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Original Article

Plant Species Identification Using Transfer Learning

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***Abstract** - Plants are essential for the survival of human life and maintaining ecological balance by providing oxygen, food, medicine, raw materials, and habitat support. They contribute significantly to climate regulation, air and water purification, and the preservation of biodiversity. Accurate plant species identification is therefore essential for biodiversity conservation, agricultural development, environmental protection, and the discovery of new medicinal resources. However, traditional plant identification methods rely heavily on expert knowledge and manual observation, making the process inefficient, require extensive manual effort, and vulnerable to subjective errors. Recent developments in deep learning have and computer vision, automated plant species identification has emerged as an effective alternative. This study explores the use of transfer learning frameworks for building an accurateand efficient plant species identification system. A pre-trained VGG16 convolutional neural network is utilized to extract meaningful features from plant images and classify species with high accuracy. The deep architecture of VGG16, consisting of convolutional and pooling layers, enables the model to capture complex visual patterns while reducing dimensionality. The use of transfer learning significantly reduces computational efficiency while maintaining strong classification performance. Experimental results demonstrate that deep learning combined with transfer learning provides a scalable, reliable, and accurate solution for plant species identification, highlighting its suitability for real-world applications in agriculture, botany, and environmental monitoring.*

***Keywords** - Plant Species Identification, Transfer Learning, Deep Learning, Convolutional Neural Networks (Cnn), Vgg16, Computer Vision, Image Classification, Biodiversity Conservation, Automated Plant Recognition.*

1. Introduction

Plant species identification is a fundamental task in agriculture, botany, forestry, and environmental science, as it supports biodiversity conservation, ecological balance, and sustainable resource management. Plants play a crucial role in human life by providing oxygen, food, medicine, and raw materials, while also contributing to climate regulation and ecosystem stability. Accurate identification of plant species helps in monitoring plant diversity, protecting endangered species, controlling invasive plants, and supporting agricultural productivity. With the increasing impact of climate change and human activities on natural ecosystems, the need for efficient and reliable plant species identification systems has become more important than ever.

Traditionally, plant species identification has been performed through manual observation by experts using morphological characteristics such as leaf shape, size, texture, color, and vein patterns. Although these methods are well established, they are time-consuming, labor-intensive, and highly dependent on expert knowledge. In many cases, visually similar species are difficult to distinguish, leading to misclassification. Additionally, the manual approach is not scalable for large datasets or real-time applications, making it unsuitable for modern requirements in agriculture and environmental monitoring. These challenges emphasize the necessity for automated plant identification techniques.

Recent advancements in image processing, computer vision, and deep learning have enabled the development of automated plant species identification systems using plant images. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable performance in image-based classification tasks by automatically extracting discriminative features from raw images. Developing deep neural networks from scratch involves high computational costs and the need for extensive labelled datasets, making it impractical in many scenarios. Transfer learning addresses these limitations by utilizing pre-trained models and transferring learned representations to domain-specific tasks, thereby reducing data requirements and training time.

In this work, plant species identification is carried out using transfer learning with the pre-trained VGG16 model, focusing on leaf image classification. The VGG16 architecture is known for its strong feature extraction capability and deep hierarchical structure, which helps in capturing both shallow and deep visual representations. By fine-tuning the pre-trained model for plant species classification, the proposed approach achieves high accuracy while reducing training time and computational cost. The developed the system offers a scalable and efficient approach for automated plant species identification and can be effectively applied in real-world scenarios such as agriculture, botanical research, and environmental monitoring.

2. Literature survey

Pimm et al. proposed a global assessment approach to estimate plant species diversity and extinction rates. Their study revealed that a large number of plant species exist worldwide, with many concentrated in tropical regions, and highlighted alarmingly high extinction rates due to environmental threats. Although the study provides valuable global insights, it is limited by uncertainties in species estimation and lack of species-level identification methods. The authors conclude that accurate plant identification and monitoring systems are essential to support biodiversity conservation efforts [1].Zhang et al. proposed a leaf image recognition method using Bag of Features combined with a Dual-output Pulse-Coupled Neural Network to classify plant species. The model achieved improved accuracy by integrating shape and texture features. However, the approach relies on handcrafted features and traditional classifiers, limiting scalability and performance on complex real-world datasets. The authors conclude that while feature-based methods are effective, advanced deep learning techniques can further improve plant species identification [2].

Cai et al. proposed a convolutional neural network–based real-time leaf recognition system that utilizes a multi-task loss function to integrate feature extraction and classification within a single framework. Experimental results showed high recognition accuracy and rapid inference speed, demonstrating the model's practicality for real-timeplant identification. However, the approach was mainly evaluated under controlled conditions and may face challenges in complex natural environments. The authors conclude that CNN-based multi-task learning improves leaf recognition performance but requires further enhancement for real-world applications [3].Li et al. proposed an optimized YOLOv5s-based deep learning model enhanced with attention mechanisms for plant-related object detection. The model achieved improved detection accuracy and real-time performance by strengthening feature extraction and multi-scale fusion. However, the study was mainly focused on a specific plant dataset, limiting its generalization to diverse plant species. The authors conclude that attention-enhanced deep learning models significantly improve plant image analysis but require further validation on broader datasets [4].

Li et al. proposed a transfer learning approach based on support vector machines that improved classification accuracy by transferring knowledge across domains. Although effective for general pattern recognition, the method was not designed for large-scale plant image classification. The authors conclude that transfer learning enhances performance but requires further adaptation for complex plant species identification tasks [5].Duan et al. proposed a hybrid CNN–ELM model that combines CNN model for feature extraction with Extreme Learning Machine classification for age and gender recognition. The model achieved improved accuracy and efficiency on benchmark datasets, but it was designed for facial images and may not generalize to plant species identification. The authors conclude that hybrid deep learning models enhance classification performance but require adaptation for other image domains [6].

Xu et al. proposed a transfer learning–based convolutional neural network for control chart pattern recognition, achieving improved recognition accuracy compared to traditional approaches. However, the method was evaluated only on control chart datasets and may not generalize well to complex image-based tasks. The authors conclude that transfer learning effectively enhances CNN performance but requires adaptation for other domains [7].Barthlott et al. introduced a feature-based leaf identification method for identifying woody plant species using features like shape and texture. The approach achieved reasonable classification accuracy but relied on handcrafted features, limiting scalability and robustness. The authors conclude that automated leaf recognition is feasible, though advanced learning methods are needed for better performance [8].

Munisami et al. proposed a plant leaf identification mechanism using shape features and color histograms with a K-NN classifier. The method achieved good classification accuracy on leaf datasets but relied on handcrafted features, limiting performance on complex images. The authors conclude that feature-based approaches are effective but less robust than deep learning methods [9].Li et al. proposed a plant leaf recognition method using Locally Linear Embedding (LLE) for feature reduction combined with a Moving Center Hypersphere classifier, achieving improved classification performance on standard leaf datasets. However, the approach relies on handcrafted embedding and classification techniques, which may not scale well to large and diverse real-world image collections. The authors conclude that advanced feature learning strategies could further enhance plant leaf recognition accuracy [10].

3. Methodology

3.1. About dataset

Before the dataset used in this study consists of labeled images of plant leaves representing multiple plant species. Each class contains an adequate number of images to ensure effective learning and accurate classification. The dataset includes variations in leaf shape, size, color, texture, and orientation, reflecting real-world conditions. To meet the input requirements of the VGG16 network, all images are resized to 224 × 224 pixels with three RGB channels. Pixel values are normalized to standardize the input data and enhance convergence during training. Additionally, data augmentation techniques, including image rotation, horizontal and vertical flipping, zooming, and shifting, are applied to the training dataset to improve model robustness and reduce overfitting. The dataset is organized into separate training, validation, and testing subsets to support effective learning and comprehensive performance evaluation.

