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Enhancing Flower Identification Using Deep Learning: A Comparative Study Using Multi-Statistical Models

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Abstract- Flower identification is a crucial aspect of plant classification and ecological research, playing a significant role in understanding biodiversity and ecosystem dynamics. This research paper presents a new approach to flower identification using advanced deep learning techniques. The proposed system used folding networks (CNNs) to automatically extract hierarchical features from high-resolution images of flowers, allowing for more accurate and efficient classification. The procedure is implemented as a multi-stage process, beginning with data preprocessing to enhance image quality and remove noise. Using another data record, educated CNN models such as modified reset 50, VGG16, or Google are then fine-tuned with commented flower images. Furthermore, transfer learning is used to properly use knowledge from large data records and improve the ability of models to generalize different types of flowers.. In the end, our approach achieved an accuracy of 82.04% using VGG16, the highest compared to other algorithms.

KeyWords - CNN (Convolutional Neural Network), Flower Recognitions, Activation function

I. INTRODUCTION

Intersection of ecology, agriculture, and artificial intelligence in floweret recognition emerges as a transformative technology driven by deep learning, which enables automated, high-precision identification of floral structures from image data. By automating the identification of individual floral structures, it provides scalable, accurate tools for monitoring plant populations, assessing environmental changes, and analyzing pollinator interactions. In ecological research, it enhances biodiversity assessment and deepens understanding of ecosystem dynamics. In agriculture, it supports precision farming through optimized planting schedules, efficient resource use, and timely harvest predictions—ultimately improving crop yield and sustainability. The integration of deep learning and computer vision technologies enable high-accuracy floral classification by capturing and analyzing distinct morphological characteristics. Such innovations are driving the development of mobile applications, educational tools, and citizen science platforms that foster broader public engagement in plant identification and environmental awareness. Overall, floral pattern analysis exemplifies how machine learning can revolutionize both scientific research and practical applications in horticulture and conservation, bridging the gap between technology and the natural world. The flower recognition system based on image processing by Tiya et.al. .[1 2014] used edge and color characteristics to classify flowers. Almogdady et al. [2, 2018] discussed a methodology for flower classification using neural networks, which included image enhancement, cropping, segmentation via the Chan–Vese active contour method, and feature extraction. An existing saliency-based CNN is fine-tuned for flower sensitivity, enabling robust detection under clutter and varying illumination to support optimized apple fruit production was studied by Dias et.al [3]

Flower Identification And Knowledge Extraction In Smart Agriculture Flower recognition plays a crucial role across various fields, contributing to biodiversity conservation, ecological research, and advancements in agriculture. By accurately identifying different flower species, researchers can monitor biodiversity, track environmental changes, and assess the health of ecosystems. It also aids in environmental education, allowing students and enthusiasts to learn about plant species and their ecological significance. Additionally, flower recognition supports the identification of medicinal plants, helping researchers discover bioactive compounds with therapeutic properties that can be used in pharmaceutical and holistic medicine.

In the field of intelligent agriculture, flower recognition and state-art technology, such as the Internet of Things (IoT), sensor networks, and remote information equipment, revolutionizes agricultural practices. These technologies allow real-time data collection for ground conditions, weather patterns and harvests, processed by advanced analytics and machine learning algorithms. This data-control approach allows farmers to identify patterns, optimize irrigation plans, improve pest control strategies, and maximize harvest revenue. Furthermore, remote sensing tools like drones and satellite imagery offer a comprehensive view of agricultural fields, aiding in early disease detection and precise resource management. Beyond agriculture, flowers hold significant medicinal potential. Many species contain bioactive compounds with anti-inflammatory, antioxidant, and antimicrobial properties, which can contribute to the development of new drugs and alternative therapies. This intersection of botany and medicine underscores the importance of accurate flower identification in pharmaceutical research and holistic healthcare. Overall, flower recognition is a powerful tool that bridges multiple disciplines, enhancing scientific research, agricultural efficiency, and environmental sustainability while unlocking new possibilities in medicinal applications.

Fig 1. Medical Benefits of Flower

ImageURL-https://in.pinterest.com/pin/medicinal-benefits-of-flowers--343821752813460589/

Flowers offer potential medical benefits, with certain varieties containing compounds known for their anti- inflammatory or antioxidant properties, contributing to holistic well-being (As per Fig 1).

