Flower Classification

A. Introduction and Problem Statement

Accurate flower classification is crucial for ecological and medicinal purposes, aiding in the proper identification, conservation, and cultivation of species, especially rare ones.

Traditional methods, like manual observation or basic image processing, struggle with variations in flower images and lack scalability, often failing to distinguish closely related species.

We propose using Convolutional Neural Networks (CNNs), a deep learning model effective in image classification. CNNs automatically extract key features from flower images, making them better at managing data complexity and variability than traditional methods.

This project aims to analyze and compare multiple Deep Learning models to identify the most effective solution for flower classification. The outcomes will have significant implications, particularly in pharmaceuticals, where accurate species identification is critical. [7]. Our ultimate goal is to develop a robust classification system that can be applied to both ecological and commercial contexts.

B. Dataset Choosen

Table 1. Overview of Flower Datasets

Name	Total Images	Classes
Flowers Dataset I	5k	5
Flowers Dataset II	11.2k	7
Flowers Dataset III	13.7k	14

For the flower classification project, three datasets from Kaggle were selected. The first, by Utkarsh Saxena, contains 6,000 JPEG images (225x225 pixels), divided into five groups, with 1,000 for testing and 5,000 for training. [5]. The second dataset, by Nadyana, has 11,200 images across seven classes, with image sizes ranging from 178x256 to 648x500 pixels. [4]. The third, by Marquis03, includes 13,700 images (256x256 pixels) divided into 14 classes, offering the most variety. [3].

C. Proposed Methodology

Before outlining the technical details, our approach begins with a systematic methodology, from data preprocessing to model design and evaluation, ensuring an effective solution for the flower classification task.

Pre-processing Steps

Resize the images to the model's required input size and normalize the pixel values. Implement data augmentation techniques like random cropping, flipping, and rotation to enhance variability. Convert the images to different color spaces (e.g., RGB, HSV, grayscale) to potentially improve classifier performance. Use one-hot encoding for categorical labels of flower images as target outputs. Finally, split the dataset into training, validation, and testing subsets, each serving a specific role in model development and evaluation.

Model Design and Implementation

In the context of flower image detection, **ResNet18** [1] is an excellent choice due to its ability to learn complex features and patterns in images while maintaining computational efficiency. Similarly, **MobileNetV2** [6] is well-suited for this task as it strikes a balance between accuracy and efficiency. By employing depthwise separable convolutions, MobileNetV2 minimizes the number of parameters and computations, making it ideal for resource-constrained devices. It has demonstrated strong performance in various computer vision applications, including image classification and object detection.

Densenet121 [2] features a dense connectivity pattern that allows each layer to receive inputs from all preceding layers. This architecture enhances feature propagation and encourages the reuse of features throughout the network Each of these three models will be applied to three different datasets, resulting in a total of nine distinct models. Additionally, two of the trained models will serve as base models for transfer learning on the other datasets.

During model training, certain parameters such as learning rate, batch size, and the number of training epochs will be adjusted to minimize coverage loss. We will employ hypothesis testing to optimize these hyperparameters effectively.

Model Metrics and Evaluation

To evaluate our classification model, we will use metrics such as accuracy, precision, recall, and F1 score, along with a confusion matrix for insights into effectiveness. The ROC curve will help assess the binary classifier's performance.

We will split the labeled dataset into training and testing sets, deriving True Positive Rate (TPR) and False Positive Rate (FPR) from model predictions across thresholds.These values will be represented on the ROC curve, with the Area Under the Curve (AUC) measuring performance. An AUC close to 1 signifies improved effectiveness.Additionally, we'll use t-SNE to visualize high-dimensional data in lower dimensions, enhancing insights into class separability.

D. Gantt Chart

Gantt chart in Fig 1 shows project tasks over a timeline.

