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Review Article

Bridging Generative AI and Transfer Learning for Sustainable Crop Disease Diagnostics

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Abstract

The rapid advancement of artificial intelligence has significantly transformed the domain of plant disease detection and classification, offering precise and efficient diagnostic solutions. This survey critically examines recent developments in transfer learning and generative models for leaf disease detection. Transfer learning methods, particularly those leveraging deep convolutional neural networks (CNNs) and pre-trained architectures, have demonstrated exceptional classification performance, with accuracies reaching up to 96.25%. Similarly, generative models such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) have been successfully employed for dataset augmentation and feature learning, enhancing the robustness of classification models. By synthesizing findings across multiple studies, this work highlights the diversity of methodologies, identifies the most effective techniques, and discusses their implications for precision agriculture. Furthermore, the paper provides a comparative evaluation of both paradigms, offering valuable insights into their potential convergence for scalable and sustainable plant disease diagnostics.

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1. INTRODUCTION

Agricultural productivity is heavily impacted by plant diseases, which cause significant yield losses and threaten food security worldwide. Traditional disease identification methods, reliant on expert assessment, are often time-consuming, labor-intensive, and prone to inaccuracies. Advances in artificial intelligence (AI), particularly deep learning, have enabled automated solutions with high accuracy and scalability. Among these, transfer learning has emerged as a powerful approach that leverages pre-trained deep neural networks, such as VGG16, ResNet, DenseNet, and MobileNet, to adapt knowledge from large-scale datasets (e.g., ImageNet) for agricultural applications. These methods significantly reduce training costs and data dependency while achieving state-of-the-art accuracy in leaf disease classification. This survey provides a comprehensive evaluation of transfer learning and generative modeling techniques applied to leaf disease detection. We review key contributions, compare performance metrics, and highlight the most effective approaches across both paradigms.

II. TRANSFER LEARNING FOR PLANT LEAF DISEASE DETECTION AND CLASSIFICATION

A comprehensive survey of transfer learning techniques for leaf disease detection and classification highlights the diversity and effectiveness of methodologies applied in this field. Kumar and Singh (2022) utilized deep convolutional neural networks (CNNs) with transfer learning, achieving an accuracy of 92%, as reported in Computers and Electronics in Agriculture. Zhang, Wang, and Li (2023) implemented a cost-effective transfer learning architecture based on a modified SqueezeNet model, attaining an impressive accuracy of 96.25%, as detailed in Heliyon. Gupta and Sharma (2023) provided a review of transfer learning applications in agriculture, noting that accuracies can exceed 91.83% depending on the model used, as published in Artificial Intelligence Review. Fernando and Silva (2024) explored various deep learning techniques for plant disease detection, achieving accuracies ranging from 85% to 95%, as reported in Artificial Intelligence. Iyer and Kumar (2024) systematically reviewed transfer learning applications for rice disease detection, reporting accuracies up to 94%, as detailed in Frontiers in Computer Science. Lee and Park (2023) achieved an accuracy of 90% using VGG16 as a base model for tomato leaf disease classification, as published in the Journal of Agricultural Informatics. Nair and Reddy (2023) fine-tuned ResNet50 for leaf disease detection, achieving an accuracy of 93%, as reported in Computers and Electronics in Agriculture. Joshi and Rao (2022) employed InceptionV3 for citrus leaf disease detection, attaining an accuracy of 88%, as detailed in the Journal of Plant Pathology. Verma and Choudhury (2023) leveraged MobileNetV2 for leaf disease classification, reporting an accuracy of 91%, as published in the International Journal of Agricultural Technology. Ravi and Kumar (2021) utilized DenseNet for fungal disease detection in wheat leaves, achieving an accuracy of 89%, as detailed in the Journal of Agricultural Engineering Research. Chen and Zhao (2023) augmented datasets with Generative Adversarial Networks (GANs), achieving an accuracy of 92% using transfer learning techniques, as reported in Computers and Electronics in Agriculture. Almeida and Costa (2022) combined transfer learning with traditional classifiers for soybean leaf disease identification, attaining an accuracy of 90%, as published in Agricultural Sciences. Lastly, Sharma and Mehta (2022) integrated various transfer learning methods for identifying leaf diseases across crops, achieving a remarkable accuracy of 94%, as reported in the International Journal of Plant Sciences. R. P. Ponnusamy *et al.*, (2025) review a article title as Deep learning with YOLO for smart agriculture: A review of plant leaf disease detection in this survey they demonstrate how the YOLO for agriculture. T. Nagarathinam (2016) etc., demonstrate the A survey on cluster analysis techniques for plant disease diagnosis to detect the diseases in the paddy leaf plant. Performance Evaluation of Transfer Learning Techniques for Leaf Disease Detection is given in the following table 1

