Efficient deep learning approach for enhancing plant leaf disease classification

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ABSTRACT

The widespread occurrence of plant diseases is a major factor in the reduction of agricultural output, affecting both crop quality and quantity. These diseases typically begin on the leaves, influenced by alterations in plant structure and growing techniques, and can eventually spread over the entire plant. This results in a notable decrease in crop variety and yield. Successfully managing these diseases depends on accurately classifying and detecting leaf infections early, which is essential for controlling their spread and ensuring healthy plant growth. To address these challenges, this paper introduces an efficient approach for detecting plant leaf diseases. A concatenation of pre-trained convolutional neural networks (CNN) for enhanced plant leaf disease using transfer learning technique is implemented, with a specific focus on accurate early detection, utilizing the comprehensive new plant diseases dataset. The combined residual network-50 (ResNet-50) with densely connected convolutional network-121 (DenseNet-121) architecture aims to provide an efficient and reliable solution to these critical agricultural concerns. Various evaluation metrics were utilized to evaluate the robustness of the proposed hybrid model. The proposed ResNet-50 with the DenseNet-121 hybrid model achieved a rate of accuracy of 99.66%.

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1. INTRODUCTION

Massive obstacles confronting the world today include the world's rapidly expanding population, climate variability, food security, ecological decline, and infectious disease pandemics. Ten billion people are expected to live on the planet by the mid-21st century. Worldwide food security is expected to become a major concern since it is predicted that food demand will increase by 70% to 100% by 2050 [1].

Enhancing the agricultural sector is vital for optimizing production and elevating quality. Creating favorable conditions for the healthy development of plants and crops is essential. Plant diseases are often the main factors contributing to their decline. Based on estimates from the Food and Agriculture Organization of the United Nations (FAO), these diseases result in an annual economic impact of around $220 billion globally, frequently causing damage or total crop loss. Plants are attacked by various pathogens, including bacteria, fungi, microscopic organisms, and viruses, which disrupt their vital functions and alter their natural structure [2]. Early identification of plant disease in the field stands as a pivotal initial phase. Conventional disease identification methods heavily lean on the assistance of agricultural extension organizations. However, these methods face constraints in countries with insufficient logistical and human infrastructure capacity, and their scalability comes at a high cost. In such contexts, the internet of things, with smartphone and unmanned aerial vehicle technologies, present novel avenues for in-field plant disease detection through automated image recognition. This approach holds promise for enabling early detection on a broad scale [3]. Crop yield reduction is a critical area of research, especially in cases where diseases or abnormalities disrupt chlorophyll production in plant leaves, resulting in plant mortality. Artificial intelligence (AI) has evolved as a major avenue for addressing this issue [4]. Researchers have introduced a variety of deep learning algorithms aimed at the identification and classification of multiple diseases of plants. Imanulloh *et al.* [5], this work proposed a custom-designed convolutional neural network (CNN) approach comprising 12 layers, with eight dedicated to feature extraction and four serving as classifiers. Utilizing a new plant diseases dataset, the proposed model achieved high performance without overfitting, attaining an accuracy rate of 97%. Belmir *et al.* [6] utilized the PlantVillage dataset which contains 38 classes and a deep CNN for the detection and classification of plant leaves diseases achieving a test accuracy of 94.33%. Different approaches have been applied to handle the classification of single crops. For example, in [7] a densely connected convolutional network-121 (DenseNet-121) deep learning model was proposed to identify six categories of apple leaf diseases. The proposed method indicated an accuracy rate of 93.71%. Additionally, these solutions [8], [9] implemented deep learning approaches for the purpose of classifying the images of apple leaf diseases, also for the classifying of tomato crop [10]-[12]. In another study [13], transfer learning with deep CNNs was employed to identify plant leaf diseases. Pre-trained models, initially trained on extensive datasets, were adapted to the specific task using the rice and maize PlantVillage dataset. Moreover, Khan *et al.* [14] and Gupta *et al.* [15] applied deep learning techniques to classify images of maize leaf diseases. The visual geometry group network (VGGNet), which is pre-trained on the ImageNet, and also the Inception model was chosen for this purpose, resulting in an accuracy of 92.00%. Chen *et al.* [16], enhanced an artificial neural network by inputting extracted pixel and feature values for image segmentation. Next, a CNN-based model was established, and the segmented images were classified using the proposed CNN model. Experimental findings indicated an average accuracy of 93.75%.

