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Smart Agriculture: Leaf Disease Detection and Treatment Recommendation System

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Abstract: *The impact of plant leaf diseases on crops can result in significant losses in agricultural productivity when left unchecked or not detected early on. Methods currently utilized to detect diseases on plants include manual inspection and personal expert insight, both of which can be extremely labour-intensive for large farms and take extended periods to complete. This paper presents an automated plant leaf disease detection system using deep learning and transfer learning techniques. The proposed approach employs the EfficientNetB0 convolutional neural network model to classify plant leaf diseases from images. A publicly available plant disease dataset containing approximately 27,000 images across 20 disease classes and 8 plant species was used for training and evaluation. Image preprocessing and data augmentation techniques were applied to improve model generalization. The experimental results show that the base model achieved an accuracy of 98%, which was further improved to 99.23% through fine-tuning. To demonstrate real-world applicability, the trained model was integrated into a mobile application developed using the Flutter framework, enabling users to capture or upload leaf images and obtain disease predictions along with recommended treatment and preventive actions. The proposed system supports early disease detection, reduces dependency on manual monitoring, and provides an effective decision-support tool for smart and sustainable agriculture.*

Key Words: *Plant leaf disease detection, deep learning, transfer learning, EfficientNetB0, image classification, smart agriculture.*

I. INTRODUCTION

Agriculture is one of the rapidly growing sectors and plays a major role in supporting the economic development of a country by providing employment and ensuring food security [1]. Crop production is increasing continuously to meet global food demand, and healthy crops are essential for maintaining agricultural productivity and trade [2], [3]. However, plant diseases remain a serious challenge in agriculture and are one of the main causes of reduced crop yield and quality. Plant leaf diseases are influenced by environmental conditions such as temperature, humidity, and improper farming practices, and they can spread rapidly if not identified at an early stage [4], [5]. Even a minor disease in a single plant can affect an entire field, resulting in significant economic loss for farmers [6]. Traditional plant disease detection methods depend on manual inspection or laboratory-based analysis, which are time-consuming and may not provide accurate results, especially for large or remote farms [7], [8]. The integration of artificial intelligence in agriculture reduces the need for continuous human monitoring and improves disease diagnosis efficiency [9]. With the help of deep learning and computer vision techniques, plant leaf diseases can be automatically identified from images without manual involvement. In this work, an automated plant leaf disease detection system using transfer learning with the EfficientNetB0 model is proposed [10]. In addition to disease identification, the system provides disease-specific treatment and preventive recommendations to assist farmers in taking timely corrective actions. This approach enables early disease detection, supports informed decision-making, and helps reduce crop losses, thereby promoting smart and sustainable agricultural practices [11].

II. RELATED WORK

Early studies on plant leaf disease detection focused on traditional image processing and machine learning techniques, where handcrafted features based on color, texture, and shape were used for disease classification [6], [7]. Although these approaches achieved reasonable performance, they required extensive manual feature design and showed limited robustness to real-world variations.

Recent research has shifted toward deep learning–based approaches, particularly convolutional neural networks, which automatically learn discriminative features from leaf images. A machine learning and CNN-based framework was presented in [1], demonstrating improved classification accuracy compared to traditional methods. However, the approach was limited to disease identification and did not provide post-detection decision support. Similarly, [2] compared classical machine learning models with CNNs and showed the superiority of deep learning for plant disease classification, though the study relied on a limited number of plant species.

Several studies have adopted deep learning and transfer learning techniques to improve classification performance. CNN-based models have been shown to achieve higher accuracy and better generalization in multi-class disease detection tasks [5]. Review and image-processing-based works emphasized the effectiveness of deep learning while highlighting the lack of real-time deployment and advisory mechanisms [4]. Transfer learning has also been successfully applied in related biological disease detection domains, further validating its effectiveness [3]. These limitations motivate the proposed work, which focuses on accurate multi-class disease detection using EfficientNetB0 along with treatment recommendation support for real-world agricultural applications.

However, many existing works consider a limited number of plant species or disease classes, and several studies do not explore fine-tuning strategies, which are essential for achieving optimal performance on domain-specific datasets. To address these limitations, this work adopts a transfer learning-based EfficientNetB0 model and applies fine-tuning techniques on a large and diverse plant disease dataset to achieve accurate and efficient multi-class plant leaf disease classification.

