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AUTOMATED PHYTOPATHOLOGICAL DIAGNOSIS AND CLASSIFICATION EMPLOYING DEEP CONVOLUTIONAL NETWORKS

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Abstract: Plant species classification and leaf disease detection are essential in modern agriculture for improving crop productivity and reducing losses. Traditional manual inspection methods are time-consuming and inefficient for bulky applications. This work presents a deep learning-based approach for automated plant species and disease classification using MobileNetV2 and ResNet50 models. MobileNetV2 is used for efficient plant species recognition, while ResNet50 is applied for accurate disease detection from leaf images. Experimental results demonstrate that the proposed system achieves high classification accuracy and better efficiency compared to conventional methods. The developed framework supports real-time crop monitoring and disease diagnosis, contributing to smart and sustainable agricultural applications.

Index Terms-deep learning, CNN, MobileNetV2, image classification, smart agriculture

I. INTRODUCTION

Farming acting a vital part in supporting universal food production, environmental sustainability, and economic development. Healthy crops and accurate plant monitoring are essential for maintaining agronomic yield and ensuring food safety for the growing population. Plant classes identification and early detection of leaf diseases are important tasks in modern agriculture because plant viruses can significantly diminish harvest profit and eminence if not identified at an primary period. Timely diagnosis of diseases helps farmers take preventive measures and minimize agricultural losses.

Traditionally, plant species classification and disease diagnosis are performed manually by agricultural experts and botanists through visual observation of plant leaves. Although manual inspection can provide accurate results, it requires extensive domain knowledge, consumes considerable time, and becomes difficult when applied to large agricultural fields. In addition, similar visual characteristics among plant species and disease symptoms may lead to incorrect diagnosis and human errors. Recent advancements in artificial intelligence, machine learning, and deep learning have introduced powerful techniques for image-based agricultural applications. Among these techniques, Convolutional Neural Networks (CNNs) have realized important achievement in image classification, article detection [1]. CNN models automatically study imperative image structures in a straight line from uncooked data without the requirement for physical feature engineering, making them highly effective for plant species recognition and plant leaf disease detection [7], [8].

In this work, two advanced deep learning models, namely ResNet50 and MobileNetV2, are employed for herbal leaf disease credentials and plant species classification. ResNet50 is used for disease detection because of its deep residual learning architecture, which enables efficient extraction of complex disease-related patterns as shown in fig 1. [3], [4]. The residual connections in ResNet50 help overcome the vanishing gradient problem and improve classification accuracy for deep neural networks.

MobileNetV2 is utilized for plant species classification due to its lightweight structure, reduced computational complexity, and efficient performance [2], [5]. The model is especially suitable for real-time applications and mobile devices where computational resources are limited. By applying transfer learning, the proposed system improves classification performance while reducing training time and computational cost [6].The trained models automatically classify plant species and identify diseased leaves with high accuracy and reliability

The developed system can assist farmers, agricultural researchers, and field experts in real-time harvest nursing and disease diagnosis. The proposed deep learning-based approach contributes to precision agriculture by enabling automated, accurate, and cost-effective plant analysis for sustainable farming and intelligent agricultural management systems.

II. Background Study

Recent technological developments in agriculture have created a strong demand for intelligent systems that can automatically recognize plant species and identify plant diseases. Maintaining healthy crops is important for improving agricultural productivity and food quality, while accurate plant classification supports biodiversity preservation and agricultural research. Traditional plant monitoring techniques mainly depend on physical examination and professional observation, which are regularly slow, labour-intensive, and not as much of suitable for bulky farming environments.

Previous research in plant analysis mainly utilized image processing and conventional machine learning approaches. In these methods, structures such as leaf texture, colour, edges, and shape were manually extracted for classification. Algorithms including Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and Decision Tree methods were commonly applied for plant species recognition and disease diagnosis. However, the performance of these techniques was limited by environmental variations, dataset size, image quality, and manual feature selection. Because of their strong feature learning capability, CNN-based models have become widely used for plant species identification and plant leaf disease detection tasks [7], [8].

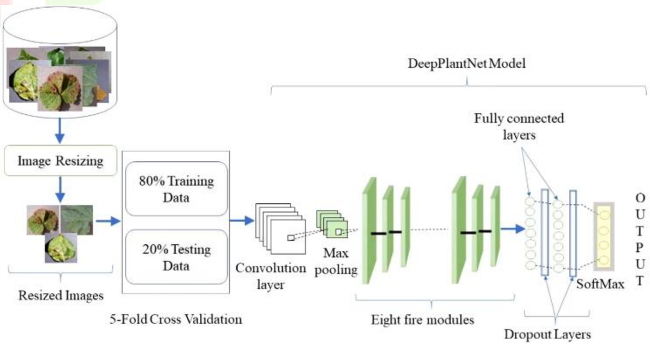

Fig1. Deep Learning pipeline for classification of plant leaf disease

In this proposed work, ResNet50 is utilized for detection of plant leaf disease because of its bottomless residual learning capability. The architecture uses residual connections that help improve feature extraction and overcome degradation problems in deep neural networks. As a result, the model can efficiently identify complex disease symptoms from plant leaf images and achieve accurate classification performance.

