# 5 Flower Types Classification Dataset

The **5 Flower Types Classification Dataset** is a collection of images belonging to five different flower classes: Lilly, Lotus, Sunflower, Orchid, and Tulip. Each flower class contains 1000 images, resulting in a total of 5000 images in the dataset.

This dataset is suitable for training and evaluating a multi-class Convolutional Neural Network (CNN) model to classify flower images into one of the five mentioned classes. The goal of the classification task is to accurately identify the type of flower from an input image.

The dataset can be used to explore various deep learning techniques for image classification, such as data augmentation, transfer learning, and model fine-tuning. It provides a challenging task due to the visual similarity and subtle differences among different flower types.

Dataset Details:

- Number of classes: 5
- Total images: 5000 (1000 images per class)
- Image format: JPG or PNG
- Image resolution: Varies (please preprocess the images to a consistent size if required)

The 5 Flower Types Classification Dataset is a valuable resource for researchers, students, and practitioners interested in the field of computer vision, specifically in image classification tasks. It can be used for educational purposes, benchmarking different models, and advancing the state-of-the-art in flower classification.

Feel free to download the dataset and start exploring the fascinating world of flower image classification!: [https://www.kaggle.com/datasets/kausthubkannan/5-flower-types-classification-dataset (https://www.kaggle.com/datasets/kausthubkannan/5-flower-types-classification-dataset)](https://www.kaggle.com/datasets/kausthubkannan/5-flower-types-classification-dataset)

In [1]:

```
# import libraries
import os
import shutil
import random
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from PIL import Image
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.layers import Conv2D, MaxPool2D, Flatten, Dense, Dropout
from tensorflow.keras import Sequential
os.environ['KAGGLE_CONFIG_DIR'] = '/content'
```

# Downloading and preparing data for model

In [2]:

```
!kaggle datasets download -d kausthubkannan/5-flower-types-classification-dataset
```

```
Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can
run 'chmod 600 /content/kaggle.json'
Downloading 5-flower-types-classification-dataset.zip to /content
 96% 232M/242M [00:02<00:00, 104MB/s]
100% 242M/242M [00:02<00:00, 115MB/s]
```

In [3]:
```
!unzip \*.zip && rm *.zip
```

```
Streaming output truncated to the last 5000 lines.
  inflating: flower_images/Lilly/00048a5c76.jpg
  inflating: flower_images/Lilly/001ff6644e.jpg
  inflating: flower_images/Lilly/001ff6656j.jpg
  inflating: flower_images/Lilly/00973ad1b1.jpg
  inflating: flower_images/Lilly/00a7d512d6.jpg
  inflating: flower_images/Lilly/00f36a3c40.jpg
  inflating: flower_images/Lilly/013628cccc.jpg
  inflating: flower_images/Lilly/01998d6fb5.jpg
  inflating: flower_images/Lilly/01a0ec319c.jpg
  inflating: flower_images/Lilly/01b4bb0289.jpg
  inflating: flower_images/Lilly/025ef3ea44.jpg
  inflating: flower_images/Lilly/02a7a2df46.jpg
  inflating: flower_images/Lilly/02be2ca388.jpg
  inflating: flower_images/Lilly/035cce082f.jpg
  inflating: flower_images/Lilly/039eba79d4.jpg
  inflating: flower_images/Lilly/04067b91d6.jpg
  inflating: flower_images/Lilly/04acfd5449.jpg
  inflating: flower_images/Lilly/05777790e2.jpg
```

In [4]:
```
!pip install split-folders
```

```
Looking in indexes: https://pypi.org/simple, (https://pypi.org/simple,) https://us-python.pkg.dev/colab-wheels/public/simple/ (https://us-python.pkg.dev/colab-wheels/public/simple/)
Collecting split-folders
  Downloading split_folders-0.5.1-py3-none-any.whl (8.4 kB)
Installing collected packages: split-folders
Successfully installed split-folders-0.5.1
```

In [5]:
```
import splitfolders
```

In [6]:
```
src_dir = '/content/flower_images'
dst_dir = '/content/Data'
```

## Data preprocessing (image augmentation)

In [7]:
```
splitfolders.ratio(input=src_dir, output=dst_dir, ratio=(0.8, 0.2))
```

