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ROLL NO: 611219106060

DATE: 08.10.2022

```
!unzip '/content/Flowers-Dataset.zip'
```

```
Archive:  /content/Flowers-Dataset.zip
  inflating: flowers/daisy/100080576_f52e8ee070_n.jpg
  inflating: flowers/daisy/10140303196_b88d3d6cec.jpg
  inflating: flowers/daisy/10172379554_b296050f82_n.jpg
  inflating: flowers/daisy/10172567486_2748826a8b.jpg
  inflating: flowers/daisy/10172636503_21bededa75_n.jpg
  inflating: flowers/daisy/102841525_bd6628ae3c.jpg
  inflating: flowers/daisy/10300722094_28fa978807_n.jpg
  inflating: flowers/daisy/1031799732_e7f4008c03.jpg
  inflating: flowers/daisy/10391248763_1d16681106_n.jpg
  inflating: flowers/daisy/10437754174_22ec990b77_m.jpg
  inflating: flowers/daisy/10437770546_8bb6f7bdd3_m.jpg
  inflating: flowers/daisy/10437929963_bc13eebe0c.jpg
  inflating: flowers/daisy/10466290366_cc72e33532.jpg
  inflating: flowers/daisy/10466558316_a7198b87e2.jpg
  inflating: flowers/daisy/10555749515_13a12a026e.jpg
  inflating: flowers/daisy/10555815624_dc211569b0.jpg
  inflating: flowers/daisy/10555826524_423eb8bf71_n.jpg
  inflating: flowers/daisy/10559679065_50d2b16f6d.jpg
  inflating: flowers/daisy/105806915_a9c13e2106_n.jpg
  inflating: flowers/daisy/10712722853_5632165b04.jpg
  inflating: flowers/daisy/107592979_aaa9cdfe78_m.jpg
  inflating: flowers/daisy/10770585085_4742b9dac3_n.jpg
  inflating: flowers/daisy/10841136265_af473efc60.jpg
  inflating: flowers/daisy/10993710036_2033222c91.jpg
  inflating: flowers/daisy/10993818044_4c19b86c82.jpg
  inflating: flowers/daisy/10994032453_ac7f8d9e2e.jpg
  inflating: flowers/daisy/11023214096_b5b39fab08.jpg
  inflating: flowers/daisy/11023272144_fce94401f2_m.jpg
  inflating: flowers/daisy/11023277956_8980d53169_m.jpg
  inflating: flowers/daisy/11124324295_503f3a0804.jpg
  inflating: flowers/daisy/1140299375_3aa7024466.jpg
  inflating: flowers/daisy/11439894966_dca877f0cd.jpg
  inflating: flowers/daisy/1150395827_6f94a5c6e4_n.jpg
  inflating: flowers/daisy/11642632_1e7627a2cc.jpg
  inflating: flowers/daisy/11834945233_a53b7a92ac_m.jpg
  inflating: flowers/daisy/11870378973_2ec1919f12.jpg
  inflating: flowers/daisy/11891885265_ccefec7284_n.jpg
  inflating: flowers/daisy/12193032636_b50ae7db35_n.jpg
  inflating: flowers/daisy/12348343085_d4c396e5b5_m.jpg
  inflating: flowers/daisy/12585131704_0f64b17059_m.jpg
  inflating: flowers/daisy/12601254324_3cb62c254a_m.jpg
  inflating: flowers/daisy/1265350143_6e2b276ec9.jpg
  inflating: flowers/daisy/12701063955_4840594ea6_n.jpg
  inflating: flowers/daisy/1285423653_18926dc2c8_n.jpg
```

```
  inflating: flowers/daisy/1286274236_1d7ac84efb_n.jpg
  inflating: flowers/daisy/12891819633_e4c82b51e8.jpg
  inflating: flowers/daisy/1299501272_59d9da5510_n.jpg
  inflating: flowers/daisy/1306119996_ab8ae14d72_n.jpg
  inflating: flowers/daisy/1314069875_da8dc023c6_m.jpg
  inflating: flowers/daisy/1342002397_9503c97b49.jpg
  inflating: flowers/daisy/134409839_71069a95d1_m.jpg
  inflating: flowers/daisy/1344985627_c3115e2d71_n.jpg
  inflating: flowers/daisy/13491959645_2cd9df44d6_n.jpg
  inflating: flowers/daisy/1354396826_2868631432_m.jpg
  inflating: flowers/daisy/1355787476_32e9f2a30b.jpg
  inflating: flowers/daisy/13583238844_573df2de8e_m.jpg
  inflating: flowers/daisy/1374193928_a52320eafa.jpg
```

```
import warnings
warnings.filterwarnings("ignore")
```

