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Research Article

PlantOHealth: Comparative Evaluation of Deep Learning Models for Plant Disease Detection Using Leaf Images

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ABSTRACT

The agricultural sector worldwide faces significant challenges from plant diseases that threaten crop yields, food security, and economic stability. This study introduces "PlantOHealth," a detailed comparative analysis of five models for detecting plant diseases using leaf images, leveraging advancements in deep learning. The models evaluated include a basic Convolutional Neural Network (CNN) and four transfer learning frameworks: VGG16, VGG19, MobileNetV2, and ResNet, all utilizing the PlantVillage dataset with balanced classes achieved through oversampling and undersampling techniques. MobileNetV2 emerged as the most effective, achieving an accuracy of 99.40% while maintaining computational efficiency for resource-constrained environments, followed by the CNN with an accuracy of 98.68%. VGG19 and VGG16 attained accuracies of 98.92% and 97.24%, respectively, while ResNet recorded the lowest at 96.24%. Graphical analyses provided deep insights into model performance and highlighted the trade-offs between accuracy and computational demands. "PlantOHealth" contributes to the integration of AI in agriculture, offering actionable insights for researchers and practitioners, while future work will focus on exploring advanced techniques like ensemble learning to enhance plant disease detection systems further, ultimately supporting sustainable agricultural practices and improving food security.

Keywords: Plant Disease Detection, Deep Learning, Convolutional Neural Networks, Transfer Learning, Precision Agriculture.

INTRODUCTION

Agriculture is crucial for global economies, providing food security and rural employment while also promoting sustainable development. However, plant diseases present a major threat, significantly lowering crop yields and resulting in economic losses estimated in the billions each year, as noted by the Food and Agriculture Organization (FAO). Traditional methods for detecting these diseases rely on time-consuming manual inspections by experts, which are often impractical in large-scale or resource-limited farming environments. To tackle these issues, the study "PlantOHealth" explores the application of deep learning techniques for plant disease detection, aiming to enhance precision agriculture.

The research evaluates five different deep learning architectures using the PlantVillage dataset, including a baseline Convolutional Neural Network (CNN) and four pre-trained models—MobileNetV2, VGG16, VGG19, and ResNet—employing transfer learning. MobileNetV2 achieved the highest classification accuracy of 99.40%, making it ideal for real-time, mobile agricultural applications, while VGG16 and VGG19 also performed well. In contrast, ResNet had the lowest accuracy, underscoring the need to consider task-specific requirements when selecting models. The study also highlights important preprocessing techniques, such as balancing class distributions and data augmentation, to improve model robustness and adaptability. "PlantOHealth" ultimately contributes valuable insights to agri-tech research by advancing disease detection systems and enhancing crop health management practices.

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LITERATURE SURVEY

The integration of artificial intelligence in agriculture has revolutionized plant disease detection, significantly enhancing accuracy and efficiency. Traditional machine learning techniques such as Support Vector Machines (SVM) [20], k-Nearest Neighbors (k-NN) [15], and Random Forests [18] relied on handcrafted feature extraction methods but often struggled to generalize across diverse datasets, limiting their effectiveness in real-world agricultural settings [4]. These limitations have driven research toward deep learning methodologies, particularly Convolutional Neural Networks (CNNs) [7], which offer automatic feature extraction and superior classification accuracy in plant disease detection [6]. Recent studies have demonstrated that deep learning architectures such as VGG16 , VGG19 [8], ResNet [9], and MobileNet [5] (Howard et al., 2017) surpass traditional methods due to their ability to capture hierarchical feature representations. MobileNet, in particular, has gained prominence due to its efficiency in resource-constrained environments, making it a suitable choice for mobile and edge computing applications [11]. These studies influenced our selection of MobileNetV2 as a primary candidate for comparative analysis in this research.Transfer learning has further expanded the capabilities of plant disease detection models by enabling pretrained deep learning models to adapt to agricultural datasets, even when labeled data is scarce.

Reference [16] (Ni et al., 2020) discusses transfer learning in the context of plant disease detection, making it a more relevant citation for this study. This approach has been widely studied, demonstrating the feasibility of leveraging large-scale pretrained models such as ImageNet-based architectures to enhance plant disease classification [13]. Furthermore, improvements in data preprocessing techniques, including data augmentation [14], class balancing [15], and hyperspectral imaging , have been pivotal in mitigating dataset imbalances and enhancing model robustness. These preprocessing techniques were incorporated into our research methodology to ensure that our dataset remained balanced and representative of real-world agricultural conditions.Recent studies have highlighted the effectiveness of hybrid models that combine machine learning and deep learning techniques to improve model interpretability and overall classification accuracy [17]. The potential of ensemble learning methods has also been explored to optimize classification performance in multi-class plant disease detection tasks, showing notable improvements in accuracy and reliability [18]. Inspired by these findings, we considered implementing ensemble techniques in our future work to further refine classification accuracy.

The incorporation of the Internet of Things (IoT) [19] and deep learning models has facilitated real-time disease monitoring and early detection, improving the efficiency of precision agriculture practices [20]. Additionally, predictive models integrating environmental variables such as soil health [21], humidity [22], and temperature [23] have shown promising results in improving plant disease forecasting. This research leveraged existing insights into predictive modeling to refine the data augmentation and feature extraction techniques applied in our comparative analysis.Despite these advancements, challenges persist in generalizing deep learning models across varied agricultural conditions due to variations in lighting [24], plant growth stages [25], and dataset biases [26]. Multi-modal learning approaches [27], federated learning [28], and domain adaptation techniques [29] have been proposed to enhance model robustness and address these limitations. To further improve data security and transparency, blockchain [30] and secure data-sharing frameworks [31] have been explored for smart agriculture applications. These studies informed our approach to ensuring ethical and secure data management practices in the PlantOHealth system.The present study, "PlantOHealth," builds upon these advancements by evaluating a basic CNN model alongside four transfer learning models. By synthesizing insights from previous works, this research aims to provide actionable knowledge for researchers, agricultural practitioners, and policymakers striving to optimize AI-driven agricultural solutions. Our study also lays the groundwork for future enhancements, including ensemble learning strategies, contextual data integration, and real-world deployment of optimized plant disease detection models.