Within the scope of this research, we introduce a specifically tailored hybrid model designed for the identification and classification of plant leaf diseases which combined pre-trained residual network-50 (ResNet-50) with DenseNet-121. The methodological framework comprises three pivotal steps: data collection, pre-processing of data, and the classification. The overarching goal is to craft a model proficient in differentiating healthy from infected plant foliage. The new plant dataset, encompassing a diverse array of plant varieties, serves as the foundation for this study. The discernible results underscore the significantly heightened accuracy exhibited by the proposed model in comparison to conventional machine learning classifiers when detecting plant leaf diseases. To assess how well our suggested solution performs, we compared its performance against a deep learning models trained on the same dataset. This study makes a contribution to combining deep transfer learning models to increase prediction accuracy. The paper is systematically structured into five distinct sections for clarity. The second section details the methods employed. The third section delves into the proposed methodology for identifying plant leaf diseases. Section four thoroughly examines the experimental results and includes comparisons of the findings. The final section concludes the research paper.

2. METHOD

2.1. Data collection

Recently, several efforts have been initiated in the realm of data gathering. One such initiative involves the acquisition of images depicting multiple plant species affected by different diseases from the Kaggle platform, specifically from the dataset titled ‘New plant diseases dataset’. This dataset has been recreated through augmentation from the original dataset “PlantVillage dataset”. The original dataset contains a wide variety of images of plant species affected by different diseases. The new plant diseases dataset includes 87,867 red, green, and blue (RGB) images of 14 different types of crop leaves, both healthy and those affected by the disease, classified into 38 classes of plant diseases categories and can be accessed at “https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset”. For predictive modeling, the dataset was splited into training (56,236 images), validation (14,059 images), and test sets (17,572 images). An experiment utilizing 14 crops was performed, Figure 1 represents classes of the apple leaf dataset include: Figure 1(a) healthy leaves, Figure 1(b) rust leaves, Figure 1(c) black rot leaves, and Figure 1(d) scab leaves.

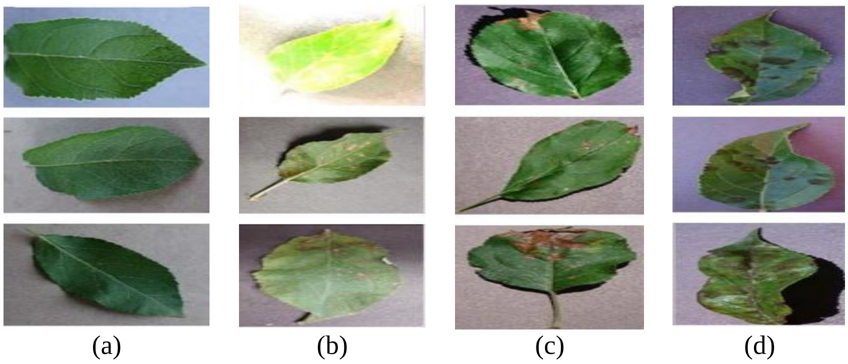


Figure 1. Sample images representing various classes within the apple leaf dataset: (a) apple healthy, (b) apple rust, (c) apple black rot, and (d) apple scab

2.2. Deep learning

One of the most significant breakthroughs in computer science, fundamentally transforming the data mining industry, is deep learning. It has taken nearly two decades to reach its current level of sophistication, driven by the increased availability of public data, the powerful parallel processing capabilities of graphics processing units (GPU), and the creation of specialized deep learning hardware [17]. Deep learning frameworks are extensively utilized in numerous applications of the classification, including image recognition [18], recognition of music [19], and medical disease recognition [20]. CNNs are a unique type of neural network designed for image recognition and classification, achieving exceptional results. Unlike traditional approaches, CNNs can automatically learn complex features from raw images, eliminating the necessity for manual feature extraction. In tasks such as identifying plant species and diagnosing diseases, CNNs have demonstrated greater effectiveness compared to conventional methods [13].