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Activation,Dropout,Conv2D,Flatten,MaxPool2D,Resh
from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras.applications.resnet50 import preprocess_input
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import ImageDataGenerator,load_img,img_to_array
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
```

```
path = 'flowers/'
```

```
train_data_gen = ImageDataGenerator(rescale = 1./255,
                             shear_range = 0.2,
                             zoom_range = 0.2,
                             horizontal_flip = True,
                             validation_split = 0.30)
test_data_gen = ImageDataGenerator(rescale = 1./255,validation_split = 0.30)
```

```
training_set = train_data_gen.flow_from_directory(path,
                                                  target_size=(64,64),
                                                  batch_size=100,
                                                  class_mode='categorical',
                                                  shuffle=True,
                                                  color_mode='rgb',
                                                  subset = 'training')

testing_set = test_data_gen.flow_from_directory(path,
                                                  target_size=(64,64),
                                                  batch_size=100,
                                                  class_mode='categorical',
                                                  shuffle=True,
                                                  color_mode='rgb',
                                                  subset = 'validation')
```

```
Found 3024 images belonging to 5 classes.
Found 1293 images belonging to 5 classes.
```

```
model = Sequential()


#convolution and Pooling layer 1
model.add(Conv2D(filters=48,kernel_size=3,activation='relu',input_shape=(64,64,3)))
model.add(MaxPool2D(pool_size=2,strides=2))
model.add(Dropout(0.2))

#convolution and Pooling layer 2
model.add(Conv2D(filters=32,kernel_size=3,activation='relu'))
model.add(MaxPool2D(pool_size=2,strides=2))
model.add(Dropout(0.2))

#Flattening the images
model.add(Flatten())

#Fully Connected layers
model.add(Dense(64,activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(5,activation='softmax'))
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 62, 62, 48)        1344      
                                                                 
 max_pooling2d (MaxPooling2D  (None, 31, 31, 48)       0         
 )                                                               
                                                                 
 dropout (Dropout)           (None, 31, 31, 48)        0         
                                                                 
 conv2d_1 (Conv2D)           (None, 29, 29, 32)        13856     
                                                                 
 max_pooling2d_1 (MaxPooling  (None, 14, 14, 32)       0         
 2D)                                                             
                                                                 