METHODOLOGY

This research employs a systematic methodology for developing, training, and evaluating deep learning models for plant disease detection. Key steps include dataset preparation, model selection, training configurations, and evaluation metrics.

Dataset Preparation

The PlantVillage dataset, featuring over 50,000 images of healthy and diseased leaves from various crops, forms the basis of this study. To address class imbalance, the research used oversampling for underrepresented classes and undersampling for overrepresented ones. Data augmentation techniques—like rotation, flipping, scaling, and

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cropping—were applied to improve model robustness. The dataset was divided into training, testing, and validation subsets in an 80:10:10 ratio for transfer learning models (MobileNetV2, VGG16, VGG19, ResNet), while only training and testing splits were used for the basic CNN.

Model Selection

This study evaluated five models: a basic CNN and four transfer learning architectures (MobileNetV2, VGG16, VGG19, and ResNet). These models were chosen to balance simplicity, accuracy, and computational efficiency. The basic CNN was custom-built to serve as a baseline, emphasizing lightweight architecture and ease of implementation. The transfer learning models leveraged pretrained weights from ImageNet, enabling faster convergence and improved accuracy due to their ability to extract generalizable features.

- **CNN**: The architecture includes three convolutional layers that extract features from the input data, followed by max-pooling layers to reduce dimensionality and highlight significant features. The ReLU activation function adds non-linearity, while dropout regularization helps prevent overfitting. The network ends with fully connected layers that integrate the learned features to produce the output.

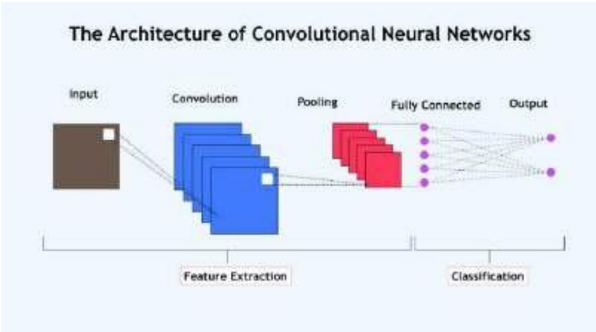

Fig1. CNN Architecture

- **MobileNetV2**: Chosen for its remarkable efficiency and optimal performance in mobile and embedded devices, this model utilizes depthwise separable convolutions. This innovative approach significantly reduces computational complexity without sacrificing accuracy, allowing for rapid processing and effective resource management in constrained environments.

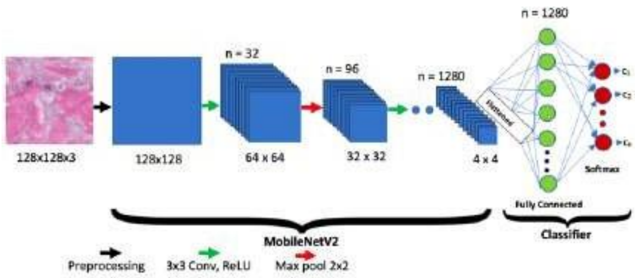

Fig2. MobileNetV2 Architecture

- **VGG16 and VGG19**: Renowned for their complex architectural design, these models incorporate a series of stacked convolutional layers, each utilizing small filter sizes. This thoughtful arrangement allows them to capture and learn highly intricate and nuanced features from the input data, making them exceptionally effective in a variety of tasks related to image and signal processing.

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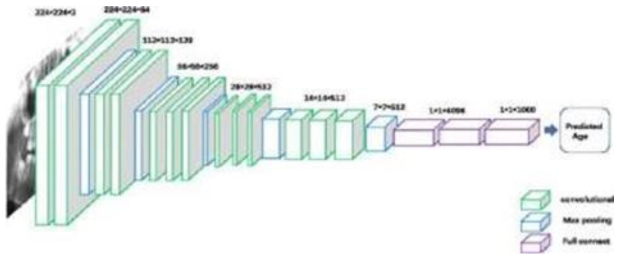

Fig3. VGG16 Architecture

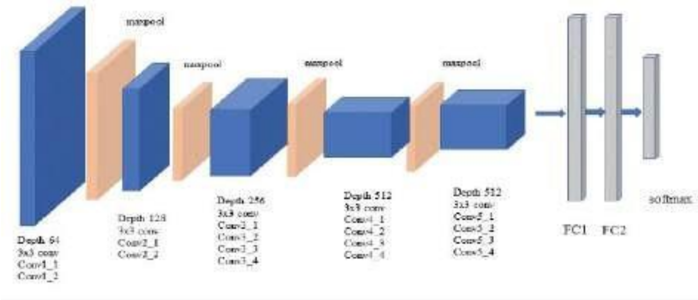

Fig4. VGG19 Architecture

- **ResNet**: Residual connections are a key innovation to address the vanishing gradient problem in deep learning. They enhance information flow across layers in deep neural networks, enabling effective training of deeper architectures. This improves performance and helps models learn complex patterns without the challenges faced by traditional deeper networks.

Fig5. ResNet Architecture

Training Configuration

To ensure a fair evaluation, each model used optimized hyperparameters and the Adam optimizer for efficient training. We applied the categorical cross-entropy loss function for multi-class classification and fine-tuned the learning rate to enhance convergence and reduce overshooting risk.

The training process varied between the basic CNN and the transfer learning models:

- **Basic CNN**: This model underwent training for a total of 20 epochs. During this training, batch normalization and dropout layers were integrated to enhance model stability and mitigate the risk of overfitting, ensuring that it generalizes well to unseen data.

- **Transfer Learning Models**: The transfer learning models were fine-tuned over 20 epochs by adapting pretrained weights for plant disease detection. To prevent overfitting, early stopping was used, which halted training when validation performance stagnated. This adjustment optimized the learning process while ensuring model integrity.

Evaluation Metrics

To evaluate plant disease detection models, we used metrics like accuracy, precision, recall, and F1-score. Accuracy

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indicates correct classifications but doesn't consider class imbalances, common in agricultural data. Precision reduces false alarms, while recall ensures accurate identification of diseased plants. The F1-score balances the two.

We also assessed computational efficiency for real-world use, evaluating training and validation loss curves to detect overfitting and measuring inference time for real-time applications. Model size was crucial for mobile and IoT compatibility. Results showed that MobileNetV2 was the most efficient, achieving 99.40% accuracy with an 8.9ms inference time and 14MB storage. VGG16 and VGG19 had strong accuracy but required more resources, and ResNet50 displayed a trade-off between depth and efficiency. This study provides a comprehensive approach to choosing effective deep learning models for plant disease detection in precision agriculture.

