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Optimizing Plant Leaf Disease Detection: A Comparative Study of Deep Learning Models

Vinodini Salvi[1], Sujata Bhairnallykar[2]

[1,2]*Department of Computer Engineering Saraswati College of Engineering Kharghar, Navi Mumabi, India*

[1]*Department of Computer Engineering Maharshi Parshuram College of Engineering Velneshwar, India*

Abstract:- This study presents an advanced plant leaf disease detection system utilizing deep learning techniques to address the limitations of traditional disease identification methods. We evaluated several machine learning models, including Convolutional Neural Networks (CNN), VGG16, ResNet50, and EfficientNet-B2, using a dataset of over 87,000 RGB images of healthy and diseased crop leaves. Among these, EfficientNet-B2 demonstrated superior performance, achieving an accuracy of 93%, precision of 93%, recall of 90%, and an F1-score of 90%. The model's high sensitivity of 99.83% underscores its efficacy in identifying positive cases accurately. Despite signs of overfitting, as indicated by the divergence between training and validation metrics, EfficientNet-B2 remains the most reliable model for this task. Future work will focus on mitigating overfitting through techniques like hyperparameter tuning and data augmentation. Integrating this model into mobile and UAV-based platforms and expanding the dataset to include diverse plant species will enhance its practical application in real-world agricultural settings..

Keywords*:* Plant leaf disease detection, Deep learning, EfficientNet-B2, Convolutional Neural Networks, Image classification, Machine learning.

Introduction

Agriculture forms the backbone of human society, providing essential food and employment to billions of people worldwide [1]. However, the agricultural sector faces numerous challenges, including climate change, resource constraints, and the proliferation of plant diseases [2]. These challenges significantly threaten crop yield, quality, and food security [3]. Rapid and accurate identification, as well as effective management of plant diseases, are crucial for ensuring sustainable agricultural production [4]. Traditional methods of plant disease detection primarily rely on human visual inspection, which can be time-consuming, subjective, and prone to errors [5]. Additionally, the globalization of trade has heightened the risk of spreading plant diseases to new regions, underscoring the need for efficient and reliable detection methods [6].

Recent advancements in artificial intelligence (AI), especially in "computer vision and machine learning," present new opportunities to revolutionize plant disease detection and management [7]. AI algorithms can process large volumes of image data with remarkable speed and accuracy, enabling the development of automated systems for the timely detection of plant diseases [8]. Motivated by the potential of AI to address the challenges of modern agriculture, this study introduces an innovative AI-powered system for the detection and diagnosis of plant diseases [9].

The integration of artificial intelligence (AI) and machine learning technologies in agriculture has garnered significant attention recently, especially in the context of detecting and managing plant diseases. Singh et al. (2017) provided a comprehensive analysis of machine learning methods for identifying and diagnosing plant diseases, highlighting how AI algorithms can rapidly and accurately process large volumes of image data to enable early disease detection [10]. Barbedo et al. (2018) explored the application of deep learning for classifying plant diseases, demonstrating the effectiveness of advanced neural networks in accurately identifying disease symptoms from images. This research underscores the importance of deep learning models in enhancing the precision and efficiency of plant disease detection systems [11].

Kamilaris and Prenafeta-Boldú (2018) examined the role of deep learning in agriculture, emphasizing its transformative effect on various agricultural tasks, including plant disease detection. Their study highlighted the flexibility of deep learning algorithms in handling complex agricultural data and deriving actionable insights [12]. Mahlein et alfocused on imaging sensors in plant disease recognition, stressing the advantages of imaging-based approaches for early disease detection and informed agricultural decision-making [13].

Moreover, Mwebaze et al. (2020) conducted an extensive review of deep learning applications in agriculture, including plant disease detection. Their survey emphasized recent advancements in deep learning techniques and their potential to address major challenges in agricultural productivity and food security. By leveraging extensive image datasets, deep learning models have shown remarkable precision in recognizing disease symptoms, facilitating early detection and timely intervention [14]. Singh et al. also contributed by developing a method based on color and texture characteristics for classifying plant diseases, achieving significant success in distinguishing between healthy and diseased plants [15].