 dropout_1 (Dropout)         (None, 14, 14, 32)        0         
                                                                 
 flatten (Flatten)           (None, 6272)              0         
                                                                 
 dense (Dense)               (None, 64)                401472    
                                                                 
 dropout_2 (Dropout)         (None, 64)                0         
                                                                 
 dense_1 (Dense)             (None, 5)                 325       
                                                                 
=================================================================
Total params: 416,997
Trainable params: 416,997
```

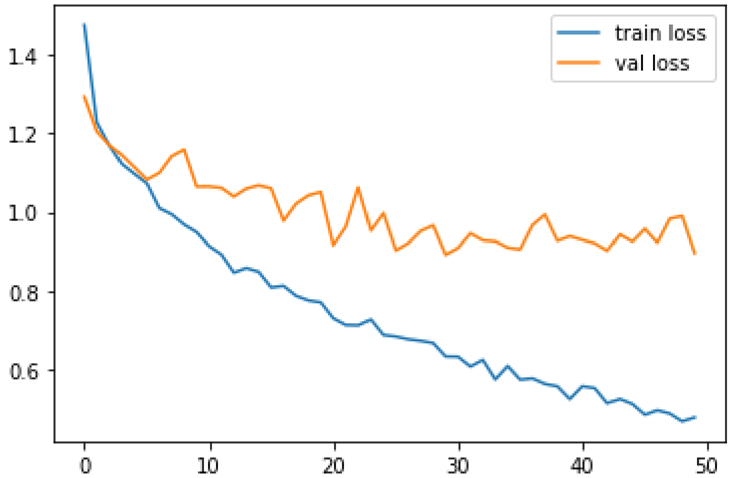
```
Non-trainable params: 0
```

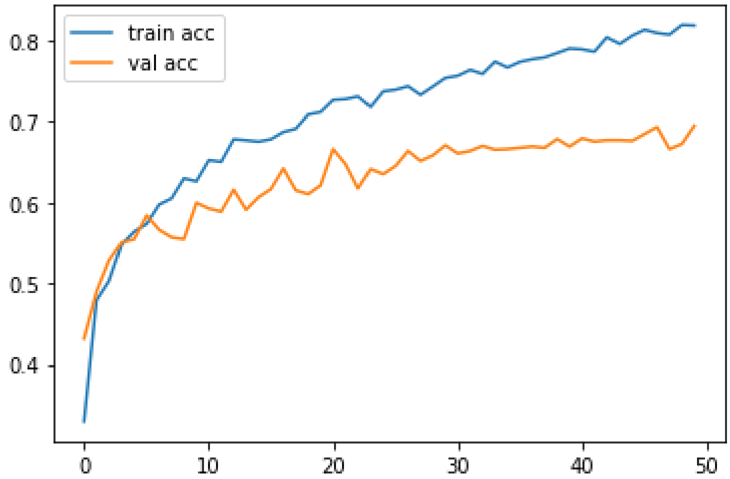
```
model.compile(loss='categorical_crossentropy',optimizer='adam',metrics=['accuracy'])


early_stop = EarlyStopping(monitor='val_accuracy',
                           patience=5,verbose=1,mode='auto')

lr = ReduceLROnPlateau(monitor='val_accuracy',
                       factor=0.2,patience=5,
                       min_lr=0.00001)

callback = [early_stop,lr]


weresult = model.fit(x=training_set, validation_data=testing_set, epochs=50)
```

```
Epoch 1/50
31/31 [==============================] - 32s 1s/step - loss: 1.4760 - accuracy: 0.
Epoch 2/50
31/31 [==============================] - 31s 984ms/step - loss: 1.2285 - accuracy:
Epoch 3/50
31/31 [==============================] - 31s 989ms/step - loss: 1.1697 - accuracy:
Epoch 4/50
31/31 [==============================] - 32s 1s/step - loss: 1.1222 - accuracy: 0.
Epoch 5/50
31/31 [==============================] - 31s 978ms/step - loss: 1.0970 - accuracy:
Epoch 6/50
31/31 [==============================] - 30s 975ms/step - loss: 1.0729 - accuracy:
Epoch 7/50
31/31 [==============================] - 30s 973ms/step - loss: 1.0100 - accuracy:
Epoch 8/50
31/31 [==============================] - 36s 1s/step - loss: 0.9943 - accuracy: 0.
Epoch 9/50
31/31 [==============================] - 31s 994ms/step - loss: 0.9683 - accuracy:
Epoch 10/50
31/31 [==============================] - 31s 976ms/step - loss: 0.9491 - accuracy:
Epoch 11/50
31/31 [==============================] - 31s 1s/step - loss: 0.9138 - accuracy: 0.
Epoch 12/50
31/31 [==============================] - 30s 973ms/step - loss: 0.8923 - accuracy:
Epoch 13/50
31/31 [==============================] - 30s 972ms/step - loss: 0.8466 - accuracy:
Epoch 14/50
31/31 [==============================] - 32s 1s/step - loss: 0.8581 - accuracy: 0.
Epoch 15/50
31/31 [==============================] - 30s 970ms/step - loss: 0.8486 - accuracy:
Epoch 16/50
31/31 [==============================] - 30s 973ms/step - loss: 0.8091 - accuracy:
Epoch 17/50
31/31 [==============================] - 30s 972ms/step - loss: 0.8130 - accuracy:
Epoch 18/50
31/31 [==============================] - 30s 972ms/step - loss: 0.7879 - accuracy:
Epoch 19/50
31/31 [==============================] - 30s 970ms/step - loss: 0.7760 - accuracy:
Epoch 20/50
31/31 [==============================] - 32s 1s/step - loss: 0.7711 - accuracy: 0.
Epoch 21/50
31/31 [==============================] - 30s 971ms/step - loss: 0.7307 - accuracy:
```

