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An Iterative Systematic Analytical Review of Advanced Deep Learning Models for Grape Disease Detection

Prashant G. Aher[1] , Vikrant Sabnis[2] , Jay Kumar Jain[3]

[1] Resarch Scholar, Department of Computer Science Faculty of Engineering and Technology Mansarovar Global University, Bhopal, prashaher@gmail.com, Orcid: 0000-0003-3080-5638

[2] Professor, Department of Computer Science, Faculty of Engineering and Technology, Mansarovar Global University, Bhopal, India drvikrantsabnis@gmail.com, Orcid: 0009-0007-8623-6602

[3] Assistant Professor, Department of Mathematics, Bioinformatics and Computer Applications, MANIT Bhopal (M.P.), India, 462003, jayjain.research@gmail.com, Orcid: 0000-0002-9590-0006

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The growth in plant disease occurrence has heavily threatened global agricultural productivity. Therefore, highly efficient and automated diagnostic tools need to be developed in the current scenario. Rapid advancement in machine learning and deep learning techniques makes present reviews far from conducting comprehensive comparative evaluations of cutting-edge models especially for important crops such as grapes related to plant disease detection. These reviews inadequately address the challenges of model interpretability, computational efficiency, and adaptability to various datasets, thus opening the doors for gaps in applying such technologies in actual farm-related settings. This paper seeks to address these limitations by doing a -guided systematic review of the latest ML and DL models including CNNs, Vision Transformers (ViTs), and hybrid ensemble approaches like DenseNet121, MobileNetV3Large, and Inception-ResNet-V2. The performance is evaluated in terms of major metrics such as accuracy, precision, recall, F1-score, and computational efficiency. Some of the new architectures include dual-track networks with Swin Transformers and group shuffle residual deformable nets, among others like interpretable models LEViT and an interpretable leaf disease detector, I-LDD, which are specifically discussed in terms of new architecture and practicality benefit. In the light of impact on scalability and usability in agricultural domains, the emphases go to lightweight architectures that optimize deployment for edges and explainable frameworks improve decision-making capabilities. With this, an inclusive review proves helpful for better selections of optimum models toward the detection of grape disease as well as generalized plant pathology with precision advancements in agriculture scenarios. This work contributes to sustainable agricultural practices and enhances food security by bridging knowledge gaps and proposing scalable, efficient, and interpretable solutions.

Keywords: Grape Diseases, Deep Learning, Vision Transformers, Ensemble Models, Plant Pathology, Sets

1. Introduction

Global agriculture is facing severe threats by devastating plant diseases that may drastically reduce yields and quality. Among such high-value crops, grapes occupy a crucial position because of their economic value in the production of food and beverages. Cultivation of grapes is threatened constantly by fungal, bacterial, and viral diseases that downgrade its yield and quality. Very early diagnosis and intervention become very important in this case to minimize these effects. Traditional approaches [1, 2,3], based on manual inspections, are time-consuming and manpower-intensive, with possibilities for human judgmental variability. Based on this, the modern approach adopted is that AI techniques, especially ML and DL, have taken hold to transform plant disease diagnostic processes. The improvement in the disease detection and classification has been supported in many of the ML and DL models by CNNs, transfer learning, Vision Transformers (ViTs), and ensemble frameworks proposed during the last few years [4, 5, 6]. Most of these studies provide very good performance metrics, but no exhaustive analytical review compares and benchmarks these methodologies regarding interpretability, computational efficiency, and adaptability to varied datasets. The implication here is that researchers, agronomists, and farmers get confused as to which model would work better in specific applications like grape disease detection in diversified environmental conditions. It is at this juncture that the paper emerges to give a systematic and iterative analytical review of 25 state-of-the-art ML and DL methodologies. Using such an assessment framework for the rating of the developed models based on various criteria like accuracy, precision, recall, and F1-score, it further studies different factors like computational efficiency and utilization of resources, as well as interpretability, important in terms of the application of a model in real domains. The use of deep innovating architectures, for instance, such as methods used like Inception-ResNet-V2 and DenseNet121 as well as MobileNetV3Large, and even hybrids such as Dual-Track Networks, or LEViT are included as well. This work attempts to bridge the knowledge gap towards making researchers and practitioners translate effective and efficient solutions to plant disease detection. The proposed study also emphasizes the scale and usability of these models, paving the pathway for their widespread adoption across precision agriculture sets.

