Scenario 1

Image Classification - Flower recognition

- in this notebook I explain how to model an image recognition model using **CNN** .
- you can see the plotting in the end of notebook.
- my notebook hasn't optimal model in this data set. if you want to take an optimal model you can se the edition in future on this notebook.
- if you like my notebook , support my by upvote it.
- **My name is Abhishek Sharma**

Connecting our file with Google Drive so that we can download the dataset

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Importing libraries and collecting images

```
import warnings
warnings.filterwarnings('always')
warnings.filterwarnings('ignore')

# data visualisation and manipulation
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import style
import seaborn as sns

#configure
# sets matplotlib to inline and displays graphs below the corressponding cell.
%matplotlib inline
style.use('fivethirtyeight')
sns.set(style='whitegrid',color_codes=True)

#model selection
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.metrics import accuracy_score,precision_score,recall_score,confusion_matrix,roc_curve,roc_auc_score
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import LabelEncoder

#preprocess.
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.regularizers import L1,L2
#dl libraraies
from keras import backend as K
from tensorflow.keras.models import Sequential
from keras.layers import Dense
from keras.optimizers import Adam,SGD,Adagrad,Adadelta,RMSprop
from keras.utils import to_categorical

# specifically for cnn
from keras.layers import Dropout, Flatten,Activation
from keras.layers import Conv2D, MaxPooling2D, BatchNormalization

import tensorflow as tf
import random as rn

# specifically for manipulating zipped images and getting numpy arrays of pixel values of images.
import cv2
import numpy as np
from tqdm import tqdm
import os
from random import shuffle
from zipfile import ZipFile
from PIL import Image
```

Double-click (or enter) to edit

Loading Dataset

About Dataset: This dataset contains 4242 images of flowers. The data collection is based on the data flicr, google images, yandex images. You can use this datastet to recognize plants from the photo.

Content: The pictures are divided into five classes: chamomile, tulip, rose, sunflower, dandelion. For each class there are about 800 photos. Photos are not high resolution, about 320x240 pixels. Photos are not reduced to a single size, they have different proportions!

```
X=[]
Z=[]
IMG_SIZE=150
FLOWER_DAISY_DIR='/content/drive/MyDrive/flowers/daisy'
FLOWER_SUNFLOWER_DIR='/content/drive/MyDrive/flowers/sunflower'
FLOWER_TULIP_DIR='/content/drive/MyDrive/flowers/tulip'
FLOWER_DANDI_DIR='/content/drive/MyDrive/flowers/dandelion'
FLOWER_ROSE_DIR='/content/drive/MyDrive/flowers/rose'
```

```
def assign_label(img,flower_type):
    return flower_type
```

```
def make_train_data(flower_type,DIR):
    for img in tqdm(os.listdir(DIR)):
        label=assign_label(img,flower_type)
        path = os.path.join(DIR,img)
        img = cv2.imread(path,cv2.IMREAD_COLOR)
        img = cv2.resize(img, (IMG_SIZE,IMG_SIZE))

        X.append(np.array(img))
        Z.append(str(label))
```

```
make_train_data('Daisy',FLOWER_DAISY_DIR)
print(len(X))
```

```
100%|██████████| 764/764 [00:10<00:00, 71.76it/s] 764
```

```
make_train_data('Sunflower',FLOWER_SUNFLOWER_DIR)
print(len(X))
```

```
100%|██████████| 733/733 [00:09<00:00, 75.27it/s] 1497
```

```
make_train_data('Tulip',FLOWER_TULIP_DIR)
print(len(X))
```

```
100%|██████████| 984/984 [00:14<00:00, 69.54it/s] 2481
```

```
make_train_data('Dandelion',FLOWER_DANDI_DIR)
print(len(X))
```

```
100%|██████████| 1052/1052 [00:16<00:00, 63.93it/s] 3533
```

```
make_train_data('Rose',FLOWER_ROSE_DIR)
print(len(X))
```

```
100%|██████████| 784/784 [00:12<00:00, 61.80it/s] 4317
```