2.3. Transfer learning

Although deep learning has demonstrated great effectiveness in numerous applications, there are a number of constraints that prevent deep learning from being used in certain contexts. To properly train the model parameters, a substantial amount of labeled data is needed. This is one major restriction. Generating large-scale tagged datasets is frequently not feasible. Overfitting can occur when a deep neural network is trained entirely from scratch using sparse data. This problem is solved through transfer learning, which applies the knowledge gained from one activity to other related tasks. Mangoes and avocados can be classified using a model that was trained to identify photos of apples and mangoes, for instance. The ImageNet dataset contains images of various real-life subjects, has been instrumental in promoting the use of transfer learning [17]. Transfer learning utilizes knowledge from models initially trained on larger benchmark datasets, such as ImageNet, and applies it to similar or different tasks, like classifying disease images. However, because of the differences between the source dataset (ImageNet) and target datasets (new plant diseases), our work focuses on experimenting with the following pre-trained models: ResNet-50 and DenseNet-121. Figure 2 shows the mechanism of this transfer learning.

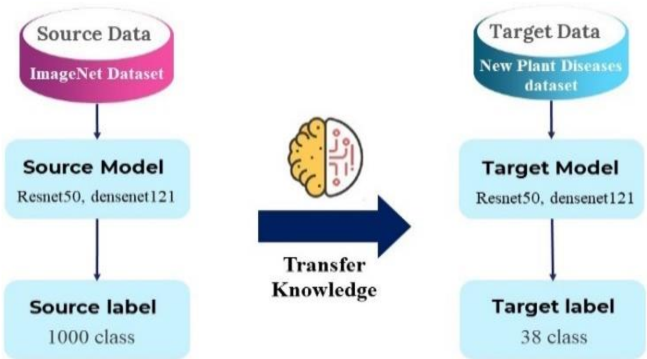


Figure 2. The mechanism of knowledge transfer within transfer learning

2.4. Performance evaluation

To convincingly demonstrate the effectiveness of the suggested hybrid model, it is essential to assess the efficiency of the prediction model thoroughly. There are numerous metrics available to assess how well a model predicts outcomes. In this study, we focus on several key performance measures, which are detailed below, to highlight the model's predictive accuracy and reliability. Accuracy, precision, recall, and F1-score these used metrics are derived from values obtained from the confusion matrix. For both binary and multiclass classification tasks, the confusion matrix is a widely used technique for evaluating the effectiveness of classification models. The counts of the expected and actual values are shown. "TN" represents true negative, denoting the quantity of negative samples that have been accurately identified. "TP" represents true positive, which indicates the quantity of positive cases that have been correctly classified. False positive (abbreviated "FP") is the number of negative cases that are mistakenly categorized as positive. False negative, or "FN" for short, is the quantity of positive examples that are mistakenly categorized as negative [21]. The percentage of the model's predictions that come true is its accuracy. A model's recall, or sensitivity, measures how well it identifies true positive events out of all the actual positive instances. The true positive to total true positive and false positive ratio is known as precision. The precision and recall balance are indicated by the F1 value [22].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$F1 - value = 2.\frac{(Precision\ .\ Recall)}{(Precision + Recall)} \tag{4}$$