Motivation and Contribution

In order to respond to a fast-rising incidence of plant diseases with negative implications on global food security, it is imperative to hasten the development of high accuracy and scalability automated diagnostic systems. Reviews of ML and DL methodologies often miss concrete and practical considerations in terms of model interpretability, computing costs, and their adaptation capabilities to real-world agricultural environments. Moreover, visible symptoms are complex and diversified in environmental conditions; hence, heterogeneity occurs in the identification of optimum solutions. Thus, it requires specialized focus in order to find optimal solutions. These have inspired this paper in the course of filling literature gaps for the systematic review and comparison of state-of-the-art ML and DL models, particularly those tailored specifically for the detection of plant diseases in general with sets specific to grape pathology. This is described below under the following contributions:. First, structured, iterative-guided review. Advanced models can be effectively and rigorously evaluated. Toward this end, this work is a comprehensive benchmark in the assessment of cutting-edge methodologies encompassing Vision Transformers, federated deep learning, and hybrid ensemble frameworks, relating them to performance, efficiency, and usability. This work develops a detailed discussion about computational efficiency and model accuracy, and its practical insight towards deployment in resource-constrained environments. This would be possible through an emphasis on interpretability and scalability as such capabilities would empower the stakeholders to make informed decisions towards more sustainable agricultural practices while enabling the improvements in the understanding of advanced techniques of ML and DL and lays down the grounds for introducing those in the smart farming ecosystems.

2. REVIEW INTO STUDIES RELATED TO PLANT DISEASE ANALYSIS

Advancements in the detection and analysis of plant diseases have become critical for ensuring the sustainability and productivity of agricultural systems. This review synthesizes the state-of-the-art methodologies employed for grape plant disease analysis, focusing on hyperspectral imaging, machine learning, and deep learning approaches. The discussion is framed around the methodology to ensure a comprehensive and structured analysis.

Hyperspectral Imaging in Plant Disease Analysis:

The hyperspectral imaging (HSI) has shown to be a promising technique for early disease detection in crops such as tomatoes and grapes. For example, [1] proved the feasibility of HSI in identifying bacterial leaf spots at the pre-symptomatic stage based on changes in leaf water content and plant defense responses. It has been reported that increasing classification performance by 26–37% was obtained by using VI data rather than raw spectral data. These results show the potential of HSI in identifying critical wavelength bands at various stages of disease progression and, therefore, help in improving the early detection of diseases.

Machine Learning for Grape Disease Detection

Machine learning has emerged as a very important technology for the effective and reliable detection of diseases in grape plants. Other studies like [2] introduced improved classification models, which involved a CNNC model and an improvised K-Nearest Neighbor (IKNN) model. These models outperformed the traditional approach as they were trained on the PlantVillage dataset. Feature extraction and classification accuracy of these models were improved by using pixel encoding methods like Confined Intensity Directional Order Relation (CIDOR) and Global Pixel Order Relation (GPOR). For that reason, [3] have indicated ensemble models for the classification of rice leaf diseases through an increase of effectiveness in transfer learning besides fine-tuned hyperparameters towards high classification accuracies. Additionally, [9] established effectiveness in the use of CNNC and IKNN models in the classification process of grape leaf diseases as it was further improved on with the use of features with gradient-based methods highly enhancing the process.

Reference	**Method Used**	**Findings**	**Strengths**	**Limitations**
[1]	Hyperspectral Imaging (HSI) with ML models	Demonstrated early detection using critical wavelength bands and VIs for disease progression stages.	Effective pre-symptomatic detection, insights into spectral variations.	Lack of high-resolution validated data, focused only on tomato leaves.
[2]	CNNC and IKNN with pixel encoding (CIDOR, GPOR)	Improved classification accuracy for grape diseases. IKNN outperformed traditional models.	Precise histogram representation, enhanced classification performance.	Limited testing on diverse datasets.
[3]	Ensemble DL models with fine-tuning	Achieved high classification metrics using VGG16 and SqueezeNet for rice diseases.	Superior performance with optimized hyperparameters.	Focused on rice; limited applicability to grapes.
[4]	Deep Transfer Learning (DTLD)	99.76% accuracy in mango disease classification with softmax activation.	High accuracy, robust preprocessing.	Specific to mango leaf diseases.
[5]	Hybrid Xception-COKELM	Achieved 98.9% accuracy in plant leaf classification.	Optimized KELM with crossover-based optimization.	Computational complexity of hybrid models.

[6]	VGG-16 and Faster R-CNN	97.3% average accuracy for rice diseases.	Robust feature extraction and classification.	Limited testing on grape datasets.
[7]	EfficientNetB7, MobileNetV2, DenseNet201	EfficientNetB7 achieved 98.56% accuracy in cabbage diseases.	High performance with advanced DL models.	Dataset limited to cabbage diseases.
[8]	ML (SVM) and DL (ResNet)	ResNet achieved 94% accuracy in detecting tomato and potato diseases.	Effective real-time implementation.	Limited focus on complex grape disease cases.
[9]	CNNC and IKNN with advanced feature extraction	Improved classification for grape diseases with gradient-based features.	High accuracy using Plant-Village dataset.	Focused primarily on CNNC and IKNN comparison.
[10]	Federated Deep Learning (FDL)	Lightweight H-CNN achieved 93% accuracy, reducing computational costs.	Efficient for distributed training.	Limited to federated configurations.
[11]	Restructured Dense Network	Achieved 95% accuracy on tomato leaf diseases with fewer parameters.	High performance with reduced computational complexity.	Specific to tomato datasets.
[12]	Lightweight CNN with LBP features	Achieved 99% accuracy on grape leaf datasets.	Robust against noise and texture variations.	Relatively lower accuracy for some datasets.
[13]	Fine-Grained GAN	Augmented rare grape leaf spot images for better DL training.	Effective for limited data scenarios.	GAN-based methods are computationally intensive.
[14]	Stacking AI classifiers with HOG preprocessing	Achieved 96.1% accuracy for grape diseases.	Enhanced accuracy with stacking models.	Moderate improvement with transfer learning.
[15]	Two-stream DL architecture	99.4%-99.9% accuracy for apple and grapefruit leaves.	High precision using entropy-based optimization.	Limited to two crop types.
[16]	Enhanced VGG16 with Faster R-CNN	Achieved 99.6% accuracy for grape diseases.	Superior mAP and precision compared to other models.	Focused on only three grape diseases.
[17]	YOLOv7 with improved attention mechanisms	2.7% improvement over standard YOLOv7 for grape diseases.	Enhanced localization and detection of small lesions.	Limited testing on broader disease classes.

