

**Assignment -3**  
Python Programming

Assignment Date	30 September 2022
Student Name	Shiny.R
Student Roll Number	311419205036
Maximum Marks	2 Marks

## Problem Statement :- Build CNN Model for Classification Of Flowers

- Download the Dataset : Dataset
- Image Augmentation
- Create Model
- Add Layers (Convolution,MaxPooling,Flatten,Dense-(Hidden Layers),Output))
- Compile The Model
- Fit The Model
- Save The Model
- Test The Model

## Solution:

```
# Used for manipulating directory paths
import os
import shutil
from os.path import isfile, join, abspath, exists, isdir, expanduser
from os import listdir, makedirs, getcwd, remove
from pathlib import Path
# Data visualisation
import pandas as pd
import seaborn as sns
from PIL import Image
from skimage.io import imread
import cv2
from tensorflow.keras.utils import to_categorical
# Specifically for manipulating zipped images and getting numpy arrays
of pixel values of images.
import matplotlib.pyplot as plt
import matplotlib.image as mimg
import numpy as np
# Plotting library
from mpl_toolkits.mplot3d import Axes3D # needed to plot 3-D surfaces
# dl libraries specifically for CNN
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.utils import load_img
from tensorflow.keras.utils import img_to_array
from tensorflow.keras.models import Sequential
```

```

from tensorflow.keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPooling2D
from keras import optimizers
# Tells matplotlib to embed plots within the notebook
%matplotlib inline

import math
# Dataset folder
flowersPath = Path('C:/Users/sri nandhini/Downloads/Flowers-Dataset/flowers')
# Each species of flower is contained in a separate folder, & this is to get all the sub-directories
flowers = os.listdir(flowersPath)
print("Number of types of flowers: ", len(flowers))
print("Types of flowers: ", flowers)
# A list which contains tuples, the type of flower and the corresponding image path
flowersList = []
for species in flowers:
    # Get all the file names
    allFlowers = os.listdir(flowersPath / species)
    # Add them to the list
    for flower in allFlowers:
        flowersList.append((species, str(flowersPath / species) + '/' + flower))
# Build a dataframe
# load the dataset as a pandas data frame
flowersList = pd.DataFrame(data=flowersList, columns=['category', 'image'], index=None)
flowersList.head()

# Build a dataframe...
# load the dataset as a pandas data frame....
flowersList = pd.DataFrame(data=flowersList, columns=['category', 'image'], index=None)
flowersList.head()

```

	category	image
0	daisy	C:\Users\sri nandhini\Downloads\Flowers-Dataset...
1	daisy	C:\Users\sri nandhini\Downloads\Flowers-Dataset...
2	daisy	C:\Users\sri nandhini\Downloads\Flowers-Dataset...
3	daisy	C:\Users\sri nandhini\Downloads\Flowers-Dataset...
4	daisy	C:\Users\sri nandhini\Downloads\Flowers-Dataset...

```

# Let's check how many samples for each category are present
print("Total number of flowers in the dataset: ", len(flowersList))
flowerNum = flowersList['category'].value_counts()
print("Flowers in each category: ")
print(flowerNum)

```

```
# Let's check how many samples for each category are present
print("Total number of flowers in the dataset: ", len(flowersList))
flowerNum = flowersList['category'].value_counts()
print("Flowers in each category: ")
print(flowerNum)
```

