

Flower Image Classification Using Convolutional Neural Networks (CNN)

1. Introduction

Flower image classification is a common computer vision task where the goal is to automatically identify the type of flower from an image.

In this project, a Convolutional Neural Network (CNN) is built using TensorFlow/Keras to classify images into three classes:

- Rose
- Dandelion
- Daisy

A simple GUI is also built using Gradio to allow users to upload images and view predictions interactively.

2. Dataset Description

The dataset contains three folders, each representing a flower category:

- Images/
 - daisy
 - dandelion
 - rose

Additionally, a separate Samples/ folder contains test images for manual evaluation.

Dataset Statistics

A script is used to count how many images exist in each class. The total dataset contains approximately:

- *Daisy*: 764 images
- *Dandelion*: 1052 images
- *Rose*: 784 images
- Total Images: 2600

These images vary in size, color intensity, and background environment, making the classification task realistic.

3. Data Visualization

A few sample images from each class are displayed to visually understand the dataset.

This helps confirm that:

- Images are correctly labeled
- Flower categories are visually distinct
- No corrupted images exist

4. Data Preprocessing

To prepare the dataset for training:

4.1. Image Resizing

All images are resized to 150×150 pixels.

4.2. Normalization

Pixel values are scaled to a range of 0 to 1.

4.3. Train–Validation Split

A 20% validation split is applied using `ImageDataGenerator`.

4.4. Data Loading

`flow_from_directory()` is used to automatically:

- Load images
- Generate batches
- Apply preprocessing
- Assign labels based on folder names

5. Model Architecture

A Convolutional Neural Network (CNN) is designed with the following components:

5.1. Convolution & Pooling Layers

Multiple convolutional blocks extract spatial features such as:

- Edges
- Petal shapes
- Textures

Each block includes:

- Conv2D layer with ReLU activation
- MaxPooling2D for dimensionality reduction

5.2. Dropout Layers

Dropout is used to reduce overfitting and improve generalization.

5.3. Fully Connected Layers

Flattening is performed to convert feature maps into a vector.

Then:

- A dense layer with 128 neurons (ReLU)
- Output layer with 3 neurons and softmax activation

5.4. Compilation

The model is compiled using:

- Loss Function: Categorical Crossentropy
- Optimizer: Adam
- Metrics: Accuracy

6. Model Training

The model is trained for 10 epochs using:

- Training data
- Validation data to check generalization

During training, both accuracy and loss curves are plotted to observe model performance.

7. Model Evaluation

7.1. Confusion Matrix

A confusion matrix is generated to identify:

- Which classes are predicted correctly
- Which classes are being confused

This visual analysis helps understand model strengths and weaknesses.

7.2. Classification Report

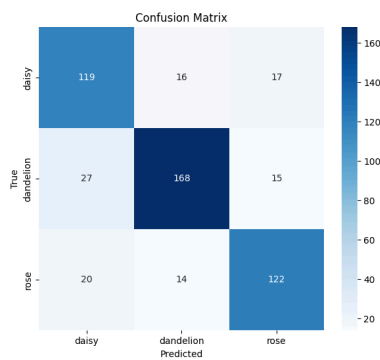
A detailed report is produced containing:

- Precision
- Recall
- F1-score
- Support (samples per class)

The model achieves approximately:

- Overall Accuracy: ~79% on validation data

This indicates strong performance for a basic CNN on a small dataset.



Classification Report:

	precision	recall	f1-score	support
daisy	0.72	0.78	0.75	152
dandelion	0.85	0.80	0.82	210
rose	0.79	0.78	0.79	156

accuracy			0.79	518
macro avg	0.79	0.79	0.79	518
weighted avg	0.79	0.79	0.79	518

8. Model Saving

The trained model is saved as:

`flower_model.h5`

This allows future use without retraining.

9. Gradio Web Application

A simple interactive user interface is created using Gradio.

Features:

- Upload any flower image
- Model predicts probabilities for all 3 classes
- Displays the top predictions with confidence scores
- Easy to use for non-technical users

This makes the project practical and accessible.

10. Conclusion

The project successfully builds a functional flower image classification system using CNNs.

Key outcomes:

- Accurate classification of rose, daisy, and dandelion images
- Strong baseline performance with validation accuracy around 79%
- Interactive prediction system using Gradio
- Detailed evaluation using confusion matrix and classification reports

The model can be further improved using techniques such as:

- Transfer Learning (MobileNet, VGG16, ResNet)
- Advanced data augmentation
- Hyperparameter tuning

11. Future Enhancements

Potential improvements include:

- Achieving >90% accuracy using pre-trained models
- Deploying the model as a web app or mobile app
- Adding more flower categories
- Creating a real-time camera-based flower detection system