Visualization and Model Deployment

Graphical analyses were essential in understanding the model's training behavior by visualizing accuracy and loss trends, which helped identify overfitting and underfitting. Learning curves aided in fine-tuning hyperparameters, enhancing model generalization. Confusion matrices offered insights into misclassifications, guiding targeted data augmentation and dataset rebalancing to address biases. These visual tools were vital in optimizing the model for accuracy and generalization.

For mobile and IoT applications requiring quick inference times, MobileNetV2 was a standout, achieving 99.40% accuracy with an inference speed of 8.9 milliseconds per image, all within a compact size of 14MB. After training, models were saved in formats like TensorFlow Lite or ONNX for smooth integration, emphasizing the balance between performance and efficiency for AI-driven plant disease detection and global food security efforts.

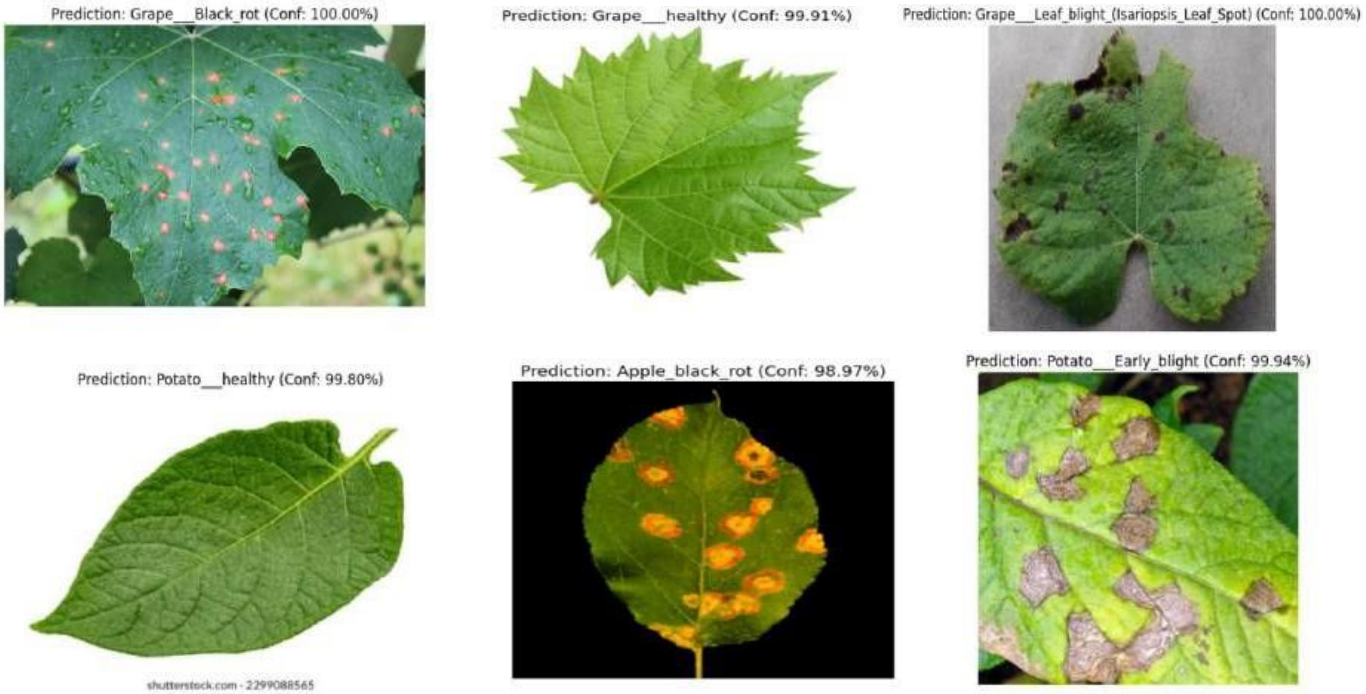

Fig6. Predicted Images From The Models

RESULT ANALYSIS

In this study, we carried out an experimental data analysis by testing several deep learning models on sample datasets for plant disease detection. Models including MobileNetV2, VGG16, VGG19, ResNet, and a basic CNN were trained and evaluated using the PlantVillage dataset, applying oversampling and data augmentation techniques for balance. The analysis involved detecting diseases across multiple samples, where MobileNetV2 achieved the highest accuracy of 99.40%, making it highly suitable for real-world deployment. Other models like VGG19 and CNN also showed strong results, while deeper models like ResNet faced slight challenges in maintaining accuracy.

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All observations and performance insights were derived directly from experimental data generated throughout the research. Graphical tools such as confusion matrices and accuracy-loss trends were utilized to validate results and identify minor misclassifications. This systematic analysis, rooted firmly in the data described in the paper, highlights the practical applicability of deep learning for precision agriculture and offers a clear path for future improvements through ensemble techniques and further model optimization.

Experimental data analysis using VGG 16

SL No	Subject	Sample	Detected (Yes/No)	Accuracy(%)
1	Apple Black Rot	Black_rot (1).JPG	Yes	100
		Black_rot (10).JPG	Yes	99.99
		Black_rot (101).JPG	Yes	95.19
		Black_rot (104).JPG	Yes	99.96
		Black_rot (110).JPG	Yes	99.88
2	Apple Cedar Rust	Cedar_rust (1).JPG	Yes	100
		Cedar_rust (10).JPG	Yes	99.99
		Cedar_rust (108).JPG	Yes	99.99
		Cedar_rust (109).JPG	Yes	99.96
		Cedar_rust (112).JPG	Yes	99.96
3	Apple Scab	Scab (1).JPG	Yes	100
		Scab (101).JPG	Yes	99.70
		Scab (109).JPG	Yes	99.70
		Scab (123).JPG	Yes	75.78
		Scab (127).JPG	Yes	99.75
4	Apple Healthy	Healthy (1).JPG	Yes	99.84
		Healthy (10).JPG	Yes	99.99
		Healthy (100).JPG	No	54.76
		Healthy (1000).JPG	Yes	100
		Healthy (1001).JPG	Yes	97.79
5	Grape Black Rot	Grape Black Rot (1).JPG	Yes	99.71
		Grape Black Rot (10).JPG	Yes	100
		Grape Black Rot (100).JPG	Yes	100
		Grape Black Rot (1000).JPG	Yes	99.98
		Grape Black Rot (1001).JPG	Yes	100
		Grape Leaf Blight (1).JPG	Yes	100
		Grape Leaf Blight (10).JPG	Yes	99.98