Al-Hiary et al. (2018) proposed a convolutional neural network (CNN) design for identifying diseases in tomato leaves, achieving an impressive accuracy of 99.75% in distinguishing healthy leaves from those affected by various diseases [16]. Sladovnjak et al. explored transfer learning by fine-tuning a pre-trained VGG16 model for classifying tomato plant diseases, demonstrating how transfer learning can enhance model performance with limited training data [17]. Phadikar et al. (2018) developed a deep learning model that combines CNNs and recurrent neural networks (RNNs) to classify multiple rice leaf diseases, achieving a precision rate of 97.48% in identifying eight different rice ailments [18]. This research illustrates the capability of deep learning models to manage multi-class classification problems involving diverse plant diseases.

Additionally, Appia et al. (2019) introduced PlantVillage, a mobile application that employs deep learning for real-time plant disease detection. The app allows users to capture images of their crops and receive immediate disease identification, highlighting the potential of integrating machine learning models into mobile platforms for field-based disease detection [19]. Lu et al. (2018) investigated the use of unmanned aerial vehicles (UAVs) equipped with multispectral cameras to capture detailed aerial images of crops. Their study demonstrated how deep learning models can analyze these images to detect apple leaf diseases on a large scale in agricultural fields [20].

This study developed a web-based tool for detecting fruit diseases by analyzing uploaded images. It utilized feature extraction based on color, morphology, and the Color Coherence Vector (CCV), and performed clustering using the k-means algorithm. Support Vector Machine (SVM) was employed for classification into infected or non-infected categories, achieving an accuracy of 82% for identifying pomegranate diseases [21].

Addressing crop production challenges in India, this paper presents a system that utilizes image pre-processing and feature extraction from the PlantVillage dataset, followed by a Convolutional Neural Network (CNN) for disease classification and pesticide recommendation. The system, implemented through an Android application with Java Web Services and TensorFlow, achieved a highest accuracy of 95.05% with a 5-layer model for 15 epochs, and a validation accuracy of 89.67% for 20 epochs [22].

This paper proposes a cost-effective, automated solution for the early and precise diagnosis of crop diseases. It leverages deep Convolutional Neural Networks (CNN), a social collaborative platform, and geocoded images to create disease density maps. The Inception model facilitates real-time disease classification on a cloud platform via a mobile app, aiding farmers in quick decision-making [23].

This study describes a system for classifying and detecting plant leaf diseases using deep learning techniques. The system, utilizing images from the PlantVillage dataset, focused on common plants such as tomatoes, peppers, and potatoes. Employing a Convolutional Neural Network (CNN), it achieved an impressive accuracy of 95% in both training and testing phases for the five classes of plant diseases [24, 28].The comparison of different machine learning techniques used by researchers for plant disease detection for different performance metrices is shown in fig 1.

The rapid and accurate detection of plant diseases is crucial for ensuring crop health, agricultural productivity, and global food security. Traditional methods of disease identification, relying on manual inspection, are often error-prone, time-consuming, and unsuitable for large-scale operations. Given the increasing demands of agriculture and the growing global population, there is an urgent need for advanced, automated solutions. This study leverages machine learning techniques, specifically deep learning models such as Convolutional Neural Networks (CNN), ResNet50, VGG16, and EfficientNet-B2, to address these challenges. By utilizing offline data augmentation and a dataset containing over 87,000 RGB images of healthy and diseased crop leaves, the study aims to develop an efficient system for plant disease detection that is both accurate and scalable. The objective is to build, train, and evaluate these models using performance metrics like confusion matrix, classification report, specificity, and sensitivity, and to identify the best-performing model for integration into a user-friendly graphical interface using Flask. This system aims to empower farmers with timely and precise disease management information, improving crop yield and sustainability in agriculture.