Industrial Development through Intelligent Flower Crops Intelligent flower crops leverage advanced technology to drive industrial development and transform the flower cultivation industry. By integrating precision agriculture, IoT devices, and data analytics, farmers can optimize every stage of production. Smart sensors monitor environmental conditions, soil health, and water usage, ensuring precise resource management. Machine learning analyzes data to determine the optimal planting time, irrigation plans, and pest control strategies. These intelligent systems enhance productivity while minimizing resource wastage and environmental impact. The adoption of smart flower crops promotes sustainability, meeting demand while reducing the industry's ecological footprint. Automated monitoring and real-time data collection improve decision-making and reduce reliance on harmful chemicals. Smart technologies also create jobs in agritech, data science, and automation, driving industrial growth. AI-driven climate control systems optimize greenhouse conditions for better flower quality and yield. Predictive analytics help prevent crop losses, lower costs, and increase market competitiveness. Government incentives for smart farming can accelerate adoption, ensuring economic and environmental benefits. By embracing intelligent flower crops, the industry moves toward a smarter, greener and sustainable future.

II. Literature Review

G. M. et al. (2023)[4] This paper introduced a method for accurately identifying flowers using image recognition techniques. Users captured an image on their mobile device, uploaded it, and obtained a prediction by clicking the Forecast button. The study utilized a 102-category flower dataset from the Visual Geometry Group at Oxford University, comprising 8,189 photos across 102 flower categories. The classification process employed machine learning algorithms such as K-nearest Neighbor (k-NN), Random Forest, and Convolutional Neural Networks (CNNs). The developed system accepted a photo of the flower as input and provided important details, including the commonly known flower name, scientific name, and family name.

Bozkurt, F. et al. (2021)[5] This study employed an open-access flower recognition dataset comprising samples gathered from multiple sources., including Google, Flickr, and Yandex Images, and made available on Kaggle by Mamaev (2018). Several well-established deep learning models—VGG16, VGG19, Squeeze Net, DenseNet-121, DenseNet-201, and InceptionResNetV2 were employed to classify flower species. Analyze experimental results to assess the classification performance of the same data record. Among the tested models, InceptionResNetV2 demonstrated superior performance, achieving the highest accuracy of 92.25%.Performance of three models Squeeze net, ResNet50, and VGG19 was evaluated on two data records: five category datasets and Flower-102 datasets. Among them, VGG19 showed the highest accuracy, reaching 88% for the 5-category dataset and 84% for the Blumen-102 data records. This study utilized the Kaggle flower recognition dataset and the Oxford Flower-102 dataset for evaluation.

Ong, Z. Y. et al. (2022)[6] This research paper investigated the creation of a flower recognition model using deep neural networks, specifically emphasizing the VGG19 architecture. To improve performance, advance fine-tuning models such as the Restet50 and VGG19 presented new models inspired by SqueezeNet.

Sangale, R. et al. (2020)[7] This paper presented a deep learning-based approach for classifying different types of flowers.. Each neuron in the model receives an input, performs a dot product operation, and optionally applies a non-linear activation function. A deep learning network was developed for flower classification using the 102- category dataset from the Visual Geometry Group (VGG), which includes 8,189 images across 102 flower classes from the University of Oxford. The study utilized Convolutional Neural Network (CNN) architecture for classification, optimizing hyper parameters to assess training and testing accuracy, showcasing its effectiveness in flower recognition.

Mishra, A. et al. (2022)[8] This research paper introduced a flower recognition application that could identify around ten different flower species, including the Bangladeshi mango blossom and various other exotic flowers. A standout feature of the system was its real-time flower identification capability. The system employed Convolutional Neural Networks (CNNs) for image classification, with confidence levels ranging from 0 to 1. It had been trained on a dataset from the open-source TensorFlow library, and the model achieved 100% accuracy for certain flower species. To address visual similarities among flowers, the application suggested the top two or three closest matches whenever it encountered uncertainty.

Patel, R. et al. (2019)[9] This review paper examined the complexities of flower image recognition, concentrating on the challenges associated with accurately identifying and distinguishing various flower species. It emphasized the necessity for a system capable of efficiently handling and processing large-scale flower datasets. The study analyzed the critical stages of flower detection, including image acquisition, preprocessing, segmentation, and feature extraction. It assessed classification models such as neural networks, decision trees, and Support Vector Machines (SVM), highlighting the significance of color, texture, and shape features. Furthermore, it reviewed algorithms and techniques for segmentation, classification, detection, and counting, underscoring the importance of standardized datasets like Oxford 17 and Oxford 102 for ensuring reliability.