6	Grape Leaf Blight (Isariopsis Leaf Spot)	Grape Leaf Blight (100).JPG	Yes	100
		Grape Leaf Blight (1000).JPG	Yes	99.85
		Grape Leaf Blight (1001).JPG	Yes	99.97
7	Grape Healthy	Grape_Healthy (1).JPG	Yes	100
		Grape_Healthy (10).JPG	Yes	100
		Grape_Healthy (100).JPG	Yes	95.71
		Grape_Healthy (1000).JPG	Yes	79.75
		Grape_Healthy (1001).JPG	Yes	98.37
8	Potato Early Blight	Potato Early Blight (1).jpg	Yes	99.97
		Potato Early Blight (10).jpg	Yes	99.98
		Potato Early Blight (100).jpg	Yes	97.30
		Potato Early Blight (101).jpg	No	76.58
		Potato Early Blight (102).jpg	Yes	78.70
9	Potato Late Blight	Potato Late Blight (1).jpg	Yes	100
		Potato Late Blight (10).jpg	Yes	91.38
		Potato Late Blight (100).jpg	Yes	99.45
		Potato Late Blight (101).jpg	Yes	95.55
		Potato Late Blight (102).jpg	Yes	99.93
10	Potato Healthy	Potato_Healthy (1).jpg	Yes	99.65
		Potato_Healthy (10).jpg	Yes	82.76
		Potato_Healthy (100).jpg	Yes	90.56
		Potato_Healthy (101).jpg	Yes	99.47
		Potato_Healthy (102).jpg	Yes	88.21
11	Rose Black Spot	Black Spot (1).jpg	Yes	99.94
		Black Spot (10).jpg	Yes	91.29
		Black Spot (100).jpg	Yes	96.62
		Black Spot (101).jpg	Yes	78.32
		Black Spot (102).jpg	Yes	99.86
12	Rose Downy Mildew	Downy Mildew (1).jpg	Yes	100
		Downy Mildew (10).jpg	Yes	99.90
		Downy Mildew (100).jpg	Yes	99.05
		Downy Mildew (101).jpg	Yes	99.98
		Downy Mildew (102).jpg	Yes	99.75

13	Rose Fresh Leaf	Fresh leaf(1).jpg	Yes	99.78
		Fresh leaf(10).jpg	Yes	96.45
		Fresh leaf(100).jpg	Yes	80.26
		Fresh leaf(101).jpg	Yes	90.95
		Fresh leaf(102).jpg	Yes	99.79

Table 1: Experimental data analysis using VGG16

Experimental data analysis using VGG 19

SL No	Subject	Sample	Detected (Yes/No)	Accuracy(%)
1	Apple Black Rot	Black_rot (1).JPG	Yes	100
		Black_rot (10).JPG	Yes	100
		Black_rot (101).JPG	Yes	99.96
		Black_rot (104).JPG	Yes	100
		Black_rot (110).JPG	Yes	100
2	Apple Cedar Rust	Cedar_rust (1).JPG	Yes	100
		Cedar_rust (10).JPG	Yes	100
		Cedar_rust (108).JPG	Yes	100
		Cedar_rust (109).JPG	Yes	100
		Cedar_rust (112).JPG	Yes	100
3	Apple Scab	Scab (1).JPG	Yes	100
		Scab (101).JPG	Yes	100
		Scab (109).JPG	Yes	100
		Scab (123).JPG	Yes	99.74
		Scab (127).JPG	Yes	100
4	Apple Healthy	Healthy (1).JPG	Yes	89.84
		Healthy (10).JPG	Yes	99.89
		Healthy (100).JPG	No	54.76
		Healthy (1000).JPG	Yes	100
		Healthy (1001).JPG	Yes	95.79
5	Grape Black Rot	Grape Black Rot (1).JPG	Yes	100
		Grape Black Rot (10).JPG	Yes	100
		Grape Black Rot (100).JPG	Yes	100
		Grape Black Rot (1000).JPG	Yes	100

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		Grape Black Rot (1001).JPG	Yes	100
6	Grape Leaf Blight (Isariopsis Leaf Spot)	Grape Leaf Blight (1).JPG	Yes	100
		Grape Leaf Blight (10).JPG	Yes	100
		Grape Leaf Blight (100).JPG	Yes	100
		Grape Leaf Blight (1000).JPG	Yes	100
		Grape Leaf Blight (1001).JPG	Yes	100
7	Grape Healthy	Grape_Healthy (1).JPG	Yes	100

		Grape_Healthy (10).JPG	Yes	100
		Grape_Healthy (100).JPG	Yes	100
		Grape_Healthy (1000).JPG	Yes	100
		Grape_Healthy (1001).JPG	Yes	100
8	Potato Early Blight	Potato Early Blight (1).jpg	Yes	100
		Potato Early Blight (10).jpg	Yes	100
		Potato Early Blight (100).jpg	Yes	99.99
		Potato Early Blight (101).jpg	Yes	99.89
		Potato Early Blight (102).jpg	Yes	100
9	Potato Late Blight	Potato Late Blight (1).jpg	Yes	100
		Potato Late Blight (10).jpg	Yes	98.48
		Potato Late Blight (100).jpg	Yes	100
		Potato Late Blight (101).jpg	Yes	97.19
		Potato Late Blight (102).jpg	Yes	100
10	Potato Healthy	Potato_Healthy (1).jpg	Yes	99.99
		Potato_Healthy (10).jpg	Yes	98.93
		Potato_Healthy (100).jpg	Yes	99.46
		Potato_Healthy (101).jpg	Yes	100
		Potato_Healthy (102).jpg	Yes	99.64
11	Rose Black Spot	Black Spot (1).jpg	Yes	100
		Black Spot (10).jpg	Yes	100
		Black Spot (100).jpg	Yes	99.98
		Black Spot (101).jpg	Yes	99.67
		Black Spot (102).jpg	Yes	99.86
		Downy Mildew (1).jpg	Yes	100
		Downy Mildew (10).jpg	Yes	100