III. PROPOSED METHODOLOGY

The proposed plant leaf disease detection system is developed using deep learning and transfer learning techniques to automatically classify leaf diseases from images. In this project, we deliver a complete workflow that includes image capturing, pre-processed data prep, model training using a pre-trained convolutional neural network (CNN), and disease classification using a CNN. The system is developed for accurate classification of various types of plant leaf diseases, and to assist with early identification for minimizing crop loss.

Plant leaf images are sourced from a large publically available dataset on plant leaf diseases. Preceding model training, the acquired images are resized so that they correspond to a pre-determined input dimension of the deep learning model and the respective pixel intensity values are normalized so as to increase stability of model training. Data augmentation techniques are used to increase model performance in the generalization of malignant/benign classification by utilizing rotation, flipping, and zooming of the image dataset to lower the rate of overfitting.

The proposed system uses an EfficientNetB0 model, which is an architecture for convolutional neural networks that has both a small footprint (i.e., not too heavy) and runs relatively few computations compared to other architectures (i.e., low computational cost). It is implemented as a transfer-learning-based feature extractor of an input image based on its use of the ImageNet dataset classification in training prior to use. The output classification layer has been altered to allow for multiple classes of plant disease to be supported by the model.

The process of fine-tuning has been accomplished by unfreezing selected layers of the model so that the model is able to learn unique characteristics associated with each type of plant disease in order to produce improved classifications or predictions for various plant diseases. When predicting which type of a plant disease the input leaf image is, the trained model produces a probability of the input leaf image containing a specific plant disease using a multi-class softmax-based classifier. The predicted outcome from the trained model identified as containing a specific plant disease generates disease-specific management and prevention recommendations. these are based on standard agricultural recommendations. Timely intervention is enhanced when farmers receive the recommendations so that farmers can take corrective actions to limit the spread of diseases.

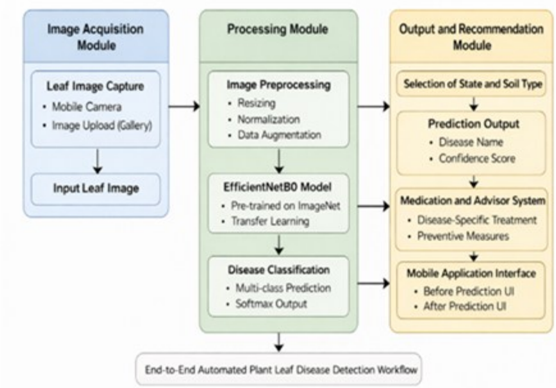

Fig. 1: Workflow of the proposed plant leaf disease detection system

By providing the accuracy of disease identification and recommendation for both management and prevention, this methodology is expected to facilitate the use of smart agricultural practices and improved decision-making related to precision agriculture.

IV. RESULTS AND DISCUSSION

4.1 Results

The proposed plant leaf disease detection system was evaluated using a publicly available plant disease dataset consisting of approximately 27,000 leaf images, covering 20 disease classes across 8 plant species. The dataset was divided into training, validation, and testing sets to ensure reliable and unbiased performance evaluation. The EfficientNetB0 model was trained using transfer learning and further fine-tuned to enhance classification performance.

During training, the model exhibited stable learning behavior. The training and validation accuracy increased gradually with each epoch, while the corresponding loss values decreased consistently, indicating effective model convergence. Figures 2 and 3 illustrate the training and validation accuracy and loss curves, respectively. The base EfficientNetB0 model initially achieved an accuracy of 98%. After fine-tuning selected layers, the final model achieved a test accuracy of 99.23%, confirming the effectiveness of transfer learning for multi-class plant leaf disease classification.

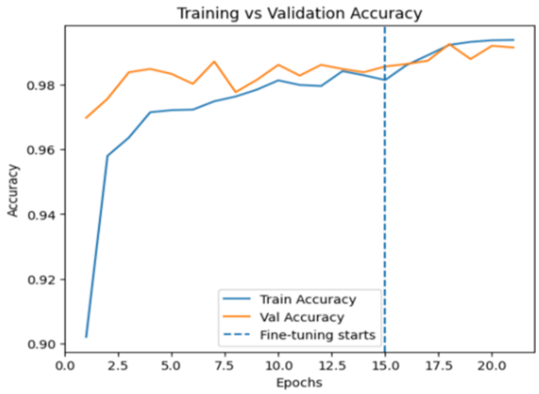

Fig.2: Training and validation accuracy of the proposed model

Fig. 3: Training and validation loss of the proposed model

To evaluate real-world usability, the trained model was integrated into a mobile application developed using the Flutter framework. Figure 4 shows the user interface before disease prediction, where users can capture or upload a plant leaf image using the camera or gallery. After image submission, the model processes the input image and predicts the disease class. Figure 5 presents the post-prediction interface, where the detected disease name is displayed along with contextual inputs such as state and soil type.