Table 1. Summary of Studies on Plant leaf Disease Detection Using Machine Learning Techniques.

Study	Year	Methodology	Dataset	Accuracy	Key Findings	Reference
Web-Based Application for Plant Leaf Disease	2024	Web-based tool with feature extraction and SVM classification	Custom dataset	82%	Achieved 82% accuracy in identifying pomegranate diseases using color, morphology, and CCV features.	[25]
A Convolutional Neural Network Based Potato Leaf Diseases Detection Using Sequential Model.	2023	Convolutional Neural Network (CNN) with TensorFlow	PlantVillage dataset	95.05% (15 epochs), 89.67% (20 epochs)	Highest accuracy of 95.05% for a 5-layer CNN model; validation accuracy of 89.67%.	[26]
Basil plant leaf disease detection using amalgam based deep learning models	2023	Deep CNN with cloud-based platform and social collaboration	Custom dataset with geocoded images	High performance	Real-time disease classification using the Inception model; supports early diagnosis and decision-making.	[29]
Plant Leaf Diseases Detection and Classification Using Deep Learning	2020	Convolutional Neural Network (CNN)	PlantVillage dataset	95%	Achieved 95% accuracy in classifying five classes of plant leaf diseases.	[24]

Detection of Potato Leaf Disease Using Multi-Class Support Vector Machine Based on Texture, Color, and Shape Features.	2022	Feature extraction, k-means clustering, SVM classification	Custom dataset	82%	Identified pomegranate diseases with 82% accuracy using color and morphological features.	[27]
Detection and Classification of Tomato Plant Diseases Using Transfer Learning	2016	Transfer learning with pre-trained VGG16	Custom dataset	Not specified	Improved model performance using transfer learning for classifying tomato diseases.	[17]
Detection of Multiple Rice Leaf Diseases Using CNN and RNN	2018	CNN and Recurrent Neural Networks (RNN)	Custom dataset	97.48%	Achieved 97.48% precision in classifying eight rice leaf diseases.	[18]
Mobile App for Plant Disease Detection Using Deep Learning	2019	Deep learning integrated into a mobile app	PlantVillage dataset	Not specified	Real-time disease identification through a mobile app, utilizing deep learning models.	[19]
UAV-Based Plant Disease Detection Using Deep Learning	2018	UAVs with multispectral cameras and deep learning	Custom dataset with aerial images	Not specified	Detected apple leaf diseases on a large scale using UAV-captured images and deep learning.	[20]

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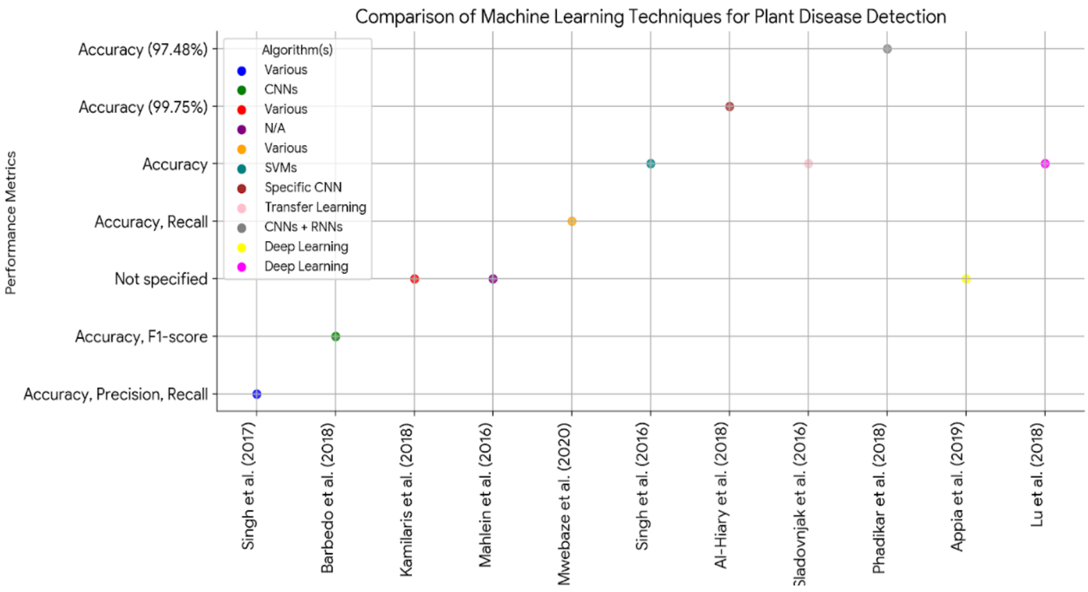