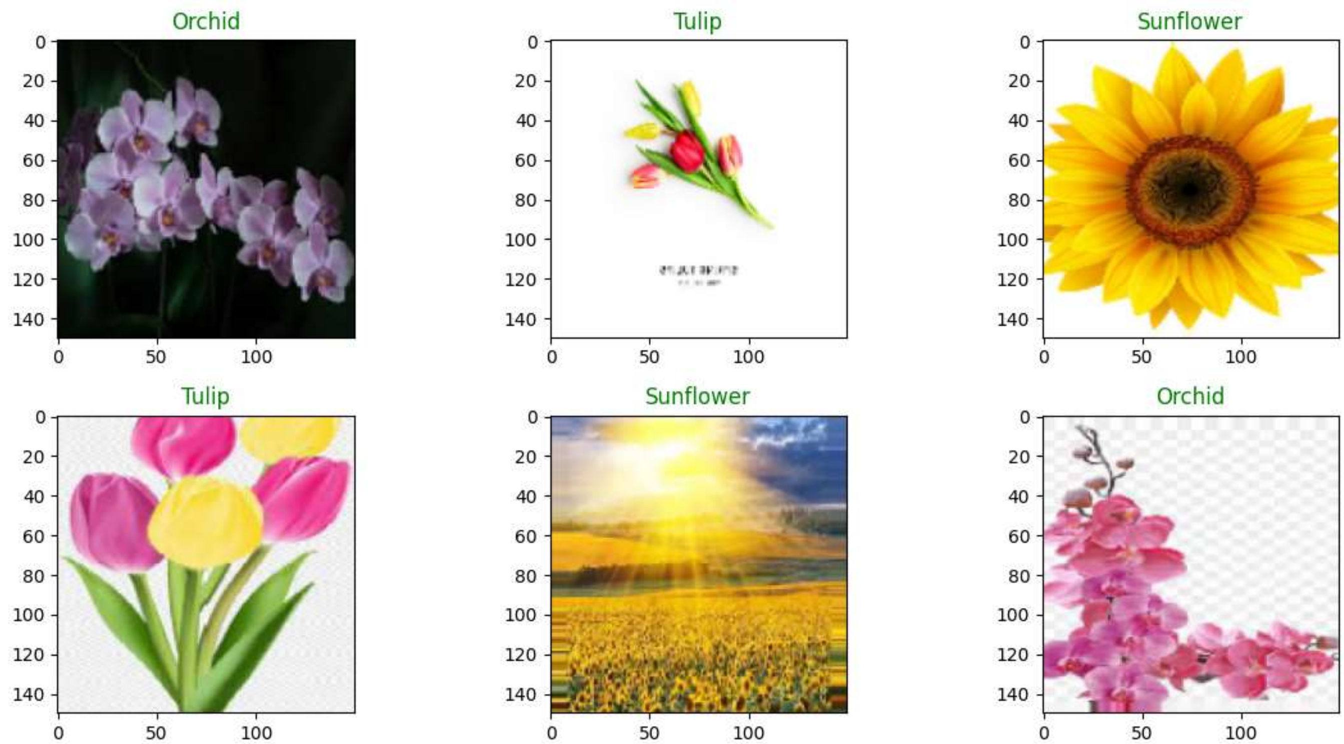
```
Copying files: 5000 files [00:00, 5625.05 files/s]
```

In [8]:
```
train_datagen = ImageDataGenerator(rescale=1/255., rotation_range=0.2,
                                  #  brightness_range=(0.2, 0.5),
                                   zoom_range=0.2, shear_range=0.2,
                                   horizontal_flip=True)
train_dataset = train_datagen.flow_from_directory('/content/Data/train',
                                                  target_size=(150, 150),
                                                  batch_size=32,
                                                  shuffle=True)


val_datagen = ImageDataGenerator(rescale=1/255.)
val_dataset = val_datagen.flow_from_directory('/content/Data/val', target_size=(150, 150)
                                              batch_size=32, shuffle=False)
```

```
Found 4000 images belonging to 5 classes.
Found 1000 images belonging to 5 classes.
```

In [9]:

```
images, labels = next(train_dataset)
labels = np.argmax(labels, axis=1)
class_names = list(train_dataset.class_indices.keys())
def plot_random_images(images, labels, class_names):
    plt.figure(figsize=(12, 6))

    for i in range(6):
        ax = plt.subplot(2, 3, i+1)
        rand_index = random.choice(range(len(images)))
        plt.imshow(images[rand_index])
        plt.title(class_names[labels[rand_index]], color='green', fontsize=12)

    plt.tight_layout()
    plt.show()

plot_random_images(images, labels, class_names)
```