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12	Rose Downy Mildew	Downy Mildew (100).jpg	Yes	100
		Downy Mildew (101).jpg	Yes	100
		Downy Mildew (102).jpg	Yes	100
13	Rose Fresh Leaf	Fresh leaf(1).jpg	Yes	99.91
		Fresh leaf(10).jpg	Yes	96.70
		Fresh leaf(100).jpg	Yes	66.73
		Fresh leaf(101).jpg	Yes	99.94
		Fresh leaf(102).jpg	Yes	99.83

Table 2: Experimental data analysis using VGG19

Experimental data analysis using MobileNet V2

SL No	Subject	Sample	Detected (Yes/No)	Accuracy(%)
1	Apple Black Rot	Black_rot (1).JPG	Yes	100
		Black_rot (10).JPG	Yes	94.02
		Black_rot (101).JPG	Yes	75.99
		Black_rot (104).JPG	Yes	97.46
		Black_rot (110).JPG	Yes	100
2	Apple Cedar Rust	Cedar_rust (1).JPG	Yes	100
		Cedar_rust (10).JPG	Yes	99.97
		Cedar_rust (108).JPG	Yes	100
		Cedar_rust (109).JPG	Yes	99.92
		Cedar_rust (112).JPG	Yes	100
3	Apple Scab	Scab (1).JPG	Yes	99.71
		Scab (101).JPG	No	99.81
		Scab (109).JPG	Yes	98.88
		Scab (123).JPG	No	93.59
		Scab (127).JPG	Yes	98.36
4	Apple Healthy	Healthy (1).JPG	Yes	100
		Healthy (10).JPG	Yes	99.99
		Healthy (100).JPG	Yes	98.77
		Healthy (1000).JPG	Yes	100
		Healthy (1001).JPG	Yes	100

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5	Grape Black Rot	Grape Black Rot (1).JPG	Yes	100
		Grape Black Rot (10).JPG	Yes	99.71
		Grape Black Rot (100).JPG	Yes	100
		Grape Black Rot (1000).JPG	Yes	99.71
		Grape Black Rot (1001).JPG	Yes	100
6	Grape Leaf Blight (Isariopsis Leaf Spot)	Grape Leaf Blight (1).JPG	Yes	99.54
		Grape Leaf Blight (10).JPG	Yes	98.69
		Grape Leaf Blight (100).JPG	Yes	100
		Grape Leaf Blight (1000).JPG	Yes	95.57
		Grape Leaf Blight (1001).JPG	Yes	99.90
7	Grape Healthy	Grape_Healthy (1).JPG	Yes	99.31
		Grape_Healthy (10).JPG	Yes	81.72
		Grape_Healthy (100).JPG	Yes	99.98
		Grape_Healthy (1000).JPG	Yes	98.52
		Grape_Healthy (1001).JPG	Yes	75.11
8	Potato Early Blight	Potato Early Blight (1).jpg	Yes	99.74
		Potato Early Blight (10).jpg	Yes	99.50
		Potato Early Blight (100).jpg	Yes	94.33
		Potato Early Blight (101).jpg	Yes	99.99
		Potato Early Blight (102).jpg	No	100
9	Potato Late Blight	Potato Late Blight (1).jpg	Yes	100
		Potato Late Blight (10).jpg	Yes	97.52
		Potato Late Blight (100).jpg	Yes	99.64
		Potato Late Blight (101).jpg	Yes	99.41
		Potato Late Blight (102).jpg	Yes	99.93
10	Potato Healthy	Potato_Healthy (1).jpg	Yes	100
		Potato_Healthy (10).jpg	Yes	100
		Potato_Healthy (100).jpg	Yes	100
		Potato_Healthy (101).jpg	Yes	100
		Potato_Healthy (102).jpg	Yes	100
11	Rose Black Spot	Black Spot (1).jpg	Yes	99.94
		Black Spot (10).jpg	Yes	92.29
		Black Spot (100).jpg	Yes	99.89

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		Black Spot (101).jpg	Yes	91.95
		Black Spot (102).jpg	Yes	99.86
12	Rose Downy Mildew	Downy Mildew (1).jpg	Yes	99.96
		Downy Mildew (10).jpg	Yes	100
		Downy Mildew (100).jpg	Yes	99.59
		Downy Mildew (101).jpg	Yes	98.28
		Downy Mildew (102).jpg	Yes	99.99
13	Rose Fresh Leaf	Fresh leaf(1).jpg	Yes	99.78
		Fresh leaf(10).jpg	Yes	96.45
		Fresh leaf(100).jpg	Yes	99.24
		Fresh leaf(101).jpg	Yes	96.11
		Fresh leaf(102).jpg	Yes	99.79

Table 3: Experimental data analysis using MobileNet V2

Experimental data analysis using ResNet

SL No	Subject	Sample	Detected (Yes/No)	Accuracy(%)
1	Apple Black Rot	Black_rot (1).JPG	Yes	99.96
		Black_rot (10).JPG	No	70.94
		Black_rot (101).JPG	Yes	99.78
		Black_rot (104).JPG	Yes	88.31
		Black_rot (110).JPG	Yes	98.35
2	Apple Cedar Rust	Cedar_rust (1).JPG	Yes	99.70
		Cedar_rust (10).JPG	Yes	58.66
		Cedar_rust (108).JPG	No	75.41
		Cedar_rust (109).JPG	Yes	97.96
		Cedar_rust (112).JPG	Yes	99.96
3	Apple Scab	Scab (1).JPG	Yes	100
		Scab (101).JPG	Yes	96.70
		Scab (109).JPG	Yes	99.60
		Scab (123).JPG	Yes	74.78
		Scab (127).JPG	Yes	91.75
		Healthy (1).JPG	Yes	88.84