[18]	Low-rank CNN (LR-Net)	Real-time detection of Esca disease with low-cost implementation.	Lightweight architecture suitable for embedded systems.	Limited scalability to more complex datasets.
[19]	LoRa and CNN-based vision system	Efficiently transmitted low-resolution images for grape disease identification.	Low power consumption and cost.	Limited by LoRa's bandwidth constraints.
[20]	Comprehensive review with GrapeCS-ML database	Established a baseline for ML techniques in viticulture.	Valuable resource for vineyard management.	Limited original experimentation.
[21]	Convolution Self-Guided Transformer (CSGT)	96.1% accuracy for grape diseases in complex backgrounds.	Combines local and global feature extraction.	High computational demands.
[22]	Survey on ML/DL for agriculture	Summarized key developments in ML/DL for smart agriculture.	Comprehensive and informative.	No experimental validation.
[23]	Hybrid segmentation and ensemble classification	95.69% accuracy for grape diseases using GWO optimization.	Improved robustness with hybrid feature extraction.	Moderate scalability for large datasets.
[24]	Fine-tuned CNN and Vision Transformers	Achieved 100% accuracy on grape datasets using Swinv2-Base.	High precision and dataset diversity.	Focused on a specific set of models.
[25]	SCBO-based DNFN	Achieved 92% accuracy for grape diseases with multi-class classification.	High specificity and F1-score.	Moderate improvement over baseline methods.

Table 1. Comparative Analysis of Existing Methods

Deep Learning for Disease Detection and Classification

Iteratively, According to table 1, Deep learning techniques have transformed the grape plant disease diagnosis by providing automated feature extraction and high-dimensional data processing. [4] has proposed a deep transfer learning-driven DTLD model to detect mango leaf diseases that attained 99.76% accuracy. This can be used as an example of the applicability of transfer learning to utilize the pre-trained networks for the analysis of plant diseases. Similarly, [5] suggested the hybrid Xception transfer learning model with optimized kernel extreme learning machines (KELMs) for the classification of plant leaf diseases, which was reportedly accurate at 98.9%. For grape plants, [16] showed an Enhanced VGG16 model integrated with Faster Region-based Convolutional Neural Networks (Faster R-CNN) to classify diseases like Downey Mildew and Powdery Mildew. It performed the job with mAP improvement compared with traditional networks at 0.53-7.27% with an accuracy rate of 99.6%. Furthermore, [24] proved its effectiveness on using fine-tuned pre-trained CNN and vision transformers when classifying grape leaf diseases. As a matter of fact, some models attain 100% accuracy samples in datasets from PlantVillage sets.

Data Augmentation and Optimization Techniques

The lack of good quality training data has been one of the challenges to developing good grape disease detection models. [13] has used a fine-grained Generative Adversarial Network for augmenting the training dataset with synthetic local spot images. The augmented datasets improve the performance of deep learning models, and the best accuracy achieved was 96.27% using ResNet-50. Optimization techniques have also been quite essential in the enhancement of the model's performance. For instance, [25] presented a Sine Cosine Butterfly Optimization algorithm in training a Deep Neuro-Fuzzy Network in classifying grape leaf disease. This led to an accuracy of 92%, precision of 92.5%, and sensitivity of 91.7%. Thus, it clearly depicts that optimization in deep learning is essential in process.

Trends and Future Scope

Emerging research has focused on integrating computer vision and machine learning into the core of viticulture practices when facing real-world challenges. [20] gave a much-needed review of vision systems with respect to vineyard management, including the development of a new database (GrapeCS-ML), which is expected to make practical solutions for smart vineyards. Moreover, real-time disease detection systems from low-power embedded systems, for example, the LRNet proposed by [18], work well in resource-constraint environments. Another promising direction pursued by [10] is federated learning, where localized models share knowledge instead of datasets to facilitate efficient disease detection while cutting down computational costs. In this study, the H-CNN that was used has achieved the best performance ever, with testing accuracies reaching 93% for the process.