Visualization

```
fig,ax=plt.subplots(5,2)
fig.set_size_inches(15,15)
for i in range(5):
    for j in range (2):
        l=rn.randint(0,len(Z))
```

```
        ax[i,j].imshow(X[l])
        ax[i,j].set_title('Flower: '+Z[l])

plt.tight_layout()
```

Flower: Dandelion Flower: Dandelion

Dataset Preprocessing

```
le=LabelEncoder()
Y=le.fit_transform(Z)
Y=to_categorical(Y,5)
X=np.array(X)
X=X/255
```

```
X.shape
```

```
(4317, 150, 150, 3)
```

```
Y.shape
```

```
(4317, 5)
```

Train Test Split

```
x_train,x_test,y_train,y_test=train_test_split(X,Y,test_size=0.25,random_state=42)
```

modeling

- I hanve use Conv@D to convolution images.
- using Maxpooling2D to reduce the size and resolution of images.
- flatten to make data set 1 dimension.

Flower: Daisy Flower: Dandelion

```
model = Sequential()

# CONVOLUTIONAL LAYER
model.add(Conv2D(filters=40, kernel_size=(3,3),input_shape = (150,150,3), activation='relu'))
# POOLING LAYER
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(filters=50, kernel_size=(3,3),input_shape = (150,150,3), activation='relu'))
# POOLING LAYER
model.add(MaxPooling2D(pool_size=(2, 2),strides=(2,2)))
model.add(Conv2D(filters=55, kernel_size=(3,3),input_shape = (150,150,3), activation='relu'))
# POOLING LAYER
model.add(MaxPooling2D(pool_size=(2, 2),strides=(2,2)))
model.add(Conv2D(filters=60, kernel_size=(3,3),input_shape = (150,150,3), activation='relu'))
# POOLING LAYER
model.add(MaxPooling2D(pool_size=(2, 2),strides=(2,2)))
# FLATTEN IMAGES FROM 28 by 28 to 764 BEFORE FINAL LAYER
model.add(Flatten())

model.add(Dense(100, activation='relu', kernel_regularizer=L2(0.01)))
model.add(Dense(200, activation='relu', kernel_regularizer=L2(0.01)))
model.add(Dense(200, activation='relu', kernel_regularizer=L2(0.01)))
model.add(Dense(100, activation='relu', kernel_regularizer=L2(0.01)))
# LAST LAYER IS THE CLASSIFIER, THUS 10 POSSIBLE CLASSES
model.add(Dense(5, activation='softmax'))
```

```
batch_size=128
epochs=50

from keras.callbacks import ReduceLROnPlateau
red_lr= ReduceLROnPlateau(monitor='val_acc',patience=3,verbose=1,factor=0.1)
```

```
model.compile(optimizer=Adam(lr=0.001),loss='categorical_crossentropy',metrics=['accuracy'])
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use the legacy optimizer, e.g.,tf.keras.optimizer:
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
```

```
=================================================================
 conv2d (Conv2D)             (None, 148, 148, 40)      1120

 max_pooling2d (MaxPooling2  (None, 74, 74, 40)        0
 D)

 conv2d_1 (Conv2D)           (None, 72, 72, 50)        18050

 max_pooling2d_1 (MaxPoolin  (None, 36, 36, 50)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 34, 34, 55)        24805

 max_pooling2d_2 (MaxPoolin  (None, 17, 17, 55)        0
 g2D)

 conv2d_3 (Conv2D)           (None, 15, 15, 60)        29760

 max_pooling2d_3 (MaxPoolin  (None, 7, 7, 60)          0
 g2D)

 flatten (Flatten)           (None, 2940)              0

 dense (Dense)               (None, 100)               294100

 dense_1 (Dense)             (None, 200)               20200

 dense_2 (Dense)             (None, 200)               40200

 dense_3 (Dense)             (None, 100)               20100

 dense_4 (Dense)             (None, 5)                 505

=================================================================
Total params: 448840 (1.71 MB)
Trainable params: 448840 (1.71 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
from tensorflow.keras.callbacks import EarlyStopping
```

```
early_stop = EarlyStopping(monitor='val_loss',patience=2)
```

