Classification of flowers

The goal of the project is to figure out the species of flowers using a dataset of input images containing 5 classes of flowers: Lilly, Lotus, Orchid, Sunflower and Tulip.

Link:

https://github.com/lenadub/FINAL-PROJECT-AI.git

Team Members:

Student Name	Student ID	Contribution in the project
CAUVIN Marion	73109	This is a joint effort. We all contributed to each of the steps.
COURSIER Fanny	73206	This is a joint effort. We all contributed to each of the steps.
DUBOIS Léna	73150	This a a joint effort. We all contributed to each of the steps.
MULLER Julie	73191	This a a joint effort. We all contributed to each of the steps.

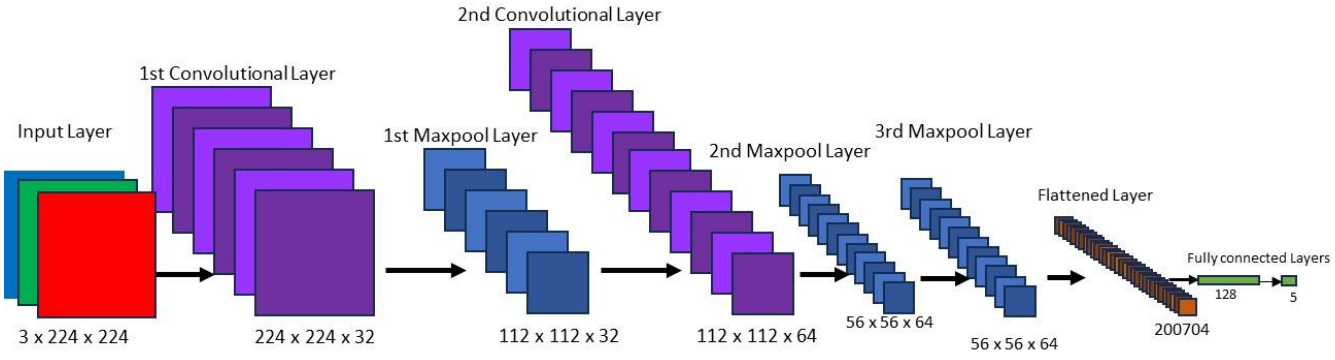
We would like to thank the Machine Learning blog authors on the Internet who helped us get an even greater insight into CNN theory and design (normalization, number of layers, dropout, pytorch code, etc)

Model Architecture:

A **Convolution Neural network architecture** was selected because CNNs have been popular and proved effective, for quite a while, to solve image classification problems. The **final** selected model is made of **9 layers including the input layer and the output layer**. It has **6 hidden layers**. The **total number of nodes excluding the input layer** is **3412101 nodes** (see table below for number of nodes per layer)**.**

The layered architecture of the final model from bottom to top is as follows:

Id	Layer Description	Activation	Specific processing	# of nodes
1	**The Image Input Layer.**	N/A	Input Normalization applied	224x224 *3 = 150,528
2	The first Convolutional Layer *Number of kernels : 32* *Stride : 1, padding 1*	ReLU	Adam optimisation backprop	224*224*32 = 1 605 632
3	A Maxpool Layer Window : 2x2 Stride : 2	None	Adam optimisation for backprop	112*112*32 = 401 408
4	A second Convolutional Layer *Number of kernels : 64* *Stride : 1, padding 1*	ReLU	Adam optimisation for backprop	64 * 112 * 112 = 802 816
5	A second Maxpool Layer Window : 2x2 Stride : 2	None	Adam optimisation for backprop	56 * 56*64 = 200 704
6	A third Convolutional Layer *Number of kernels : 64* *Stride : 1, padding 1*	ReLU	Adam optimisation for backprop	56 * 56*64 = 200 704
7	A flattened layer.		Adam optimisation for backprop	200 704
8	A fully connected layer	ReLU	Adam optimisation for backprop Dropout for regularization	128
9	**The output layer made a fully connected layer used for classification**	None	Adam optimisation	5



The dropout at the 8th layer (fully-connected) was added to narrow down the overfitting (training loss decreasing while validation loss increasing).

We tested 4 other models, which did not have a better accuracy and had overfitting issues:

- The model above without the third convolutional layer
- The model above without the third convolutional layer and no dropout
- The model above without the third convolutional layer and with 32 kernels in the second convolutional layer instead of 64.
- The model above without the third convolutional layer and with a larger size kernel (6x6) in the first two convolutional layersThe 4 alternate models. Some of them had overiffing issues.