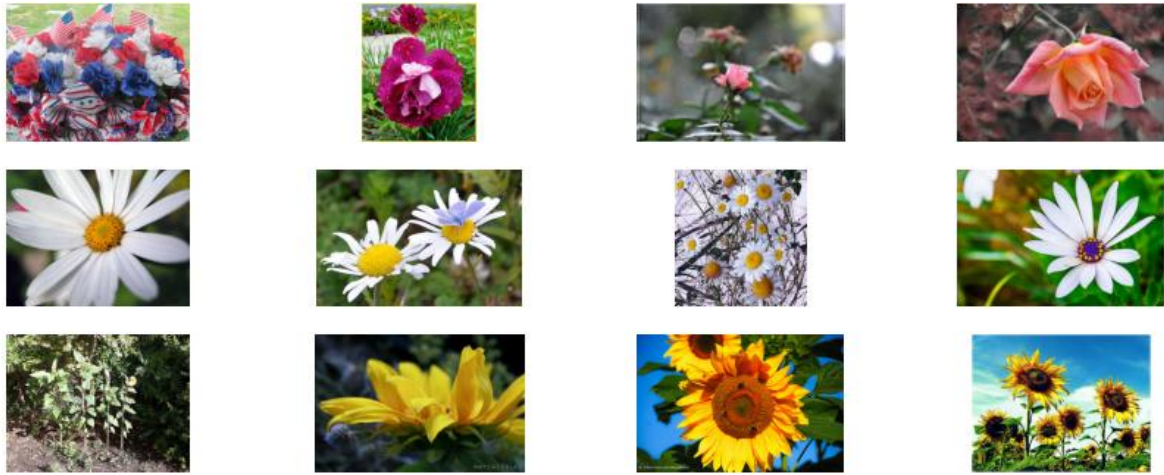
```
Total number of flowers in the dataset: 4317
Flowers in each category:
dandelion    1052
tulip        984
rose         784
daisy        764
sunflower    733
Name: category, dtype: int64
```

```
# A list for storing names of some random samples from each category
RanSamples = []
# Get samples fom each category
for category in flowerNum.index:
    samples = flowersList['image'][flowersList['category'] == category]
    .sample(4).values
    for sample in samples:
        RanSamples.append(sample)

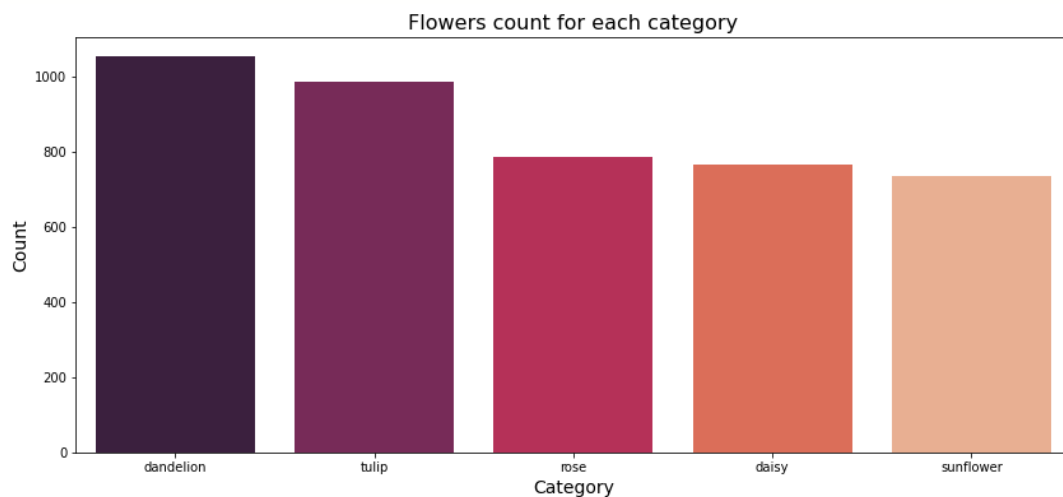
# Plot the samples
f, ax = plt.subplots(5,4, figsize=(15,10))
for i,sample in enumerate(RanSamples):
    ax[i//4, i%4].imshow(mimg.imread(RanSamples[i]))
    ax[i//4, i%4].axis('off')
plt.show()

# Plot the samples
f, ax = plt.subplots(5,4, figsize=(15,10))
for i,sample in enumerate(RanSamples):
    ax[i//4, i%4].imshow(mimg.imread(RanSamples[i]))
    ax[i//4, i%4].axis('off')
plt.show() |
```





```
# Let's do some visualization and see how many samples we have for each
category
f, axe = plt.subplots(1,1,figsize=(14,6))
sns.barplot(x = flowerNum.index, y = flowerNum.values, ax = axe, palett
e="rocket")
axe.set_title("Flowers count for each category", fontsize=16)
axe.set_xlabel('Category', fontsize=14)
axe.set_ylabel('Count', fontsize=14)
plt.show()
```



```
# Make directory 'test', with 2 sub directories, 'trainDir', & 'validDir'
trainDir = './test/trainDir'
valDir = './test/valDir'
# test_dir = './test/test_dir'
def create_directory(dirName):
    if os.path.exists(dirName):
        shutil.rmtree(dirName)
    os.makedirs(dirName)
    # Inside the trainDir & valDir sub-directories, sub-
    directories for each flower is created
    for flower in flowers:
        os.makedirs(os.path.join(dirName, flower))
create_directory(trainDir)
create_directory(valDir)
```

```

# lists for training & validation image & label
trainImg = []
trainLabel = []
validImg = []
validLabel = []
# for copying 100 samples to the validation dir & others to the train dir
for flower in flowerNum.index:
    samples = flowersList['image'][flowersList['category'] == flower].values
    diffPics = np.random.permutation(samples)

    for i in range(100):
        name = diffPics[i].split('/')[-1]
        shutil.copyfile(diffPics[i], './test/valDir/' + str(flower) + '/' + name)

        try:
            # add image to list
            img = plt.imread('./test/valDir/' + str(flower) + '/' + name)

            #resize all of the image to 150*150
            img = cv2.resize(img, (150,150))
            validImg.append(np.array(img))

            # add label to list
            if (str(flower)=="dandelion"):
                validLabel.append(0)
            elif (str(flower)=="tulip"):
                validLabel.append(1)
            elif (str(flower)=="rose"):
                validLabel.append(2)
            elif (str(flower)=="daisy"):
                validLabel.append(3)
            elif (str(flower)=="sunflower"):
                validLabel.append(4)
        except Exception as e:
            None

    for i in range(101, len(diffPics)):
        name = diffPics[i].split('/')[-1]
        shutil.copyfile(diffPics[i], './test/trainDir/' + str(flower) + '/' + name)

        try:
            # add image to list
            img = plt.imread('./test/trainDir/' + str(flower) + '/' + name)

            #resize all of the image to 150*150
            img = cv2.resize(img, (150,150))
            trainImg.append(np.array(img))

            # add label to list
            if (str(flower)=="dandelion"):

