

IMAGE CLASSIFICATION

Abstract

The project focuses on building a model to recognize different types of flowers from images using machine learning techniques. The goal is to classify flower images into various categories based on their features. The flower recognition project aims to classify images of flowers into various species using machine learning techniques. This involves training a model on a labeled dataset of flower images to recognize and predict the species of flowers in new images.

About Dataset

The dataset contains 5 types of flower type put in separate folders. The flowers are Rose, Daisy, Tulip, Sunflower and Dandelion. We have 764 images of Daisy,1052 images of Dandelion, 784 images of Rose,733 images of Sunflower and 984 images of Tulip. Total we have 4,317 in which we perform image classification using CNN.

Algorithm

Data Preprocessing:

- Image resizing and normalization.
- Data augmentation techniques like rotation, flipping, and zooming to increase dataset variability.

Model Selection:

- Convolutional Neural Networks (CNNs): These are the most widely used models for image classification tasks.
- Transfer Learning: Utilizing pre-trained models like VGG16, ResNet, or InceptionV3 and fine-tuning them for the specific flower dataset.

Training:

- Splitting the dataset into training, validation, and test sets.
- Using a loss function (e.g., categorical cross-entropy) and an optimizer (e.g., Adam) to train the model.
- Monitoring performance on the validation set to avoid overfitting.

Code

*Importing the Libraries

```
#Importing Libraries
import os
import numpy as np

import tensorflow as tf
from tensorflow keras import layers
from tensorflow keras preprocessing image import load img, ImageDataGenerator
from tensorflow keras models import Sequential, load_model
from tensorflow keras models import Conv2D, MaxPooling2D, Dense, Dropout, Flatten

[1] 

22.1s

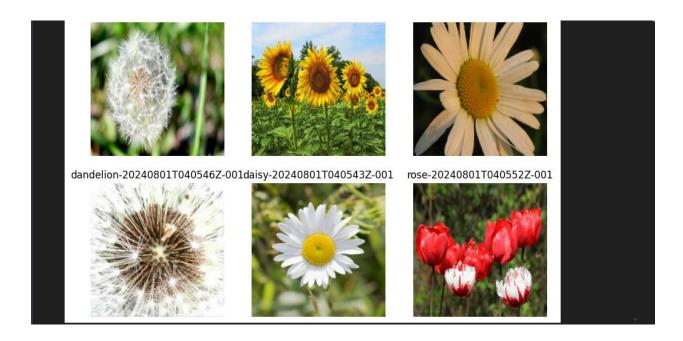
Python
```

*Fetching the count of images from the folders

*Loading the images into the arrays as Dataset

```
Python
        base_dir = 'Images/'
        img_size = 180
        batch = 32
[3] 			 0.0s
                                                                                                                                 Python
        train_ds = tf.keras.utils.image_dataset_from_directory( base_dir,
                                                               validation_split=0.2,
                                                               subset = 'training',
                                                               batch_size=batch,
                                                               image_size=(img_size,img_size))
        val_ds = tf.keras.utils.image_dataset_from_directory( base_dir,
                                                               seed = 123,
                                                               validation_split=0.2,
                                                               batch_size=batch,
                                                               image_size=(img_size,img_size))
    Found 4317 files belonging to 5 classes.
    Using 3454 files for training.
    Found 4317 files belonging to 5 classes.
    Using 863 files for validation.
```





*Doing the data augmentation

```
AUTOTUNE = tf.data.AUTOTUNE

v 0.0s Python

train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size = AUTOTUNE)

val_ds = val_ds.cache().prefetch(buffer_size = AUTOTUNE)

python

#Data Augmentation

#Dython

#
```