Rajalakshmi, M. et al. (2021)[10] This paper presented a flower classification model using deep learning, specifically the CNN algorithm with TensorFlow, to automate image classification. The study compared CNN accuracy with traditional methods and highlighted deep learning's potential in flower recognition. Methodologies included data collection, preprocessing, segmentation, feature extraction, and CNN implementation. Imagenet databases of five different flowers—dandelions, roses, tulips, and sunflowers—were used, with 10% of the data allocated for testing and training, and 90% used for the remaining dataset. The CNN model, optimized with MobileNet for efficiency, underwent training, testing, and evaluation, achieving an accuracy of 82.56%.

Meghala, E. et al. (2023)[11] This study examined the application of Convolutional Neural Networks (CNNs) for flower recognition, focusing on challenges, objectives, and methodologies. The dataset was divided into 80% for training and 20% for validation, comprising 2,512 images across eight flower classes—2,010 images for training and 502 for testing. The research also reviewed standardized datasets such as Oxford 17 and Oxford 102. Furthermore, it explored the use of the OverFeat CNN network, various machine learning techniques, and methods for dataset evaluation. The proposed model achieved an accuracy rate of 80% in classifying the eight flower species.

Table 1 provides a summary of the literature reviewed in the study

Title and Author's Name	Introduction	Data Set and Algorithms	Gap Analysis
A application for Nursery with Flower Recognition System: A Survey (G,M. et al., 2023) [4].	In this paper an attempt has been made to give an introduction to the accurate identification of flowers.	KNN, Random Forest and CNN algorithms with Oxford 17 and Oxford 102 dataset	High Computation Cost
A Study on CNN Based Transfer Learning for Recognition of Flower Species	In this study, we employed an open-access flower recognition dataset that includes samples gathered from various sources	Mamaev (2018) with models, namely VGG16, VGG19, SqueezeNet,	Prone to over-fitting

	(Bozkurt,F. et. al, 2021)[5]	such	DenseNet-121, DenseNet-201, and Inception Res NetV2,	
	Flower Recognition Model based on Deep Neural Network with VGG19 Ong,Z,Y.et. al, (2022)[6]	This research paper explores the creation of a flower recognition model utilizing deep neural networks, specifically focusing on the VGG19 model.	Squeeze Net, ResNet50, and VGG19 with Oxford 17 and Oxford 102 dataset	High energy Consumption
	Flower Recognition Using Deep Learning Sangale,R., et. al, (2020) [7]	)In this paper, Each neuron receives some input, executes a dot productandoptionally follows it with a non-linear operational profound learning network has been created for characterization of various blossoms	CNN used with Oxford flower dataset	Different algorithms can give better accuracy
	Image Classification of the Flower Species Identification using Machine Learning Mishra, A. et. al, (2022) [8]	In this research paper It is said that their application can distinguish around 10 blossoms. Bangladeshi mango bloom with something outlandish Blossoms as well	The open source library TensorFlow dataset with CNN	Only about specific area
	A Review on Flower Image Recognition Patel,R. et. al, (2019) [9]	The paper delves into multiple phases of the recognition process, including image acquisition, pre-processing, segmentation, and feature extraction	Decision trees, support vector machines and CNN with Oxford 17 and Oxford 102 dataset	Accuracy is low
	Flower Classification Based On Deep Learning Using TensorFlow Rajalakshmi,M. et. al, (2021)[10]	The purpose is to automate the grouping of flower images based on their features.	Mobile Net and CNN with Image Net database	Very small Dataset
	Flower Recognition Meghala,E. et. al, (2023)[11]	It emphasizes the significance of flower recognition in various fields, including botany and agriculture	Oxford 17 and Oxford 102 dataset with CNN algorithm	Accuracy is low

III. EXPERIMENTAL DESIGN AND IMPLEMENTATION

In this study, a robust flower recognition system was developed using advanced convolutional neural network (CNN) architectures, VGG16, GoogLeNet, and ResNet-50, to classify images from a curated flower dataset containing 4,242 images. These images represented a wide range of flower species, colors, sizes, and environmental conditions such as varying lighting and weather, ensuring model robustness. The team began by identifying the core problems, establishing detailed instructions, and conducting surveys in agricultural and natural settings to understand the variations in flower appearance. This was followed by comprehensive data collection, including image recordings and representative

samples. The goal of sampling was to capture diverse data to ensure the model generalizes well to real world conditions. The collected images underwent preprocessing, including normalization, enhancement, and image augmentation techniques to improve input consistency and model generalization. Using TensorFlow, each CNN architecture was implemented with adjustments to fit the dataset's dimensions. Transfer learning was applied by initializing the models with pre-trained weights from standard image datasets and fine-tuning them specifically on the flower dataset to extract floral characteristics with high precision. The dataset was split into training, validation, and test sets. The training set enabled the model to learn patterns, the validation set assisted in hyperparameter tuning and prevented overfitting, and the test set evaluated the model's ability to generalize to new data. Evaluation metrics such as accuracy, precision, recall, and F1-score were used to assess model performance, and iterative hyperparameter optimization improved classification results.