```

```

        trainLabel.append(0)
    elif (str(flower)=="tulip"):
        trainLabel.append(1)
    elif (str(flower)=="rose"):
        trainLabel.append(2)
    elif (str(flower)=="daisy"):
        trainLabel.append(3)
    elif (str(flower)=="sunflower"):
        trainLabel.append(4)
except Exception as e:
    None
# Let computer read the 5 category
validLabel = to_categorical(validLabel,num_classes = 5)
trainLabel = to_categorical(trainLabel,num_classes = 5)
print(validLabel)
print(trainLabel)

# Make new test and validation images as pixel
validImg=np.array(validImg)
validImg=validImg/255

trainImg=np.array(trainImg)
trainImg=trainImg/255

print("\nLengths of the corresponding array dimensions: \n")
print(np.shape(validImg),np.shape(validLabel),np.shape(trainImg),np.sha
pe(trainLabel))
[[1. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0.]
 ...
 [0. 0. 0. 0. 1.]
 [0. 0. 0. 0. 1.]
 [0. 0. 0. 0. 1.]]
[[1. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0.]
 ...
 [0. 0. 0. 0. 1.]
 [0. 0. 0. 0. 1.]
 [0. 0. 0. 0. 1.]]

Lengths of the corresponding array dimensions:

(500, 150, 150, 3) (500, 5) (3812, 150, 150, 3) (3812, 5)