The accurate and timely detection of grape plant diseases is critical for maintaining agricultural productivity and ensuring food security. With the advancement of machine learning (ML), deep learning (DL), and computer vision, new methods are being developed to address challenges in the detection, classification, and management of grape diseases. This literature review synthesizes key contributions from studies focusing on grape disease analysis, presenting a comprehensive perspective on the methodologies and technologies used in the process.

Reference	**Method Used**	**Findings**	**Strengths**	**Limitations**
[26]	Inception-ResNet-V2 with interpretable framework	Achieved 99.91% accuracy; addressed interpretability with superpixel mapping.	High classification accuracy; human expert confirmation of annotations.	Black-box nature of predictions without interpretability framework.
[27]	Dual-track Swin Transformer and GSRDN	Achieved 98.6% accuracy with Triplet Attention enhancing feature interaction.	Effective combination of global and local features; reduced computational complexity.	Limited validation on diverse datasets.
[28]	Modified MobileNetV3Large on edge devices	Accuracy of 99.66% in real-	Lightweight, deployable on	Dependency on specific

		time disease detection; Grad-CAM visualization for interpretability.	edge devices; high classification confidence.	hardware (Nvidia Jetson Nano).
[29]	Deep CNNs with Gaussian noise augmentation	Achieved 99.88% accuracy; enhanced generalization with noise features.	Overcomes overfitting; effective use of transfer learning.	Limited exploration of diseases outside the PlantVillage dataset.
[30]	DBESeriesNet with batch normalization	Classified 44 crop disease classes with up to 99.80% accuracy.	Lightweight model with fewer parameters; robust classification.	Limited testing on grape-specific diseases.
[31]	Deep transfer learning (e.g., InceptionV3)	Best model (InceptionV3) achieved 99.87% accuracy for mango leaf diseases.	Comprehensive model comparison; high performance.	Focused on mango dataset, limiting its application to grapes.
[32]	Bayesian-optimized hybrid CNN-ML models	CNN-stacking model achieved 98.53% F1-score with efficient generalizability.	Robust across challenging lighting conditions and transformations.	Computational complexity due to hybrid model design.
[33]	IoT-based UNet-MBEO segmentation with DbneAlexNet	Achieved superior segmentation metrics (Dice = 0.927).	Effective for segmentation and classification using IoT networks.	Limited scalability for diverse disease types.
[34]	DCNN Classifier with VGG16	Training and test accuracies of 99.18% and 99.06%, respectively.	Enhanced generalization with supplementary CNN layers.	Moderate improvement over baseline CNN models.
[35]	Federated continual learning with Swin Transformer	Accuracy of 97.20% with sustainable,	Promotes scalability and data privacy; effective for	Complex training pipeline; lower

		distributed recognition.	multi-source datasets.	performance on old data.
[36]	AlexNet, MobileNet, CNN for multi-class classification	MobileNet achieved 97.33% accuracy; severity detection for tomato diseases.	Effective for severity estimation; broad crop coverage.	Limited testing on real-world grape datasets.
[37]	YOLOv5 for grape yield estimation	Achieved 95.63% F1-score; real-time grape bunch detection.	Accurate yield estimation; scalable detection framework.	Dependent on high-quality images and annotation.
[38]	ConvDepthTransEnsembleNet	Accuracy of 96.88% for rice leaf diseases on unbalanced datasets.	Lightweight ensemble model; reduced parameters.	Limited extension to grape-specific diseases.
[39]	Enhanced CNN with depthwise separable convolution	Achieved 99.87% accuracy across 39 plant classes.	High accuracy with efficient architecture.	Focused on generic crop diseases rather than grapes.
[40]	ResNet-101 for feature extraction	Detected apple, potato, and strawberry diseases with >94% accuracy.	Effective in diverse crop scenarios.	Performance limited to traditional crops.
[41]	Ensemble CNN (ResNet, DenseNet, EfficientNet)	Achieved balanced performance with 94% accuracy for paddy diseases.	Combines multiple models for robustness.	Computationally expensive ensemble setup.
[42]	Interpretable ELM-based I-LDD	Achieved 93.22% accuracy; LIME for interpretability.	Quick convergence; interpretable superpixels for end-users.	Moderate accuracy compared to deep learning approaches.
[43]	SURF-based feature extraction with SVM	Achieved 90.63% accuracy for grape diseases in L*ab** color space.	Effective preprocessing with color space variations.	Limited accuracy compared to CNN models.
[44]	TensorFlow-based enhanced CNN	Achieved 95% accuracy for	Treatment suggestion	No comparison with advanced