3.2. VGG16 for Plant species identification

This study adopts a transfer learning–based deep learning methodology for plant species identification using the pre-trained VGG16 convolutional neural network. Transfer learning enables the reuse of knowledge learned from large-scale image datasets and applies it to a specific task with limited data, thereby improving performance while reducing training time and computational cost. Instead of training a deep network from scratch, the learned visual features from earlier layers of the VGG16 model are leveraged and fine-tuned for plant species classification.

In the proposed approach, input leaf images are resized to 224 × 224 × 3, matching the input requirements of the VGG16 architecture. As illustrated in Figure 1, the input image is processed forwarded through a cascade of convolutional layers with small 3 × 3 filters and ReLU activation functions, which extract low-level features edges and textures and advancing to more complex representations in deeper layers. Max pooling layers are applied after convolution to reduce spatial dimensions that progressively reduce the spatial dimensions while preserving important feature information.

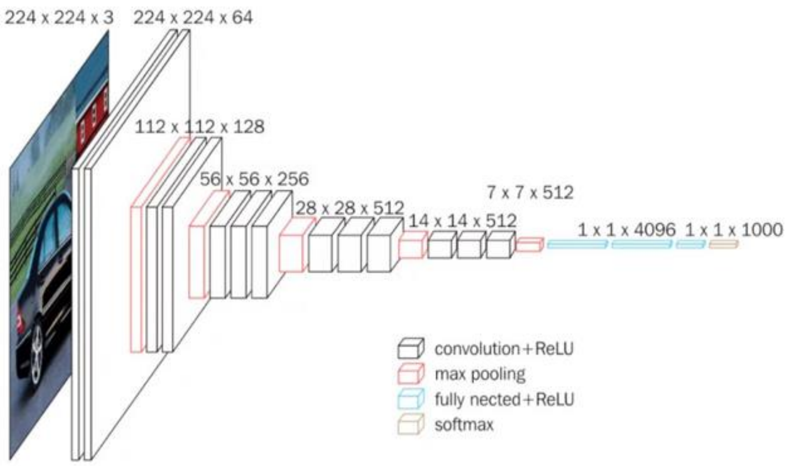

Fig 1: VGG16 Architecture

The detailed mapping of the VGG16 architecture is shown in Figure 2, which highlights the structured flow of data through the network. The model includes 13 convolutional layers, 5 max pooling layers, and 3 fully connected layers, resulting in 16 trainable layers. Filter sizes increase from 64 to 512 across the network, allowing the extraction of increasingly complex feature representations and hierarchical feature representations from plant leaf images. The convolutional and pooling layers are kept frozen during training to retain generic image features learned from the ImageNet dataset, while the fully connected layers are fine-tuned to adapt the model to the plant species classification task.

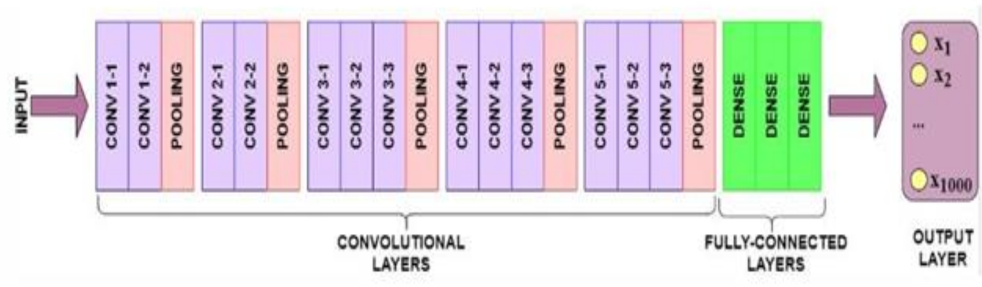

Fig 2: VGG16 Architecture Map

After feature extraction, flattened convolutional outputs are passed to the fully connected layers for classification, as depicted in Figure 1. These layers transform the extracted features into a compact representation suitable for classification. The final classification is performed using a softmax layer, which outputs the probability distribution across different plant species classes. This enables the model to assign each input image to the most likely plant species.