```

---

```

def createModel():
    model = Sequential()
    # learn a total of 32 filters, kernel size 3x3
    model.add(Conv2D(32, (3, 3), input_shape=(150,150,3), padding="Same
", activation='relu'))
    model.add(MaxPooling2D((2, 2)))

    # learn a total of 64 filters, kernel size 3x3

```



max_pooling2d_3 (MaxPooling 2D)	(None, 9, 9, 128)	0
flatten (Flatten)	(None, 10368)	0
dense (Dense)	(None, 256)	2654464
dense_1 (Dense)	(None, 5)	1285

```
=====
Total params: 2,841,253
Trainable params: 2,841,253
Non-trainable params: 0
```

---

```
# Create data argument to prevent overfitting
datagen = ImageDataGenerator(
    featurewise_center=False, # set input mean to 0 over the datas
    et
    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=90, # randomly rotate images in the range (90,
0 to 180)
    zoom_range = 0.1, # Randomly zoom image
    width_shift_range=0.1, # randomly shift images horizontally (fr
raction of total width)
    height_shift_range=0.1, # randomly shift images vertically (fr
action of total height)
    shear_range=0.1,
    horizontal_flip=True, # randomly flip images
    vertical_flip=False # randomly flip images
)
datagen.fit(trainImg)
# start training
'''
verbose - 0 shows nothing; 1 will show animated progress bar; 2 will on
ly mention the number of epoch.
batch_size - the number of samples that will be propagated through the
network.
epochs - an arbitrary cutoff, use to separate training into distinct ph
ases.
'''
History = model.fit(trainImg, trainLabel, batch_size=batch_size, epochs
= epochs, validation_data = (validImg, validLabel), verbose=1)
```



