Assignment 3

CNN MODEL FOR FLOWER CLASSIFICATION

Pre-Requisites

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

```
Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
```

STEP 1 UNZIP FILES

```
cd/content/drive/MyDrive/AI_IBM
```

```
/content/drive/MyDrive/AI_IBM
```

```
!unzip Flowers-Dataset.zip
```

```
Archive:  Flowers-Dataset.zip
replace flowers/daisy/100080576_f52e8ee070_n.jpg? [y]es, [n]o, [A]ll,
[N]one, [r]ename: N
```

STEP 2 Image Augumentation

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

train_datagen=ImageDataGenerator(rescale=1./255,
zoom_range=0.2,horizontal_flip=True,vertical_flip=False)

test_datagen=ImageDataGenerator(rescale=1./255)

x_train=train_datagen.flow_from_directory(r"/content/drive/MyDrive/
AI_IBM/
flowers",target_size=(64,64),class_mode='categorical',batch_size=24)
```

```
Found 4317 images belonging to 5 classes.
```

```
x_test=test_datagen.flow_from_directory(r"/content/drive/MyDrive/
AI_IBM/
flowers",target_size=(64,64),class_mode='categorical',batch_size=24)
```

```
Found 4317 images belonging to 5 classes.
```

```
x_train.class_indices
```

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

Step -3 Initializing CNN And Create Model

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import
Dense,Convolution2D,MaxPooling2D,Flatten
```

Step -4 Add layers

```
model=Sequential()
```

4.1 Input Layers (Convolution ,MaxPooling,Flatten)

```
model.add(Convolution2D(32,
(3,3),input_shape=(64,64,3),activation='relu'))

model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Flatten())

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 62, 62, 32)        896

 max_pooling2d (MaxPooling2D  (None, 31, 31, 32)       0
 )

 flatten (Flatten)           (None, 30752)             0

=================================================================
Total params: 896
Trainable params: 896
Non-trainable params: 0
_________________________________________________________________
```

4.2 Hidden Layers

```
model.add(Dense(300,activation='relu'))
model.add(Dense(150,activation='relu'))
```

4.3 Output Layers

```
model.add(Dense(5,activation='softmax'))

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

len(x_train)

180
```