## creating model

In [10]:
```
model = Sequential([

                    Conv2D(filters=16, kernel_size=(3,3), strides=1, activation='relu', i
                    MaxPool2D(pool_size=(2,2), strides=2, padding='valid'),

                    Conv2D(filters=32, kernel_size=(3,3), strides=2, activation='relu'),
                    MaxPool2D(pool_size=(2,2), strides=1, padding='same'),

                    Conv2D(filters=64, kernel_size=(3,3), strides=2, activation='relu'),
                    MaxPool2D(pool_size=(2,2), strides=1, padding='same'),

                    Flatten(),
                    Dense(256, activation='relu'),
                    Dense(128, activation='relu'),
                    Dense(64, activation='relu'),
                    Dense(5, activation='softmax')

])
```

In [11]:
```
model.compile(optimizer=Adam(), loss=tf.keras.losses.CategoricalCrossentropy(), metrics=[
```

In [12]:
```
model.summary()
```

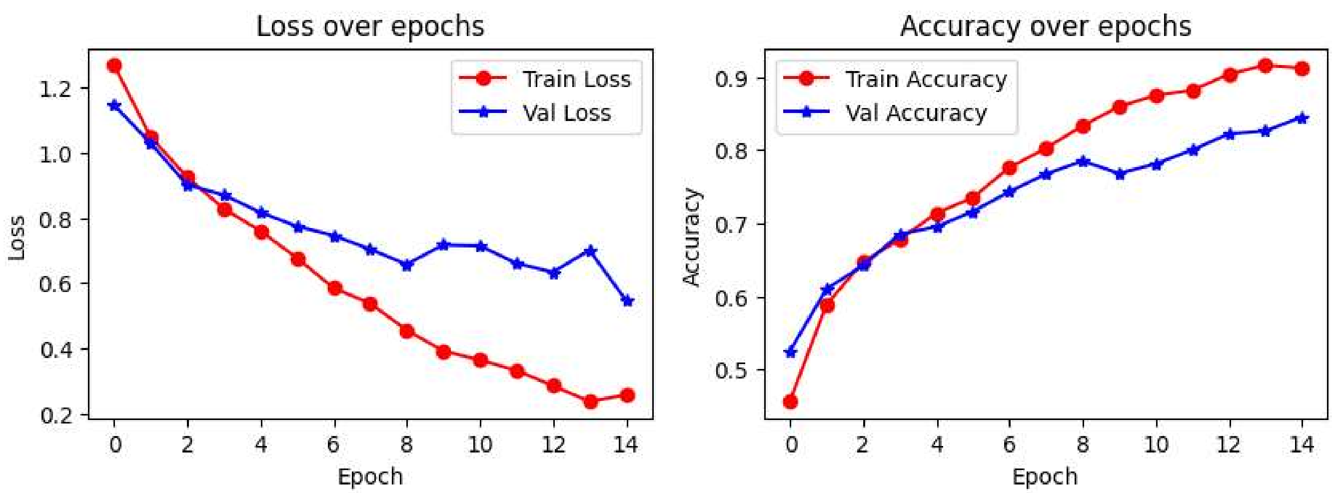
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 148, 148, 16)      448

 max_pooling2d (MaxPooling2D  (None, 74, 74, 16)       0
 )

 conv2d_1 (Conv2D)           (None, 36, 36, 32)        4640

 max_pooling2d_1 (MaxPooling  (None, 36, 36, 32)       0
 2D)

 conv2d_2 (Conv2D)           (None, 17, 17, 64)        18496

 max_pooling2d_2 (MaxPooling  (None, 17, 17, 64)       0
 2D)

 flatten (Flatten)           (None, 18496)             0

 dense (Dense)               (None, 256)               4735232

 dense_1 (Dense)             (None, 128)               32896

 dense_2 (Dense)             (None, 64)                8256

 dense_3 (Dense)             (None, 5)                 325

=================================================================
Total params: 4,800,293
Trainable params: 4,800,293
Non-trainable params: 0
_________________________________________________________________
```

In [13]:
```
history = model.fit(train_dataset, epochs=15, validation_data=(val_dataset))
```