Epoch 1/50  
30/30 [=====] - 81s 3s/step - loss: 1.6917 - accuracy: 0.2922 - val\_loss: 1.8472 - val\_accuracy: 0.2320  
Epoch 2/50  
30/30 [=====] - 76s 3s/step - loss: 1.3195 - accuracy: 0.4557 - val\_loss: 1.1729 - val\_accuracy: 0.5260  
Epoch 3/50  
30/30 [=====] - 76s 3s/step - loss: 1.1525 - accuracy: 0.5391 - val\_loss: 1.0298 - val\_accuracy: 0.6220  
Epoch 4/50  
30/30 [=====] - 76s 3s/step - loss: 1.0546 - accuracy: 0.5847 - val\_loss: 1.2276 - val\_accuracy: 0.5220  
Epoch 5/50  
30/30 [=====] - 76s 3s/step - loss: 0.9765 - accuracy: 0.6267 - val\_loss: 0.9820 - val\_accuracy: 0.6060  
Epoch 6/50  
30/30 [=====] - 75s 3s/step - loss: 0.8994 - accuracy: 0.6388 - val\_loss: 1.0915 - val\_accuracy: 0.6040  
Epoch 7/50  
30/30 [=====] - 75s 3s/step - loss: 0.8571 - accuracy: 0.6700 - val\_loss: 0.9734 - val\_accuracy: 0.6520  
Epoch 8/50  
30/30 [=====] - 76s 3s/step - loss: 0.7530 - accuracy: 0.7122 - val\_loss: 0.9513 - val\_accuracy: 0.6440  
Epoch 9/50  
30/30 [=====] - 76s 3s/step - loss: 0.7285 - accuracy: 0.7251 - val\_loss: 0.8217 - val\_accuracy: 0.6660  
Epoch 10/50  
30/30 [=====] - 76s 3s/step - loss: 0.6202 - accuracy: 0.7636 - val\_loss: 1.0112 - val\_accuracy: 0.6020  
Epoch 11/50  
30/30 [=====] - 76s 3s/step - loss: 0.5634 - accuracy: 0.7946 - val\_loss: 0.9757 - val\_accuracy: 0.6740  
Epoch 12/50  
30/30 [=====] - 76s 3s/step - loss: 0.4831 - accuracy: 0.8200 - val\_loss: 0.9257 - val\_accuracy: 0.6700  
Epoch 13/50  
30/30 [=====] - 76s 3s/step - loss: 0.4029 - accuracy: 0.8507 - val\_loss: 0.9934 - val\_accuracy: 0.6620  
Epoch 14/50  
30/30 [=====] - 241s 8s/step - loss: 0.3064 - accuracy: 0.8901 - val\_loss: 1.1231 - val\_accuracy: 0.6840  
Epoch 15/50  
30/30 [=====] - 76s 3s/step - loss: 0.2870 - accuracy: 0.8993 - val\_loss: 1.3973 - val\_accuracy: 0.6320  
Epoch 16/50  
30/30 [=====] - 76s 3s/step - loss: 0.1974 - accuracy: 0.9370 - val\_loss: 1.3903 - val\_accuracy: 0.6720  
Epoch 17/50  
30/30 [=====] - 76s 3s/step - loss: 0.2098 - accuracy: 0.9334 - val\_loss: 1.2315 - val\_accuracy: 0.6760  
Epoch 18/50  
30/30 [=====] - 268s 9s/step - loss: 0.2109 - accuracy: 0.9465 - val\_loss: 1.3186 - val\_accuracy: 0.6820  
Epoch 19/50  
30/30 [=====] - 76s 3s/step - loss: 0.1306 - accuracy: 0.9586 - val\_loss: 1.3738 - val\_accuracy: 0.7000  
Epoch 20/50  
30/30 [=====] - 75s 2s/step - loss: 0.1326 - accuracy: 0.9633 - val\_loss: 1.3699 - val\_accuracy: 0.7120  
Epoch 21/50  
30/30 [=====] - 75s 2s/step - loss: 0.0931 - accuracy: 0.9732 - val\_loss: 1.4408 - val\_accuracy: 0.7000  
Epoch 22/50  
30/30 [=====] - 75s 3s/step - loss: 0.1330 - accuracy: 0.9675 - val\_loss: 1.4551 - val\_accuracy: 0.7140  
Epoch 23/50  
30/30 [=====] - 76s 3s/step - loss: 0.1027 - accuracy: 0.9698 - val\_loss: 1.4749 - val\_accuracy: 0.6880  
Epoch 24/50  
30/30 [=====] - 76s 3s/step - loss: 0.0735 - accuracy: 0.9811 - val\_loss: 1.6582 - val\_accuracy: 0.6800  
Epoch 25/50  
30/30 [=====] - 76s 3s/step - loss: 0.0967 - accuracy: 0.9740 - val\_loss: 1.6456 - val\_accuracy: 0.6820  
Epoch 26/50  
30/30 [=====] - 289s 10s/step - loss: 0.1099 - accuracy: 0.9756 - val\_loss: 1.4278 - val\_accuracy: 0.6820  
Epoch 27/50  
