

## Assignment – 3

### Build CNN Model for Classification of Flowers

Assignment Date	02 October 2022
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Maximum Marks	2 Marks

#### TASKS:

1. Download the dataset
2. Image Augmentation

```
In [7]: from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

```
In [5]: train_datagen = ImageDataGenerator(rescale=1./255,
                                           zoom_range=0.2,
                                           horizontal_flip=True)
```

```
In [6]: test_datagen = ImageDataGenerator(rescale=1./255)
```

```
In [8]: xtrain = train_datagen.flow_from_directory('/content/flowers',
                                                  target_size=(64,64),
                                                  class_mode='categorical',
                                                  batch_size=100)
```

Found 4317 images belonging to 5 classes.

```
In [10]: xtest = test_datagen.flow_from_directory('/content/flowers',
                                                  target_size=(64,64),
                                                  class_mode='categorical',
                                                  batch_size=100)
```

Found 4317 images belonging to 5 classes.

3. Create model

```
In [11]: from tensorflow.keras.models import Sequential
         from tensorflow.keras.layers import Convolution2D,MaxPooling2D,Flatten,Dense
```

```
In [12]: model = Sequential()
```

#### 4. Adding Layers

```
In [13]: model.add(Convolution2D(32,(3,3),activation='relu',input_shape=(64,64,3)))
```

### MaxPooling

```
In [14]: model.add(MaxPooling2D(pool_size=(2,2)))
```

### Flatten

```
In [15]: model.add(Flatten())
```

### Dense Layer

```
In [16]: model.add(Dense(300,activation='relu')) #hiddenlayer 1
model.add(Dense(150,activation='relu')) #hiddenlayer 2
```

#### 5. Compile the model

```
In [18]: model.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
```

#### 6. Fit the model

```
In [19]: from keras.callbacks import EarlyStopping, ReduceLROnPlateau
```

```
In [20]: early_stopping = EarlyStopping(monitor='val_accuracy',
                                       patience=5)
reduce_lr = ReduceLROnPlateau(monitor='val_accuracy',
                              patience=5,
                              factor=0.5,min_lr=0.00001)