```
Epoch 1/15
125/125 [==============================] - 69s 411ms/step - loss: 1.2671 - accuracy: 0.4565
- val_loss: 1.1449 - val_accuracy: 0.5250
Epoch 2/15
125/125 [==============================] - 50s 399ms/step - loss: 1.0477 - accuracy: 0.5885
- val_loss: 1.0282 - val_accuracy: 0.6100
Epoch 3/15
125/125 [==============================] - 48s 387ms/step - loss: 0.9237 - accuracy: 0.6470
- val_loss: 0.9004 - val_accuracy: 0.6420
Epoch 4/15
125/125 [==============================] - 48s 386ms/step - loss: 0.8279 - accuracy: 0.6775
- val_loss: 0.8699 - val_accuracy: 0.6850
Epoch 5/15
125/125 [==============================] - 49s 390ms/step - loss: 0.7596 - accuracy: 0.7138
- val_loss: 0.8166 - val_accuracy: 0.6950
Epoch 6/15
125/125 [==============================] - 50s 398ms/step - loss: 0.6770 - accuracy: 0.7347
- val_loss: 0.7740 - val_accuracy: 0.7160
Epoch 7/15
125/125 [==============================] - 53s 422ms/step - loss: 0.5846 - accuracy: 0.7760
- val_loss: 0.7458 - val_accuracy: 0.7430
Epoch 8/15
125/125 [==============================] - 49s 390ms/step - loss: 0.5382 - accuracy: 0.8023
- val_loss: 0.7037 - val_accuracy: 0.7670
Epoch 9/15
125/125 [==============================] - 48s 387ms/step - loss: 0.4564 - accuracy: 0.8330
- val_loss: 0.6574 - val_accuracy: 0.7850
Epoch 10/15
125/125 [==============================] - 49s 395ms/step - loss: 0.3924 - accuracy: 0.8593
- val_loss: 0.7169 - val_accuracy: 0.7680
Epoch 11/15
125/125 [==============================] - 52s 418ms/step - loss: 0.3647 - accuracy: 0.8748
- val_loss: 0.7141 - val_accuracy: 0.7810
Epoch 12/15
125/125 [==============================] - 48s 388ms/step - loss: 0.3328 - accuracy: 0.8815
- val_loss: 0.6606 - val_accuracy: 0.8000
Epoch 13/15
125/125 [==============================] - 49s 391ms/step - loss: 0.2856 - accuracy: 0.9035
- val_loss: 0.6334 - val_accuracy: 0.8220
Epoch 14/15
125/125 [==============================] - 50s 399ms/step - loss: 0.2379 - accuracy: 0.9160
- val_loss: 0.7007 - val_accuracy: 0.8260
Epoch 15/15
125/125 [==============================] - 48s 389ms/step - loss: 0.2576 - accuracy: 0.9120
- val_loss: 0.5470 - val_accuracy: 0.8450
```

In [14]:

```python
loss_df = pd.DataFrame(history.history)

def plot_predictions(data=loss_df):
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 3))

    ax1.plot(loss_df['loss'], color='red',marker='o', label='Train Loss')
    ax1.plot(loss_df['val_loss'], color='blue',marker='*', label='Val Loss')

    ax1.set_title('Loss over epochs')
    ax1.set_xlabel('Epoch')
    ax1.set_ylabel('Loss')
    ax1.legend()

    ax2.plot(loss_df['accuracy'], color='red',marker='o', label='Train Accuracy')
    ax2.plot(loss_df['val_accuracy'], color='blue',marker='*', label='Val Accuracy')

    ax2.set_title('Accuracy over epochs')
    ax2.set_xlabel('Epoch')
    ax2.set_ylabel('Accuracy')
    ax2.legend()
plot_predictions(loss_df)
```




# making predictions

In [15]:

```python
predictions = np.argmax(model.predict(val_dataset), axis=1)
y_true = val_dataset.labels
```