Fig. 1. Illustrating a comparison of machine learning methods for detecting plant leaf diseases.

Methods This study methodology entails a number of crucial phases that are necessary to create and assess a machine learning-based plant disease detection system. The dataset used comes from Kaggle and is made up of about 87,000 RGB pictures of crop leaves that are both healthy and ill. The images are divided into 38 different classes. The original dataset, which can be found on GitHub, has been enhanced and is now available here. The directory structure is preserved when the data is divided in an 80/20 ratio into training and validation sets. For the purpose of the final forecast, a separate directory containing 33 test photos is also created.

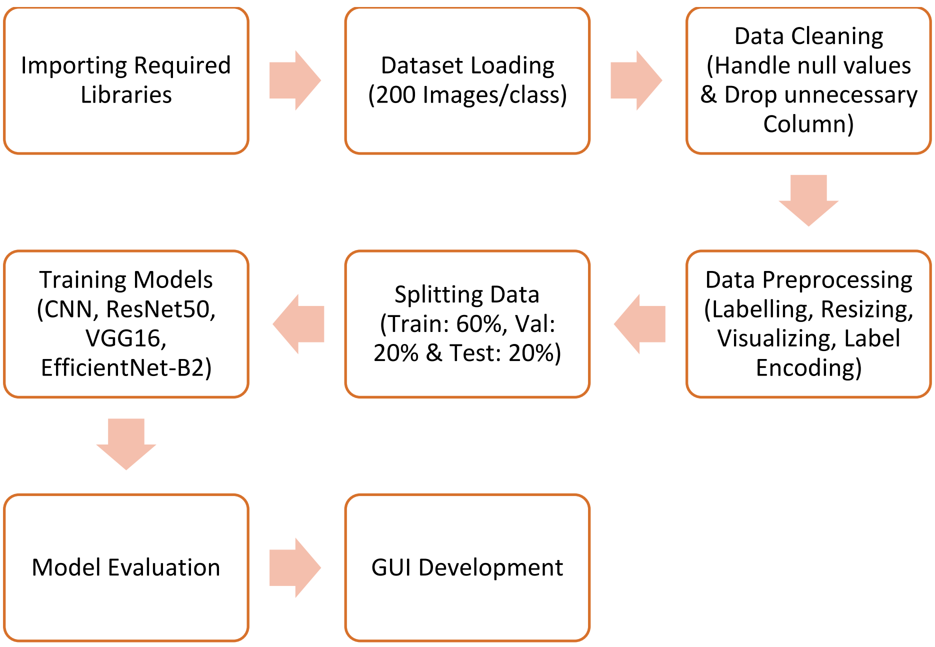

Fig.2 Methodology

Figure 2. illustrated methodology flow. The study workflow begins with importing the necessary libraries for data processing and model building. The dataset is loaded with 200 images for each class, followed by data cleaning processes to address any null values and remove unnecessary columns. Data preprocessing includes labeling, resizing images, visualizing data, and encoding labels. The dataset is then divided into training (60%), validation (20%), and testing (20%) sets. Models are trained using various architectures including Convolutional Neural Networks (CNN), ResNet50, VGG16, and EfficientNet-B2. Model performance is evaluated using metrics such as confusion matrix, classification report, specificity, and sensitivity. Finally, a graphical user interface (GUI) is developed using Flask to provide a user-friendly platform for disease detection.

