Optimizing Crop Health: Evaluating CNN Performance in Plant Disease Detection

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Abstract. Plant diseases represent a significant challenge in agriculture, significantly impacting crop yield. Addressing this issue is imperative to ensure agricultural productivity. Convolutional Neural Networks (CNNs) have emerged as a promising solution for image-based disease detection. Detecting diseases in their early stages using CNN models can potentially enhance crop yield for farmers. Given the multi-class nature of most plant diseases, we conducted a comprehensive comparative study of CNNs to assess their effectiveness. Our study compared three CNN models: AlexNet, VGG-19, and ResNet18. ResNet18 demonstrated superior performance, achieving a validation accuracy of 95.68%. Furthermore, we developed a web application to enable farmers to utilize the trained model effectively.

Keywords: Plant diseases · CNN · Multi-class classification · Transfer Learning · Farmer assistance

1 Introduction

In today's rapidly advancing world, technology, particularly artificial intelligence (AI), is transforming various sectors. AI, often likened to smart computers capable of performing tasks almost as proficiently as humans, is revolutionizing diverse fields, including agriculture. With agriculture being a crucial sector for global sustenance, the integration of AI, particularly Convolutional Neural Networks (CNNs), has become increasingly important, especially in addressing pressing issues such as plant diseases.

Plant diseases present a significant challenge to global crop yield and agricultural productivity. According to the Food and Agriculture Organization (FAO) of the United Nations, plant diseases account for an estimated 20–40% of crop yield losses globally each year, severely impacting food security and economic stability, particularly in regions heavily reliant on agriculture [1].

Beyond direct yield losses, plant diseases incur substantial economic costs through reduced marketable yields, increased production expenses associated with disease management, and the need for costly preventive measures like pesticides and fungicides.

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These losses not only undermine the profitability of farming operations but also exacerbate food insecurity and poverty, particularly among smallholder farmers in developing countries.

Furthermore, the prevalence and severity of plant diseases are exacerbated by factors such as climate change, globalization of trade and travel, and intensification of agricultural practices. Climate variability and extreme weather events create favorable conditions for disease development and spread, while global trade facilitates the rapid dissemination of pathogens across borders [2, 3]. Intensified agricultural practices, including monoculture cropping systems and reduced genetic diversity in cultivated crops, further exacerbate the vulnerability of agricultural ecosystems to disease outbreaks.

Addressing the impact of plant diseases on crop yield and agricultural productivity is imperative for ensuring global food security, reducing poverty, and fostering sustainable agricultural development. Effective disease management strategies and innovative technologies are urgently needed to mitigate the adverse effects of plant diseases and safeguard the resilience of agricultural systems in the face of evolving environmental and socio-economic pressures.

Amidst the complex landscape of plant diseases and the challenges faced by farmers in detecting and managing them effectively, technological advancements offer hope. In recent years, Convolutional Neural Networks (CNNs) have emerged as a groundbreaking tool for addressing disease detection, not only in agriculture but across various fields [4, 5]. These deep learning algorithms excel in image recognition tasks, making them particularly well-suited for image-based disease detection crucial for implementing effective disease management strategies.

In conclusion, this research aims to assess the efficacy of Convolutional Neural Networks (CNNs) in detecting plant diseases and compare the performance of various CNN models. By evaluating the accuracy and reliability of CNN-based disease detection systems, this study seeks to provide insights into the potential of AI-driven technologies to revolutionize disease management practices in agriculture. Through empirical analysis and comparison of different CNN architectures, our research aims to contribute to the advancement of agricultural technology and enhance crop yield improvement strategies, ultimately promoting sustainable agricultural practices and ensuring global food security in the face of evolving environmental and socio-economic challenges.