Diagrams and their Description

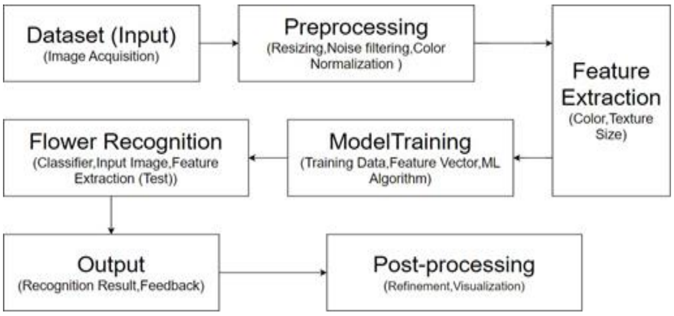

Fig 2. Block Diagram of Floweret Recognition

The entire flower recognition process follows a structured workflow. It begins with high-resolution image acquisition, followed by preprocessing to highlight key features and reduce noise. A feature extraction module then identifies vital attributes such as color, shape, and texture. These features are processed by a classification module using CNN-based models to accurately categorize flower species. The system produces recognition outputs that are valuable for real-world applications in agriculture, ecology, and biodiversity research. The finalized and validated model is capable of being deployed in practical scenarios to automate flower seed classification and enhance decision-making in related domains (as shown in Fig 2).

IV. RESULTS AND FINDINGS

Category Wise Flower Images Data This dataset consisted of 4,242 flower images sourced from various platforms, including Flickr, Google Images, and Yandex Images. It was classified into five categories: Daisy, Tulip, Rose, Sunflower, and Dandelion, with each class containing approximately 800 images. The images were of relatively low resolution, typically around 320×240 pixels (as shown in Fig 3 to 7).

Fig 3.Sample Dataset-2Daisy

Fig 4. Sample Dataset-3Dandelion

Fig 5. Sample Dataset-4 Rose

Fig 6. Sample Dataset-5 Sunflower

Fig 7.Sample Dataset-5 Tulip

Models Used for Flower Image Classification A.VGG-16 consisted of 4,896 units with a ReLU activation function, followed by a second high-density layer with 4,096 units, also using ReLU. The final output layer contained five units with a softmax activation function, allowing for classification into five distinct categories. This model leveraged transfer learning, where a pre-trained network was adapted for a new task. By utilizing pre-learned low-level features, this approach enhanced efficiency and reduced training time. The frozen base model preserved essential feature representations, while the added dense layers enabled fine-tuning for the specific dataset. This combination made it a robust and effective CNN-based image classification solution.

Input shape: The VGG16 model took input images of size [224, 224, 3], meaning each image had dimensions of 224×224 pixels with three color channels (RGB).

Output Shape: The model produced an output shape of (5,), indicating that it generated a probability distribution across five distinct classes. This meant that for each input image, the model assigned a probability score to each of the five categories, thereby determining the most likely classification.

Learning Performance of Model

Fig 8. Inference for Training and Validation Accuracy and Training and Validation Loss Graphs of a VGG16 Model

Inference for Training and Validation Accuracy Graphs of the VGG16 Model
Training Accuracy: The training accuracy increased steadily over time, reaching approximately 98% by the end of the training process. This indicated that the model learned the training data well and was able to correctly classify most training examples (as shown in Fig 8).

Validation Accuracy: The validation accuracy also improved over time, though not as rapidly as the training accuracy. This suggested that while the model generalized reasonably well, it did not perform as strongly on unseen data as it did on the training data. Conclusion from Training and Validation Loss Graphs of the VGG16 Model

Training Loss: The training loss decreased consistently over the epochs, indicating that the model's predictions on the training data became more accurate with time—a positive sign of learning.