Table 1 summarizes the comparison between the base paper and the proposed plant leaf disease detection system in terms of dataset size, model architecture, performance, and practical applicability.

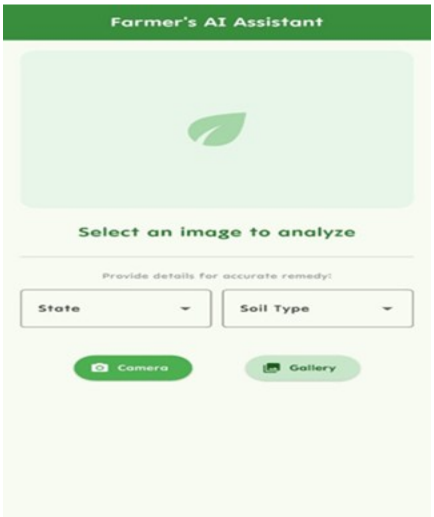

Fig.4: Mobile application interface before plant leaf disease prediction

Based on the predicted disease, the application provides disease-specific recommended actions, including cultural practices and chemical treatment suggestions. This demonstrates the end-to-end functionality of the proposed system, from image acquisition to disease prediction and actionable decision support, making it suitable for real-world smart agriculture applications.

Fig. 5: Mobile application interface after plant leaf disease prediction

The overall performance of the proposed model was evaluated using precision, recall, and F1-score metrics. The model achieved an overall precision of **0.9935**, recall of **0.9934**, and an F1-score of **0.9934**, confirming its reliable and balanced performance for multi-class plant leaf disease detection

Aspect	Base Paper [1]	Proposed Work
Dataset Size	Small dataset	~27,000 images
Plant / Disease Coverage	Limited species & classes	8 plants, 20 diseases
Model	CNN / ML models	EfficientNetB0
Learning Strategy	Standard training	Transfer learning + fine-tuning
Accuracy	~97–98%	99.23%
Decision Support	Not available	Treatment recommendations
Deployment	Classification only	Mobile app (Flutter)

Table 1. Comparison between the existing system and the proposed system

4.2 Discussion

Farmers are given easy access to disease identification and recommended treatments through the simple image input and clear post-prediction output of the proposed plant disease detection and treatment recommendation system that uses a pre-trained deep learning model (EfficientNetB0) for plant disease detection. Furthermore, the addition of crop-specific treatment recommendations enhances the functional capability of the proposed system beyond simple classification and supports farmers when making practical agricultural decisions. Finally, this proposed system demonstrates that it has the ability to deliver superior accuracy and to be applied in real-world smart agriculture applications.

The plant leaf disease detection and treatment recommendation system presented in this research utilizes deep learning and a pre-trained convolutional neural network to identify crop diseases and provide treatment recommendations. The results of this work demonstrate that the developed model is capable of identifying multiple types of crop diseases with high levels of accuracy, based on the performance metrics that were measured on the dataset used to train the model, such as precision, recall, and F1-score.

The newly developed/created mobile app integrated with the developed model provides farmers with an easy-to-use method of obtaining crop disease identification and treatment recommendations by providing users with the ability to take pictures of leaves or upload leaf images to obtain predictions of whether or not a leaf represents a diseased leaf, and if so, to receive treatment recommendations for the detected diseased leaf. The proposed model is intended to assist in early disease detection and support timely decision making by providing timely identification of diseases and recommendations of treatments to farmers. The future work will include the development of an expanded version of the system for additional crop types, and efforts to improve the system's scalability for use in smart agriculture.

V.CONCLUSION

This work presented a deep learning–based plant leaf disease detection and treatment recommendation system using transfer learning with EfficientNetB0. The proposed model achieved high classification accuracy with balanced precision, recall, and F1-score, demonstrating reliable performance for multi-class disease detection.

The integration of the trained model into a mobile application enables practical usage by allowing users to capture or upload leaf images and receive disease predictions along with treatment recommendations. Overall, the proposed system supports early disease detection and assists farmers in timely decision-making. Future work will focus on extending the system to additional crops and enhancing scalability for smart agriculture applications.

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