2 Related Work

Researchers have explored various machine learning models, including decision trees, support vector machines (SVM), random forests, and deep learning algorithms such as Convolutional Neural Networks (CNNs), for plant disease prediction. These models analyze various factors such as environmental conditions, crop characteristics, and disease symptoms to predict the likelihood and severity of disease outbreaks [6]. Image-based disease detection using deep learning algorithms has gained traction in recent years. CNNs, in particular, have demonstrated remarkable accuracy in identifying and classifying plant diseases based on images of diseased leaves or crops. Researchers have developed CNN-based models trained on large datasets of labeled images to enable rapid and accurate diagnosis of plant diseases in real-time [7]. Sensor-based approaches, including spectral imaging and hyperspectral imaging, have been employed for non-destructive and early detection of plant diseases. These techniques analyze the spectral signatures of plants to identify subtle changes associated with disease infection before visible symptoms appear. These sensor-based approaches offer potential for early disease detection and precise monitoring of disease progression [8].

Integrating multiple sources of data, including weather data, soil moisture levels, and historical disease incidence, has been explored to improve the accuracy of disease prediction models. Data fusion techniques combine information from diverse sources to enhance the robustness and reliability of predictive models, enabling more accurate forecasting of disease outbreaks [9]. Remote sensing technologies, such as satellite imagery and unmanned aerial vehicles (UAVs), have been utilized for large-scale monitoring of crop health and disease outbreaks. These technologies enable timely detection of disease hotspots and facilitate targeted intervention strategies to mitigate disease spread and minimize crop losses [10].

Despite significant advancements, several challenges remain in plant disease prediction, including the need for large and diverse datasets, model interpretability, and generalization across different regions and crop species [11]. Future research directions include the development of hybrid models combining machine learning algorithms with domain knowledge, the integration of real-time sensor data for dynamic disease monitoring, and the deployment of automated monitoring systems for precision agriculture applications [12].

3 Dataset

To develop an effective prediction model, we utilized the Plant Village dataset, comprising approximately 50,000 images of healthy and infected plants. These images were sourced from the Plant Village website and are compatible with modern web devices. This dataset serves as the foundation for an ongoing crowdsourcing initiative aimed at leveraging deep learning neural network approaches to address yield losses caused by plant infectious diseases.

The dataset encompasses 38 distinct labels representing various diseases and healthy states across 14 different plant variants. A selection of sample images from the dataset is presented in Fig. 1. The figure is showcasing a random assortment of infected and healthy plants. Additionally, Table 1 provides further details on the types of plants included in the dataset, corresponding disease labels, and the number of images allocated for training the model.

Given the inherent imbalances in the dataset, preprocessing techniques were applied to ensure balanced representation across all labels. Figure 2 visually presents the imbalance in the dataset. Techniques such as resizing, cropping, down-sampling, and data augmentation were employed to standardize the dataset. Specifically, the count of each image label was adjusted to 1000 to achieve balance. Subsequently, the dataset was divided into a 60:20:20 ratio for training, testing, and validation sets, respectively, to facilitate model training and evaluation processes.

Fig. 1. Sample Images of Dataset

Table 1. Images count of plant disease labels

S. No	Plant_disease_labels	Image count
1	Tomato___Late_blight	1909
2	Corn_(maize)___Common_rust	1192
3	Corn_(maize)___healthy	1162
4	Grape___healthy	423
5	Squash___Powdery_mildew	1835
6	Blueberry___healthy	1502
7	Apple___Black_rot	621
8	Tomato__septorai_leaf_spot	1771
9	Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	1076
10	Tomato___Leaf_Mold:	952
11	Tomato___Tomato_mosaic_virus	373
12	Apple___Cedar_apple_rust	275
13	Potato___Early_blight	1000

(*continued*)

Table 1. (*continued*)