Validation Loss: The validation loss also declined over time, but at a slower rate compared to the training loss. This trend suggested some level of overfitting, where the model performed better on training data than on validation data.

GoogLeNet
The high training accuracy of 98.76% achieved by the VGG16 model indicated that its architecture was highly effective in learning the essential features required for accurate flower classification on the given training dataset. In contrast, the ResNet50 model achieved the lowest training accuracy, at approximately 50%, suggesting that it was not effective at extracting sufficient features from flower images for precise classification. The 4-Conv CNN model closely followed, with a training accuracy of 95.34%, confirming the positive impact of increasing convolutional layers in capturing complex features for this task. The 3-Conv CNN also performed well, achieving 94.91% training accuracy. This suggested that even with fewer layers, the model was capable of learning valuable features from this specific dataset, as illustrated in Fig 9 and 10.

Learning Performance of Model

Fig 9. Inference for Training and Validation Accuracy and Training and Validation Loss Graphs of a Google Net Model

Comprehensive model training accuracy:

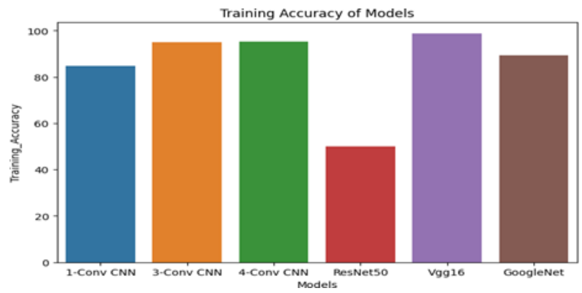

Fig 10.Comparsion of Training Accuracy of Models

Comparison Of Validation Accuracy Of Models

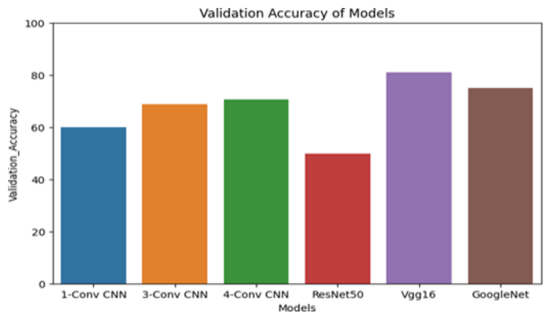

Fig 11. Comparison Of Validation Accuracy Of Models

Based on validation accuracy, VGG16 emerged as the clear winner, achieving an impressive 81.04%. This result highlighted the effectiveness of its architecture, which, with 138 million parameters and multiple convolutional layers, excelled at extracting relevant features from flower images for accurate classification. GoogLeNet also demonstrated strong performance, attaining a respectable 75.12% validation accuracy. Its unique Inception modules contributed significantly to effective feature extraction and classification. The 4-Conv CNN secured third place with a validation accuracy of 70.58%, outperforming both the 1-Conv and 3-Conv models. This supported the notion that increasing the number of convolutional layers generally enhances a model's ability to learn complex features and improve accuracy. In contrast, ResNet50 underperformed, achieving a validation accuracy of only 49.79%, which was unexpected given its deep architecture and reputation. This outcome could be attributed to factors such as suboptimal hyperparameters, insufficient fine-tuning, or limitations in the dataset size. Further investigation would be necessary to fully understand this surprising result. The results emphasized the importance of model architecture and complexity in flower classification accuracy. Deeper convolutional networks like VGG16 and GoogleNet tended to outperform simpler models (such as 1-Conv and 3-Conv). However, transfer learning models like ResNet50 were still effective depending on the training process and dataset characteristics, as illustrated in Fig 11.

V. CONCLUSION

In summary, this study demonstrated the effectiveness of deep learning in flower image classification, particularly using convolutional neural networks (CNNs). Various CNN architectures, including VGG16, GoogLeNet, ResNet-50, and a custom 4-Conv CNN, were evaluated on a dataset consisting of 4,242 flower images. The findings revealed that VGG16 achieved the highest accuracy and efficiency, consistently outperforming the other models in classifying flower images.

Future Scope

Future work in flower recognition will focus on improving model accuracy and adaptability, particularly in distinguishing closely related species under varying environmental conditions. Advancements in this area may involve integrating more diverse and high-resolution datasets, applying advanced augmentation techniques, and experimenting with hybrid deep learning architectures. Addtionally, enhanced collaboration between computer scientists and botanists is expected to drive interdisciplinary research, leading to the development of more refined, accurate, and biologically insightful recognition models.

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