callback = [reduce_lr,early_stopping]
```

```
In [21]: # Train model

model.fit_generator(xtrain,
                   steps_per_epoch=len(xtrain),
                   epochs=100,
                   callbacks=callback,
                   validation_data=xtest,
                   validation_steps=len(xtest))
```

Epoch 1/100  
44/44 [=====] - 40s 894ms/step - loss: 1.4975 - accuracy: 0.4003 - val\_loss: 1.2238 - val\_accuracy: 0.4964 - lr: 0.0010  
Epoch 2/100  
44/44 [=====] - 39s 883ms/step - loss: 1.1079 - accuracy: 0.5548 - val\_loss: 1.1712 - val\_accuracy: 0.5395 - lr: 0.0010  
Epoch 3/100  
44/44 [=====] - 40s 907ms/step - loss: 1.0301 - accuracy: 0.5956 - val\_loss: 0.9753 - val\_accuracy: 0.6284 - lr: 0.0010  
Epoch 4/100  
44/44 [=====] - 39s 886ms/step - loss: 0.9719 - accuracy: 0.6206 - val\_loss: 0.9336 - val\_accuracy: 0.6275 - lr: 0.0010  
Epoch 5/100  
44/44 [=====] - 39s 878ms/step - loss: 0.8994 - accuracy: 0.6518 - val\_loss: 0.8369 - val\_accuracy: 0.6919 - lr: 0.0010  
Epoch 6/100  
44/44 [=====] - 39s 886ms/step - loss: 0.8470 - accuracy: 0.6750 - val\_loss: 0.8504 - val\_accuracy: 0.6889 - lr: 0.0010  
Epoch 7/100  
44/44 [=====] - 39s 884ms/step - loss: 0.8215 - accuracy: 0.6891 - val\_loss: 0.7804 - val\_accuracy: 0.7100 - lr: 0.0010  
Epoch 8/100  
44/44 [=====] - 40s 918ms/step - loss: 0.7763 - accuracy: 0.7074 - val\_loss: 0.7501 - val\_accuracy: 0.7206 - lr: 0.0010  
Epoch 9/100  
44/44 [=====] - 39s 887ms/step - loss: 0.7232 - accuracy: 0.7301 - val\_loss: 0.7413 - val\_accuracy: 0.7285 - lr: 0.0010  
Epoch 10/100  
44/44 [=====] - 39s 884ms/step - loss: 0.6905 - accuracy: 0.7352 - val\_loss: 0.6529 - val\_accuracy: 0.7607 - lr: 0.0010  
Epoch 11/100  
44/44 [=====] - 39s 885ms/step - loss: 0.6785 - accuracy: 0.7461 - val\_loss: 0.7277 - val\_accuracy: 0.7246 - lr: 0.0010  
Epoch 12/100  
44/44 [=====] - 40s 911ms/step - loss: 0.6417 - accuracy: 0.7626 - val\_loss: 0.6243 - val\_accuracy: 0.7688 - lr: 0.0010  
Epoch 13/100  
44/44 [=====] - 39s 890ms/step - loss: 0.6232 - accuracy: 0.7642 - val\_loss: 0.5709 - val\_accuracy: 0.7869 - lr: 0.0010  
Epoch 14/100  
44/44 [=====] - 39s 882ms/step - loss: 0.5917 - accuracy: 0.7741 - val\_loss: 0.6153 - val\_accuracy: 0.7772 - lr: 0.0010  
Epoch 15/100  
44/44 [=====] - 39s 884ms/step - loss: 0.5703 - accuracy: 0.7878 - val\_loss: 0.5209 - val\_accuracy: 0.8050 - lr: 0.0010  
Epoch 16/100  
44/44 [=====] - 39s 881ms/step - loss: 0.5262 - accuracy: 0.8087 - val\_loss: 0.5211 - val\_accuracy: 0.8117 - lr: 0.0010  
Epoch 17/100  
44/44 [=====] - 40s 907ms/step - loss: 0.5024 - accuracy: 0.8156 - val\_loss: 0.3861 - val\_accuracy: 0.8622 - lr: 0.0010  
Epoch 18/100  
44/44 [=====] - 39s 889ms/step - loss: 0.4733 - accuracy: 0.8288 - val\_loss: 0.3981 - val\_accuracy: 0.8536 - lr: 0.0010  
Epoch 19/100  
44/44 [=====] - 39s 887ms/step - loss: 0.4625 - accuracy: 0.8309 - val\_loss: 0.3904 - val\_accuracy: 0.8582 - lr: 0.0010  
Epoch 20/100

44/44 [=====] - 39s 889ms/step - loss: 0.4534 - accuracy: 0.8309 - val\_loss: 0.5840 - val\_accuracy: 0.7802 - lr: 0.0010  
Epoch 21/100  
44/44 [=====] - 39s 887ms/step - loss: 0.4899 - accuracy: 0.8251 - val\_loss: 0.4176 - val\_accuracy: 0.8464 - lr: 0.0010  
Epoch 22/100  
44/44 [=====] - 39s 885ms/step - loss: 0.3994 - accuracy: 0.8543 - val\_loss: 0.3450 - val\_accuracy: 0.8728 - lr: 0.0010  
Epoch 23/100  
44/44 [=====] - 39s 896ms/step - loss: 0.4214 - accuracy: 0.8434 - val\_loss: 0.3122 - val\_accuracy: 0.8955 - lr: 0.0010  
Epoch 24/100  
44/44 [=====] - 39s 880ms/step - loss: 0.3556 - accuracy: 0.8740 - val\_loss: 0.3274 - val\_accuracy: 0.8795 - lr: 0.0010  
Epoch 25/100  
44/44 [=====] - 39s 882ms/step - loss: 0.3834 - accuracy: 0.8608 - val\_loss: 0.2577 - val\_accuracy: 0.9099 - lr: 0.0010  
Epoch 26/100  
44/44 [=====] - 40s 915ms/step - loss: 0.3258 - accuracy: 0.8870 - val\_loss: 0.2300 - val\_accuracy: 0.9187 - lr: 0.0010  
Epoch 27/100  
44/44 [=====] - 39s 886ms/step - loss: 0.3285 - accuracy: 0.8819 - val\_loss: 0.2780 - val\_accuracy: 0.8969 - lr: 0.0010  
Epoch 28/100  
44/44 [=====] - 39s 881ms/step - loss: 0.3346 - accuracy: 0.8809 - val\_loss: 0.2399 - val\_accuracy: 0.9166 - lr: 0.0010  
Epoch 29/100  
44/44 [=====] - 39s 884ms/step - loss: 0.2992 - accuracy: 0.8911 - val\_loss: 0.2409 - val\_accuracy: 0.9085 - lr: 0.0010  
Epoch 30/100  
44/44 [=====] - 39s 882ms/step - loss: 0.3078 - accuracy: 0.8883 - val\_loss: 0.2281 - val\_accuracy: 0.9155 - lr: 0.0010  
Epoch 31/100  
44/44 [=====] - 40s 910ms/step - loss: 0.2466 - accuracy: 0.9155 - val\_loss: 0.2137 - val\_accuracy: 0.9266 - lr: 0.0010  
Epoch 32/100  
44/44 [=====] - 39s 886ms/step - loss: 0.2508 - accuracy: 0.9148 - val\_loss: 0.2318 - val\_accuracy: 0.9192 - lr: 0.0010  
Epoch 33/100  
44/44 [=====] - 39s 898ms/step - loss: 0.2238 - accuracy: 0.9201 - val\_loss: 0.1724 - val\_accuracy: 0.9358 - lr: 0.0010  
Epoch 34/100  
44/44 [=====] - 39s 883ms/step - loss: 0.2174 - accuracy: 0.9247 - val\_loss: 0.1982 - val\_accuracy: 0.9314 - lr: 0.0010  
Epoch 35/100  
44/44 [=====] - 40s 911ms/step - loss: 0.1841 - accuracy: 0.9375 - val\_loss: 0.1722 - val\_accuracy: 0.9405 - lr: 0.0010  
Epoch 36/100  
44/44 [=====] - 39s 885ms/step - loss: 0.1896 - accuracy: 0.9361 - val\_loss: 0.1426 - val\_accuracy: 0.9502 - lr: 0.0010  
Epoch 37/100  
44/44 [=====] - 39s 888ms/step - loss: 0.1942 - accuracy: 0.9349 - val\_loss: 0.1617 - val\_accuracy: 0.9442 - lr: 0.0010  
Epoch 38/100  
44/44 [=====] - 39s 886ms/step - loss: 0.2163 - accuracy: 0.9229 - val\_loss: 0.1500 - val\_accuracy: 0.9470 - lr: 0.0010  
Epoch 39/100  
44/44 [=====] - 39s 883ms/step - loss: 0.1751 - accuracy: 0.9363 - val\_loss: 0.1106 - val\_accuracy: 0.9622 - lr: 0.0010

