

In [1]:

```
1 import pandas as pd
2 import numpy as np
3 import os
4 import cv2
5 import matplotlib.pyplot as plt
```

In [2]:

```
1 from zipfile import ZipFile
2 ZipFile("flowers-new.zip").extractall("C:/Users/Acer")
```

In [3]:

```
1 X=[]
2 y=[]
```

In [4]:

```
1 def readingFiles(folderpath, foldername):
2     #os.listdir - get names of files inside a folder
3     paths = os.path.join(folderpath, foldername)
4
5
6     for img in os.listdir(paths):
7         #read first file name
8         filepath = os.path.join(paths, img)
9         #read image
10        img_read = cv2.imread(filepath, cv2.IMREAD_COLOR)
11        #resize image
12        img_resized = cv2.resize(img_read, (256,256))
13        #convert to numpy
14        img_np = np.array(img_resized)
15        #add to X
16        X.append(img_np)
17        #add foldername as label to y
18        y.append(foldername)
```

In [5]:

```
1 folderpath='flowers/'
2
3 flowername = os.listdir('flowers/')
```

In [6]:

```
1 for i in flowername:
2     readingFiles(folderpath, i)
```

In [7]:

```
1 X
```

Out[7]:

```
[array([[133, 135, 135],
        [138, 139, 139],
        [144, 144, 144],
        ...,
        [152, 154, 154],
        [155, 155, 155],
        [149, 149, 149]]],

       [[132, 134, 134],
        [136, 138, 138],
        [142, 143, 143],
        ...,
        [152, 154, 154],
        [155, 155, 155],
        [149, 149, 149]]],

       [[131, 133, 133],
        [136, 138, 138].
```

In [8]:

```
1 y
```

Out[8]:

```
['daisy',  
'daisy',  
'daisy',  
'daisy',  
'daisy',  
'daisy',  
'daisy',  
'daisy',  
'daisy',  
'daisy',  
'daisy',  
'daisy',  
'daisy',  
'daisy',  
'daisy',  
'dandelion',  
'dandelion',  
'dandelion',  
'dandelion',  
'dandelion'.
```

In [9]:

```
1 len(X)
```

Out[9]:

117

In [10]:

```
1 from sklearn.preprocessing import LabelEncoder  
2 from tensorflow.keras.utils import to_categorical  
3  
4 enc = LabelEncoder()  
5 y_le = enc.fit_transform(y)  
6
```

In [11]:

```
1 enc
```

Out[11]:

```
▼ LabelEncoder  
LabelEncoder()
```

In [12]:

```
1 y_le
```

Out[12]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1,  
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2,  
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 3,  
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,  
       3, 3, 3, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,  
       4, 4, 4, 4, 4, 4, 4], dtype=int64)
```

In [13]:

```
1 y_ohe = to_categorical(y_le, num_classes=5)  
2 X_np = np.array(X)  
3 y_np = np.array(y_ohe)  
4
```

In [14]:

```
1 y_ohe
```

Out[14]:

```
array([[1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 1., 0., 0., 0.]])
```

In [15]:

```
1 y_ohe.shape
```

Out[15]:

```
(117, 5)
```

In [16]:

```
1 X_np
```

Out[16]:

```
array([[[133, 135, 135],
        [138, 139, 139],
        [144, 144, 144],
        ...,
        [152, 154, 154],
        [155, 155, 155],
        [149, 149, 149]],
       [[132, 134, 134],
        [136, 138, 138],
        [142, 143, 143],
        ...,
        [152, 154, 154],
        [155, 155, 155],
        [149, 149, 149]],
       [[131, 133, 133],
        [136, 138, 138],
        [142, 143, 143],
        ...,
        [152, 154, 154],
        [155, 155, 155],
        [149, 149, 149]]])
```

In [17]:

```
1 X_np.shape
```

Out[17]:

```
(117, 256, 3)
```

In [18]:

```
1 X_scaled = X_np / 255.0
2
```

In [19]:

```
1 X_scaled
```

Out[19]:

```
array([[ [0.52156863, 0.52941176, 0.52941176],
        [0.54117647, 0.54509804, 0.54509804],
        [0.56470588, 0.56470588, 0.56470588],
        ...,
        [0.59607843, 0.60392157, 0.60392157],
        [0.60784314, 0.60784314, 0.60784314],
        [0.58431373, 0.58431373, 0.58431373]],

       [ [0.51764706, 0.5254902 , 0.5254902 ],
        [0.53333333, 0.54117647, 0.54117647],
        [0.55686275, 0.56078431, 0.56078431],
        ...,
        [0.59607843, 0.60392157, 0.60392157],
        [0.60784314, 0.60784314, 0.60784314],
        [0.58431373, 0.58431373, 0.58431373]],

       [ [0.51372549, 0.52156863, 0.52156863],
        [0.53333333, 0.54117647, 0.54117647],
```

In [20]:

```
1 X_scaled.shape
2
```

Out[20]:

```
(117, 256, 256, 3)
```

In [21]:

```
1 y_np.shape
```

Out[21]:

```
(117, 5)
```

In [22]:

```
1 test_size=0.2
2 random_state=34
3 shuffle=True
4 stratify=y_np
```

In [23]:

```
1 from sklearn.model_selection import train_test_split
2 Xtrain, Xtest, ytrain, ytest = train_test_split(X_scaled, y_np, test_size=0.2, random_state=34, shuffle=True, stratify=y_np)
3
```

In [24]:

```
1 Xtrain, Xval, ytrain, yval = train_test_split(Xtrain, ytrain, test_size=0.2, random_state=34, shuffle=True, stratify=ytrain)
```

In [25]:

```
1 Xtrain.shape
```

Out[25]:

```
(74, 256, 256, 3)
```

In [26]:

```
1 Xval.shape
```

Out[26]:

```
(19, 256, 256, 3)
```

In [27]:

```
1 ytrain.shape
```

Out[27]:

```
(74, 5)
```

In [28]:

```
1 Xtest.shape
```

Out[28]:

```
(24, 256, 256, 3)
```

In [29]:

```
1 yval.shape
```

Out[29]:

```
(19, 5)
```

## ANN#

In [30]:

```
1 from keras.models import Sequential
2 from keras.layers import Dense, Flatten
```

In [31]:

```
1 flowerANN = Sequential()
```

In [32]:

```
1 flowerANN.add(Flatten())
```

In [33]:

```
1 #256*256*3 - input dimensions
2 flowerANN.add(Dense(units=1024, activation='relu'))
3 #final layer - classification problem with 5 classes
4 flowerANN.add(Dense(units=5, activation='softmax'))
```

In [34]:

```
1 flowerANN.compile(loss='categorical_crossentropy', metrics=['accuracy'], optimizer='adam')
```

In [35]:

```
from keras.callbacks import ModelCheckpoint
2
mc = ModelCheckpoint(filepath='D:\\Ashwini\\IMAGE\\bestModel.h5', monitor='val_accuracy', mode='max', verbose=1, save_best_only=True)
```

In [36]:

```
1 history = flowerANN.fit(Xtrain, ytrain, epochs=10, validation_data=(Xval, yval), callbacks=[mc])
```

Epoch 1/10  
3/3 [=====] - ETA: 0s - loss: 267.8847 - accuracy: 0.1757  
Epoch 1: val\_accuracy improved from -inf to 0.21053, saving model to D:\Ashwini\IMAGE\bestModel.h5  
3/3 [=====] - 21s 5s/step - loss: 267.8847 - accuracy: 0.1757 - val\_loss: 475.1231 - val\_accuracy: 0.2105  
Epoch 2/10  
3/3 [=====] - ETA: 0s - loss: 392.5522 - accuracy: 0.2703  
Epoch 2: val\_accuracy improved from 0.21053 to 0.31579, saving model to D:\Ashwini\IMAGE\bestModel.h5  
3/3 [=====] - 11s 4s/step - loss: 392.5522 - accuracy: 0.2703 - val\_loss: 207.6998 - val\_accuracy: 0.3158  
Epoch 3/10  
3/3 [=====] - ETA: 0s - loss: 241.7541 - accuracy: 0.3243  
Epoch 3: val\_accuracy did not improve from 0.31579  
3/3 [=====] - 9s 3s/step - loss: 241.7541 - accuracy: 0.3243 - val\_loss: 222.8740 - val\_accuracy: 0.3158  
Epoch 4/10  
3/3 [=====] - ETA: 0s - loss: 213.7950 - accuracy: 0.4595  
Epoch 4: val\_accuracy improved from 0.31579 to 0.36842, saving model to D:\Ashwini\IMAGE\bestModel.h5  
3/3 [=====] - 11s 4s/step - loss: 213.7950 - accuracy: 0.4595 - val\_loss: 112.8398 - val\_accuracy: 0.3684  
Epoch 5/10  
3/3 [=====] - ETA: 0s - loss: 117.1641 - accuracy: 0.5270  
Epoch 5: val\_accuracy did not improve from 0.36842  
3/3 [=====] - 7s 2s/step - loss: 117.1641 - accuracy: 0.5270 - val\_loss: 100.9803 - val\_accuracy: 0.3158  
Epoch 6/10  
3/3 [=====] - ETA: 0s - loss: 85.4432 - accuracy: 0.5270  
Epoch 6: val\_accuracy did not improve from 0.36842  
3/3 [=====] - 7s 2s/step - loss: 85.4432 - accuracy: 0.5270 - val\_loss: 59.0970 - val\_accuracy: 0.3684  
Epoch 7/10  
3/3 [=====] - ETA: 0s - loss: 39.6178 - accuracy: 0.5000  
Epoch 7: val\_accuracy did not improve from 0.36842  
3/3 [=====] - 8s 3s/step - loss: 39.6178 - accuracy: 0.5000 - val\_loss: 36.6176 - val\_accuracy: 0.3684  
Epoch 8/10  
3/3 [=====] - ETA: 0s - loss: 28.7426 - accuracy: 0.5541  
Epoch 8: val\_accuracy improved from 0.36842 to 0.42105, saving model to D:\Ashwini\IMAGE\bestModel.h5  
3/3 [=====] - 13s 5s/step - loss: 28.7426 - accuracy: 0.5541 - val\_loss: 43.0471 - val\_accuracy: 0.4211  
Epoch 9/10  
3/3 [=====] - ETA: 0s - loss: 25.9535 - accuracy: 0.6351  
Epoch 9: val\_accuracy improved from 0.42105 to 0.52632, saving model to D:\Ashwini\IMAGE\bestModel.h5  
3/3 [=====] - 11s 4s/step - loss: 25.9535 - accuracy: 0.6351 - val\_loss: 23.2375 - val\_accuracy: 0.5263  
Epoch 10/10  
3/3 [=====] - ETA: 0s - loss: 6.9328 - accuracy: 0.8378  
Epoch 10: val\_accuracy did not improve from 0.52632  
3/3 [=====] - 8s 2s/step - loss: 6.9328 - accuracy: 0.8378 - val\_loss: 38.5553 - val\_accuracy: 0.4211

In [37]:

```
1 #ANN architecture
2
3 flowerANN.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 196608)	0
dense (Dense)	(None, 1024)	201327616
dense_1 (Dense)	(None, 5)	5125