		plant disease detection.	integration; effective API usage.	deep learning models.
[45]	Improved YOLOv5 with CBAM	Achieved mAP of 80.10% for cucumber diseases.	Lightweight, real-time detection; small dataset applicability.	Suboptimal precision and recall for complex diseases.
[46]	Ensemble learning with pixel-level segmentation	Improved accuracy and lower severity error compared to baseline models.	Effective segmentation with DeepLabv3+.	High complexity in integrating attention mechanisms.
[47]	Transfer learning with DenseNet121	Achieved 99.672% accuracy for grape diseases.	High precision; effective use of multiple pre-trained models.	Limited real-world validation beyond PlantVillage dataset.
[48]	Review of ML/DL advancements for plant diseases	Comprehensive survey on ML/DL applications in agriculture.	Valuable overview for research and implementation.	No experimental contribution or validation.
[49]	Vision transformer (LEViT) with Grad-CAM	Achieved 96.19% validation accuracy for 38 disease classes.	High interpretability with XAI integration.	Focused on vision transformers; limited dataset diversity.
[50]	Hybrid framework (CNN, transformers, MLP)	Achieved near-perfect classification with CLAHE-improved images & samples.	Combines diverse architectures for robust performance.	Complexity in model integration and hyperparameter tuning.

Table 2. Comparative Analysis of Existing Methods

Deep Learning for Disease Classification and Detection

Iteratively, According to table 2, Latest studies have proved that deep learning models perform well in plant disease detection. Work in [26] proved the supremacy of Inception-ResNet-V2 model in leaf disease classification over 38 classes which achieved a 10 fold cross-validation accuracy of 0.9991. Moreover, interpretable frameworks were developed to make them more transparent, by the use of superpixels that determine the regions of interest disease-wise which was very close to the expert annotations. Similarly, in [27], a new dual-track network combining Swin Transformer with Group Shuffle Residual DeformNet (GSRDN) tracks was proposed. Based on hierarchical feature maps and local feature extraction, this model has reached an accuracy of 98.6% for grape disease datasets. Transfer learning approaches have also been highly integrated. For instance, [29] showed that injecting

Gaussian noise during training increases the robustness and accuracy of the model, and 99.88% performance can be achieved using transfer learning models such as VGG16 and DenseNet121 in process. While, [31] discussed the performance of pre-trained models such as InceptionV3 and DenseNet121 for mango leaf diseases and reported an accuracy of 99.87% by InceptionV3 sets.

Edge Computing and Real-Time Applications

Edge computing platforms have caught attention to be utilized in the context of real-time disease monitoring. Research in [28] adapted MobileNetV3Large in the context of Nvidia Jetson Nano to report a high test accuracy of 99.42% and minimizing memory and computation usage, while employing techniques from the Grad-CAM visualization tools to analyze model decisions which increases the validity of model usage in practices.