S. No	Plant_disease_labels	Image count
14	Tomato___healthy	1591
15	Pepper,_bell___Bacterial_spot	997
16	Apple___Apple_scab	630
17	Raspberry___healthy	371
18	Apple___healthy	1645
19	Grape___Esca_(Black_Measles)	1383
20	Tomato___Early_blight: 1000	1000
21	Orange___Haunglongbing_(Citrus_greening)	5507
22	Strawberry___healthy	456
23	Grape___Black_rot	1180
24	Peach___Bacterial_spot	2297
25	Soybean___healthy	5090
26	Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	513
27	Tomato___Tomato_Yellow_Leaf_Curl_Virus	5357
28	Tomato___Bacterial_spot	2127
29	Pepper,_bell___healthy	1478
30	Cherry_(including_sour)___healthy	854
31	Potato___Late_blight	1000
32	Strawberry___Leaf_scorch	1109
33	Corn_(maize)___Northern_Leaf_Blight	985
34	Cherry_(including_sour)___Powdery_mildew	1052
35	Potato___healthy	152
36	Peach___healthy	360
37	Tomato___Spider_mites Two-spotted_spider_mite	1676
38	Tomato___Target_Spot	1404

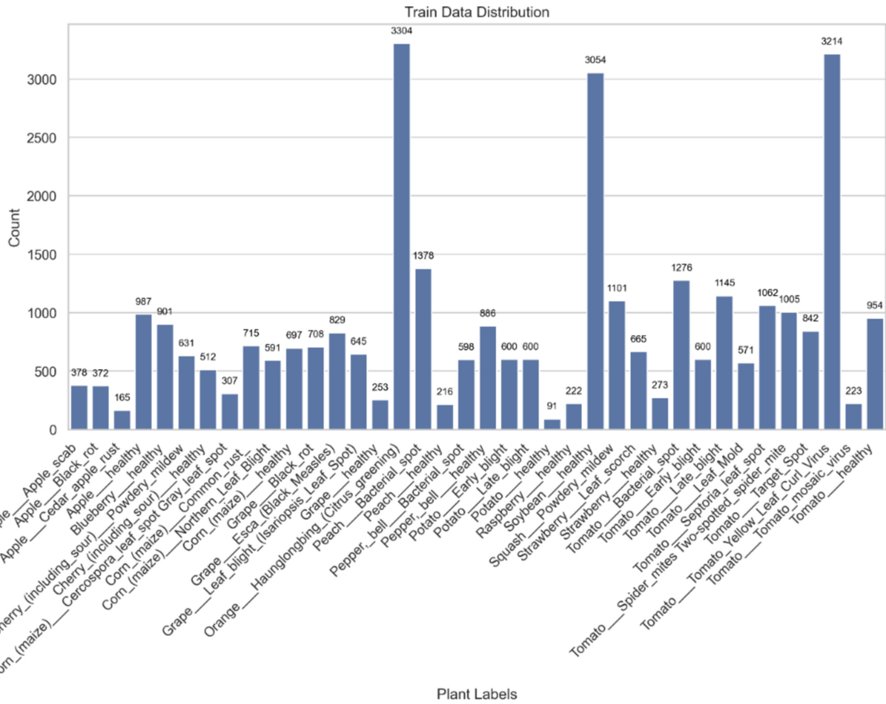

Fig. 2. Image Distribution

4 Methodology

This section outlines the methodology employed in this study. The entire workflow is depicted in the Fig. 3. The dataset utilized underwent preprocessing and was subsequently divided into train, test, and validation sets. To determine the optimal CNN architecture, three distinct models were trained: AlexNet, VGG19, and ResNet18. AlexNet, renowned for its breakthrough performance in the 2012 ImageNet Large Scale Visual Recognition Challenge, played a pivotal role in popularizing deep learning for image classification tasks [12]. VGG19, characterized by its depth and simplicity, consists of 19 layers and features a uniform architecture with small 3×3 convolutional filters, showcasing strong performance across various image recognition tasks [6]. ResNet, also known as Residual Neural Network, addresses the vanishing gradient problem through residual connections, enabling the training of very deep neural networks with improved performance [13].

The optimizer plays a crucial role in generalizing a deep learning model to achieve better performance and ensure effective learning from the training data while avoiding overfitting [14]. Optimizers are pivotal in adjusting the model's parameters during the training process to minimize the error or loss function. To assess the effectiveness of the optimizers, models were trained using both SGD and Adam optimizers. The performance of all six trained models was evaluated using Accuracy and F1-score.