ImageGenerator to prevent Overfitting

```
from keras.preprocessing.image import ImageDataGenerator, array_to_img, img_to_array, load_img
datagen = ImageDataGenerator(
        featurewise_center=False,  # set input mean to 0 over the dataset
        samplewise_center=False,  # set each sample mean to 0
        featurewise_std_normalization=False,  # divide inputs by std of the dataset
        samplewise_std_normalization=False,  # divide each input by its std
        zca_whitening=False,  # apply ZCA whitening
        rotation_range=10,  # randomly rotate images in the range (degrees, 0 to 180)
        zoom_range = 0.1, # Randomly zoom image
        width_shift_range=0.2,  # randomly shift images horizontally (fraction of total width)
        height_shift_range=0.2,  # randomly shift images vertically (fraction of total height)
        horizontal_flip=True,  # randomly flip images
        vertical_flip=False)  # randomly flip images
```

```
datagen.fit(x_train)
```

Fitting my model

Here I have used 50 epoches

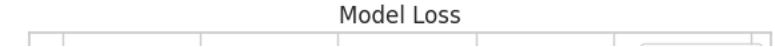
```
History = model.fit_generator(datagen.flow(x_train,y_train, batch_size=batch_size),
                              epochs = epochs, validation_data = (x_test,y_test),
                              verbose = 1, steps_per_epoch=x_train.shape[0] // batch_size)
```

```
Epoch 1/50
25/25 [==============================] - 35s 840ms/step - loss: 6.1596 - accuracy: 0.2708 - val_loss: 4.3814 - val_accuracy: 0.33
Epoch 2/50
25/25 [==============================] - 21s 841ms/step - loss: 3.6790 - accuracy: 0.3159 - val_loss: 3.0303 - val_accuracy: 0.37
Epoch 3/50
25/25 [==============================] - 23s 829ms/step - loss: 2.6382 - accuracy: 0.3889 - val_loss: 2.2499 - val_accuracy: 0.45
Epoch 4/50
25/25 [==============================] - 19s 775ms/step - loss: 2.0033 - accuracy: 0.4651 - val_loss: 1.8610 - val_accuracy: 0.50
```

```
Epoch 5/50
25/25 [==============================] - 21s 854ms/step - loss: 1.7146 - accuracy: 0.4915 - val_loss: 1.6018 - val_accuracy: 0.49
Epoch 6/50
25/25 [==============================] - 22s 863ms/step - loss: 1.5353 - accuracy: 0.5111 - val_loss: 1.4630 - val_accuracy: 0.54
Epoch 7/50
25/25 [==============================] - 21s 850ms/step - loss: 1.4312 - accuracy: 0.5301 - val_loss: 1.3422 - val_accuracy: 0.57
Epoch 8/50
25/25 [==============================] - 19s 771ms/step - loss: 1.3177 - accuracy: 0.5677 - val_loss: 1.2703 - val_accuracy: 0.58
Epoch 9/50
25/25 [==============================] - 21s 841ms/step - loss: 1.2656 - accuracy: 0.5696 - val_loss: 1.3055 - val_accuracy: 0.55
Epoch 10/50
25/25 [==============================] - 19s 752ms/step - loss: 1.2050 - accuracy: 0.5989 - val_loss: 1.1617 - val_accuracy: 0.62
Epoch 11/50
