

How to determine the class of a flower

Link:

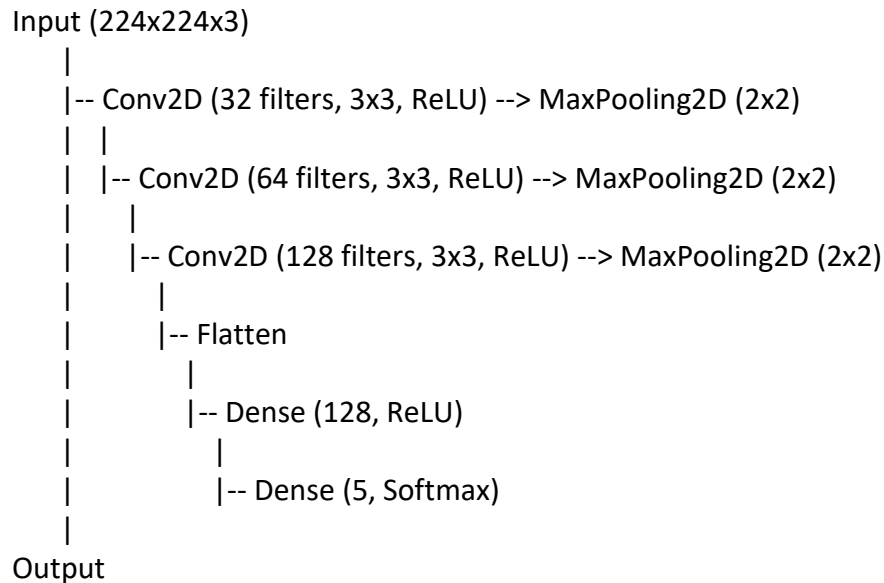
https://github.com/SabirAliESILV/Data_IA_Final_Project/tree/main

Team Members:

Student Name	Student ID	Contribution in the project
Bennis Marwan	73190	Data augmentation, flowing of images into batches
Sabir Ali	73196	Splitting of the images between training and testing sets
D'Aboville Edouard	73169	Creating the model, drawing plots

Model Architecture:

- The chosen model architecture is a Convolutional Neural Network (CNN). CNNs are particularly effective for image classification tasks, making them a suitable choice for recognizing different types of flowers in images.
- Architecture diagram:



- Number of layers:
 - Convolutional layers: 3 layers
 - Pooling layers: 3 layers
 - Dense (fully connected) layers: 2 layers
- Hidden layers and neurons:
 - Convolutional layers:
 - Conv2D (32 filters, 3x3, ReLU)
 - Conv2D (64 filters, 3x3, ReLU)
 - Conv2D (128 filters, 3x3, ReLU)
 - Dense layers:
 - Dense (128 neurons, ReLU)
 - Dense (5 neurons, Softmax)

Dataset Description:

- Dataset details:
 - o Number of classes: 5 (Lilly, Lotus, Orchid, Sunflower, Tulip)
 - o Total images: 5000 (1000 per class)
- We organize flower images into training and validation sets within a main directory named 'flower_images'. We iterate through subdirectories for different flower types ('Lilly', 'Lotus', 'Orchid', 'Sunflower', 'Tulip'). For each flower type, we split the image filenames into training and validation sets, moving a specified percentage (20%) of images to a newly created 'validation' subdirectory within the respective flower directory. We used the scikit-learn library for the image split and the shutil library for moving files.
- Data augmentations:
 - o Rescaling: images are rescaled by dividing pixel values by 255 to normalise them.
 - o Shear range: randomly applying shear transformations with a range of 0.2.
 - o Zoom range: randomly applying zoom transformations with a range of 0.2.
 - o Horizontal flip: randomly flipping images horizontally.

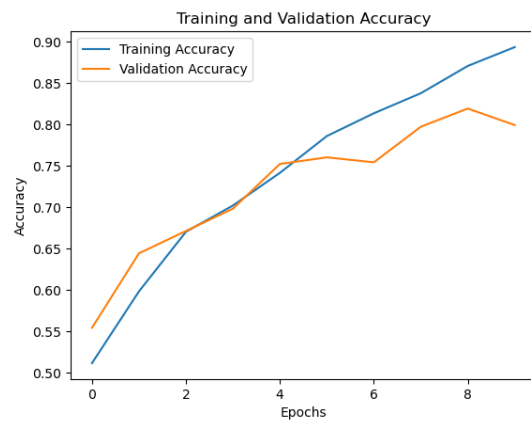
We apply these to the training dataset to artificially increase the diversity of the training set, which helps our model react better to never-seen-before data.

Methodology:

- Training parameters:
 - Number of epochs: Our model goes through 10 epochs, which means that it processes the entire training dataset 10 times.
 - Batch size: Our batch size of 32 determines the number of samples used in each iteration, meaning that the model updates its internal parameters after processing 32 images.
 - Optimizer: We chose Adam, an optimization algorithm that adapts the learning rate during training, for its improvements of model accuracy and speed.
- For the loss function, we used categorical crossentropy which is suitable for our multi-class classification problem. It works by measuring the dissimilarity between the predicted probabilities and the true class distribution.
- One parameter that significantly affected model results is the learning rate, which controls the size of the step taken by Adam during parameter updates. At the end, we preferred keeping the default value.
- How we improved the results:
 - Adjusting and modifying the number and types of layers in the model.
 - Tuning hyperparameters like the learning rate, the batch size, the number of epochs, etc.
 - Implementing additional data augmentation techniques.

Results:

- Accuracy of the model:



- Loss of the model:



- Direct results example:

