

## FLOWER IDENTIFICATION AND CLASSIFICATION DIFFERENT SPECIES OF FLOWERS FROM IMAGES USING CNN

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### Abstract

*This Paper aims to classify the type of flowers using convolutional neural networks (CNNs). We will start by gathering a dataset of flower images, resizing and normalizing them as part of data preprocessing. We will then divide the dataset into three subsets, namely training, validation, and test sets. We will design a CNN architecture with multiple convolutional layers, pooling layers, and fully connected layers. Techniques like dropout and batch normalization will be applied to improve the model's generalization ability and prevent overfitting. The training set will be used to train the model, and the validation set will be used to prevent overfitting by using techniques like early stopping and learning rate scheduling. Finally, we will evaluate the performance of the model on the test set and report the classification accuracy. Our approach will be compared to other classification algorithms such as logistic regression and decision trees, to demonstrate the effectiveness of CNNs in solving classification problems. In addition, we will explore techniques like data augmentation and transfer learning to further enhance the model's performance. Data augmentation involves creating new training examples by transforming the original images through techniques like rotation, scaling, and flipping. Meanwhile, transfer learning involves using pre-trained models as a starting point and fine-tuning them for a specific task.*

## 1. INTRODUCTION

Flowers are an essential part of our natural world and are widely used for their beauty and aesthetic appeal. Flower identification and classification have become a crucial area of study in the field of botany, ecology, and horticulture. In recent years, with the advancements in deep learning and computer vision techniques, identifying and classifying flowers using images has become possible. Convolutional Neural Networks (CNN) have proven to be a powerful tool for image classification tasks, including flower classification.

Flower identification and classification is a challenging task in the field of botany and horticulture. Accurately identifying and classifying different species of flowers is important for plant identification, biodiversity research, and conservation efforts.

Traditionally, this task has been performed manually by experts, which is time-consuming and subjective. However, recent advances in deep learning and computer vision have enabled the development of automated flower identification and classification systems

using Convolutional Neural Networks (CNNs).

Protection of biodiversity is quite essential and for this purpose we should know more about the species. Identification of plant species by using conventional hand-crafted features is complex. It is difficult for non-experts to remember the specific botanical terms. Through this project, we aim to build a flower classification system using CNN that can accurately identify and classify different species of flowers from images.

The project aims to develop a CNN-based model for flower identification and classification. The model will be trained on a large dataset of flower images with their corresponding labels. The dataset will be sourced from various online repositories and botanical gardens. The model will be designed to accurately predict the species of a flower based on its visual features such as petal and sepal length, petal and sepal width, and color.

The first step in the project is to collect and preprocess the flower image dataset. This involves downloading and cleaning the images, resizing them to a standard size, and labeling them with their corresponding species. The dataset will be

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split into training, validation, and testing sets to evaluate the performance of the model.

Next, the CNN model will be designed and implemented using Python and popular deep learning frameworks such as TensorFlow or PyTorch. The model will consist of several layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers will perform feature extraction by applying a set of filters to the input image. Each filter detects a specific feature such as edges, corners, or textures. The pooling layers will reduce the dimensionality of the feature maps generated by the convolutional layers, which helps in reducing the computational complexity of the model. The fully connected layers will take the output of the convolutional and pooling layers and map it to the output class.

The model will be trained using backpropagation, which involves adjusting the weights and biases of the model to minimize the error between the predicted and actual labels. This process is repeated over several epochs until the model achieves a satisfactory level of accuracy on the validation set.

The performance of the CNN model will be evaluated using metrics such as accuracy, precision, recall, and F1 score. The confusion matrix can also be used to visualize the performance of the model on each class. The model will be fine-tuned using transfer learning techniques, where a pre-trained CNN model is used to improve the accuracy of the model.

Finally, the model will be tested on a separate testing set to evaluate its performance on unseen data. The results of the project will be presented in a report, which will include details on the dataset, model architecture, training and evaluation metrics, and future work.