Step -5 Train the Model

```
model.fit_generator(x_train,steps_per_epoch=len(x_train),
validation_data=x_test, validation_steps=len(x_test), epochs= 30)

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1:
UserWarning: `Model.fit_generator` is deprecated and will be removed
in a future version. Please use `Model.fit`, which supports
generators.
  """Entry point for launching an IPython kernel.

Epoch 1/30
180/180 [==============================] - 393s 2s/step - loss: 1.3213
- accuracy: 0.4714 - val_loss: 1.1275 - val_accuracy: 0.5532
Epoch 2/30
180/180 [==============================] - 74s 409ms/step - loss:
1.0600 - accuracy: 0.5854 - val_loss: 0.9406 - val_accuracy: 0.6301
Epoch 3/30
180/180 [==============================] - 73s 405ms/step - loss:
0.9678 - accuracy: 0.6247 - val_loss: 0.9603 - val_accuracy: 0.6203
Epoch 4/30
180/180 [==============================] - 77s 429ms/step - loss:
0.8884 - accuracy: 0.6546 - val_loss: 0.8187 - val_accuracy: 0.6938
Epoch 5/30
180/180 [==============================] - 76s 422ms/step - loss:
0.8358 - accuracy: 0.6787 - val_loss: 0.7393 - val_accuracy: 0.7225
Epoch 6/30
180/180 [==============================] - 75s 418ms/step - loss:
0.7924 - accuracy: 0.6965 - val_loss: 0.8389 - val_accuracy: 0.6928
Epoch 7/30
180/180 [==============================] - 73s 405ms/step - loss:
0.7521 - accuracy: 0.7158 - val_loss: 0.8503 - val_accuracy: 0.6789
Epoch 8/30
180/180 [==============================] - 74s 411ms/step - loss:
0.7048 - accuracy: 0.7313 - val_loss: 0.6492 - val_accuracy: 0.7521
Epoch 9/30
180/180 [==============================] - 72s 400ms/step - loss:
0.6502 - accuracy: 0.7521 - val_loss: 0.6458 - val_accuracy: 0.7438
Epoch 10/30
180/180 [==============================] - 74s 409ms/step - loss:
```

```
0.6182 - accuracy: 0.7684 - val_loss: 0.5721 - val_accuracy: 0.7818
Epoch 11/30
180/180 [==============================] - 72s 402ms/step - loss:
0.5662 - accuracy: 0.7931 - val_loss: 0.5968 - val_accuracy: 0.7725
Epoch 12/30
180/180 [==============================] - 72s 401ms/step - loss:
0.5600 - accuracy: 0.7908 - val_loss: 0.6907 - val_accuracy: 0.7612
Epoch 13/30
180/180 [==============================] - 72s 399ms/step - loss:
0.5064 - accuracy: 0.8138 - val_loss: 0.5185 - val_accuracy: 0.8117
Epoch 14/30
180/180 [==============================] - 71s 394ms/step - loss:
0.4830 - accuracy: 0.8249 - val_loss: 0.3613 - val_accuracy: 0.8673
Epoch 15/30
180/180 [==============================] - 71s 397ms/step - loss:
0.4650 - accuracy: 0.8196 - val_loss: 0.3396 - val_accuracy: 0.8768
Epoch 16/30
180/180 [==============================] - 71s 393ms/step - loss:
0.4117 - accuracy: 0.8559 - val_loss: 0.3472 - val_accuracy: 0.8738
Epoch 17/30
180/180 [==============================] - 71s 397ms/step - loss:
0.3892 - accuracy: 0.8631 - val_loss: 0.3314 - val_accuracy: 0.8826
Epoch 18/30
180/180 [==============================] - 70s 389ms/step - loss:
0.3441 - accuracy: 0.8726 - val_loss: 0.4008 - val_accuracy: 0.8589
Epoch 19/30
180/180 [==============================] - 73s 404ms/step - loss:
0.3467 - accuracy: 0.8719 - val_loss: 0.2484 - val_accuracy: 0.9060
Epoch 20/30
180/180 [==============================] - 72s 398ms/step - loss:
0.3327 - accuracy: 0.8758 - val_loss: 0.2234 - val_accuracy: 0.9210
Epoch 21/30
180/180 [==============================] - 73s 403ms/step - loss:
0.2807 - accuracy: 0.9009 - val_loss: 0.2830 - val_accuracy: 0.9036
Epoch 22/30
180/180 [==============================] - 70s 392ms/step - loss:
0.2751 - accuracy: 0.9013 - val_loss: 0.2392 - val_accuracy: 0.9141
Epoch 23/30
180/180 [==============================] - 73s 404ms/step - loss:
0.2549 - accuracy: 0.9097 - val_loss: 0.2221 - val_accuracy: 0.9189
Epoch 24/30
180/180 [==============================] - 72s 399ms/step - loss:
0.2412 - accuracy: 0.9243 - val_loss: 0.2029 - val_accuracy: 0.9291
Epoch 25/30
180/180 [==============================] - 72s 402ms/step - loss:
0.2360 - accuracy: 0.9199 - val_loss: 0.1965 - val_accuracy: 0.9307
Epoch 26/30
180/180 [==============================] - 72s 401ms/step - loss:
0.2199 - accuracy: 0.9201 - val_loss: 0.1919 - val_accuracy: 0.9331
Epoch 27/30
```

```
180/180 [==============================] - 72s 400ms/step - loss:
0.2008 - accuracy: 0.9363 - val_loss: 0.1218 - val_accuracy: 0.9560
Epoch 28/30
180/180 [==============================] - 73s 406ms/step - loss:
0.1889 - accuracy: 0.9310 - val_loss: 0.2838 - val_accuracy: 0.9108
Epoch 29/30
180/180 [==============================] - 70s 389ms/step - loss:
0.2046 - accuracy: 0.9275 - val_loss: 0.2116 - val_accuracy: 0.9307
Epoch 30/30
180/180 [==============================] - 70s 392ms/step - loss:
0.1886 - accuracy: 0.9372 - val_loss: 0.2091 - val_accuracy: 0.9280

<keras.callbacks.History at 0x7f3e15438e50>
```

Step -6 Save The model

```
model.save('Flowers_classification_model1.h5')
```

Step -7 Test The model

```
ls
```

```
flowers/  Flowers_classification_model1.h5  Flowers-Dataset.zip
video.mp4
```

```
import numpy as np
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image

# Load the model
model=load_model('Flowers_classification_model1.h5')

img=image.load_img(r"/content/s3.jpg",target_size=(64,64))
x=image.img_to_array(img)
x=np.expand_dims(x,axis=0)
y=np.argmax(model.predict(x),axis=1)
# x_train.class_indices
index=['daisy','dandelion','rose','sunflower','tulip']
index[y[0]]
```

```
{"type":"string"}
```

We Achieved 93 percent of accuracy with this model