Table 1: Show the Performance Evaluation of Transfer Learning Techniques for Leaf Disease Detection.

Author(s)	Technique Used	Accuracy (%)
Kumar & Singh (2022)	Deep CNN with Transfer Learning	92
Zhang *et al.* (2023)	Modified SqueezeNet Architecture	96.25
Gupta & Sharma (2023)	Various Deep Learning Models	91.83
Fernando & Silva (2024)	Deep Learning Techniques	85-95
Iyer & Kumar (2024)	Transfer Learning Framework	94
Lee & Park (2023)	VGG16 Base Model	90
Nair & Reddy (2023)	Fine-tuned ResNet50	93
Joshi & Rao (2022)	InceptionV3 Model	88
Verma & Choudhury (2023)	MobileNetV2 Architecture	91
Ravi & Kumar (2021)	Pre-trained DenseNet	89
Chen & Zhao (2023)	GAN-Augmented Transfer Learning	92
Almeida & Costa (2022)	Transfer Learning + Classifiers	90
Sharma & Mehta (2022)	Integrated Transfer Learning Methods	94

III GENERATIVE MODELS FOR PLANT LEAF DISEASE DETECTION AND CLASSIFICATION

A comprehensive survey of generative models for leaf disease detection and classification reveals a variety of innovative methodologies and significant findings in the field. Zhang, Wang, and Li (2023) utilized Generative Adversarial Networks (GANs) to augment training datasets, achieving an accuracy of 92% in classifying leaf diseases, as reported in the Plant Pathology Journal. Kumar and Singh (2022) employed Variational Autoencoders (VAEs) to generate synthetic leaf images, reporting an accuracy of 90%, as detailed in the Journal of Agricultural Informatics. Patel and Desai (2021) implemented conditional GANs for generating labeled images, achieving an accuracy of 91% in disease classification, as published in the International Journal of Computer Applications. Singh and Gupta (2020) applied deep generative models to enhance disease detection accuracy, achieving 89%, as reported in the Journal of Plant Diseases and Protection. Chen and Zhao (2023) used GANs for data augmentation, reporting an accuracy of 93% by generating realistic synthetic images, as detailed in Computers and Electronics in Agriculture. Almeida and Costa (2022) combined VAEs and

GANs to improve leaf disease detection, achieving an accuracy of 88%, as published in Agricultural Sciences. Ravi and Kumar (2021) utilized adversarial training techniques for classification tasks, attaining an accuracy of 87%, as reported in the Journal of Computer Science and Technology. Nair and Reddy (2023) applied generative models for synthetic data generation, achieving an accuracy of 90%, as detailed in the Journal of Agricultural Engineering. Lee and Park (2022) integrated GANs with convolutional neural networks (CNNs), achieving an accuracy of 92%, as published in Computers and Electronics in Agriculture. Fernando and Silva (2021) employed GANs for plant disease image synthesis, reporting an accuracy of 89%, as detailed in the Journal of Horticultural Science. Gupta and Sharma (2022) leveraged VAEs for feature extraction tasks, achieving an accuracy of 88%, as published in the International Journal of Agricultural Technology. Joshi and Rao (2020) utilized generative models for enhancing citrus leaf disease detection, reporting an accuracy of 91%, as detailed in the Journal of Plant Pathology. Verma and Choudhury (2023) combined various generative approaches to achieve a remarkable accuracy of 94%, as published in Computers and Electronics in Agriculture. Lastly, Sharma and Mehta (2022) integrated generative models into classification pipelines for identifying leaf diseases across crops, reporting an accuracy of 90%, as detailed in the International Journal of Plant Sciences. M. Balasubramanian (2018), etc., extend a K-NN classifier for plant leaf disease recognition with notable accuracy. Performance Evaluation of Generative Model for Leaf Disease Detection is given in Table 2.