Dataset Description:

The dataset included 5000 images of flowers divided into 5 species, with 1000 samples for each species.
We divided the dataset into 3 parts:

- Training dataset
  - This dataset was used to train the CNN
  - Its size was set to 80% of the initial dataset
- Validation dataset
  - This dataset including 500 images (10% of the initial dataset) was used to check the progress and performance of the training. After each training epoch, the trained CNN model was evaluated against the validation dataset. In other words, we recorded the loss and accuracy trends measured against the validation dataset while the model was getting trained. It was a way to check whether the model was learning properly (training loss and validation loss decreasing together and accuracy improving) and detect sign of overfitting (training loss decreasing while validation loss increasing)
- Test dataset
  - This dataset of 500 images (10% of the initial dataset) was used to test the model on unseen data once the training phase was completed.

The data was augmented with random rotation (0 to 20 degress) as well as horizontal flips (with propbability 0.1) to make the data closer to what we get in real life.

Methodology:

Machine Learning Coding Environment
We relied upon Google Colab using a T4 GPU and used the Pytorch environment.

Mini-batch
The model was submitted batches of 32 images for each epoch. Mini-batch is computationally efficient and is also memory efficient especially in the google colab environment where GPU memory is limited. It is also mentioned mini-batch helps against overfitting.

Learning rate:
The learning rate was set to 0.001. It is the recommended learning rate on multiple Machine Learning Internet sites when using the Adam optimisation. We were concerned such a small value would make the training phase very long on a Google Colab T4 GPU. However, we found training was quite fast so we kept this value for all the models tested for this project

Number of epochs:
The number of epochs was set to 50 for the selected model. After that, there were signs of overfitting.

The second best model (selected model without third convolutional layer) did get an accuracy close to the best model with an number of epochs set to 100 . After that, there were signs of overfitting.

Loss function
The loss function used for training was cross entropy.

Changes in parameters affecting the model results
The alternate models and selected model were trained using Input Normalization with the following mean and standard deviation for the three RGB colour channels.

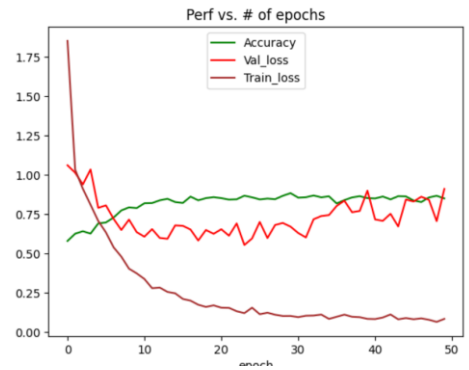
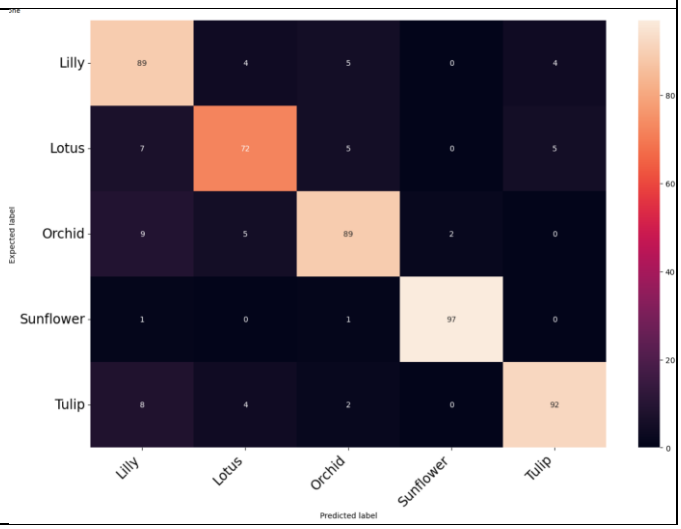
	First models		Final Model	
RGB	Mean	STD	Mean	STD
R	0.5	0.5	0.485	0.229
G	0.5	0.5	0.456	0.224
B	0.5	0.5	0.406	0.225

Normalization is used to mitigate gradient descent or explosion and help convergence.

As mentionned in the model architecture section, we adjusted the size and the number of kernels without any significant increase in accuracy

How have you improved the results?
The normalization mentioned above further increased the accuracy.
The green values which are considered as best on many Internet sites improved accuracy compared with the orange values

Results :

Training and validation performance	Confusion matrix on testing dataset
	

We can notice that after 50 epochs the validation accuracy is still increasing asymptotitely just over 85%. The validation loss is stabilizing and has not really started increasing yet while the training loss keeps decreasing. Overfitting is unlikely.

For the testing phase, we got:

- we got a testing accuracy of 0.8778831958770752which is quite fair.
- the confusion matrix below

Example of prediction on testing dataset (note the image below is normalized)

```
Expected label 4 - Predicted label 4
```