For plant species classification, MobileNetV2 is adopted due to its lightweight structure and computational efficiency. The model requires lower memory and processing power while maintaining strong classification accurateness, suitable for actual agricultural applications. Compared to conventional deep learning networks, MobileNetV2 provides faster prediction and reduced computational complexity.

Transfer learning is applied to both ResNet50 and MobileNetV2 to improve model performance and minimize training time. Instead of training the models from scratch, pretrained weights are tuned using plant leaf image datasets. This method enhances classification precision and improves learning efficiency, exclusively when limited training data is available.

Therefore, the combination of ResNet50 for disease identification and MobileNetV2 for plant species recognition provides an efficient framework for automated plant analysis and smart farming systems.

In agricultural applications, CNN models can automatically learn complex image features directly from plant images without requiring manual feature extraction. Due to their strong performance, CNN-based systems are extensively used in precision agriculture, biodiversity studies, and automated crop monitoring [8].

Leaf images are commonly used in plant identification systems because leaves contain unique characteristics such as shape, venation, and texture. CNN models can effectively analyse these features and provide reliable classification results under different environmental conditions. Compared with traditional machine learning methods, CNN-based approaches improve automation and reduce dependency on manual feature engineering.

Pretrained models such as MobileNetV2 and ResNet50 are frequently employed in plant analysis applications because of their high efficiency and classification capability. MobileNetV2 is preferred for lightweight applications with limited computational resources, whereas ResNet50 offers improved deep feature extraction through residual learning. Transfer learning further improves the performance of these models by reducing training complexity and enhancing accuracy [8].

III.METHODOLGY

An automated deep learning framework for plant species classification and plant leaf disease detection was introduced this proposed system. The methodology combines MobileNetV2 for plant species recognition and ResNet50 for disease identification.

A. Image Dataset Preparation

The proposed system uses a dataset containing plant leaf images from multiple plant species and disease categories. Healthy and infected leaf samples collected from publicly available agricultural datasets and experimental image sources. All images are organized into separate folders based on their corresponding class labels to support supervised learning.

Before model training, image preprocessing techniques are applied to improve image consistency and quality. Image normalization is performed to stabilize the learning process and improve training performance. Additional enhancement methods are used to reduce noise and improve the visibility of important leaf features.

B. Plant Species Classification Using MobileNetV2

The plant species recognition module is implemented using MobileNetV2 because of its lightweight architecture and computational efficiency. Transfer learning is employed by loading pretrained weights and modifying the final classification layers according to the number of plant species classes.MobileNetV2 automatically extracts important leaf characteristics including texture, shape, edge patterns, and venation structures for accurate plant species classification.

C. Disease Detection Using ResNet50

ResNet50 uses residual learning mechanisms that allow deep neural networks to learn complex image features efficiently without performance degradation to identify plant diseases.

The pretrained ResNet50 model is fine-tuned using plant disease image datasets to identify symptoms such as leaf spots, discoloration, lesions, and abnormal texture patterns. The model classifies input leaf images into healthy and diseased categories with improved classification accuracy and reliability.

D. Model Training Procedure

Training and testing is done by using the prepared dataset for model progress and valuation. Both MobileNetV2 and ResNet50 models are trained using the Adam optimizer and categorical cross-entropy loss function.

During training, the models iteratively update network parameters to minimize classification errors and improve prediction accuracy. Training and validation processes are continuously monitored to ensure stable model convergence and effective learning performance.

E. Performance Evaluation

Work is evaluated using different statistical metrics in which accuracy and confusion matrix analysis is included. Experimental outcomes validate that the proposed deep learning framework delivers accurate, consistent, and efficient performance for plant species sorting and plant leaf disease identification as shown in fig 2. The developed system can support smart agriculture applications by enabling automated crop monitoring and real-time disease diagnosis.

