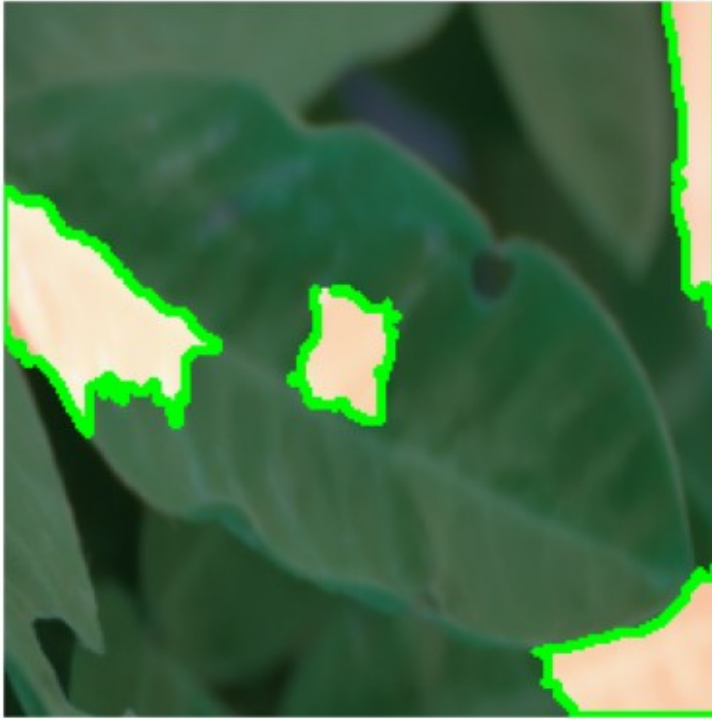
```

# Code for turning off x and y labels
plt.imshow(temp)
plt.title('LIME Explanation ')
plt.xticks([]) # Turn off x labels
plt.yticks([]) # Turn off y labels

```

```
#plt.savefig('F:/Paper6_vit+cnn/results/P6_Xception_lime.jpg',  
dpi=600)  
plt.show()
```

### LIME Explanation



```
import datetime  
cur_date=datetime.datetime.now()  
print("current date and time",cur_date)  
current date and time 2024-02-18 18:26:07.315914
```