3. THE PROPOSED SYSTEM

In this paper, the suggested process consists of five steps, as illustrated in Figure 3. The methodology of this work starts with the step of data collection, which involves gathering a variety of plant leaf images from the new plant diseases dataset, offering a rich array of data for analysis. Following this, data pre-processing becomes crucial, as it deals with the diverse shapes and resolutions of the collected images. To ensure consistency across all images, we resize them to a standardized dimension of 256×256×3 and apply techniques like image augmentation. With the pre-processed dataset in hand, the subsequent step is model building, where a hybrid model is constructed. This mixed model combined pretrained ResNet-50-DenseNet-121 is specifically designed to classify plant diseases. The step after building the model is to train and test it. Model evaluation becomes pivotal. This stage assesses the efficacy of the hybrid model, determining its accuracy and effectiveness in classifying plant diseases based on the provided test data. Through this comprehensive evaluation, insights are gained into the model's capabilities.

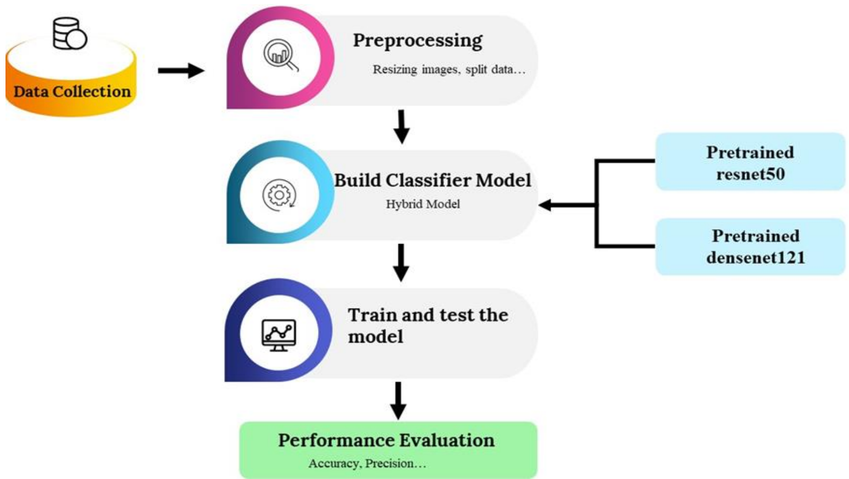


Figure 3. Diagram for the suggested model

3.1. Proposed transfer learning framework

The ResNet-50 and DenseNet-121 models pre-trained on the ImageNet dataset are used. In this scientific experiment, we have employed ResNet-50 and DenseNet-121 stemming for the following reasons:

- The training process of the ResNet-50 and DenseNet-121 models is efficient, with ResNet-50 famous for its proficiency in deep network training effectively through residual connections and DenseNet-121 for its feature reuse, thereby reducing parameter count and enhancing computational efficiency.
- ResNet-50 and DenseNet-121 are both highly recommended deep learning models for various applications, providing strong performance and robustness.

3.1.1. ResNet-50 architecture

ResNet-50 introduced by He *et al.* [23], it emerges as a streamlined architecture within the realm of deep CNNs. Comprising 50 layers, it diverges from conventional approaches by redefining its learning process: instead of grappling with unrestrained functions, it pivots towards mastering residual functions while staying grounded in reference to the layer inputs. This ResNet model is structured around a series of residual blocks, each functioning akin to a stack of convolutional layers. Notably, the output of each block intertwines with its own input via an identity mapping pathway. This design not only upholds the time complexity per layer but also perpetuates the downsampling of feature mapping through strided convolution, concurrently amplifying channel depth [23], [24].

3.1.2. DenseNet-121 architecture

DenseNet-121 has gained recognition in the realm of CNNs due to its distinctive dense connectivity pattern, which encourages effective feature reuse and propagation across the network. The architecture consists of 121 layers organized into dense blocks and transition layers, concluding with a global average pooling layer followed by a SoftMax classifier. Within dense blocks, convolutional layers are densely interconnected, while transition layers regulate spatial dimensions and feature map quantities between dense blocks. These transition layers frequently employ techniques such as batch normalization, 1×1 convolutions, and average pooling to achieve dimensionality reduction and downsampling [25].