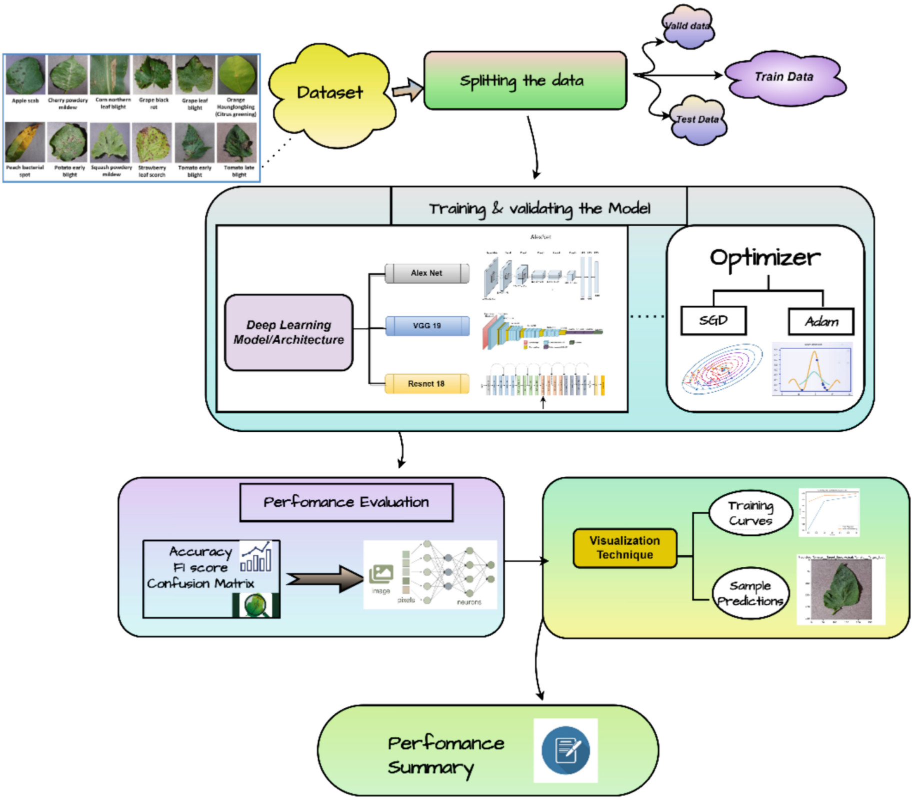

Fig. 3. Adopted Methodology

5 Results

Visual representations of the accuracy and loss curves for the three models, using both SGD and Adam optimizers, are provided in the figures. Analysis of the curves reveals that the ResNet-18 model outperforms the other two models consistently. Specifically, when paired with the Adam optimizer, ResNet-18 achieves the highest accuracy at 96%, demonstrating its effectiveness in learning and generalizing from the training data. In comparison, the AlexNet version achieves an accuracy of 88%, while the VGG-19 model achieves 84% accuracy.

Upon examination of these results, it becomes evident that the ResNet-18 model, particularly when optimized with Adam, showcases superior performance in terms of accuracy. This finding underscores the robustness and efficacy of ResNet-18 in handling complex image recognition tasks. Moreover, the consistent trend observed across both optimizers reaffirms the reliability of ResNet-18 as a powerful architecture for image classification tasks.

Table 2 presents a comprehensive summary of the model performances, highlighting the accuracy scores achieved by each model under different optimization settings. These results provide valuable insights into the comparative performance of the three models and underscore the significance of selecting an appropriate architecture and optimizer combination for achieving optimal performance in deep learning tasks (Figs. 4, 5, 6, 7, 8, 9 and 10).