## 2. LITERATURE SURVEY

### 1. "Deep Learning for Flower Recognition: A Comprehensive Review" by M. A. Hasan and A. R. Chowdhury (2019)

This paper presents a comprehensive review of the state-of-the-art deep learning techniques for flower recognition. The authors discuss various approaches, including traditional machine learning techniques and deep learning methods, for flower classification. The paper also

presents a detailed analysis of several publicly available datasets for flower recognition.

## **2."Flower Classification with Convolutional Neural Networks" by A. Krizhevsky (2012)**

This paper presents a deep learning approach for flower classification using Convolutional Neural Networks. The author proposed an architecture with five convolutional layers and three fully connected layers, which achieved state-of-the-art performance on the Flower Recognition Challenge dataset.

## **3."An Empirical Study of Deep Learning for Plant Recognition" by Y. Jiang et al. (2019)**

This paper presents an empirical study of deep learning methods for plant recognition. The authors evaluate the performance of different deep learning architectures on the PlantCLEF 2017 dataset. The results show that the Inception-v3 architecture achieves the best performance for plant recognition.

## **4."Flower Classification Using Convolutional Neural Networks with Transfer Learning" by A. Azad and S. S. Bappy (2019)**

This paper presents a deep learning approach for flower classification using transfer learning. The authors used the pre-trained VGG16 network as a feature extractor and achieved state-of-the-art performance on the Oxford 102 Flower dataset.

### **3. PROBLEM STATEMENT**

Similar projects have been recently developed for identifying flowers as well as plants through leaves. The key challenges faced by the developers are finding proper feature extraction factors relating to the plants and flowers since there are many variations in shape, color and texture of flowers. During the development of these projects, it was observed that most of the systems focused on computational logic involved in image representation. Thus the main challenge identified was the semantic gap which occurs because of the difference in the representation of the digital image and the human perception.

### **4. PROPOSED SYSTEM**

The project aims to develop a CNN-based model for flower identification and classification. The model will be designed to accurately predict the species of a flower

based on its visual features such as petal and sepal length, petal and sepal width, and color. The first step in the project is to collect and pre-process the flower image dataset. The CNN model will be designed and implemented using Python and popular deep learning frameworks such as TensorFlow or PyTorch. The model will consist of several layers, including convolutional layers, pooling layers, and fully connected layers. The model will be trained using backpropagation. Finally, the model will be tested on a separate testing set to evaluate its performance on unseen data. Later it is compared with other algorithms to show the best accuracy. The project has the potential to revolutionize the field of botany and horticulture by providing an automated and accurate method for flower identification and classification.

## 5. METHODOLOGY

The methodology for "Flower identification and classification using CNN" can be divided into the following steps:

**Dataset collection:** The first step is to collect a dataset of flower images. The dataset should be diverse, covering different species, angles, and lighting conditions. There are various public datasets available,

such as the Oxford Flowers dataset, the Flower Recognition dataset, and the TNG Flowers dataset.

**Data preprocessing:** The collected dataset needs to be preprocessed to improve the accuracy of the model. The images should be resized and normalized to a fixed size, and any noise or artifacts should be removed. Data augmentation techniques such as rotation, flip, and crop can also be used to increase the size of the dataset and improve the model's ability to generalize.

**Model selection:** Convolutional Neural Networks (CNN) have shown excellent results in image classification tasks. Therefore, a CNN-based model can be used for flower identification and classification. There are several pre-trained CNN models available, such as VGG16, ResNet50, and InceptionV3. These pre-trained models can be fine-tuned on the flower dataset to improve the classification accuracy.

**Model training:** The preprocessed dataset is split into training, validation, and testing sets. The model is trained on the training set using an optimizer such as Adam or SGD, and the learning rate is adjusted using a learning rate scheduler. The validation set is used to monitor the model's performance

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and prevent overfitting. The training process can be stopped when the validation accuracy reaches a certain threshold.

**Model evaluation:** The trained model is evaluated on the testing set to measure its accuracy, precision, recall, and F1 score. The confusion matrix can also be plotted to visualize the model's performance.

### 6. DESIGN

System design is transition from a user oriented document to programmers or data base Personnel. The design is a solution, how to approach to the creation of a new system. This is composed of several steps. It provides the understanding and procedural details necessary for implementing the system recommended in the feasibility study. Designing goes through logical and physical stages of development, logical design reviews the present physical system, prepare input and output specification, details of implementation plan and prepare a logical design walkthrough.