3.2. The proposed hybrid model

Training a deep neural network from scratch requires a significant amount of data. Therefore, we utilize two pre-trained deep learning models, ResNet-50 and DenseNet-121, both of which have been trained on the ImageNet dataset. Each model processes the data independently, and their outputs are merged before passing through fully connected layers for image classification into 38 categories. The final classification layer addresses 38 classes of plant leaf diseases, as depicted in Figure 4. Subsequently, the model is fine-tuned on the PlantVillage dataset. To adjust the weights of the neural network, we utilize the Adam optimizer. We implement early stopping based on the lowest validation loss, with a patience parameter of 5. Treating the task as a multiple classes' categorization issue, every instance is classified into one of the 38 classes. The hyperparameters for training are: learning rate=1e-3, batch size=32, epochs=20, and patience=5. These values, recommended by previous research, ensure optimal performance. The model's architecture is developed and evaluated using Keras library that operates with TensorFlow as its backend.

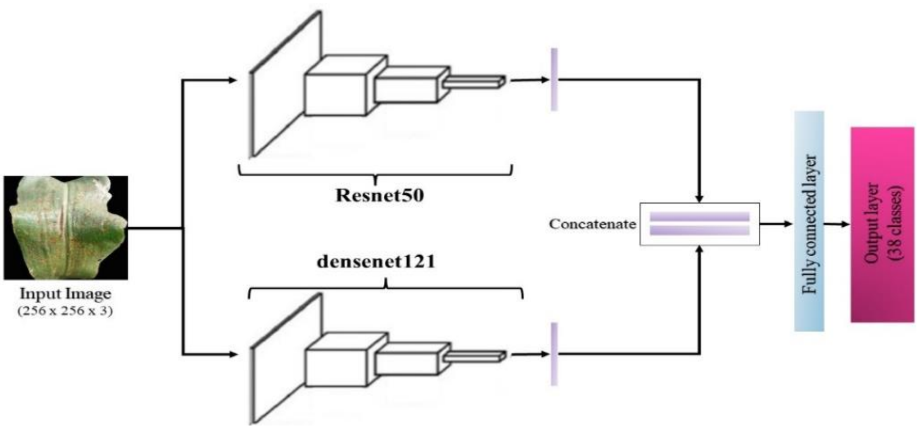
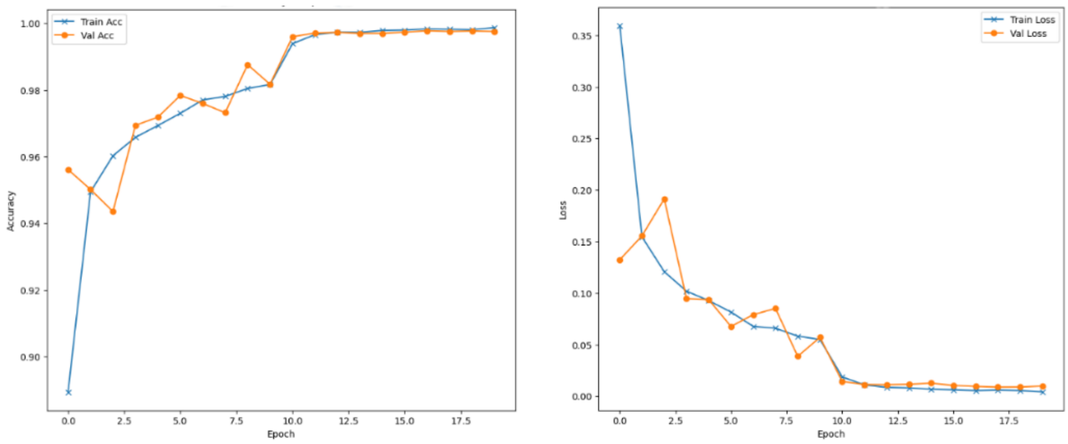