*Creating model for prediction

```
model.summary()

v 0.4s

Model: "sequential_1"

...

Layer (type)

Sequential (Sequential)

(None, 180, 180, 3)

Conv2d (Conv2D)

(None, 180, 180, 10)

Conv2d (Conv2D)

(None, 180, 180, 10)

Conv2d_1 (Conv2D)

(None, 90, 90, 10)

Conv2d_1 (Conv2D)

(None, 90, 90, 32)

Conv2d_1 (Conv2D)

(None, 90, 90, 32)

Conv2d_2 (Conv2D)

(None, 45, 45, 32)

Conv2d_2 (Conv2D)

(None, 45, 45, 64)

Max_pooling2d_1 (MaxPooling2D)

(None, 22, 22, 64)

dropout (Dropout)

(None, 22, 22, 64)

flatten (Flatten)

(None, 30976)

dense (Dense)

(None, 128)

3,965,056
```

```
dense_1 (Dense) (None, 5) 645

...

Total params: 11,967,857 (45.65 MB)

...

Trainable params: 3,989,285 (15.22 MB)

...

Non-trainable params: 0 (0.00 B)

...

Optimizer params: 7,978,572 (30.44 MB)
```

```
history = model.fit(train_ds, epochs=15, validation_data=val_ds)
[17] 		✓ 20m 1.8s
                                                                                                                                  Python
··· Epoch 1/15
     108/108
                                - 90s 778ms/step - accuracy: 0.3259 - loss: 1.5923 - val_accuracy: 0.5759 - val_loss: 1.0868
    Epoch 2/15
    108/108 -
                                - 87s 809ms/step - accuracy: 0.5342 - loss: 1.1167 - val accuracy: 0.5910 - val loss: 1.0579
    Epoch 3/15
                                <mark>– 89s</mark> 823ms/step - accuracy: 0.6024 - loss: 0.9832 - val_accuracy: 0.5771 - val_loss: 1.0203
     108/108 -
    Epoch 4/15
     108/108
                                  84s 781ms/step - accuracy: 0.6255 - loss: 0.9475 - val_accuracy: 0.6211 - val_loss: 0.9960
    Epoch 5/15
                                  82s 758ms/step - accuracy: 0.6529 - loss: 0.9022 - val accuracy: 0.6570 - val loss: 0.8800
    108/108
    Epoch 6/15
     108/108
                                  78s 725ms/step - accuracy: 0.6860 - loss: 0.8196 - val_accuracy: 0.6640 - val_loss: 0.8562
     Epoch 7/15
     108/108
                                  77s 711ms/step - accuracy: 0.7052 - loss: 0.7670 - val_accuracy: 0.6883 - val_loss: 0.8067
    Epoch 8/15
    108/108 -
                                - 76s 706ms/step - accuracy: 0.6941 - loss: 0.8059 - val_accuracy: 0.6895 - val_loss: 0.8113
    Epoch 9/15
     108/108 -
                                - 78s 725ms/step - accuracy: 0.7358 - loss: 0.7063 - val_accuracy: 0.7022 - val_loss: 0.7646
     Epoch 10/15
                                - 79s 729ms/step - accuracy: 0.7463 - loss: 0.7046 - val_accuracy: 0.6964 - val_loss: 0.7720
     108/108
    Epoch 11/15
                                 - 76s 702ms/step - accuracy: 0.7423 - loss: 0.6737 - val_accuracy: 0.7138 - val_loss: 0.7606
     108/108
     Epoch 12/15
     108/108
                                - 76s 707ms/step - accuracy: 0.7487 - loss: 0.6618 - val_accuracy: 0.7254 - val_loss: 0.7109
     Epoch 13/15
     Epoch 14/15
```

```
Epoch 14/15
108/108 -
                             - 75s 691ms/step - accuracy: 0.7745 - loss: 0.6066 - val_accuracy: 0.7231 - val_loss: 0.7140
Epoch 15/15
108/108
                             - 78s 725ms/step - accuracy: 0.7868 - loss: 0.5765 - val_accuracy: 0.7416 - val_loss: 0.6881
Output is truncated. View as a <u>scrollable element</u> or open in a <u>text editor</u>. Adjust cell output <u>settings</u>...
   def classify_images(image_path):
       input_image = tf.keras.utils.load_img(image_path, target_size=(180,180))
        input_image_array = tf.keras.utils.img_to_array(input_image)
       input_image_exp_dim = tf.expand_dims(input_image_array,0)
       predictions = model.predict(input image exp dim)
       result = tf.nn.softmax(predictions[0])
       outcome = 'The Image belongs to ' + flower_names[np.argmax(result)] + ' with a score of '+ str(np.max(result)*100)
       return outcome
                                                                                                                                   Python
```

```
classify_images('D:/Jupyter Notebook/Sample/tulip.jfif')

[20] 

3.7s

Python

1/1 

1s 1s/step

The Image belongs to tulip-20240801T040606Z-001 with a score of 54.11316156387329'
```

*Compiling the model

OUTPUT

Here when we gave the sample image it was predicted correctly with an accuracy of 93.28%.

