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A Review on Deep Learning Approaches for Grape Leaf Disease Detection: Methods, Datasets and Challenges

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Abstract - Grapes are a valuable source of income for farmers; however, leaf diseases caused by bacteria, fungi, or viruses can significantly reduce their yield and quality. Recent advances in artificial intelligence and deep learning have enabled the automatic detection of such diseases, helping to prevent their spread and protect crop productivity. We discuss the application of deep learning methodologies for disease detection in grape leaves based on a literature survey. It compares and analyzes the performance of different deep learning approaches for leaf disease detection and classification, as well as various commonly applied data sources. The quality and variety of plant datasets are stressed by the study, and practical problems that might be encountered when implementing these models in actual agricultural conditions. This study provides insights and directions for future research on improving the automated detection of grape leaf diseases and sustainable crop management by overcoming the current limitations and challenges.

Keywords - Grape leaf disease, deep learning, CNN, Disease detection, Dataset,Challenges

1. INTRODUCTION

Grapes are among the most extensively cultivated fruit crops worldwide and have rich historical significance that spans several millennia. They are grown for multiple purposes, including fresh consumption and the production of value-added products, such as wine, raisins, and fruit juice. Grapes are used for food, wine, and other industrial uses, contributing significantly to horticulture and agriculture worldwide. The production and processing of grapes generate jobs and support primary agriculture and ancillary services such as food processing, packaging, storage, and transport. The grape industry is a major contributor to rural

employment, export income, and agricultural growth.

Over the past several years, there has been a substantial increase in the demand for grapes and grape-derived products owing to changes in consumer behavior, an increase in personal health awareness, and the increasing popularity of fruits with nutritional value.. This expanding market has further strengthened the economic importance of grape cultivation at both the national and global levels. To meet the increasing demand while addressing environmental and resource constraints, the grape industry has witnessed notable advancements in cultivation practices, including precision agriculture, improved irrigation techniques, and sustainable vineyard management. The adoption of modern technologies has enhanced productivity, optimized resource utilization, and supported sustainable farming practices. These developments are essential for maintaining the long-term competitiveness and resilience of the grape industry within the global agricultural landscape

2. RESEARCH BACKGROUND

Grapevine Cultivation is of substantial agricultural and economic importance; however, its productivity is severely threatened by foliar diseases such as downy mildew,black rot, leaf blight, and black measles. These diseases often exhibit visually similar symptoms in their early stages, making timely and accurate diagnosis difficult. Delayed or incorrect identification can lead to rapid disease spread, excessive pesticide use, and significant yield and quality losses. Therefore, early, accurate, and scalable disease detection remains a critical problem in vineyard management.

Traditional disease diagnosis primarily relies on manual visual inspection by experts. While effective in controlled settings, this approach is inherently time-consuming, labour-intensive ,and prone to subjectivity and human error, particularly under varying field conditions, such as changing illumination, background clutter, and disease severity. These limitations highlight the need for automated disease detection systems that can operate reliably in real-world vineyard environments and support consistent decision-making at scale.

Recent advances in image processing and machine learning have enabled the development of automated leaf disease

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detection techniques using high-resolution imagery. In particular, deep learning models, especially convolutional neural networks (CNN), have demonstrated strong capabilities in learning discriminative visual features directly from raw images, reducing dependence on handcrafted features. Transfer learning from pretrained architectures further improved performance, even when labelled grape leaf datasets were limited. These developments directly address the challenge of achieving a higher detection accuracy under diverse environmental conditions.

Beyond image-level classification, modern deep learning frameworks now include object detection and segmentation models that allow the localization of diseased regions and assessment of disease severity, which are essential for precision treatment and targeted intervention. Emerging transformer-based and hybrid CNN transformer architectures have further enhanced fine-grained disease recognition, although they introduce challenges related to data requirements and computational costs. Simultaneously, lightweight architectures and model optimization techniques are being explored to enable real-time deployment on mobile and edge devices, aligning with the objective of practical field-level adoption.

Despite these advancements, several challenges remain unresolved, including dataset imbalance, domain shift across vineyards and imaging conditions, limited model interpretability, and constraints on real-time deployment. Addressing these issues is essential for developing robust, trustworthy, and scalable grape leaf disease detection systems. Consequently, this study was motivated by the need to systematically analyze existing deep learning methods, datasets, and evaluation strategies, identify key research gaps, and outline future directions that can guide the development of reliable and deployable solutions for precision viticulture.