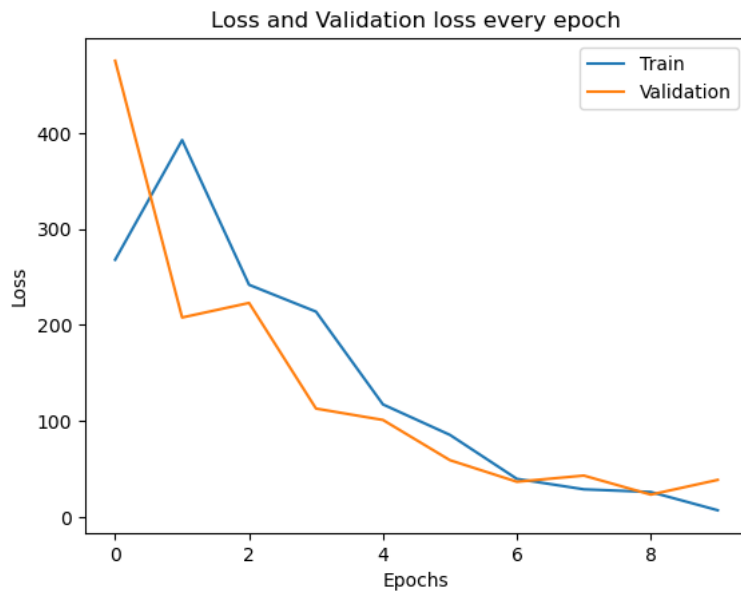
=====  
Total params: 201,332,741  
Trainable params: 201,332,741  
Non-trainable params: 0  
=====

In [38]:

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

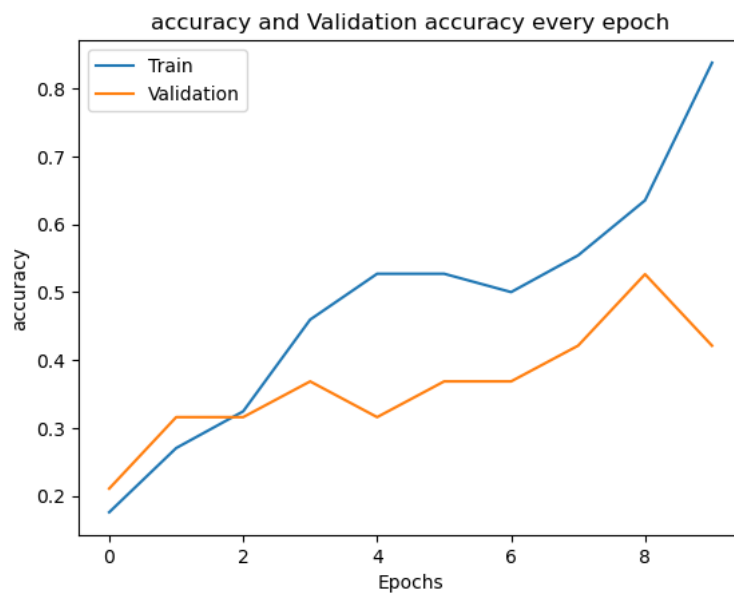
In [39]:

```
1 plt.plot(history.history['loss'])
2 plt.plot(history.history['val_loss'])
3 plt.xlabel('Epochs')
4 plt.ylabel('Loss')
5 plt.legend(['Train', 'Validation'])
6 plt.title('Loss and Validation loss every epoch')
7 plt.show()
```



In [40]:

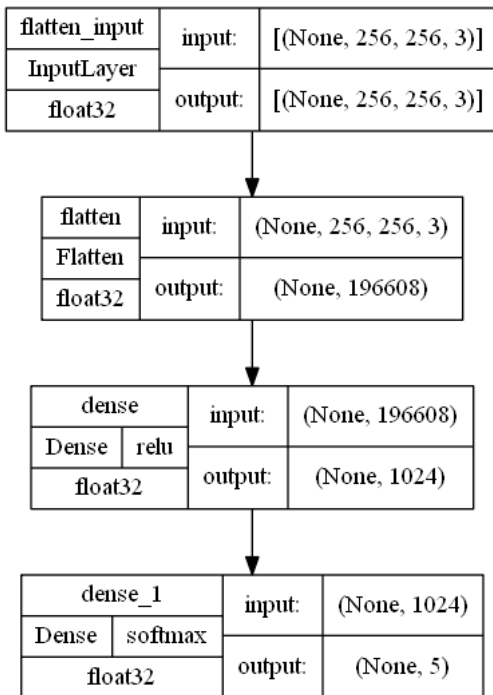
```
1 plt.plot(history.history['accuracy'])
2 plt.plot(history.history['val_accuracy'])
3 plt.xlabel('Epochs')
4 plt.ylabel('accuracy')
5 plt.legend(['Train', 'Validation'])
6 plt.title('accuracy and Validation accuracy every epoch')
7 plt.show()
```