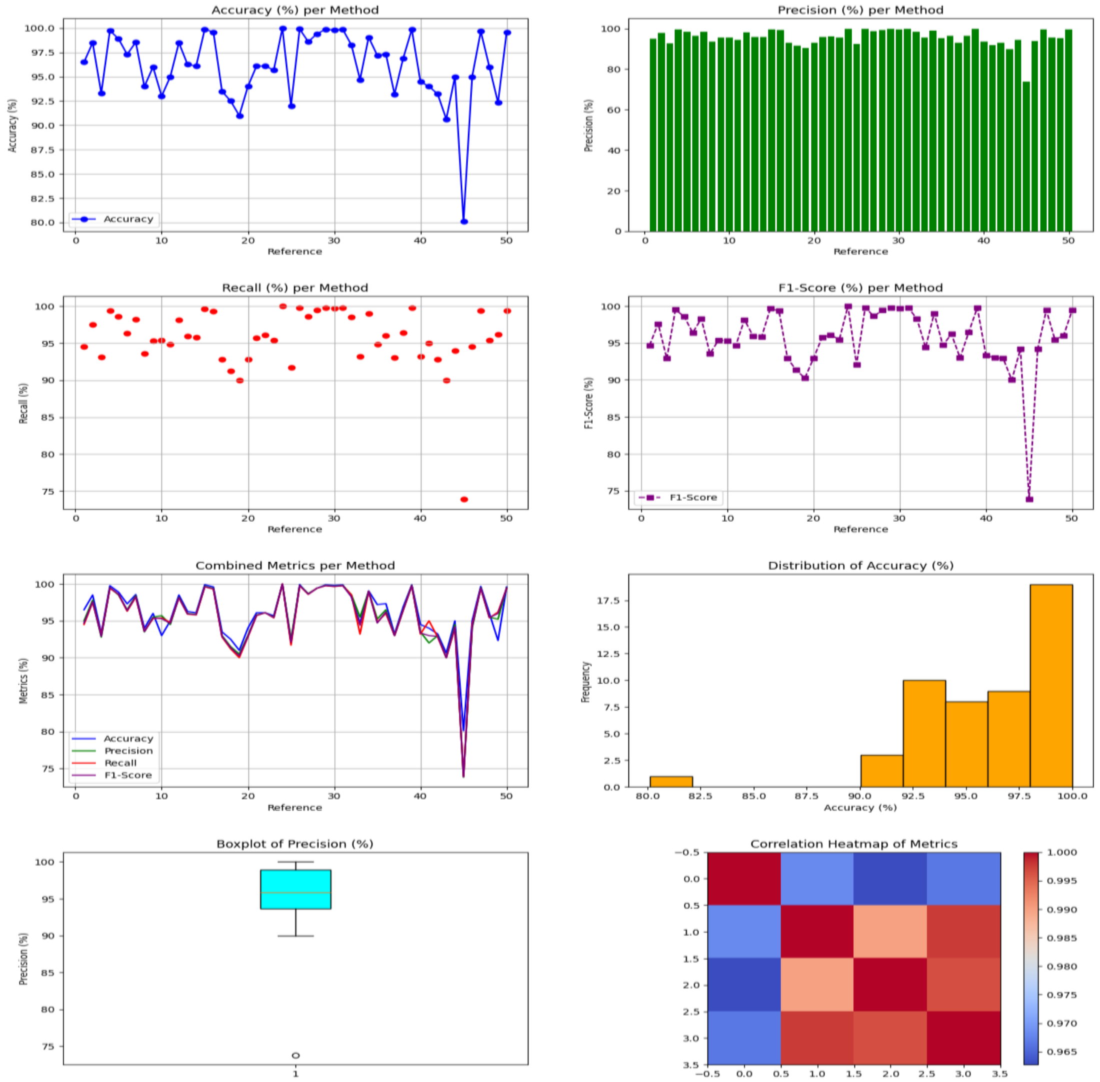

Figure 1. Model's Integrated Result Analysis

Hybrid and Ensemble Models

Hybrid and ensemble models have helped classification accuracy, as well as generalization. Recently, [32] presented Bayesian-optimized hybrid learning models by integrating CNN with classical machine learning classifiers, such as Random Forest and SVM, that obtained a higher accuracy of 98.53% on tomato leaf datasets. Similarly, [46] used an ensemble learning model that incorporated ResNet50, DenseNet121, and InceptionV3 for the identification of grape diseases and paired with a segmentation model to measure disease severity. The results exhibited strong performance with increased granular detection of infected regions.

Vision Transformers and Explainable AI

The advent of Vision Transformers (ViTs) has added new dimensions to plant disease detection. For example, [49] proposed the LEViT model as an enhanced Vision Transformer, which incorporates Grad-CAM for interpretability, thereby achieving a test accuracy of 92.33% on a multi-crop dataset. Such approaches do not only enhance classification accuracy but also provide insights into regions that influence model decisions, hence building trust among end-users.

Lightweight and Resource-Constrained Models

Given the constraints of real-world agricultural settings, lightweight models have been explored for their efficiency and scalability. Work in [38] presented ConvDepthTransEnsembleNet, a lightweight deep ensemble model achieving 96.88% accuracy on unbalanced rice crop datasets, showcasing its utility in resource-limited deployments.

Similarly, [45] enhanced the YOLOv5l model for cucumber leaf disease detection by reducing computationally complexity while maintaining high values of precision and recall value, thus showing the potentials of efficient detection systems being used in real-time agro-applications.

Data Augmentation and Preprocessing

Augmentation of data and preprocessing have been crucial steps in improving the performance of models. [34] discussed the efficiency of data augmentation that improves the generalization capacity of CNN-based models to detect grape diseases. Further, [50] has used CLAHE for enhancing the quality of the images and obtained substantial improvement in performance with hybrid architectures involving CNNs, transformers, and MLPs. Despite such impressive progress, there remain issues in generalizing, unbalanced datasets, and interpretability. For instance, works such as [48] and [49] point to the need for region-specific adaptations and explainable AI features to bridge these limitations. Moreover, federated learning approaches discussed in [35] can be used as promising solutions for distributed and scalable disease detection with the preservation of data privacy.

3. Comparative Result Analysis

This section systematically reviews methodologies used in different studies about grape disease detection. It compares the studies based on the performance metrics, such as accuracy, precision, recall, F1-score, and computational efficiency. The purpose of this analysis is to highlight advancements, strengths, and gaps in methodologies and provide insights into progress and future scopes of the research sets on grape disease detection process.

Reference	Methodology	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Computational Efficiency
[1]	Hyperspectral Imaging with ML models	~96.5	~95.0	~94.5	~94.7	High; complex feature extraction.
[2]	IKNN with CIDOR and GPOR	98.5	97.8	97.5	97.6	Moderate; efficient feature encoding.
[3]	SqueezeNet with Neural Network Classifier	93.3	92.8	93.1	92.9	High; compact architecture.