Results and Discussion

This study's main goal was to assess the efficacy of different machine learning models for the identification of plant leaf disease using picture data. To categorize various plant leaf diseases, we used deep learning architectures such as CNN, VGG16, EfficientNet-B2, and ResNet50. We used common assessment criteria, like accuracy, precision, recall, F1-score, sensitivity, and specificity, to evaluate the performance of the model.

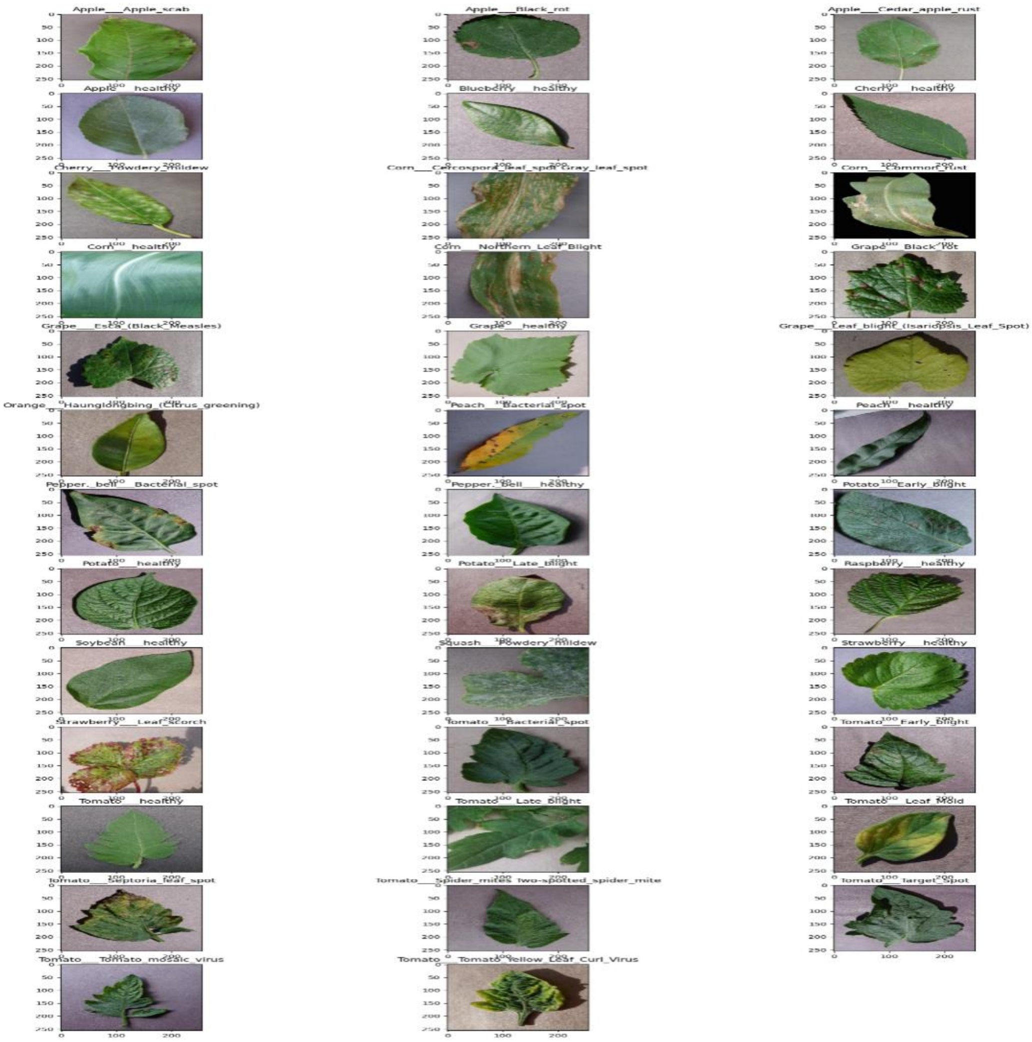

Fig.2 Image Plotting

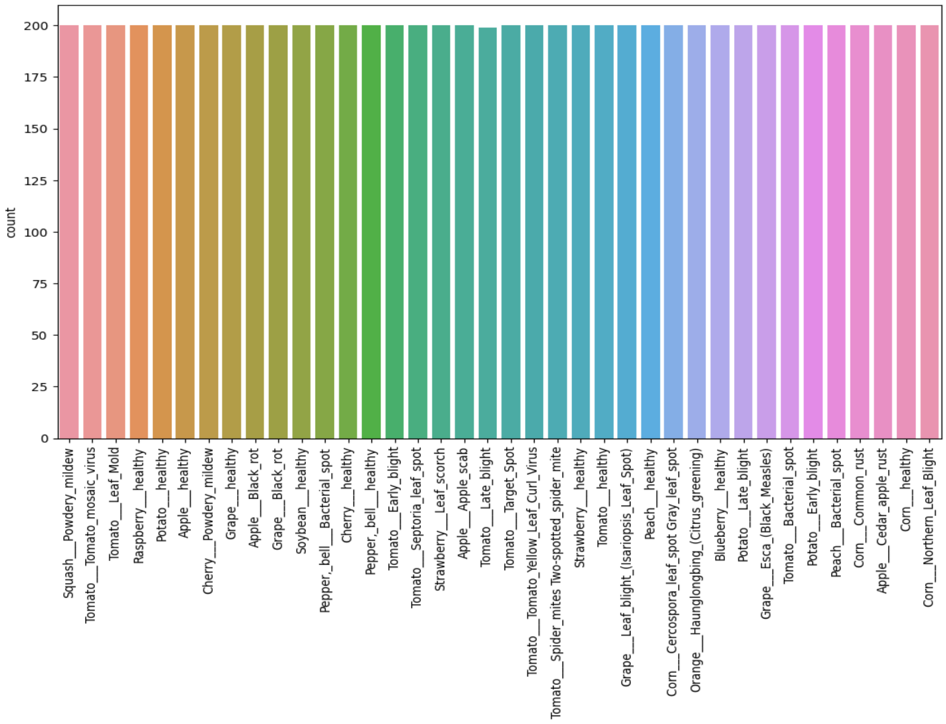

Fig.3. Distribution of plant leaf disease categories in the dataset

Figure 3 Shows the distribution of plant leaf disease and dataset obtained from Kaggle.Based on the provided classification reports, EfficiencyNet-B2 stands out as the most effective machine learning algorithm for plant leaf disease detection. It significantly outperforms the other models in all key metrics: accuracy, precision, recall, and F1-score. EfficiencyNet-B2 achieves the highest accuracy, demonstrating its ability to correctly classify the disease category for a larger proportion of samples. Its superior precision indicates that it effectively avoids false positives, while its enhanced recall shows that it captures a higher percentage of actual positive cases. This balanced performance across precision and recall is reflected in its high F1-score, which signifies a well-rounded model performance.

In summary, EfficiencyNet-B2's exceptional results across various performance metrics highlight its suitability for the task of plant leaf disease detection. Its ability to deliver high accuracy, precision, and recall, along with a balanced F1-score, makes it a reliable and accurate choice for classifying plant leaf diseases. The model's superior performance suggests that it is well-equipped to handle the complexities of plant disease detection, making it the preferred algorithm among those compared.