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Project Start: Wed 09-04-2024

Task Name	Start Date	End Date	Duration
First Sprint: Preparation and Project Establishment	09-04-2024	09-29-2024	25
Define team member roles	09-04-2024	09-10-2024	6
Evaluate project feasibility	09-11-2024	09-15-2024	4
Analyze model trade-offs	09-16-2024	09-29-2024	13
Second Sprint: Dataset Research	09-30-2024	10-30-2024	30
Conduct research on suitable datasets	09-30-2024	10-15-2024	15
Submit detailed project proposal	10-16-2024	10-30-2024	14
Third Sprint: Development of Working Model	10-31-2024	11-01-2024	1
Create an initial working model	10-31-2024	11-01-2024	1
Fourth Sprint: Code Enhancement and Model Refinement	11-01-2024	11-15-2024	14
Improve the code	11-01-2024	11-07-2024	6
Refine the model	11-08-2024	11-12-2024	4
Submit Project Progress Report	11-13-2024	11-15-2024	2
Fifth Sprint: Final Project Report and Presentation	11-15-2024	12-01-2024	16
Prepare the final project report	11-15-2024	11-25-2024	10
Deliver the final presentation	11-26-2024	12-01-2024	5

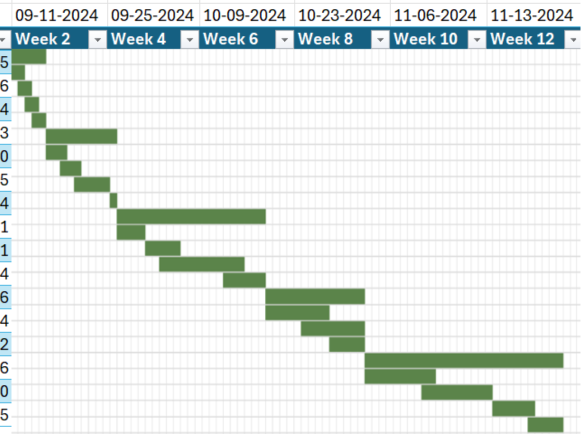

Figure 1. Gantt Chart

E. Project Milestones

1. **Milestone I: First Sprint Completion**
In this sprint, we analyze the problem's complexity, identify essential components, finalize models and datasets, and assign team tasks.

2. **Milestone II: Second Sprint Completion**
This phase involves evaluating datasets for quality and quantity, resulting in a refined project proposal based on team and professor feedback.

3. **Milestone III: Third Sprint Completion**
In this sprint, we will implement and script all models in Python, delivering tested, functional models with adjusted parameters for accurate results, ready for the next phase of optimization.

4. **Milestone IV: Fourth Sprint Completion**
With a working model, we will fine-tune hyperparameters to enhance performance, monitor evaluation metrics, and compile a progress report for review.

5. **Milestone V: Fifth Sprint Completion**
At this stage, we will conduct a comprehensive analysis, leading to the final report and project presentation.

F. Project Results

1. **First Sprint:** Define team member roles, evaluate project feasibility, and analyze model trade-offs.

2. **Second Sprint:** Conduct research to identify suitable datasets for the project and submit a detailed project proposal.

3. **Third Sprint:** Create an initial working model.

4. **Fourth Sprint:** Improve the code and refine the model, followed by the submission of the Project Progress Report.

5. **Fifth Sprint:** Prepare the final project report and deliver the presentation.

References

[1] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. *arXiv preprint arXiv:1512.03385*, 2015. 1

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[3] Marquis03. Flower classification : 14 types of flower image classification. Kaggle, 2024. Available at: https://www.kaggle.com/datasets/marquis03/flower-classification. 1

[4] Nadyana. Flowers dataset. Kaggle, 2024. Available at: https://www.kaggle.com/datasets/nadyana/flowers. 1

[5] Utkarsh Saxena. Flower classification — 10 classes. Kaggle, 2024. Available at: https://www.kaggle.com/datasets/utkarshsaxenadn/flower-classification-5-classes-roselilyetc. 1

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[7] Mesut Toğaçar, Burhan Ergen, and Zafer Cömert. Classification of flower species using features from the intersection of feature selection methods in cnn models. *Measurement*, 158:107703, 2020. 1