```

Epoch 40/100
44/44 [=====] - 40s 912ms/step - loss: 0.1849 - ac
curacy: 0.9338 - val_loss: 0.2038 - val_accuracy: 0.9266 - lr: 0.0010
Epoch 41/100
44/44 [=====] - 39s 883ms/step - loss: 0.1617 - ac
curacy: 0.9486 - val_loss: 0.1293 - val_accuracy: 0.9560 - lr: 0.0010
Epoch 42/100
44/44 [=====] - 39s 886ms/step - loss: 0.1336 - ac
curacy: 0.9583 - val_loss: 0.1023 - val_accuracy: 0.9641 - lr: 0.0010
Epoch 43/100
44/44 [=====] - 39s 890ms/step - loss: 0.1275 - ac
curacy: 0.9590 - val_loss: 0.0941 - val_accuracy: 0.9720 - lr: 0.0010
Epoch 44/100
44/44 [=====] - 40s 912ms/step - loss: 0.1351 - ac
curacy: 0.9581 - val_loss: 0.1591 - val_accuracy: 0.9456 - lr: 0.0010
Epoch 45/100
44/44 [=====] - 39s 891ms/step - loss: 0.1275 - ac
curacy: 0.9574 - val_loss: 0.1165 - val_accuracy: 0.9625 - lr: 0.0010
Epoch 46/100
44/44 [=====] - 39s 885ms/step - loss: 0.1260 - ac
curacy: 0.9574 - val_loss: 0.0675 - val_accuracy: 0.9773 - lr: 0.0010
Epoch 47/100
44/44 [=====] - 39s 882ms/step - loss: 0.1650 - ac
curacy: 0.9423 - val_loss: 0.1186 - val_accuracy: 0.9618 - lr: 0.0010
Epoch 48/100
44/44 [=====] - 39s 885ms/step - loss: 0.1151 - ac
curacy: 0.9627 - val_loss: 0.0573 - val_accuracy: 0.9822 - lr: 0.0010
Epoch 49/100
44/44 [=====] - 40s 912ms/step - loss: 0.0819 - ac
curacy: 0.9743 - val_loss: 0.0733 - val_accuracy: 0.9764 - lr: 0.0010
Epoch 50/100
44/44 [=====] - 39s 878ms/step - loss: 0.1102 - ac
curacy: 0.9627 - val_loss: 0.1269 - val_accuracy: 0.9578 - lr: 0.0010
Epoch 51/100
44/44 [=====] - 39s 882ms/step - loss: 0.1004 - ac
curacy: 0.9666 - val_loss: 0.0730 - val_accuracy: 0.9778 - lr: 0.0010
Epoch 52/100
44/44 [=====] - 39s 883ms/step - loss: 0.0952 - ac
curacy: 0.9701 - val_loss: 0.0715 - val_accuracy: 0.9787 - lr: 0.0010
Epoch 53/100
44/44 [=====] - 40s 912ms/step - loss: 0.0953 - ac
curacy: 0.9683 - val_loss: 0.0742 - val_accuracy: 0.9761 - lr: 0.0010
Out[21]:
<keras.callbacks.History at 0x7f438af89490>

```

## 7. Save the model