25/25 [==============================] - 20s 795ms/step - loss: 1.1647 - accuracy: 0.6150 - val_loss: 1.2054 - val_accuracy: 0.57
Epoch 12/50
25/25 [==============================] - 19s 745ms/step - loss: 1.1536 - accuracy: 0.6118 - val_loss: 1.1056 - val_accuracy: 0.64
Epoch 13/50
25/25 [==============================] - 20s 799ms/step - loss: 1.1043 - accuracy: 0.6253 - val_loss: 1.1122 - val_accuracy: 0.61
Epoch 14/50
25/25 [==============================] - 19s 752ms/step - loss: 1.1159 - accuracy: 0.6166 - val_loss: 1.1371 - val_accuracy: 0.60
Epoch 15/50
25/25 [==============================] - 21s 859ms/step - loss: 1.1073 - accuracy: 0.6179 - val_loss: 1.0756 - val_accuracy: 0.64
Epoch 16/50
25/25 [==============================] - 22s 898ms/step - loss: 1.0895 - accuracy: 0.6256 - val_loss: 1.0833 - val_accuracy: 0.63
Epoch 17/50
25/25 [==============================] - 20s 808ms/step - loss: 1.0297 - accuracy: 0.6433 - val_loss: 1.0688 - val_accuracy: 0.63
Epoch 18/50
25/25 [==============================] - 20s 796ms/step - loss: 1.0444 - accuracy: 0.6356 - val_loss: 1.0629 - val_accuracy: 0.59
Epoch 19/50
25/25 [==============================] - 20s 788ms/step - loss: 1.0176 - accuracy: 0.6529 - val_loss: 1.0716 - val_accuracy: 0.62
Epoch 20/50
25/25 [==============================] - 21s 844ms/step - loss: 0.9944 - accuracy: 0.6542 - val_loss: 1.0041 - val_accuracy: 0.65
Epoch 21/50
25/25 [==============================] - 19s 773ms/step - loss: 1.0048 - accuracy: 0.6594 - val_loss: 1.0016 - val_accuracy: 0.65
Epoch 22/50
25/25 [==============================] - 21s 828ms/step - loss: 0.9648 - accuracy: 0.6603 - val_loss: 0.9583 - val_accuracy: 0.68
Epoch 23/50
25/25 [==============================] - 21s 830ms/step - loss: 0.9695 - accuracy: 0.6587 - val_loss: 0.9695 - val_accuracy: 0.67
Epoch 24/50
25/25 [==============================] - 20s 770ms/step - loss: 0.9663 - accuracy: 0.6674 - val_loss: 1.0492 - val_accuracy: 0.63
Epoch 25/50
25/25 [==============================] - 20s 807ms/step - loss: 1.0018 - accuracy: 0.6526 - val_loss: 0.9634 - val_accuracy: 0.65
Epoch 26/50
25/25 [==============================] - 19s 764ms/step - loss: 0.9560 - accuracy: 0.6719 - val_loss: 0.9492 - val_accuracy: 0.65
Epoch 27/50
25/25 [==============================] - 21s 858ms/step - loss: 0.9389 - accuracy: 0.6722 - val_loss: 0.9403 - val_accuracy: 0.68
Epoch 28/50
25/25 [==============================] - 20s 791ms/step - loss: 0.9530 - accuracy: 0.6719 - val_loss: 0.9394 - val_accuracy: 0.69
```

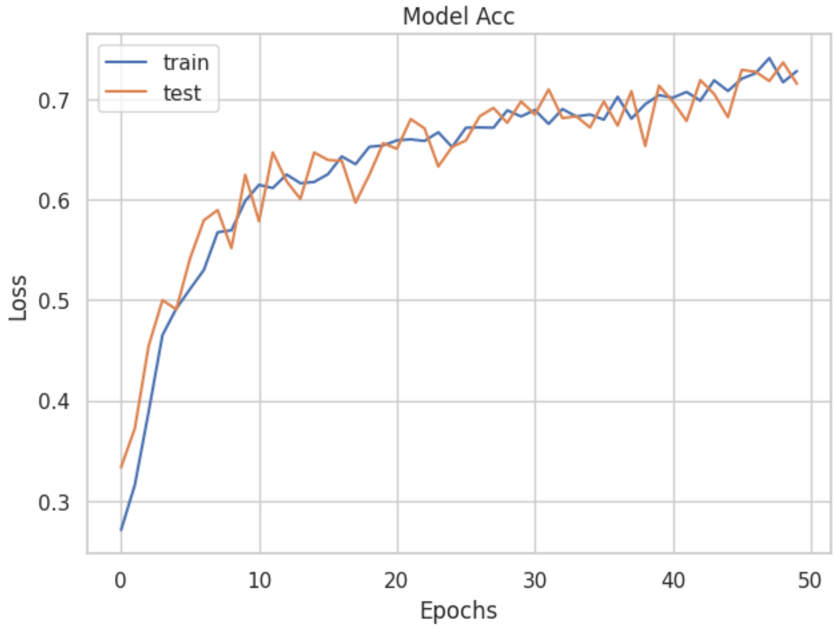
Graphs

```
plt.plot(History.history['loss'])
plt.plot(History.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epochs')
plt.legend(['train', 'test'])
plt.show()
```