```
Epoch 22/50
31/31 [==============================] - 30s 968ms/step - loss: 0.7135 - accuracy:
Epoch 23/50
31/31 [==============================] - 30s 967ms/step - loss: 0.7127 - accuracy:
Epoch 24/50
31/31 [==============================] - 32s 1s/step - loss: 0.7274 - accuracy: 0.
Epoch 25/50
31/31 [==============================] - 30s 969ms/step - loss: 0.6881 - accuracy:
Epoch 26/50
31/31 [==============================] - 30s 968ms/step - loss: 0.6842 - accuracy:
Epoch 27/50
31/31 [==============================] - 30s 971ms/step - loss: 0.6772 - accuracy:
Epoch 28/50
31/31 [==============================] - 30s 970ms/step - loss: 0.6731 - accuracy:
```

```
#plot the loss
plt.plot(result.history['loss'], label='train loss')
plt.plot(result.history['val_loss'], label='val loss')
plt.legend()
plt.show()

# plot the accuracy
plt.plot(result.history['accuracy'], label='train acc')
plt.plot(result.history['val_accuracy'], label='val acc')
plt.legend()
plt.show()
```





```
model.save('flower.h5')
```

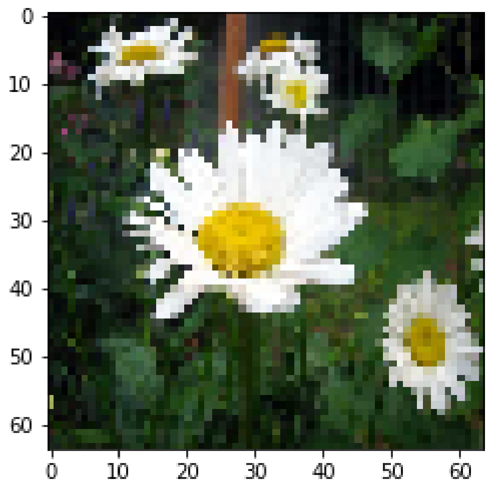
```
training_set.class_indices
```

```
{'daisy': 0, 'dandelion': 1, 'rose': 2, 'sunflower': 3, 'tulip': 4}
```

```
classes = ['Daisy','Dandelion','Rose','Sunflower','Tulip']
def testing(img):
    img = image.load_img(img,target_size=(64,64))
    x = image.img_to_array(img)
    x = np.expand_dims(x,axis=0)
    pred = np.argmax(model.predict(x))
    return print("Predicted class as:",classes[pred])

def img_show(img):
    img1 = image.load_img(img,target_size=(64,64))
    plt.imshow(img1)
```

```
#test1
img_show('/content/flowers/daisy/25360380_1a881a5648.jpg')
testing('/content/flowers/daisy/25360380_1a881a5648.jpg')
```

```
Predicted class as: Daisy
```




```
#test2
img_show('/content/flowers/tulip/3238068295_b2a7b17f48_n.jpg')
testing('/content/flowers/tulip/3238068295_b2a7b17f48_n.jpg')
```

Predicted class as: Rose


```
#test3
img_show('/content/flowers/rose/3753920123_c7ebc18ee3.jpg')
testing('/content/flowers/rose/3753920123_c7ebc18ee3.jpg')
```

Predicted class as: Rose