Overall, the methodology effectively combines the strong feature extraction capability of the VGG16 architecture with transfer learning to build a robust and accurate plant species identification system. The structured convolutional pipeline shown in the figures ensures efficient learning of visual patterns, while fine-tuning the final layers helps the model specialize in domain-specific representations of plant leaf image

4. Results

The performance of the proposed transfer learning model based on the VGG16 architecture was evaluated to assess its suitability for plant species identification. The results section reports the model's classification accuracy and reliability, achieving an overall accuracy of 98.2%, which reflects the model's strong ability to accurately distinguish between different plant species using leaf image data.

The graph shown in Figure 3 illustrates the accuracy curves for the training, validation, and test datasets over 50 epochs, highlighting the model's learning behaviour and performance across different data splits. The training and validation accuracies both improve rapidly in the early epochs and then plateau, reaching nearly 100%. The test accuracy, represented by the red dashed line, remains consistent and close to 100%, results indicate good model performance with limited overfitting. The close correspondence between the training and validation curves confirms the model's ability to generalize effectively to new data.

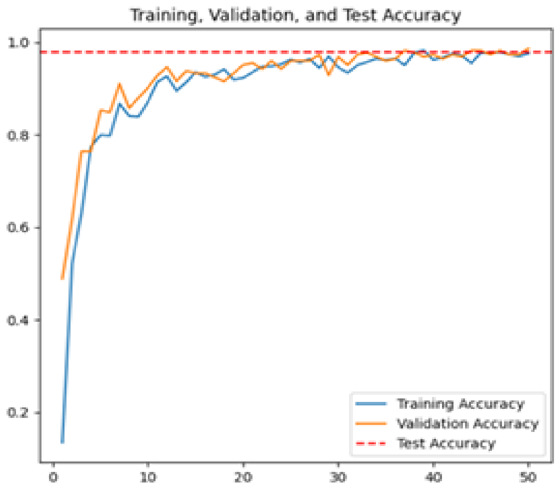

Fig 3: Plot diagram of validation accuracy, training accuracy and test accuracy

The graph shown in Figure 4 illustrates the loss curves for the training, validation, and test datasets over 50 epochs, showing how the model's error changes during the learning process across different data splits. Both the training and validation losses decrease significantly in the early epochs and continue to decline, approaching zero, indicating effective learning. The test loss, represented by the red dashed line, is very low and stable, suggesting that the model is performing well without overfitting. The similarity between the training and validation loss curves suggests effective generalization to unseen samples.

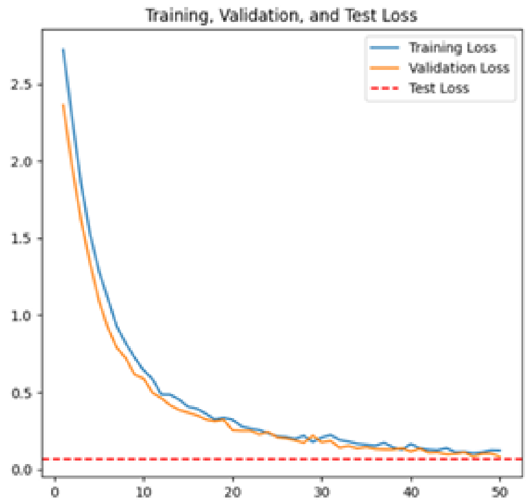

Fig 4: Plot diagram of training loss, validation loss and test loss

5. Conclusion

This study shows that transfer learning with the VGG16 model effectively improves plant species identification by achieving high accuracy with reduced computational cost and training data. The automated framework overcomes the limitations of traditional methods and is useful for applications in biodiversity conservation, agriculture, and ecological research. Future enhancements can include advanced deep learning models, larger datasets, real-time processing, and mobile integration to further improve accuracy, accessibility, and practical usefulness

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