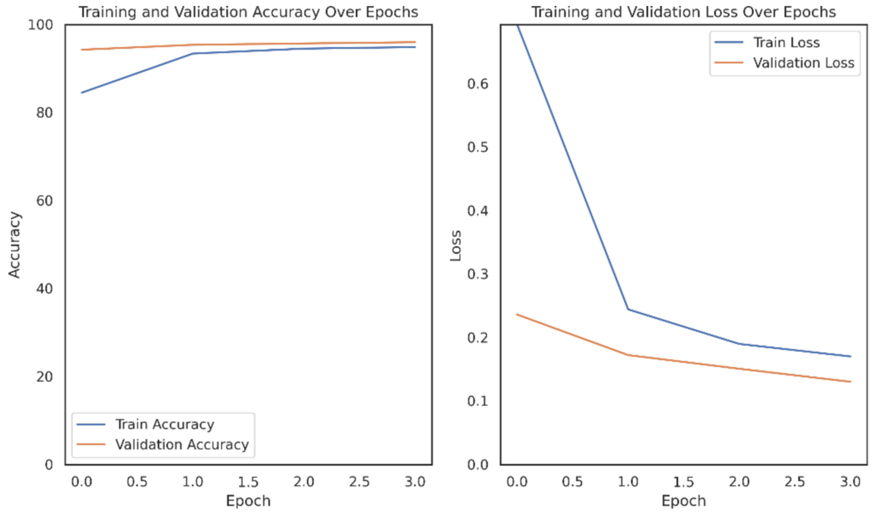

Fig. 4. Training and Validation Metrics for Resnet-18 with Adam Optimizer

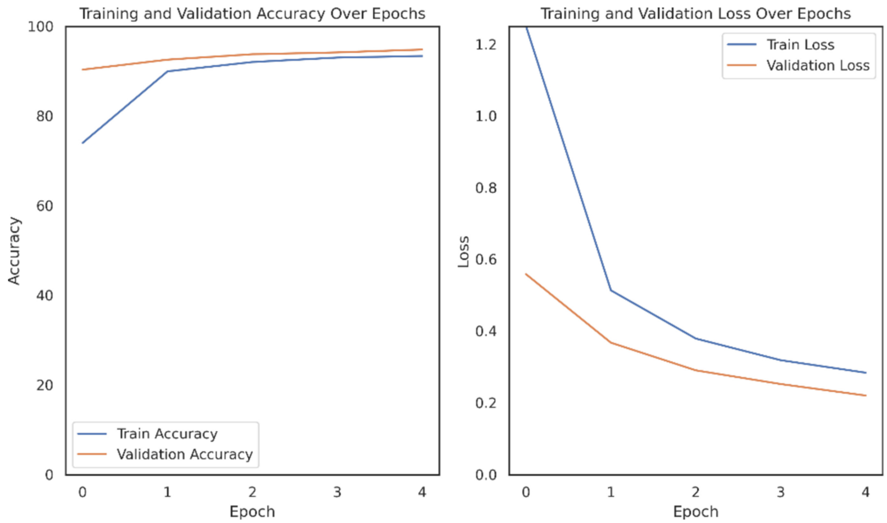

Fig. 5. Training and Validation Metrics for Resnet-18 with SGD Optimizer

Table 2 presents a comprehensive summary of the model performances, highlighting the accuracy scores achieved by each model under different optimization settings. These results provide valuable insights into the comparative performance of the three models