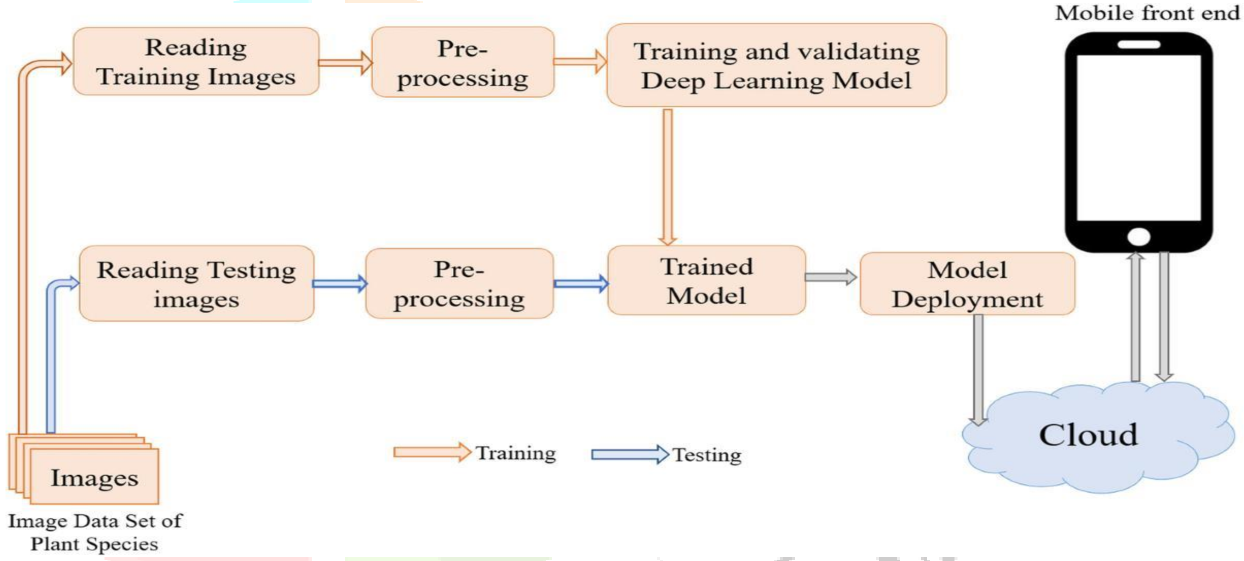

Fig 2. An End-to-End Deep Learning Framework for Plant Species Identification on a Mobile-Cloud Architecture

F. MobileNetV2 Architecture

MobileNetV2 is a lightweight CNN widely used for image sorting and mobile-based deep learning applications in fig 3. It is calculated to provide high classification accuracy with reduced computational complexity and lower memory usage, making it appropriate for real-time systems.

Depth wise separable convolution significantly reduces the number of computations and model limitations, thereby improving

processing speed and efficiency. Inverted residual blocks help preserve important feature information while maintaining a lightweight network structure. Linear bottleneck layers further reduce information loss during feature extraction.Transfer learning is applied using pretrained ImageNet weights to improve model accuracy and minimize training time.

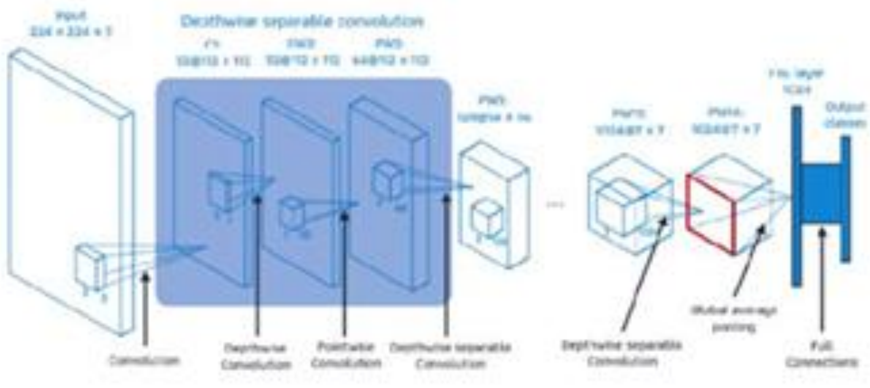

Fig 3.MobileNetV2 Architecture

G.ResNet50 Architecture

ResNet50 is a deep CNN used for imag sorting and feature withdrawal tasks as shown in fig 4. The main feature of ResNet50 is the enduring wedge, which uses shortcut connections between layers. These connections improve feature propagation and help the model learn complex image patterns more effectively.Transfer learning with pretrained ImageNet weights is applied to improve accuracy and reduce training time. The model extracts disease-related features such as spots, discoloration, and texture variations from leaf images for accurate classification.