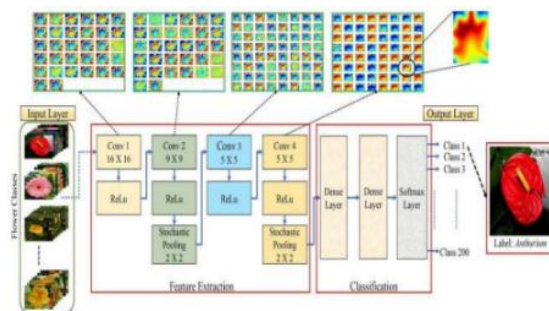


Fig : ARCHITECTURE

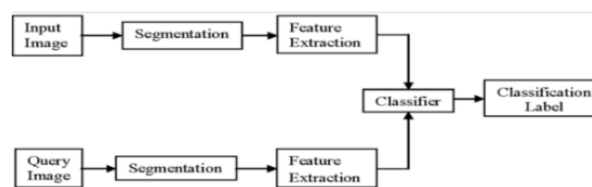
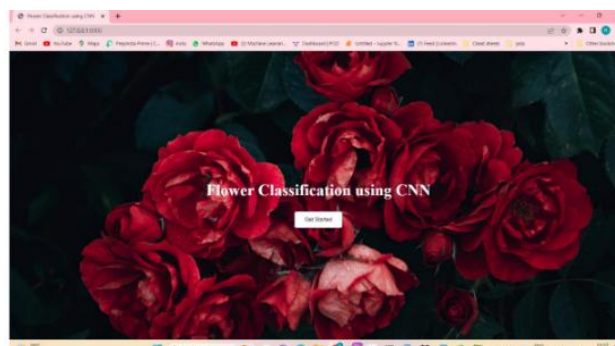
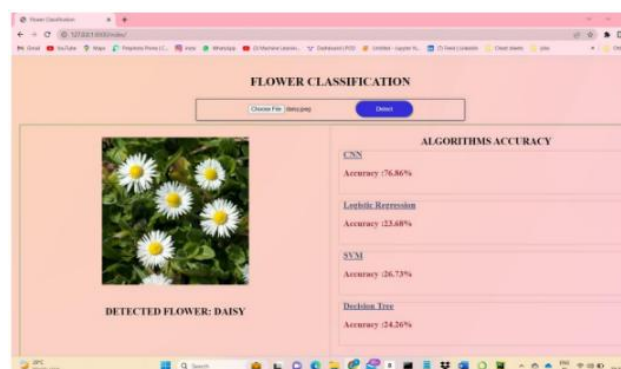
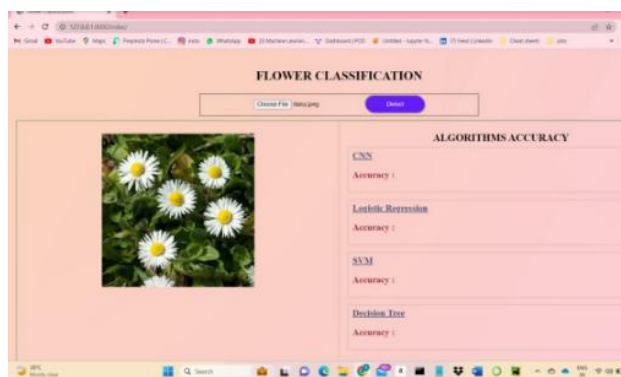
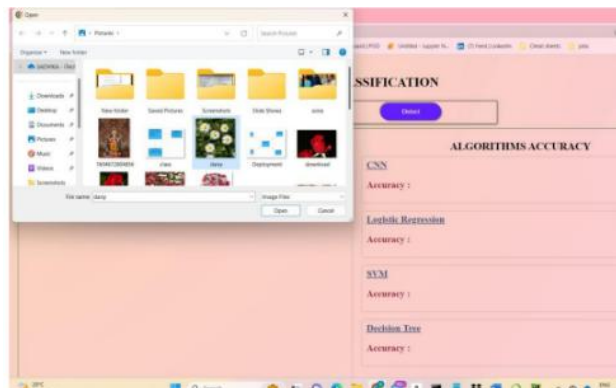