```
32/32 [==============================] - 6s 172ms/step
```

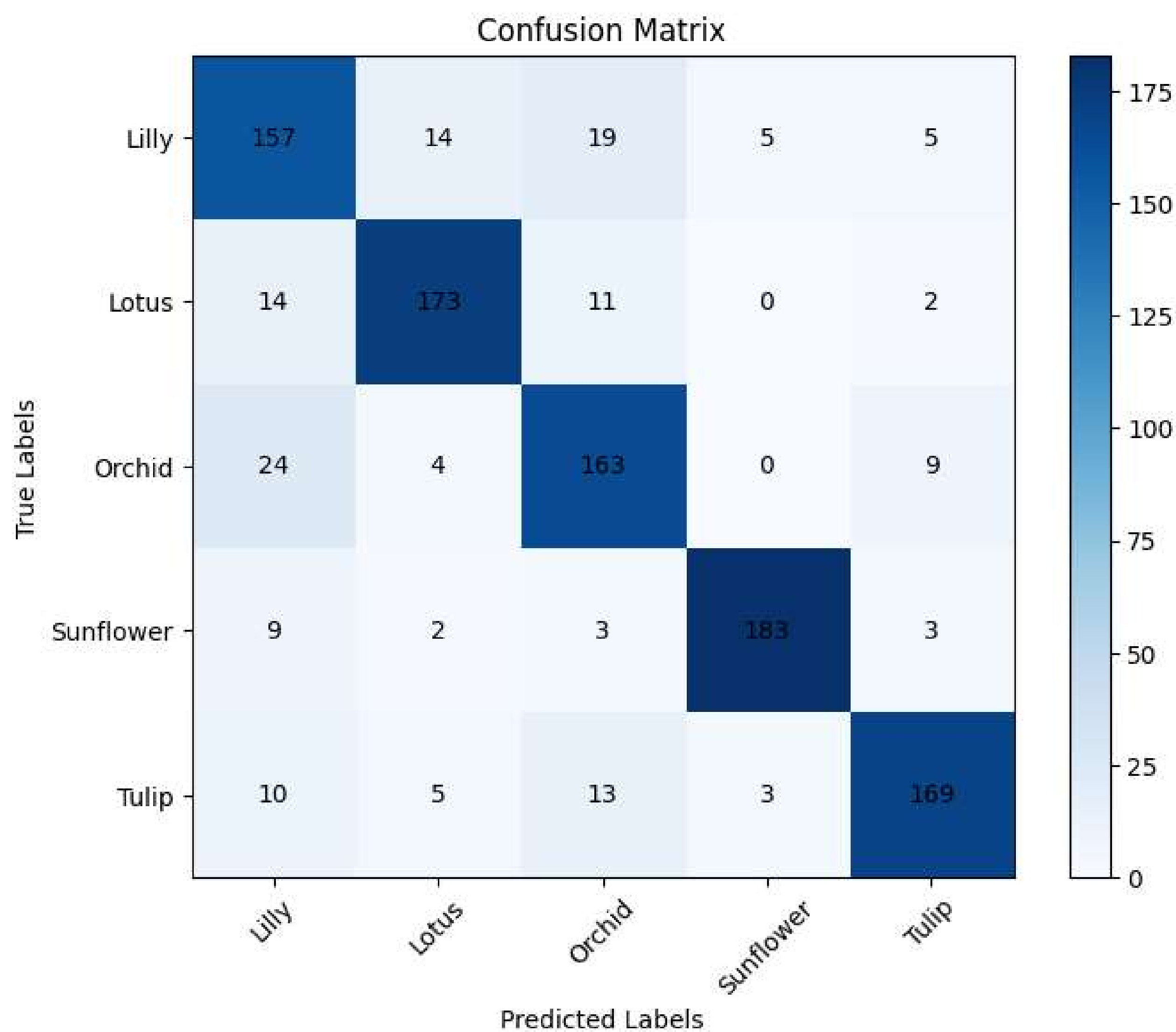
In [16]:

```python
print(accuracy_score(predictions, y_true))
```

```
0.845
```

In [17]:

```python
def plot_confusion_matrix(y_true, predictions, class_names):

    cm = confusion_matrix(y_true, predictions)
    plt.figure(figsize=(8, 6))
    heatmap = plt.imshow(cm, cmap='Blues')

    # Set axis labels and title
    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.title('Confusion Matrix')

    # Set xticks and yticks with class names
    tick_labels = class_names
    plt.xticks(ticks=np.arange(len(class_names)), labels=tick_labels, rotation=45)
    plt.yticks(ticks=np.arange(len(class_names)), labels=tick_labels)

    # Add numbers to the heatmap cells
    for i in range(len(class_names)):
        for j in range(len(class_names)):
            plt.text(j, i, str(cm[i, j]), ha='center', va='center', color='black')

    plt.colorbar(heatmap)
    plt.show()
plot_confusion_matrix(y_true, predictions, class_names)
```



In [20]:

```python
def plot_random_image(model, val_data, classes):

    images = []
    labels = []
    for _ in range(len(val_data)):
        batch_images, batch_labels = next(val_data)
        images.extend(batch_images)
        labels.extend(batch_labels)

    # Shuffle the images and labels together
    combined = list(zip(images, labels))
    random.shuffle(combined)
    images, labels = zip(*combined)
    labels = np.argmax(labels, axis=1)
    plt.figure(figsize=(12, 6))
    for i in range(6):
        ax = plt.subplot(2, 3, i + 1)
        rand_index = random.choice(range(len(images)))
        target_image = images[rand_index]
        pred_probs = model.predict(tf.expand_dims(target_image, axis=0), verbose=0)
        pred_label = classes[pred_probs.argmax()]
        true_label = classes[labels[rand_index]]

        plt.imshow(target_image)

        if pred_label == true_label:
            color = "green"
        else:
            color = "red"

        plt.title("Pred: {} {:2.0f}% (True: {})".format(pred_label,
                                                          100 * tf.reduce_max(pred_probs),
                                                          true_label),
                  color=color, fontsize=10)

    plt.tight_layout()
plot_random_image(model, val_dataset, class_names)
plt.show()
```