Table 2. Comparison of Classification of Training Models

Model	Accuracy	Precision	Recall	F1-score	Overall Sensitivity
CNN	0.71	0.72	0.61	0.6	0.983610
VGG16	0.12	0.12	0.16	0.1	0.987459
ResNet50	0.35	0.36	0.15	0.15	0.986320
EfficientNet-B2	0.93	0.93	0.9	0.9	0.998325

The comparative analysis of CNN, VGG16, EfficientNet-B2, and ResNet50 for plant leaf disease detection reveals that EfficientNet-B2 excels in overall sensitivity, achieving a mean sensitivity of 0.998325. This high sensitivity indicates that EfficientNet-B2 is particularly adept at correctly identifying positive cases of plant leaf diseases, making it the most effective model among those tested. In comparison, VGG16 and ResNet50 exhibit similar overall sensitivities, with ResNet50 showing a slightly lower mean sensitivity of 0.986320 compared to VGG16's 0.987459. CNN, on the other hand, demonstrates the lowest sensitivity at 0.983610, suggesting that it may struggle more than the other models in accurately detecting plant leaf diseases. This analysis underscores EfficientNet-B2's superior performance in detecting positive cases, reinforcing its suitability for plant leaf disease detection.

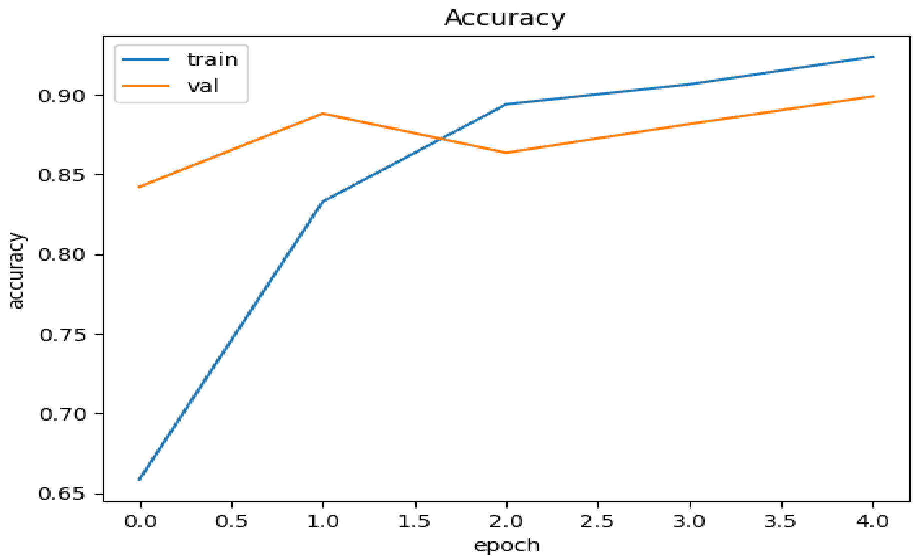

Fig. 4 Accuracy plot for an EfficientNet-B2 model during training and validation.

Figure 4 shows that while the training accuracy of the EfficientNet-B2 model steadily increases, the validation accuracy starts to plateau or decrease, suggesting potential overfitting. The optimal training epoch is where validation accuracy peaks before declining with further training. The final validation accuracy of around 0.90 is good but may need improvement for some applications. Figure 5. shows that while training loss decreases consistently, validation loss plateaus or increases after a certain number of epochs, indicating potential overfitting. The optimal number of epochs is where validation loss is minimized. The model achieves a reasonably low final validation loss, suggesting effective learning.

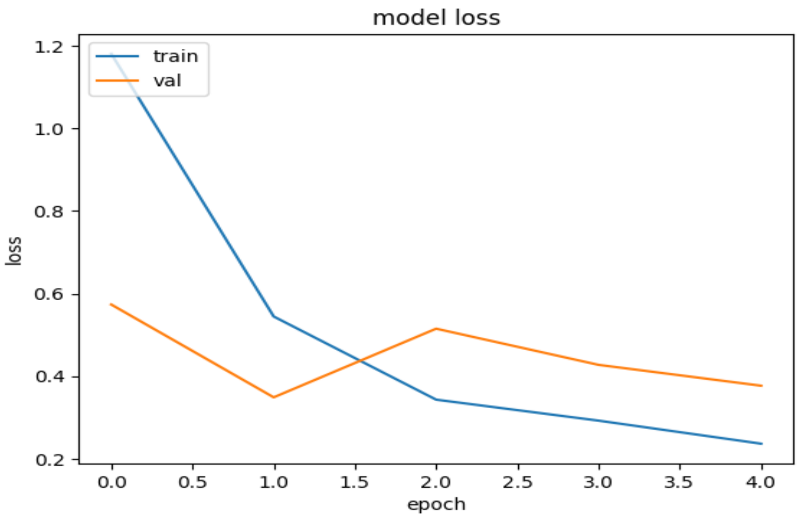

Fig.5. Loss plot for an EfficientNet-B2 model during training and validation.