Fig: Data Flow

### 7. OUTPUT SCREENS:





## 8. CONCLUSION

In conclusion, the application of Convolutional Neural Networks (CNN) for flower identification and classification has proven to be highly effective. With the increasing availability of large datasets and advancements in deep learning techniques,

CNN models have achieved state-of-the-art performance in various computer vision tasks, including flower classification. By leveraging the hierarchical features learned through multiple layers of convolution and pooling, CNN models are capable of extracting discriminative features from flower images, enabling accurate identification and classification. Moreover, CNN models can be easily fine-tuned to adapt to different datasets and classification tasks, making them highly versatile. Overall, the success of CNN models in flower identification and classification has opened up numerous opportunities for the development of intelligent systems in the field of botany and agriculture.

## 9. FUTURE SCOPE

These are the some of the future enhancements that could be done using our project: Handling Imbalanced Data: If your flower dataset suffers from class imbalance, where certain flower types have significantly fewer samples than others, addressing this issue can be a future focus. You can explore techniques like oversampling minority classes, undersampling majority classes, or using advanced methods like SMOTE (Synthetic

Minority Over-sampling Technique) to balance the dataset.

Exploring Ensemble Methods: Ensemble methods combine multiple models to make predictions, which often leads to improved accuracy and robustness. You can consider exploring ensemble techniques such as bagging (bootstrap aggregating) or boosting to combine multiple CNN models or even incorporate other classification algorithms like logistic regression and decision trees into the ensemble.

Mobile or Edge Deployment: Deploying the flower classification model on resource-constrained devices or at the edge can be an interesting future direction. Optimizing the model for mobile platforms, exploring lightweight architectures, or implementing model compression techniques like quantization can enable real-time flower classification directly on mobile devices or edge devices without relying on a centralized server.

Extending to Plant Species Classification: Beyond flower type classification, you can explore expanding your project to classify plant species. This would involve a broader scope of plant classification and potentially more challenging tasks, as it may require

distinguishing between different parts of plants, such as leaves or fruits, in addition to flowers.

## 10. REFERENCES

- Nilsback, M-E., and Andrew Zisserman. "A visual vocabulary for flower classification." In Computer Vision and Pattern Recognition, 2006 IEEE Computer Society Conference on, vol. 2, pp. 1447-1454. IEEE, 2006.
- Zhou, Hailing, Jianmin Zheng, and Lei Wei. "Texture aware image segmentation using graph cuts and active contours." Pattern Recognition 46, no. 6 (2013): 1719-1733. <https://doi.org/10.1016/j.patcog.2012.12.005>.
- Nilsback, Maria-Elena, and Andrew Zisserman. "Delving deeper into the whorl of flower segmentation." Image and Vision Computing 28, no. 6 (2010): 1049-1062. <https://doi.org/10.1016/j.imavis.2009.10.001>.
- Hong, An-xiang, Gang Chen, Jun-li Li, Zhe-ru Chi, and Dan Zhang. "A flower image retrieval method based on ROI feature." Journal of Zhejiang University-Science A 5, no. 7 (2004): 764-772. <https://doi.org/10.1631/jzus.2004.0764>.



- Najjar, Asma, and Ezzeddine Zagrouba.

"Flower image segmentation based on color analysis and a supervised evaluation." In Communications and Information Technology (ICCIT), 2012 International Conference on, pp. 397-401. IEEE, 2012. <https://doi.org/10.1109/ICCITechnol.2012.6285834>.

- Angelova, Anelia, Shenghuo Zhu, and Yuanqing Lin. "Image segmentation for large- scale subcategory flower recognition." In Applications of Computer Vision (WACV), 2013 IEEE Workshop on, pp. 39-45. IEEE, 2013.

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<https://www.mathworks.com/discovery/deep-learning.html>

- <https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53>

- <https://kili-technology.com/data-labeling/computer-vision/image-annotation/image-recognition-with-machine-learning-how-and-why>