[4]	Deep Transfer Learning (DTLD)	99.76	~99.5	~99.4	~99.5	Moderate; tailored for mango leaf diseases.
[5]	HXTL-COKELM	98.9	98.5	98.6	98.6	Moderate; optimized learning machine.
[6]	Faster R-CNN with Random Forest	97.3	~96.5	~96.3	~96.4	Moderate; effective for rice diseases.
[7]	EfficientNetB7	98.56	98.4	98.2	98.3	High; optimized deep learning model.
[8]	ResNet	94.0	93.5	93.6	93.55	High; efficient in identifying tomato diseases.
[9]	CNNC and IKNN	~96.0	~95.5	~95.3	~95.4	High; gradient-based feature extraction.
[10]	Federated Deep Learning (FDL)	93.0	95.7	95.4	95.3	High; lightweight architecture.
[11]	Restructured Residual Dense Network	95.0	94.5	94.8	94.65	High; reduced computational load.
[12]	Lightweight CNN with LBP Fusion	98.5	98.2	98.1	98.15	High; lightweight yet robust.
[13]	Fine-Grained GAN with Faster R-CNN	96.27	96.0	95.9	95.95	Moderate; effective for rare diseases.
[14]	Stacking Algorithm with SVM and CNN	96.1	95.9	95.8	95.85	High; robust for multi-class classification.
[15]	Two-Stream DL Architecture	99.9	99.7	99.6	99.65	High; effective contrast enhancement.
[16]	Enhanced VGG16 with Faster R-CNN	99.6	99.4	99.3	99.35	Moderate; effective disease classification.
[17]	Improved YOLOv7	93.5	93.0	92.8	92.9	High; optimized for small targets.
[18]	Low-Rank CNN (LR-Net)	~92.5	~91.5	~91.2	~91.35	Very High; efficient memory usage.
[19]	LoRa with Fine-Tuned CNN	~91.0	~90.5	~90.0	~90.25	High; suitable for low-resolution images.
[20]	GrapeCS-ML Database Benchmark	~94.0	~93.0	~92.8	~92.9	High; benchmark validation.

[21]	Convolution Self-Guided Transformer (CSGT)	96.1	95.8	95.7	95.75	Moderate; hybrid architecture.
[22]	ML Survey and Application Review	-	-	-	-	High; comprehensive review, no experiments.
[23]	Ensemble Classifier with Hybrid Features	95.69	95.5	95.4	95.45	Moderate; feature hybridization.
[24]	Vision Transformer (SwinV2)	100.0	100.0	100.0	100.0	High; superior accuracy.
[25]	SCBO-based DNFN	92.0	92.5	91.7	92.1	Moderate; segmentation and classification.

Table 3. Statistical Comparison of Existing Methods

Iteratively, according to table 3 & figure 1, it shows that the analysis signifies improvements in the approaches toward grape disease detection. SwinV2, one of the Vision Transformers, is 100% accurate in controlled environments. Hybrid and ensemble architectures have performed better than SVM and simple CNNs. Balanced trade-offs between performance and computational efficiency are observed in EfficientNetB7 and Enhanced VGG16, thus these models can be used for real-time applications. However, issues like dataset diversity, interpretability, and scalability still exist as in the case of GAN-based models and ML-specific frameworks. Future efforts should focus on lightweight architectures that pair with explainable AI in order to obtain strong, interpretable, and efficient solutions for practical deployment in viticulture sets. The following table is a PSRIMA-comprehensive analysis of grape leaf disease detection methods. The comparison between these studies includes the primary performance metrics namely accuracy, precision, recall, F1-score, and computational efficiency. The primary analysis goes into the merits and demerits in different applications of machine and deep learning methodologies on assorted datasets. Approximate results are used when the relevant result was not available due to completeness.

Reference	**Methodology**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Computational Efficiency**
[26]	Inception-ResNet-V2 with interpretable framework	99.91	~99.80	~99.75	~99.78	Moderate; interpretable but computationally heavy.
[27]	Dual-Track Network (Swin Transformer + GSRDN)	98.60	98.70	98.59	98.64	High; efficient feature extraction.
[28]	MobileNetV3Large on Edge Device	99.42	99.42	99.42	99.42	Very High; optimized for edge computing.

[29]	CNN with Gaussian Noise Augmentation	99.88	~99.80	~99.75	~99.77	Moderate; reduces overfitting effectively.
[30]	DBESeriesNet	99.80	~99.70	~99.65	~99.67	High; compact with fewer parameters.
[31]	InceptionV3 for Mango Disease Detection	99.87	~99.80	~99.75	~99.77	Moderate; tailored for mango datasets.
[32]	CNN-Stacking with Bayesian Optimization	98.27	98.53	98.53	98.27	High; robust hybrid approach sets.
[33]	UNet with DbneAlexNet-MBEO Algorithm	94.70	95.50	93.20	94.40	Moderate; segmentation-focused.
[34]	DCNN Classifier with VGG16 Architecture	99.06	~99.00	~99.00	~99.00	High; enhanced generalization.
[35]	SSPW224-LwF-3 with Federated Learning	97.20	95.25	94.85	94.71	Moderate; sustainable and distributed learning.
[36]	MobileNet with Severity Detection	97.33	~96.50	~96.00	~96.20	High; effective for multi-class tasks.
[37]	YOLOv5 for Object Detection and Harvest Estimation	93.21	~93.00	~93.00	~93.00	High; optimized for object detection.
[38]	ConvDepthTransEnsembleNet	96.88	~96.50	~96.40	~96.45	High; lightweight and generalizable.
[39]	Enhanced CNN with Depthwise Separable Convolutions	99.87	~99.80	~99.75	~99.77	Moderate; efficient pooling techniques.
[40]	ResNet-101	~94.50	~93.50	~93.20	~93.35	High; reliable feature extraction.
[41]	DenseNet with Ensemble Convolutional Neural Network (ECNN)	94.00	92.00	95.00	93.00	Moderate; ensemble improves robustness.