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4	Apple Healthy	Healthy (10).JPG	No	44.56
		Healthy (100).JPG	No	54.76
		Healthy (1000).JPG	Yes	100
		Healthy (1001).JPG	Yes	97.79
5	Grape Black Rot	Grape Black Rot (1).JPG	Yes	99.61
		Grape Black Rot (10).JPG	Yes	100
		Grape Black Rot (100).JPG	Yes	100
		Grape Black Rot (1000).JPG	Yes	99.88
		Grape Black Rot (1001).JPG	Yes	100
6	Grape Leaf Blight (Isariopsis Leaf Spot)	Grape Leaf Blight (1).JPG	Yes	100
		Grape Leaf Blight (10).JPG	Yes	97.98
		Grape Leaf Blight (100).JPG	Yes	100
		Grape Leaf Blight (1000).JPG	Yes	99.85
		Grape Leaf Blight (1001).JPG	Yes	99.98
7	Grape Healthy	Grape_Healthy (1).JPG	Yes	100
		Grape_Healthy (10).JPG	Yes	100
		Grape_Healthy (100).JPG	Yes	95.71
		Grape_Healthy (1000).JPG	Yes	78.75
		Grape_Healthy (1001).JPG	Yes	98.37
8	Potato Early Blight	Potato Early Blight (1).jpg	Yes	99.97
		Potato Early Blight (10).jpg	Yes	99.98
		Potato Early Blight (100).jpg	Yes	97.31
		Potato Early Blight (101).jpg	No	76.58
		Potato Early Blight (102).jpg	Yes	78.70
9	Potato Late Blight	Potato Late Blight (1).jpg	Yes	100
		Potato Late Blight (10).jpg	Yes	92.38
		Potato Late Blight (100).jpg	Yes	99.55
		Potato Late Blight (101).jpg	Yes	95.55
		Potato Late Blight (102).jpg	Yes	99.93
10	Potato Healthy	Potato_Healthy (1).jpg	Yes	99.65
		Potato_Healthy (10).jpg	Yes	84.76
		Potato_Healthy (100).jpg	Yes	90.56
		Potato_Healthy (101).jpg	Yes	99.47

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		Potato_Healthy (102).jpg	Yes	88.21
11	Rose Black Spot	Black Spot (1).jpg	Yes	99.94
		Black Spot (10).jpg	Yes	91.29
		Black Spot (100).jpg	Yes	96.62
		Black Spot (101).jpg	Yes	78.32
		Black Spot (102).jpg	Yes	99.86
12	Rose Downy Mildew	Downy Mildew (1).jpg	Yes	100
		Downy Mildew (10).jpg	Yes	99.90
		Downy Mildew (100).jpg	Yes	99.67
		Downy Mildew (101).jpg	Yes	99.93
		Downy Mildew (102).jpg	Yes	99.72
13	Rose Fresh Leaf	Fresh leaf(1).jpg	Yes	99.78
		Fresh leaf(10).jpg	Yes	96.55
		Fresh leaf(100).jpg	Yes	80.56
		Fresh leaf(101).jpg	Yes	90.45
		Fresh leaf(102).jpg	Yes	99.89

Table 4: Experimental data analysis using ResNet

Experimental data analysis using CNN

SL No	Subject	Sample	Detected (Yes/No)	Accuracy(%)
1	Apple Black Rot	Black_rot (1).JPG	Yes	100
		Black_rot (10).JPG	Yes	100
		Black_rot (101).JPG	Yes	99.96
		Black_rot (104).JPG	Yes	100
		Black_rot (110).JPG	Yes	100
2	Apple Cedar Rust	Cedar_rust (1).JPG	Yes	100
		Cedar_rust (10).JPG	Yes	99.78
		Cedar_rust (108).JPG	Yes	100
		Cedar_rust (109).JPG	Yes	92.38
		Cedar_rust (112).JPG	Yes	92.48
3	Apple Scab	Scab (1).JPG	Yes	100
		Scab (101).JPG	Yes	100
		Scab (109).JPG	Yes	100

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		Scab (123).JPG	Yes	99.74
		Scab (127).JPG	Yes	100
4	Apple Healthy	Healthy (1).JPG	Yes	94.84
		Healthy (10).JPG	Yes	97.99
		Healthy (100).JPG	No	54.76
		Healthy (1000).JPG	Yes	99.00
		Healthy (1001).JPG	Yes	97.79
5	Grape Black Rot	Grape Black Rot (1).JPG	Yes	100
		Grape Black Rot (10).JPG	Yes	91.74
		Grape Black Rot (100).JPG	Yes	92.74
		Grape Black Rot (1000).JPG	Yes	100
		Grape Black Rot (1001).JPG	Yes	100
6	Grape Leaf Blight (Isariopsis Leaf Spot)	Grape Leaf Blight (1).JPG	Yes	100
		Grape Leaf Blight (10).JPG	Yes	92.54
		Grape Leaf Blight (100).JPG	Yes	100
		Grape Leaf Blight (1000).JPG	Yes	98.57
		Grape Leaf Blight (1001).JPG	Yes	100
7	Grape Healthy	Grape_Healthy (1).JPG	Yes	100
		Grape_Healthy (10).JPG	Yes	100
		Grape_Healthy (100).JPG	Yes	100
		Grape_Healthy (1000).JPG	Yes	100
		Grape_Healthy (1001).JPG	Yes	100
8	Potato Early Blight	Potato Early Blight (1).jpg	Yes	100
		Potato Early Blight (10).jpg	Yes	100
		Potato Early Blight (100).jpg	Yes	99.99
		Potato Early Blight (101).jpg	Yes	99.89
		Potato Early Blight (102).jpg	Yes	100
9	Potato Late Blight	Potato Late Blight (1).jpg	Yes	100
		Potato Late Blight (10).jpg	Yes	98.48
		Potato Late Blight (100).jpg	Yes	100
		Potato Late Blight (101).jpg	Yes	97.19
		Potato Late Blight (102).jpg	Yes	100
		Potato_Healthy (1).jpg	Yes	99.99

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10	Potato Healthy	Potato_Healthy (10).jpg	Yes	98.93
		Potato_Healthy (100).jpg	Yes	99.46
		Potato_Healthy (101).jpg	Yes	100
		Potato_Healthy (102).jpg	Yes	99.64
11	Rose Black Spot	Black Spot (1).jpg	Yes	100
		Black Spot (10).jpg	Yes	100
		Black Spot (100).jpg	Yes	99.98
		Black Spot (101).jpg	Yes	99.67
		Black Spot (102).jpg	Yes	99.86
12	Rose Downy Mildew	Downy Mildew (1).jpg	Yes	100
		Downy Mildew (10).jpg	Yes	100
		Downy Mildew (100).jpg	Yes	100
		Downy Mildew (101).jpg	Yes	100
		Downy Mildew (102).jpg	Yes	100
13	Rose Fresh Leaf	Fresh leaf(1).jpg	Yes	99.91
		Fresh leaf(10).jpg	Yes	96.70
		Fresh leaf(100).jpg	Yes	66.73
		Fresh leaf(101).jpg	Yes	99.94
		Fresh leaf(102).jpg	Yes	99.83