the above graph shows that, the Test and Train losses are highest in the initial and at the last when the number of epoches increases loss also decreases.

```
plt.plot(History.history['accuracy'])
plt.plot(History.history['val_accuracy'])
plt.title('Model Acc')
plt.ylabel('Loss')
plt.xlabel('Epochs')
plt.legend(['train', 'test'])
plt.show()
```



the above graph shows the test and train accuracy of the model with respect to the increase in the number of epoches

```
pred=model.predict(x_test)
pred_digits=np.argmax(pred,axis=1)
```

```
34/34 [==============================] - 1s 11ms/step
```

```
i=0
prop_class=[]
mis_class=[]

for i in range(len(y_test)):
    if(np.argmax(y_test[i])==pred_digits[i]):
        prop_class.append(i)
    if(len(prop_class)==8):
        break

i=0
for i in range(len(y_test)):
    if(not np.argmax(y_test[i])==pred_digits[i]):
        mis_class.append(i)
    if(len(mis_class)==8):
        break
```

```
y_test1=np.copy(y_test)
print(y_test1.shape)
y_test1.flatten()
```

```
(1080, 5)
array([0., 0., 1., ..., 1., 0., 0.], dtype=float32)
```

```
prop_class1=np.copy(prop_class)
print(prop_class1.shape)
prop_class1.flatten()
```

```
(8,)
array([ 1,  2,  5,  7,  9, 10, 12, 13])
```

```
pred_digits.shape
```

```
(1080,)
```

```
y_test.shape
```

```
(1080, 5)
```

Model Evaluation

Evaluation includes the hyperparameter tuning if the model is not giving good results. You can also play with different parameters for better predictions.

```
model.evaluate(x_test,y_test)
```

```
34/34 [==============================] - 1s 15ms/step - loss: 0.8196 - accuracy: 0.7157
[0.8195780515670776, 0.7157407402992249]
```

Saving the model

```
from tensorflow.keras.models import load_model
model.save('Model.h5')

# load model
savedModel=load_model('Model.h5')
```

Printing the classes of flowers

From here, my system got crashed 2 times due to less computational techniques.

```
x_train.class_indices
```

Checking the results

```
from keras.preprocessing import image

#Creating list for mapping
list_ = ['Daisy','Danelion','Rose','sunflower', 'tulip']

#Input image
test_image = image.load_img('img.jpg',target_size=(224,224))

#For show image
plt.imshow(test_image)
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image,axis=0)

# Result array
result = savedModel.predict(test_image)
print(result)

#Mapping result array with the main name list
i=0
for i in range(len(result[0])):
if(result[0][i]==1):
    print(list_[i])
    break
```

Double-click (or enter) to edit

```
#Input image
test_image = image.load_img('img2.jpg',target_size=(224,224))
```

```
#For show image
plt.imshow(test_image)
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image,axis=0)

# Result array
result = savedModel.predict(test_image)
print(result)

#Mapping result array with the main name list
i=0
for i in range(len(result[0])):
if(result[0][i]==1):
    print(list_[i])
    break
```

Finally

- my trying to make the model accuracy more better.