Assignment - 3, authored by Kishore Akash YS

1. Download the dataset https://drive.google.com/file/drive.google.com/file/dri

Importing necessary Libraries

```
In [1]: import warnings
    warnings.filterwarnings("ignore")

In [2]: 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,Ma
    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,i
    from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
```

Data Augumentation

- · Dataset consist of 5 classes.
- Daisy European Species of Aster family.
- Sunflower Identified as the genus of Helianthus.
- Tulip Belong to the species of spring blooming geophytes.
- Rose Belongs to the family of rosaceae.
- Dandelion Indentifies as the genus of Asterceae.

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

Model building using CNN

1. Create the model

```
In [6]: model = Sequential()

#convolution and Pooling Layer 1
model.add(Conv2D(filters=48,kernel_size=3,activation='relu',input_shape=(64,64
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'))
```

In [7]: model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 62, 62, 48)	1344
<pre>max_pooling2d (MaxPooling2D)</pre>	(None, 31, 31, 48)	0
dropout (Dropout)	(None, 31, 31, 48)	0
conv2d_1 (Conv2D)	(None, 29, 29, 32)	13856
<pre>max_pooling2d_1 (MaxPooling 2D)</pre>	(None, 14, 14, 32)	0
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

2. Compile the Model

```
In [8]:
        model.compile(loss='categorical_crossentropy',optimizer='adam',metrics=['accur
```

3. Adding callbacks to avoid overfitting

```
In [9]: 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]
```

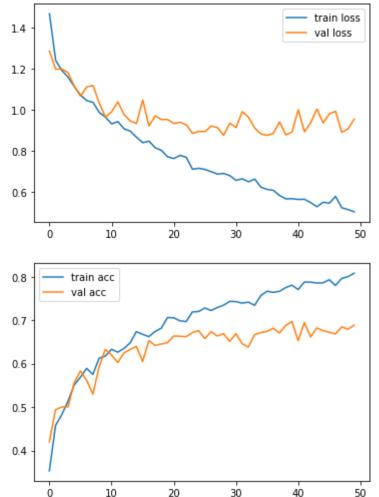
4. Training the Model

```
In [10]: result = model.fit(x=training_set, validation_data=testing_set, epochs=50)
      Epoch 1/50
      31/31 [=============== ] - 17s 536ms/step - loss: 1.4674 - accu
      racy: 0.3532 - val_loss: 1.2853 - val_accuracy: 0.4200
      Epoch 2/50
      racy: 0.4580 - val_loss: 1.1973 - val_accuracy: 0.4942
      Epoch 3/50
      31/31 [=============== ] - 17s 544ms/step - loss: 1.1910 - accu
      racy: 0.4825 - val_loss: 1.1977 - val_accuracy: 0.5004
      Epoch 4/50
      racy: 0.5136 - val_loss: 1.1799 - val_accuracy: 0.5004
      racy: 0.5509 - val_loss: 1.1133 - val_accuracy: 0.5561
      Epoch 6/50
      31/31 [============ ] - 19s 626ms/step - loss: 1.0707 - accu
      racy: 0.5688 - val_loss: 1.0658 - val_accuracy: 0.5831
      Epoch 7/50
                                    20- 655---/--- 1--- 4 0444
```

5. Loss and Accuracy check using plot

```
In [11]: #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()
```



6. Save the Model

```
In [12]: model.save('flower.h5')
```

Testing the Model

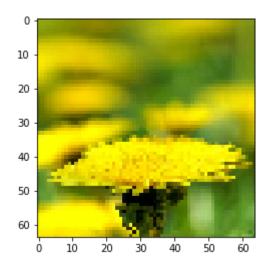
```
In [13]: training_set.class_indices
Out[13]: {'daisy': 0, 'dandelion': 1, 'rose': 2, 'sunflower': 3, 'tulip': 4}
```

```
In [26]: 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)
```

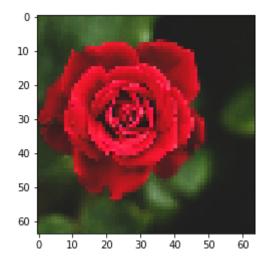
```
In [35]: #test1
    img_show('flower1.jpg')
    testing('flower1.jpg')
```

Predicted class as: Dandelion



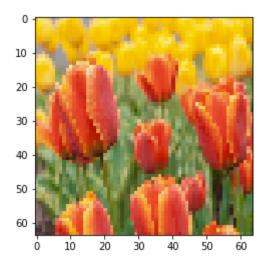
```
In [31]: #test2
    img_show('flower2.jpg')
    testing('flower2.jpg')
```

Predicted class as: Rose



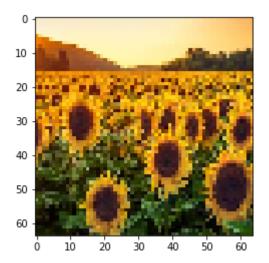
```
In [30]: #test3
   img_show('flower3.jpg')
   testing('flower3.jpg')
```

Predicted class as: Tulip



```
In [32]: #test4
   img_show('flower4.jpg')
   testing('flower4.jpg')
```

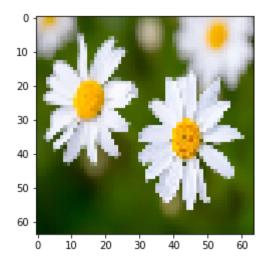
Predicted class as: Sunflower



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```
In [33]: #test5
    img_show('flower5.jpg')
    testing('flower5.jpg')
```

Predicted class as: Daisy



Conclusion:

- The dataset has about 4317 images from 5 different classes.
- Each classes have more than 500 images for training the data.
- 30% of the data taken for validation.
- The accuracy of the model is around 80%.
- The validation accuracy is around 70%.
- The model is built with 2 layered convolutional network considering 1344 trainable parameters.
- Testing the model with unknown images gives 95% accuracy.

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