Table 5: Experimental data analysis using CNN

Accuracy & Key Observations For Each Model

Model	Accuracy (%)	Epochs Trained	Key Observations
MobileNetV2	99.40	20	Exceptional efficiency and highest accuracy.
VGG19	98.92	20	High accuracy but computationally intensive.
CNN	98.68	20	Simple architecture with competitive performance.
VGG16	97.24	20	Effective but requires significant computational resources.
ResNet	96.24	20	Lowest accuracy; potential overfitting due to model depth.

Table 6: Accuracy & Key Observation For Each Model

MobileNetV2 emerged as the best-performing model, achieving an accuracy of 99.40%, making it ideal for real-world deployment in resource-constrained environments. The CNN model, despite its simplicity, demonstrated a strong accuracy of 98.68%, suggesting its feasibility for lightweight applications. The transfer learning models, VGG19 and VGG16, performed well but at the cost of higher computational requirements. ResNet achieved the lowest accuracy of 96.24%, likely due to its complexity, which did not translate effectively to the given dataset.

To enhance understanding, graphical visualizations such as accuracy trends, loss curves, and confusion matrices were generated. These plots illustrate the learning behavior of each model across training and validation phases, emphasizing MobileNetV2's consistent performance.

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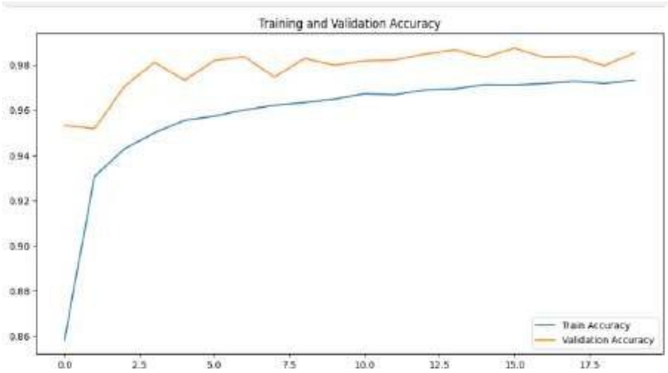