Figure 4. Architecture of the suggested hybrid model

4. RESULTS AND DISCUSSION

The primary aim of the suggested paper is to assess the efficacy of the pretrained ResNet-50 with DenseNet-121 hybrid architecture in classifying plant leaf diseases and to compare its performance with that of state-of-the-art deep learning models in the literature. To assess the proposed system, we utilized a range of classification performance indicators including the confusion matrix, accuracy, precision, recall, and the F1-score. This selection was made due to the prevalence of these criteria in papers evaluating their approaches on the PlantVillage dataset. Adopting these metrics facilitates comparison and enables us to effectively position our work in the context of other state-of-the-art methods. The mixed ResNet-50-DenseNet-121 model was trained used GPU. We achieved 99.87% on the training accuracy. The achieved outcomes are depicted in Figures 5 and 6. The results of the suggested ResNet-50-DenseNet-121 approach indicate an accuracy of 99.66%, precision of 99.67%, recall of 99.65%, and F1-score of 99.66%. Figure 5 illustrates the evolution of the training/validation loss function and also the fluctuations of the accuracy across the training epochs. Observing Figure 5(a) which represents the graph of train and validation accuracy, it's evident that the model's accuracy initially increases rapidly, stabilizes after a certain number of epochs, and eventually reaches its peak performance, achieving 99.87% accuracy after 20 epochs. In Figure 5(b) which represents the graph of train and validation loss, the loss function exhibits an inverse trend, steadily decreasing initially, then stabilizing, and ultimately converging to its minimum value. The confusion matrix produced by the suggested model is shown in Figure 6. The primary diagonal components of the matrix, which stand for true positives that are highly valued in all categories, indicating that the dataset's examples within each class were accurately categorized. This confirms the precision of the proposed model in categorizing effectively.



(a) (b)

Figure 5. Obtained results using hybrid model of (a) train and validation accuracy and (b) train and validation loss graph

The outcomes from this research paper highlight the robustness of the mixed model in tackling the challenges of plant leaf disease classification. Our model achieved impressive findings, with an accuracy rate of 99.66%. These outcomes emphasize the model's robustness in image-based plant disease identification tasks. Evaluating the hybrid model's performance further reveals its exceptional capabilities in plant disease classification. The model exhibited remarkable precision, recall, and F1-score values across multiple disease types, indicating remarkable accuracy and reliability. Precision values consistently reflect the model's skill in precisely identifying successful instances while minimizing false positives. Similarly, recall values within the same range demonstrate the model's effectiveness in recognizing most true positive cases. The consistently high F1-scores underscore the model's accuracy and robustness in distinguishing between healthy and diseased plants. In summary, these results affirm the model's suitability for the critical task of plant disease detection, presenting a promising solution to improve agricultural practices and crop management.

To gain a comprehensive perspective, we compared our results with those from previous studies, as shown in Table 1, focusing on crop type, dataset used, number of classes, models used, and obtained results. While some studies focused on a single crop like apple, maize, or rice, our experiment encompassed multiple crops. Additionally, we used a dataset with 38 classes, which is larger than those in some other studies that used smaller datasets. The plant disease identification method using ResNet-50-DenseNet-121 hybrid model presented in this work is compared with several other classification approaches, including CNN [5], [6], DenseNet-121 [7], pre-trained VGGNet with Inception [13], and segmentation with CNN model-based classification [16]. Table 1 illustrates the accuracy comparison for the categorization of the PlantVillage dataset. The obtained outcomes demonstrate that the proposed hybrid model achieves superior performance. In our analysis, we observed the limited use of hybrid models across most studies, with the exception in [13] and it achieved lower accuracy in the outcomes compared to this study. In contrast, our research leverages the strengths of hybrid models, which combine various methodologies to enhance performance.