30/30 [=====] - 76s 3s/step - loss: 0.0334 - accuracy: 0.9945 - val\_loss: 3.0830 - val\_accuracy: 0.5840  
Epoch 28/50  
30/30 [=====] - 76s 3s/step - loss: 0.0711 - accuracy: 0.9814 - val\_loss: 1.8990 - val\_accuracy: 0.7040  
Epoch 29/50  
30/30 [=====] - 76s 3s/step - loss: 0.1002 - accuracy: 0.9780 - val\_loss: 1.7395 - val\_accuracy: 0.7000  
Epoch 30/50  
30/30 [=====] - 76s 3s/step - loss: 0.0648 - accuracy: 0.9850 - val\_loss: 2.1520 - val\_accuracy: 0.6580  
Epoch 31/50  
30/30 [=====] - 76s 3s/step - loss: 0.0446 - accuracy: 0.9908 - val\_loss: 2.0066 - val\_accuracy: 0.6840  
Epoch 32/50  
30/30 [=====] - 211s 7s/step - loss: 0.0675 - accuracy: 0.9808 - val\_loss: 1.8640 - val\_accuracy: 0.7100  
Epoch 33/50  
30/30 [=====] - 76s 3s/step - loss: 0.0981 - accuracy: 0.9795 - val\_loss: 1.6887 - val\_accuracy: 0.7100  
Epoch 34/50  
30/30 [=====] - 76s 3s/step - loss: 0.0327 - accuracy: 0.9903 - val\_loss: 1.9431 - val\_accuracy: 0.6700  
Epoch 35/50  
30/30 [=====] - 76s 3s/step - loss: 0.0128 - accuracy: 0.9971 - val\_loss: 1.9119 - val\_accuracy: 0.7140  
Epoch 36/50  
30/30 [=====] - 76s 3s/step - loss: 0.1129 - accuracy: 0.9769 - val\_loss: 1.6934 - val\_accuracy: 0.6900

```

Epoch 37/50
30/30 [=====] - 237s 8s/step - loss: 0.0086 - accuracy: 0.9984 - val_loss: 1.7980 - val_accuracy: 0.6980
Epoch 38/50
30/30 [=====] - 75s 2s/step - loss: 0.1073 - accuracy: 0.9801 - val_loss: 1.8164 - val_accuracy: 0.6580
Epoch 39/50
30/30 [=====] - 54s 2s/step - loss: 0.0138 - accuracy: 0.9963 - val_loss: 2.1048 - val_accuracy: 0.6700
Epoch 40/50
30/30 [=====] - 55s 2s/step - loss: 0.0083 - accuracy: 0.9982 - val_loss: 1.9964 - val_accuracy: 0.6960
Epoch 41/50
30/30 [=====] - 55s 2s/step - loss: 0.0668 - accuracy: 0.9811 - val_loss: 2.0973 - val_accuracy: 0.6820
Epoch 42/50
30/30 [=====] - 55s 2s/step - loss: 0.0049 - accuracy: 0.9984 - val_loss: 2.2556 - val_accuracy: 0.6940
Epoch 43/50
30/30 [=====] - 56s 2s/step - loss: 0.1110 - accuracy: 0.9785 - val_loss: 2.1043 - val_accuracy: 0.7000
Epoch 44/50
30/30 [=====] - 56s 2s/step - loss: 0.0073 - accuracy: 0.9974 - val_loss: 2.1646 - val_accuracy: 0.7020
Epoch 45/50
30/30 [=====] - 57s 2s/step - loss: 0.1225 - accuracy: 0.9808 - val_loss: 2.0253 - val_accuracy: 0.6840
Epoch 46/50
30/30 [=====] - 56s 2s/step - loss: 0.0061 - accuracy: 0.9982 - val_loss: 2.3290 - val_accuracy: 0.6800
Epoch 47/50
30/30 [=====] - 57s 2s/step - loss: 0.0643 - accuracy: 0.9819 - val_loss: 2.2455 - val_accuracy: 0.6700
Epoch 48/50
30/30 [=====] - 57s 2s/step - loss: 0.0055 - accuracy: 0.9984 - val_loss: 2.4101 - val_accuracy: 0.6820
Epoch 49/50
30/30 [=====] - 58s 2s/step - loss: 0.0523 - accuracy: 0.9861 - val_loss: 2.1841 - val_accuracy: 0.6740
Epoch 50/50
30/30 [=====] - 57s 2s/step - loss: 0.0061 - accuracy: 0.9987 - val_loss: 2.0135 - val_accuracy: 0.6800
# start training
'''

```

verbose - 0 shows nothing; 1 will show animated progress bar; 2 will only mention the number of epoch.

batch\_size - the number of samples that will be propagated through the network.

epochs - an arbitrary cutoff, use to separate training into distinct phases.

```

'''
History = model.fit(trainImg, trainLabel, batch_size=batch_size, epochs
= epochs, validation_data = (validImg, validLabel), verbose=1)

```