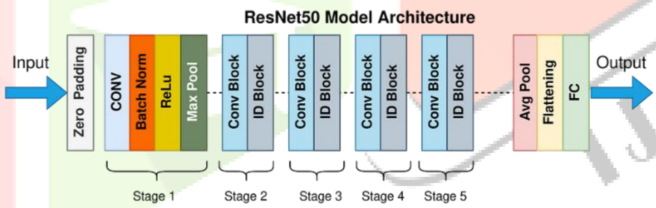

Fig 4. ResNet50 Architecture

IV.RESULTS

The curves represent the learning performance of the proposed deep learning models throughout the training stage. The steady increase in training accuracy indicates that the networks successfully learned meaningful patterns from the plant leaf image dataset. Similarly, the improvement in validation accuracy demonstrates the ability of the models to perform effectively on previously unseen data.

The obtained results show that both MobileNetV2 and ResNet50 achieved stable learning behaviour with minimal overfitting. This approves the usefulness of the projected framework for plant species recognition and plant leaf disease detection applications.

For the MobileNetV2 model, the training accuracy improved from 98.0% to 99.5%, while the validation accuracy remained approximately around 90% as shown in fig 5. These observations indicate that the model efficiently captured important leaf characteristics such as texture, shape, and venation patterns for accurate plant species classification.

In the case of ResNet50, both training and validation performance improved progressively during the training process. The training accuracy increased from 30.0% to 85.6%, whereas validation accuracy improved from 65.0% to 84.5% as shown in fig 6. The model effectively learned disease-related visual features including discoloration, lesion patterns, and texture abnormalities, resulting in reliable disease identification performance.

TABLE 1 Training and Validation Accuracy per Epoch MobileNetV2

Epoch	Training Accuracy	Validation Accuracy
1	98.0%	89.5%
2	98.0%	90.0%
3	99.3%	89.5%
4	99.5%	90.0%

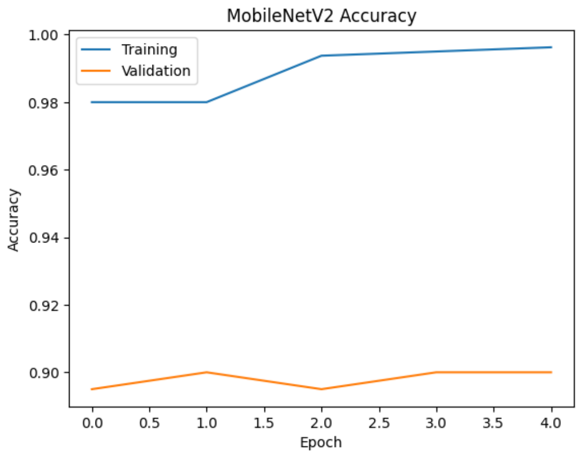

Fig 5 .Training and validation accuracy of MobileNetV2 for plant leaf disease classification.

TABLE 2 Training and Validation Accuracy per Epoch ResNet50 models

Epoch	Training Accuracy	Validation Accuracy
1	30.0%	65.0%
2	70.1%	78.0%
3	81.8%	80.5%
4	85.6%	84.5%

V CONCLUSION

This work presented a deep learning-based framework for plant species classification and plant leaf disease detection using MobileNetV2 and ResNet50 models. The proposed system successfully identified plant species and detected leaf diseases from image data with high accuracy and efficient processing performance

By achieving these results, the mobile version of the network, MobileNetV2, could be considered an appropriate solution for light and real-time applications in agriculture. ResNet50 learned the features of the disease namely discoloration, leaf spot, and texture variations successfully for accurate disease recognition.

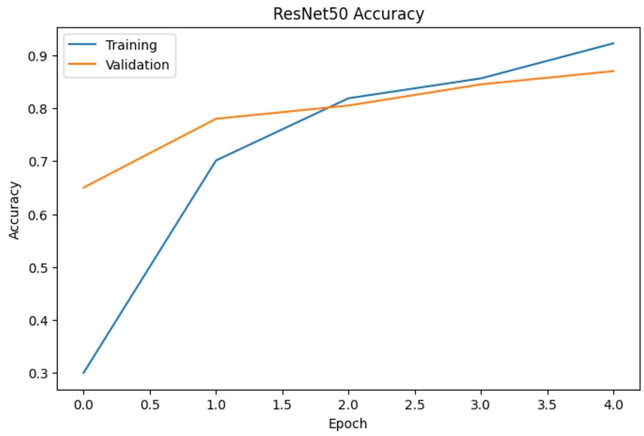

Fig 6 .Training and validation accuracy ResNet50 for plant leaf disease classification.

The implementation of transfer culture and pre-processing the images helped to increase the overall accurateness of the model, decrease the complexity of the training and minimize execution time. Furthermore, data augmentation methods were used to increase the model's capacity to specify and to avoid overfitting during training.

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