In [41]:

```
1 from tensorflow.keras.utils import plot_model
2 plot_model(flowerANN, show_shapes=True, show_dtype=True, show_layer_activations=True, show_layer_names=True)
```

Out[41]:



In [42]:

```
1 ypred = flowerANN.predict(Xtest)
```

1/1 [=====] - 0s 341ms/step

In [43]:

```
1 Xtest[0].shape
```

Out[43]:

(256, 256, 3)

In [44]:

```
1 sampleimage = np.reshape(Xtest[0],(1,256,256,3))
```

In [45]:

```
1 sampleimage.shape
```

Out[45]:

(1, 256, 256, 3)

In [46]:

```
1 ypred_first = flowerANN.predict(sampleimage)
```

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

In [47]:

```
1 ypred_first
```

Out[47]:

```
array([[0.0000000e+00, 0.0000000e+00, 1.0000000e+00, 3.2733997e-15,
        0.0000000e+00]], dtype=float32)
```

In [48]:

```
1 ypredclasses_first = np.argmax(ypred_first, axis=-1)
2 ypredclasses_first
```

Out[48]:

array([2], dtype=int64)



In [49]:

```
1 import numpy as np
2 ypredclasses = np.argmax(ypred, axis=-1)
```

In [50]:

```
1 ypredclasses
```

Out[50]:

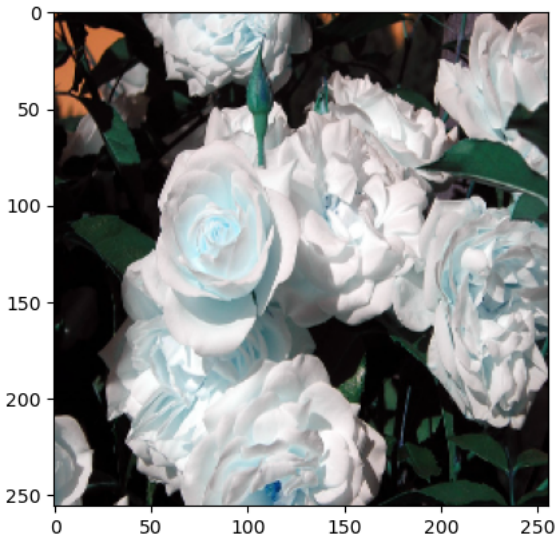
```
array([2, 2, 2, 3, 3, 2, 2, 3, 2, 0, 2, 2, 3, 3, 3, 2, 2, 2, 2, 3, 2, 2,
       3, 2], dtype=int64)
```

In [51]:

```
1 plt.imshow(Xtest[9])
```

Out[51]:

```
<matplotlib.image.AxesImage at 0x1b31aa55760>
```



In [52]:

```
1 ytest[1]
```

Out[52]:

```
array([0., 1., 0., 0., 0.], dtype=float32)
```

In [53]:

```
1 ypredclasses[1]
```

Out[53]:

```
2
```

In [54]:

```
1 ##/content//bestmodel.h5 #having error
```

In [55]:

```
1 flowerANN.evaluate(Xtest, ytest)
```

```
1/1 [=====] - 0s 125ms/step - loss: 62.6970 - accuracy: 0.3750
```

Out[55]:

```
[62.697017669677734, 0.375]
```

In [56]:

```
1 from keras.models import load_model
2 bestmodel = load_model("D:\\Ashwini\\IMAGE\\bestModel.h5")
```

In [57]:

```
1 bestmodel.evaluate(Xtest, ytest)
```

1/1 [=====] - 1s 975ms/step - loss: 30.5506 - accuracy: 0.4167

Out[57]:

[30.550600051879883, 0.416666567325592]

In [ ]:

```
1
```