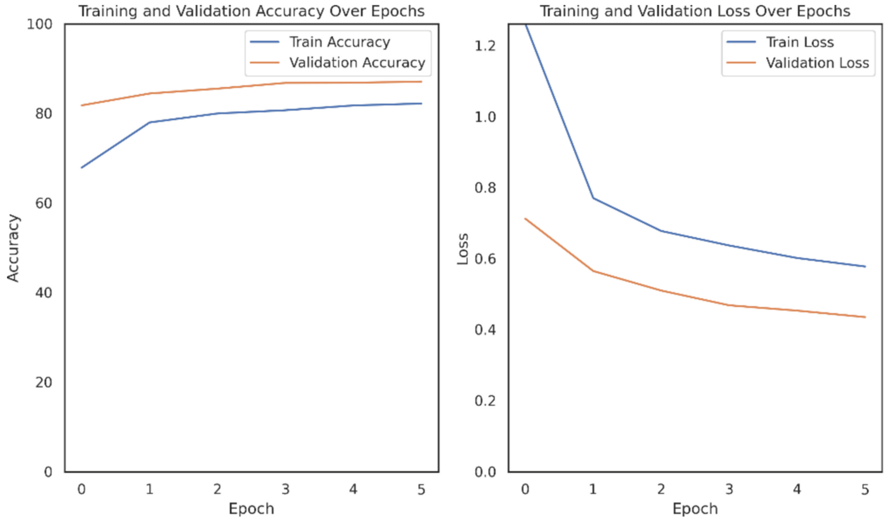

Fig. 6. Training and Validation Metrics for VGG-19 with Adam Optimizer

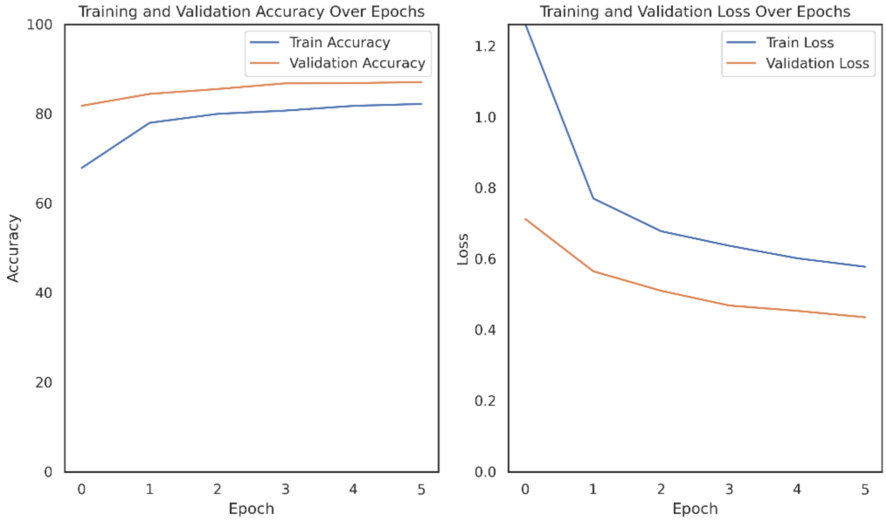

Fig. 7. Training and Validation Metrics for VGG-19 with SGD Optimizer

and underscore the significance of selecting an appropriate architecture and optimizer combination for achieving optimal performance in deep learning tasks.