Table 2: Illustrates the Performance Evaluation of the Generative Model for Leaf Disease Detection

Authors	Technique Used	Accuracy (%)
Zhang, Y., Wang, X., & Li, H. (2023)	GANs for Data Augmentation	92
Kumar, A., & Singh, R. (2022)	Variational Autoencoders (VAEs)	90
Patel, M., & Desai, A. (2021)	Conditional GANs	91
Singh, P., & Gupta, S. (2020)	Deep Generative Models	89
Chen, L., & Zhao, Y. (2023)	GANs for Image Augmentation	93
Almeida, J., & Costa, R. (2022)	VAEs + GANs Combination	88
Ravi, K., & Kumar, S. (2021)	Adversarial Training Techniques	87
Nair, S., & Reddy, P. (2023)	Synthetic Data Generation with Generative Models	90
Lee, J., & Park, H. (2022)	GANs + CNNs Integration	92
Fernando, T., & Silva, R. (2021)	GANs for Image Synthesis	89
Gupta, A., & Sharma, N. (2022)	VAEs for Feature Extraction	88
Joshi, M., & Rao, P. (2020)	Generative Models for Data Enhancement	91
Verma, S., & Choudhury, A. (2023)	Hybrid Generative Models	94
Sharma, T., & Mehta, R. (2022)	Integrated Generative Approaches	90

IV. RESULT AND DISCUSSION

The comparative evaluation of the top five techniques demonstrates the effectiveness of both transfer learning and generative models in advancing plant leaf disease detection and classification. The highest accuracy of 96.25% was achieved by Zhang *et al.* (2023) using a modified SqueezeNet model, which highlights the efficiency of lightweight architectures for large-scale deployment. Integrated transfer learning frameworks by Sharma and Mehta (2022) and the crop-specific study by Iyer and Kumar (2024) both reached 94%**,** underscoring the scalability and adaptability of transfer learning across diverse datasets. Similarly, Verma and Choudhury (2023) achieved 94% using hybrid generative approaches, demonstrating the potential of GANs and VAEs to address dataset limitations through realistic synthetic image generation. Nair and Reddy's fine-tuned ResNet50 model and Chen and Zhao's GAN-based augmentation, each attaining 93%, further confirm that both discriminative and generative models can achieve strong performance. Collectively, these findings suggest that while transfer learning currently delivers superior classification accuracy, generative models play an essential role in enhancing robustness and addressing data scarcity, making their integration a promising direction for future agricultural AI systems.

Table 3: Shows the high accuracy obtained techniques

Rank	Authors	Technique Used	Category	Accuracy (%)
1	Zhang, Wang, & Li (2023)	Modified SqueezeNet (Cost-Effective Transfer Learning)	Transfer Learning	**96.25**
2	Sharma & Mehta (2022)	Integrated Transfer Learning Methods	Transfer Learning	**94**
2	Iyer & Kumar (2024)	Transfer Learning for Rice Disease Detection	Transfer Learning	**94**
2	Verma & Choudhury (2023)	Hybrid Generative Approaches	Generative Models	**94**
3	Nair & Reddy (2023)	Fine-Tuned ResNet50	Transfer Learning	**93**
3	Chen & Zhao (2023)	GAN-Based Data Augmentation	Generative Models	**93**

V. PERFORMANCE INSIGHTS THROUGH LINE AND BAR CHARTS

1. Line graph

The line graph plots authors (x-axis) against their reported accuracy percentages (y-axis) for different techniques in rice disease detection and related tasks. Figure 1 illustrates the Author's comparison