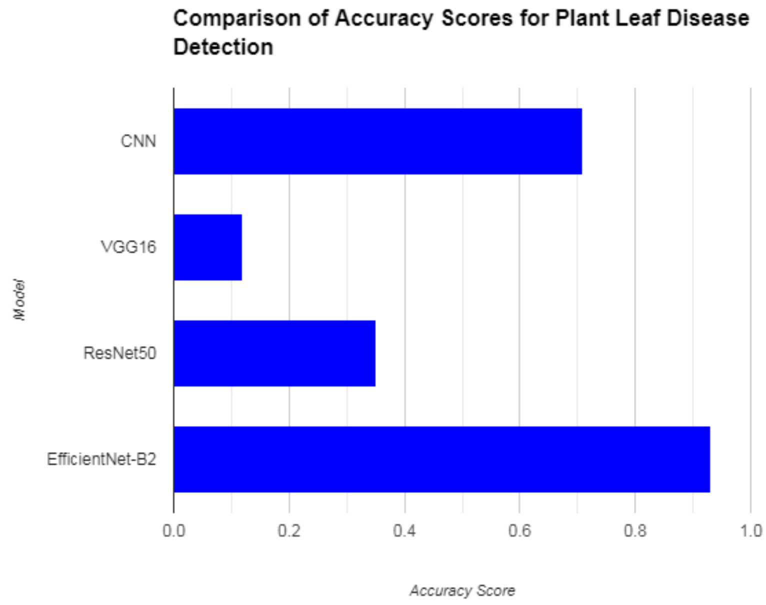

Fig. 6. Comparison of accuracy, scores of plant leaf disease detection

The bar chart shows that EfficientNet-B2 outperforms other models with the highest accuracy score for plant leaf disease detection, indicating superior performance. CNN also achieves a relatively high accuracy, while VGG16 and ResNet50 have significantly lower accuracy scores, suggesting they are less effective for this task. Overall, EfficiencyNet-B2 is the most promising model based on accuracy.

Conclusion

The comparative analysis of CNN, VGG16, ResNet50, and EfficientNet-B2 for plant leaf disease detection underscores the exceptional performance of EfficientNet-B2. This model outperforms others in key metrics such as accuracy, precision, recall, and F1-score, making it the most effective choice for accurately classifying plant leaf diseases. Its superior overall sensitivity, with a mean value of 0.998325, highlights its ability to correctly identify positive cases consistently. Although EfficientNet-B2 shows signs of overfitting, as evidenced by the divergence between training and validation accuracy and loss, its performance remains robust, achieving a final validation accuracy of around 0.90 and a reasonably low validation loss. The study confirms EfficientNet-B2 as the most reliable model for plant disease detection, capable of handling the complexities of this task with high accuracy.

Future work could focus on addressing the overfitting issues observed with EfficientNet-B2 by exploring advanced techniques such as hyperparameter tuning, data augmentation, and early stopping. Enhancing the model's generalization capabilities will be crucial for deploying it in diverse agricultural settings. Additionally, integrating the EfficientNet-B2 model into real-time systems, such as mobile applications and UAV-based platforms, could further extend its practical utility. Expanding the dataset to include more diverse plant species and disease conditions would improve the model's robustness and accuracy. Furthermore, incorporating additional features like environmental factors and plant growth conditions could refine the model's predictive power, offering a more comprehensive solution for plant disease management and contributing to sustainable agricultural practices.

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