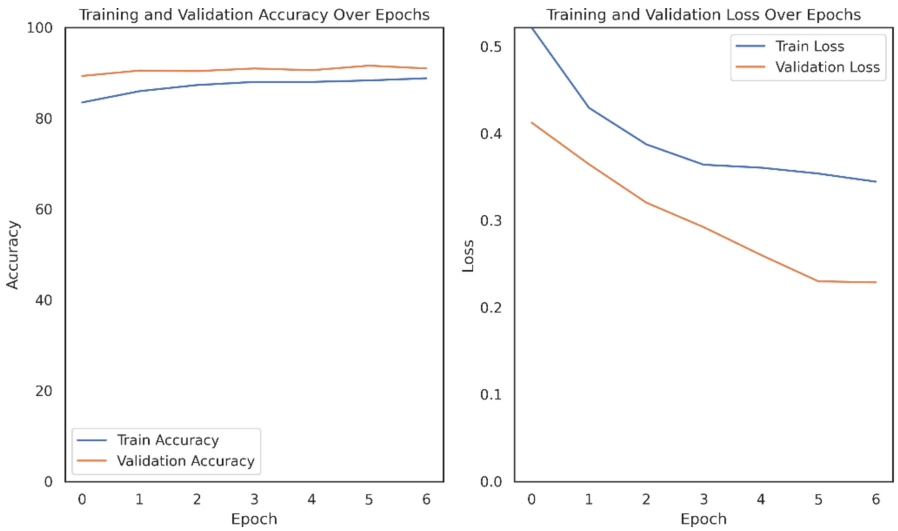

Fig. 8. Training and Validation Metrics for AlexNet with Adam Optimizer

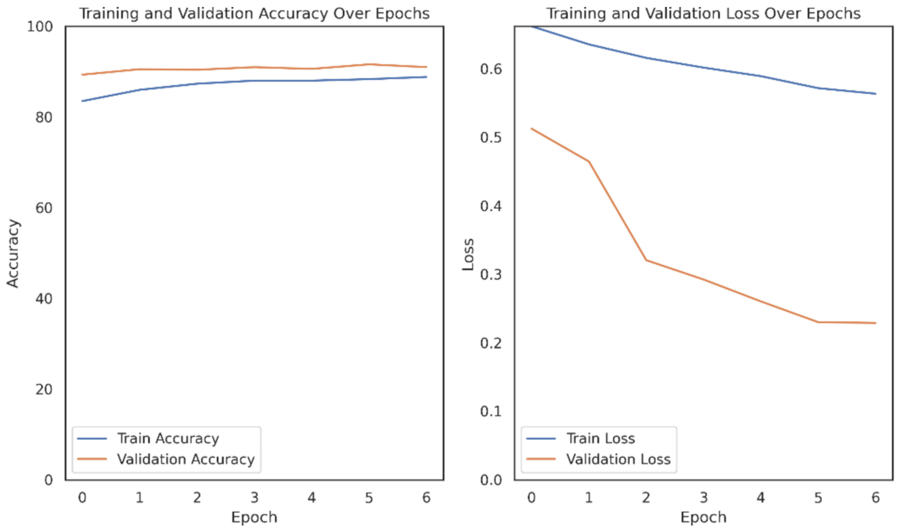

Fig. 9. Training and Validation Metrics for AlexNet with SGD Optimizer

Table 2. Comparison of Model Accuracies with different optimizers

Models	Train Accuracy		Validation Accuracy	
	SGD	ADAM	SGD	ADAM
AlexNet	83.94	88.32	87.53	91.37
VGG -19	82.19	83.88	87.10	89.77
Resnet-18	93.42	95.27	94.74	95.68

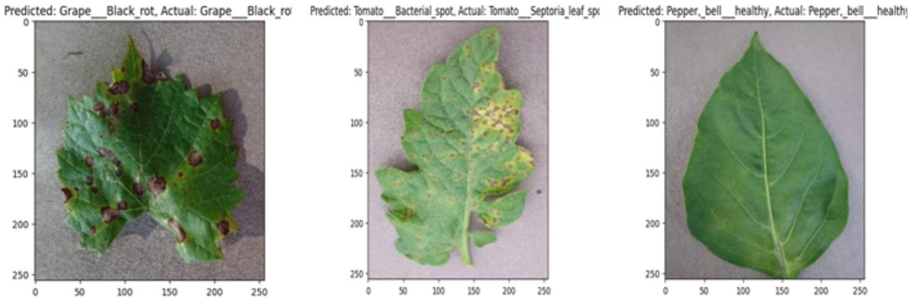

Fig. 10. Presents the predictions on the sample images on unseen data

6 Conclusion

In our study of computer vision techniques for plant disease detection, we explored pre-trained models like ResNet-18, VGG-19, and AlexNet using the PlantVillage dataset. ResNet-18 emerged as the most successful model, achieving high accuracy in tackling various plant diseases' complexities. ResNet-18's success demonstrates its potential for practical implementation in agriculture, enabling early and accurate disease detection crucial for crop yield and quality. These findings significantly contribute to expanding computer vision techniques' applications in agriculture and plant pathology. Our exploration also revealed valuable dataset transformations and refinements, highlighting the emerging role of visual transformers in computer vision. Future research should focus on advanced transfer learning strategies, particularly domain adaptation, and incorporate real-world datasets for more extensive image corpus, aiming for practical applications benefiting farmers and refining models for improved crop yield amid plant diseases.

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