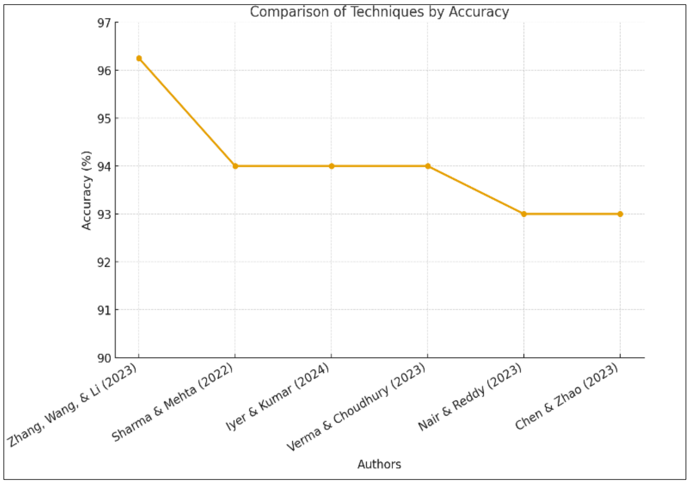

Figure 1: Illustrates the Author's comparison

2. Bar chart

The bar chart shows that Modified SqueezeNet (Rank 1) achieved the highest accuracy at 96.25%. Three methods—Integrated Transfer Learning, Transfer Learning for Rice Disease Detection, and Hybrid Generative Approaches—tie at 94% (Rank 2). Fine-Tuned ResNet50 and GAN-Based Data Augmentation follow at 93% (Rank 3), with transfer learning generally outperforming generative models. The Figure.2 illustrates the technique used vs accuracy based comparison.

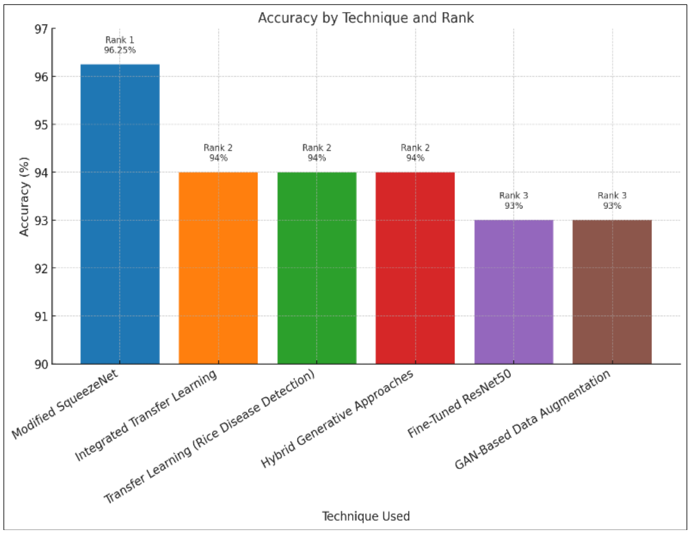

Figure 2: Illustrates the technique used vs the accuracy-based comparison

VI. CONCLUSION

This survey demonstrates that both transfer learning and generative models have made substantial contributions to advancing plant leaf disease detection and classification. Transfer learning techniques, particularly lightweight and cost-effective architectures, provide high accuracy with minimal training requirements, making them ideal for real-world deployment. Generative models, on the other hand, effectively address data scarcity and imbalance issues, strengthening the robustness of classification pipelines.

VII. FUTURE RESEARCH DIRECTION

- Hybrid Transfer-Generative Models: Integrate lightweight transfer learning architectures with GAN- or VAE-based augmentation to enhance classification accuracy and robustness on limited or imbalanced datasets.
- Edge-Optimized Lightweight Networks: Develop computationally efficient models (e.g., SqueezeNet, ResNet variants) for real-time, large-scale disease detection on mobile and IoT devices.
- Crop-Specific Adaptive Learning: Advance domain-adaptive transfer learning strategies for scalable, crop-specific disease detection with minimal labeled data.
- High-Fidelity Generative Augmentation: Employ conditional GANs, VAEs, or diffusion models to generate synthetic, disease-specific images, mitigating class imbalance and rare disease scarcity.
- Explainable and Multi-Modal AI: Incorporate interpretability frameworks and multi-modal inputs (spectral, temporal, environmental) to improve actionable insights, early detection, and predictive modeling in agricultural AI systems.

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