Fig7. Training & Validation Accuracy Graph For VGG16

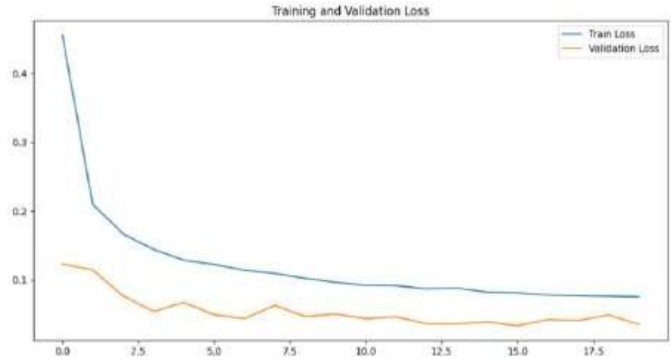

Fig8. Training & Validation Loss Graph For VGG16

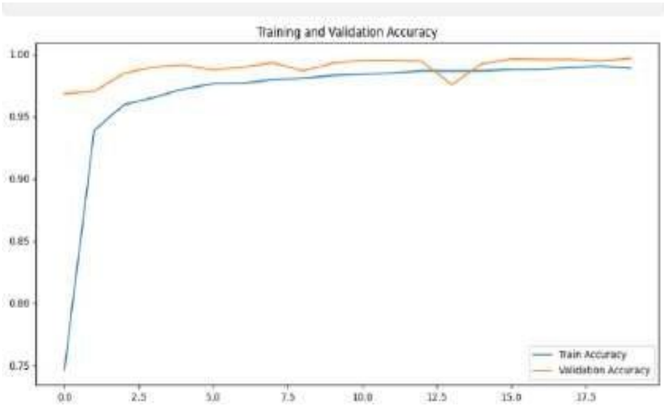

Fig9. Training & Validation Accuracy Graph For VGG19

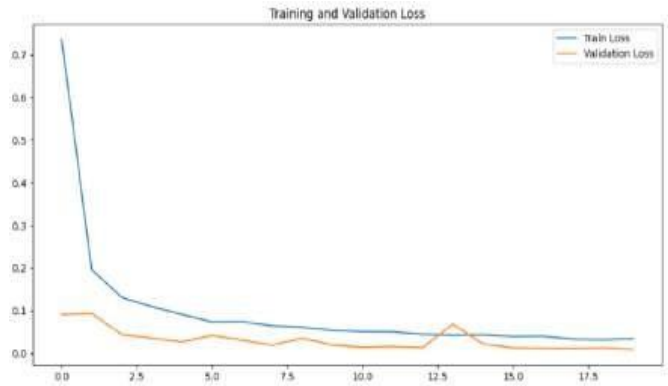

Fig10. Training & Validation Loss Graph For VGG19

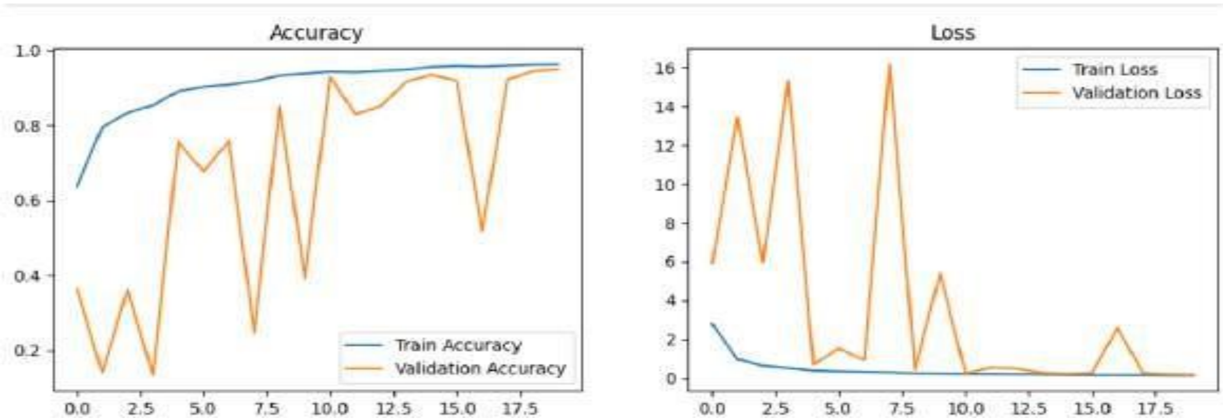

Fig11. Both Accuracy & Loss Graph For Train & Validation in MobileNetV2

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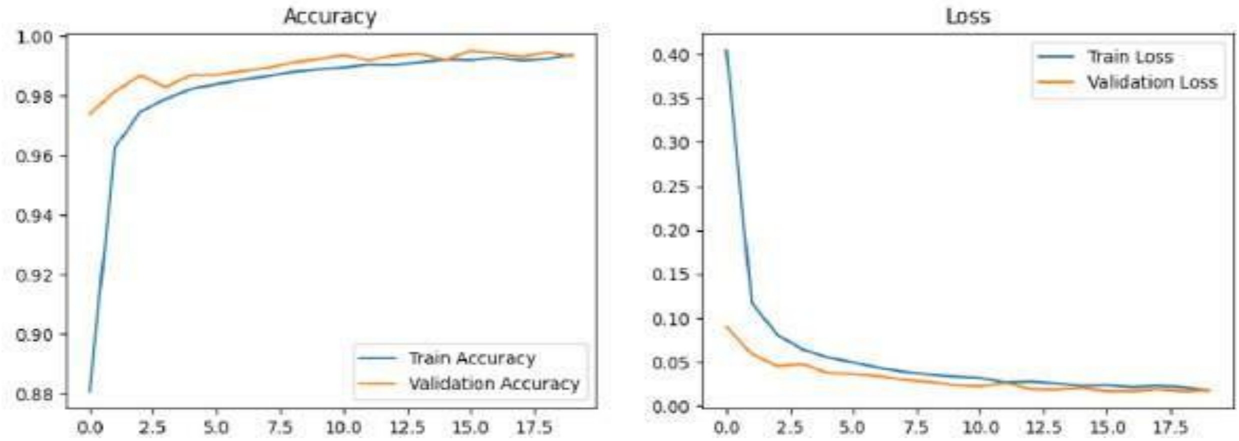
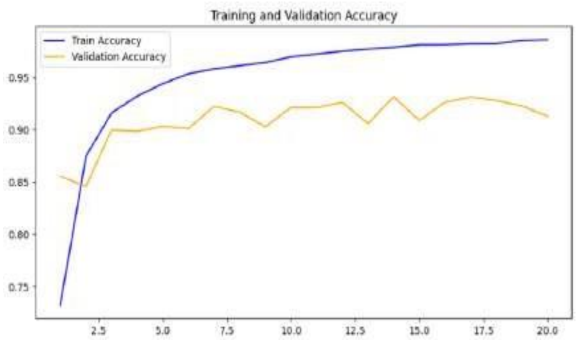


Fig12. Both Accuracy & Loss Graph For Train & Validation in ResNet



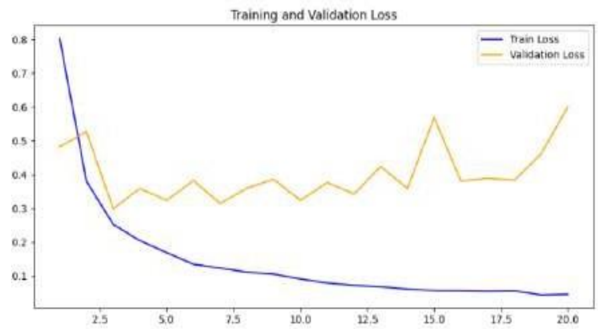


Fig13. Training & Validation Accuracy Graph For CNN **Fig14.** Training & Validation Loss Graph For CNN

Visual Insights

1. **Accuracy Graph**: This graph showcases the accuracy trends of all five models across epochs, visually confirming MobileNetV2's superior and stable accuracy.
2. **Loss Graph**: A comparative loss curve illustrates the convergence of each model during training, highlighting their efficiency and potential overfitting.
3. **Confusion Matrices**: Class-wise performance is detailed, showing misclassification rates for each model.

These visualizations can be integrated into the analysis to provide a holistic view of model performance, allowing readers to assess trade-offs in terms of complexity, accuracy, and resource requirements.

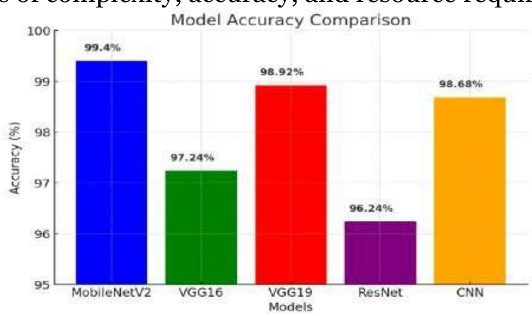


Fig15. Accuracy Comparison Of Plant Disease Detection Model

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CONCLUSION

This research study explores the potential of deep learning in agriculture, specifically for automated plant disease detection, which is vital for global food security. It evaluates five deep learning models—MobileNetV2, VGG16, VGG19, ResNet, and a basic CNN—using the PlantVillage dataset. MobileNetV2 proved most effective with an accuracy of 99.40%, paired with high computational efficiency for resource-limited environments. The basic CNN also performed well at 98.68%, while VGG16 and VGG19 achieved 97.24% and 98.92%, respectively, but have higher computational needs. ResNet had the lowest accuracy at 96.24% due to overfitting.

The study emphasizes the importance of a systematic framework for evaluating deep learning in agriculture, highlighting preprocessing techniques like data augmentation and class balancing to enhance model performance. Future improvements could involve ensemble methods and integrating contextual factors such as weather and soil health. Overall, "PlantOHealth" represents a significant step in applying AI for sustainable agriculture, providing valuable insights for innovation in agricultural practices.

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