```
In [22]: model.save('Flowers.h5')
```

## 8. Test the model

```
In [23]: import numpy as np
         from tensorflow.keras.preprocessing import image
```

```
In [24]: img = image.load_img('/content/flowers/daisy/10300722094_28fa978807_n.jpg',target_size=(64,64))
```

In [25]: `img`

Out[25]:



In [26]: `x = image.img_to_array(img)`  
`x`

```
array([[ 35.,  12.,  56.],
       [ 52.,  32.,  60.],
       [ 59.,  46.,  63.],
       ...,
       [151., 156., 124.],
       [109., 133.,  73.],
       [162., 166., 141.],

       [ 65.,  54.,  68.],
       [ 92.,  88.,  77.],
       [ 89.,  85.,  74.],
       ...,
       [158., 165., 132.],
       [104., 126.,  77.],
       [140., 153., 125.],

       [123., 128.,  88.],
       [135., 143., 106.],
       [132., 136.,  99.],
       ...,
       [148., 158., 121.],
       [140., 163., 111.],
       [138., 152., 117.],

       ...,

       [  3.,   1.,  14.],
       [101., 122.,  83.],
       [ 78., 103.,  63.],
       ...,
       [ 79., 122.,   6.],
       [ 83., 113.,  17.],
       [ 98., 135.,  39.],

       [147., 172., 140.],
       [145., 173., 135.],
       [152., 175., 133.],
       ...,
       [ 61.,  99.,  38.],
       [133., 166., 113.],
       [  0.,  10.,   7.],

       [149., 171., 135.],
       [137., 156., 124.],
       [147., 170., 126.]
```

```
....,
[ 97., 123.,  60.],
[145., 182., 105.],
[105., 128.,  58.] ]], dtype=float32)
```

```
In [27]: x = np.expand_dims(x,axis=0)
x
```

```
array([[[[ 35.,  12.,  56.],
          [ 52.,  32.,  60.],
          [ 59.,  46.,  63.],
          ....,
          [151., 156., 124.],
          [109., 133.,  73.],
          [162., 166., 141.]],

        [[ 65.,  54.,  68.],
          [ 92.,  88.,  77.],
          [ 89.,  85.,  74.],
          ....,
          [158., 165., 132.],
          [104., 126.,  77.],
          [140., 153., 125.]],

        [[123., 128.,  88.],
          [135., 143., 106.],
          [132., 136.,  99.],
          ....,
          [148., 158., 121.],
          [140., 163., 111.],
          [138., 152., 117.]],

        ....,

        [[  3.,   1.,  14.],
          [101., 122.,  83.],
          [ 78., 103.,  63.],
          ....,
          [ 79., 122.,   6.],
          [ 83., 113.,  17.],
          [ 98., 135.,  39.]],

        [[147., 172., 140.],
          [145., 173., 135.],
          [152., 175., 133.],
          ....,
          [ 61.,  99.,  38.],
          [133., 166., 113.],
          [  0.,  10.,   7.]],

        [[149., 171., 135.],
          [137., 156., 124.],
          [147., 170., 126.],
          ....,
          [ 97., 123.,  60.],
          [145., 182., 105.],
          [105., 128.,  58.] ] ]], dtype=float32)
```

In [28]: `model.predict(x)`

Out[28]: `array([[0., 0., 0., 1., 0.]], dtype=float32)`

In [29]: `xtrain.class_indices`

Out[29]: `{'daisy': 0, 'dandelion': 1, 'rose': 2, 'sunflower': 3, 'tulip': 4}`

In [31]: `op = ['daisy', 'sunflower', 'rose', 'tulip', 'dandelion']  
pred = np.argmax(model.predict(x))  
op[pred]`

Out[31]: `'tulip'`