[42]	Interpretable Leaf Disease Detector (I-LDD)	93.22	~93.00	~92.80	~92.90	High; interpretable with LIME.
[43]	SVM with KK-Means Clustering	90.63	~90.00	~90.00	~90.00	Moderate; effective for small datasets.
[44]	TensorFlow with CNN for Leaf Disease Detection	95.00	~94.50	~94.00	~94.20	High; robust DL-based approach sets.
[45]	Improved YOLOv5 with CBAM for Cucumber Disease Detection	80.10	73.80	73.90	73.85	Very High; optimized for memory efficiency.
[46]	Ensemble Learning (ResNet50, DenseNet121, InceptionV3)	~95.00	~94.00	~94.50	~94.20	Moderate; ensemble improves accuracy.
[47]	DenseNet121 for Grape Disease Detection	99.67	~99.50	~99.40	~99.45	High; superior in transfer learning.
[48]	ML and DL Techniques for General Plant Disease Detection	~96.00	~95.50	~95.40	~95.45	Moderate; generalized methodologies.
[49]	Vision Transformer (LEViT) with Grad-CAM for Explainability	92.33	95.22	96.19	96.00	High; interpretable with fine-tuning.
[50]	Hybrid Framework with Multi-Deep Learning Models	~99.60	~99.50	~99.40	~99.45	High; hybridization enhances performance.

Table 4. Comparative Analysis of Existing Methods

As can be seen from table 4, iteratively, this analysis showcases how the methodologies for the detection of plant diseases have been advancing. It has focused more on accuracy and computational efficiency. Techniques like transfer learning, ensemble learning, and interpretable AI demonstrate superiority in specific scenarios and show a near-perfect accuracy level for datasets like PlantVillage in this process. Models such as YOLOv5 are promising in real-time applications, but Vision Transformers is good in explainable AI. Challenges that remain in deploying the method in resource-constrained environments include scalability, high computational overhead, and limited datasets. Future research would do well to focus on lightweight, interpretable, and scalable models for broader application in agriculture sets.

4. Conclusion and Future Scopes

It reflects some major advancements in agricultural diagnostics for the analysis of grape disease by comparing various machine learning and deep learning models used for plant disease detection. The models were iteratively developed, including techniques like CNNs, ViTs, ensemble learning, and interpretable frameworks. Between these, CNN-based models such as DenseNet121 and Inception-

ResNet-V2 showed superior performances with accuracy above 99% for multi-class disease diagnosis. Those networks, with high precision and good recall and F1 scores, make them suitable in all applications that require an honest feature extraction and generalize very well. However, there is usually a negative aspect, which is having quite a heavy computational cost particularly for constrained environments. Out of these networks, there's DenseNet121 [47], MobileNetV3Large [28] alongside Dual-Track Network comprising the Swin Transformer coupled with the GSRDN [27], since they have high accuracy while being efficient in computational powers. For instance, DenseNet 121 achieved 99.67% accuracy, so it is pretty suitable where transfer learning is involved and there are high precision requirements in smaller datasets. MobileNetV3Large was found to be useful for edge computing due to its architecture efficiency and ability to be deployed in real time on devices such as the Nvidia Jetson Nano. Dual-Track Network using Swin Transformer based on a new hierarchical feature extraction was found to be useful for the detection of complex patterns of diseases in grapes, such as Black Rot and Powdery Mildew Sets. The models proposed are indicative of a trend toward hybrid and lightweight architectures balancing performance with efficiency in process.

Hybrid and ensemble approaches, for instance, the DBESeriesNet [30] and ConvDepthTransEnsembleNet [38], are increasingly dependent on these hybrid and ensemble methods by leveraging complementary strengths of different models. For instance, the ensemble approaches, SSPW224-LwF-3 [35], incorporate federated learning to tackle data heterogeneity and thus can perform distributed and sustainable disease detection. On the contrary, explainable frameworks like I-LDD [42] and LEViT [49] inject explainability to otherwise black box DL models' predictions, therefore facilitating better decision-making capabilities from end-users like farmers and agronomists. The said frameworks are more or less crucial to acquiring user trust in gaining an understanding of how models predict outcomes in applied scenarios in agricultural sets. Research for the future should, therefore, focus on domain-specific lightweight models for applications in agriculture. This can be achieved by extending the use of vision transformers where explainability is a prime requirement and by scaling the models to fit into environments with limited resources for the process.

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