As a result, we achieve a higher level of accuracy and robustness in our findings, showcasing the advantages of incorporating hybrid approaches in data analysis and predictive modeling. Our results underscore the potential of hybrid models to outperform traditional methods, highlighting the importance of innovation and integration in advancing the field.

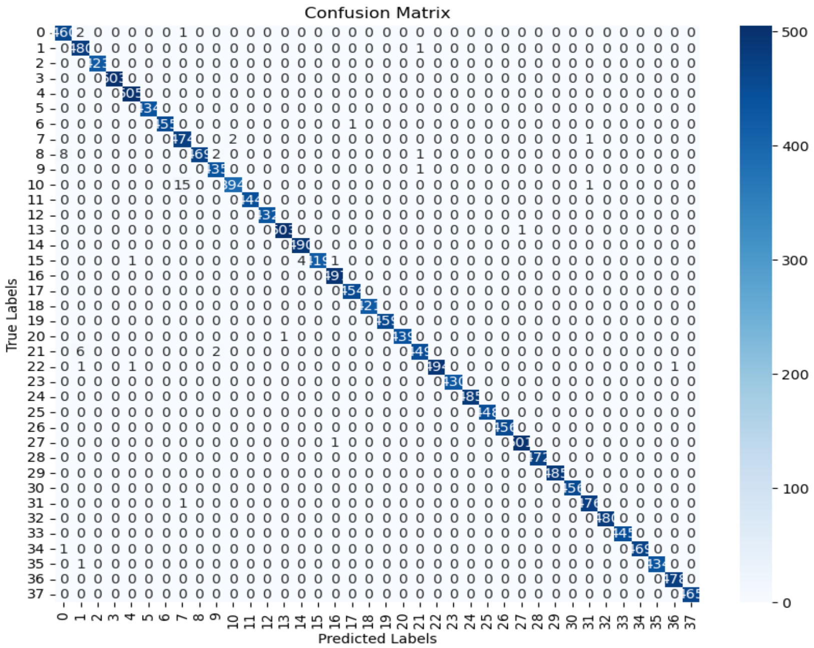


Figure 6. Confusion matrix

Table 1. Comparative analyses of similar works and the proposed hybrid architecture

References	Crop focus	Dataset	Number of classes	Model	Results
[5]	Several	New plant diseases	38	CNN	Accuracy: 97%
[6]	Several	PlantVillage	38	CNN	Accuracy: 94.33%
[7]	Apple	AI-challenger plant disease recognition	6	DenseNet-121	Accuracy: 93.71%
[13]	Rice and maize	PlantVillage	4	VGGNet with inception	Accuracy: 92%
[16]	Grape	PlantVillage	4	SegCNN	Accuracy: 93.75%
Proposed work	Several	New plant diseases	38	ResNet-50 with DenseNet-121	Accuracy 99.66%

5. CONCLUSION

This paper investigates the application of transfer learning to improve leaf disease detection. It examines how leveraging pre-trained models can enhance the accuracy and efficiency of disease detection in plant leaves. We proposed a deep learning architecture called ResNet-50 and DenseNet-121 for identifying plant disease images. Our experiment utilized the new plant diseases dataset for classifying 38 types of plant leaf diseases. Our hybrid model achieved an accuracy rate, surpassing results reported in other studies. Our experiment was unique in that we considered multiple crops and used a modified dataset with more classes. Overall, our experiment offers an efficient approach for multi-crop disease detection. The hybrid pre-trained model demonstrated an impressive accuracy rate of 99.66%, precision of 99.67%, recall of 99.65%, and F1-score of 99.66% demonstrating the efficacy of our method in enhancing the accuracy of plant disease classification endeavors. The research community will benefit greatly from these findings as they enhance the accuracy and dependability of leaf disease detection. Additionally, they demonstrate the promise of AI-driven, scalable solutions, opening the door for more study into the development of effective monitoring systems that may be used in large-scale farming operations. Our upcoming projects include engaging with plantations to increase the diversity of datasets by utilizing drones or RGB camera to collect data.

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