3. OVERVIEW OF GRAPE LEAF DISEASES

Despite the economic importance of the grape sector, it continues to face difficulties owing to a number of diseases that can cause significant crop losses by affecting grape leaves. These diseases, including downy mildew, powdery mildew, leaf blight, esca, and black rot, can have a major impact on the health of the vines, quality of the fruit, and total yield.

Some common diseases, their symptoms, and impact are as follows:

Diseases	Symptoms	Impact
Downy mildew	Yellow “oil spots” on upper surface; white downy growth on underside; browning & leaf drop	Reduce sugar accumulation in berries, and hinder ripening.
Powdery mildew	White/gray powdery coating on both sides; leaves distorted, brittle	Reduce yield and wine quality, and predispose grapes to secondary infections.
leaf blight	Small reddish-brown lesions enlarge into irregular dark patches; shot-hole appearance	Reduces photosynthetic activity, weakens vines and berries, lowering yield.
Esca	“Tiger-stripe” pattern: interveinal yellow/red-brown necrosis, veins remain green	Reduces productivity
black rot	Tiny reddish-brown spots expand to tan centers with dark borders; black pycnidia present	Reduces leaf area, impairs fruit development and lowers overall yield.

4. DEEP LEARNING APPROACHES FOR GRAPE LEAF DISEASE DETECTION

Deep learning (DL) is a subset of machine learning (ML) that uses multi-layered artificial intelligence networks to identify and represent difficult patterns within data. It is widely used in

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areas such as object recognition, object detection, speech analysis, and text-to-speech conversion.[3]

Deep learning methods for leaf disease detection can generally be grouped into four main categories: basic CNN models, transfer learning approaches, hybrid models, and ensemble methods

Category	Method	Dataset Range	Models	Use in Leaf Disease Detection
Basic CNN	Custom CNN from scratch	1k – 10k images	LeNet, small 5–6 layer CNNs	Early studies, baseline models
Transfer Learning	Pre-trained CNNs (fine-tuned)	2k – 50k+ images	AlexNet, VGG16, ResNet, DenseNet, InceptionV3, Xception, MobileNet, EfficientNet, ViT	Most popular (2017–2025), high accuracy
Hybrid Models	CNN + other techniques	3k – 20k images	CNN+SVM, CNN+RF, CNN+RNN, CNN+Transformer, CNN+Segmentation	Improves generalization, robustness
Ensemble Methods	Combination of multiple CNNs	5k – 50k+ images	VGG+Xception, ResNet+DenseNet, Majority Voting, Feature Fusion	Achieves best performance on grape/banana leaf datasets

5. DATASETS USED IN GRAPE LEAF DISEASE DETECTION

The success of deep learning methods in detecting grape leaf diseases is heavily reliant on dataset quality and availability. A well-structured dataset guarantees that models learn to generalize effectively across multiple disease situations, although the dataset size, class distribution, and image quality constraints can limit performance.

The PlantVillage dataset on Kaggle is the most popular resource for grape leaf disease diagnosis, with thousands of tagged photos of healthy and diseased leaves, including Black Rot, Esca, and Leaf Blight. Its availability and well-structured labels make it suitable for training and benchmarking; however, its controlled surroundings limit its practical application. To address this, researchers have collected unique field datasets that are smaller yet still capture natural fluctuations in lighting, leaf orientation, and complicated vineyard landscapes. To guarantee appropriate illness labelling, these field pictures are generally annotated by experts.

The properties of grape leaf databases vary among investigations. Dataset sizes range from tiny collections of approximately 1,000 photos to medium-sized sets of 5,000-10,000 images, with larger datasets potentially exceeding 20,000 samples when numerous diseases are included. The number of classes also varies, with some datasets focused on binary categorization (healthy vs. diseased) and others including to 3-5 disease categories.

To improve dataset quality, researchers frequently utilize picture pre-processing techniques such as background removal, intensity normalization, and bilateral filtering to minimize noise and emphasize disease features. Furthermore, data augmentation is often used to artificially enlarge datasets and improve the resilience of deep learning models. This involves applying changes, such as rotation, flipping, zooming, and adding noise.

6. COMPARATIVE ANALYSIS OF DEEP LEARNING MODELS FOR GRAPE LEAF DISEASE DETECTION:

Ref	Dataset	Model	Accuracy	Diseases Covered
[4]	PlantVillage subset (1619 images)	UnitedModel (InceptionV3 + ResNet50)	**98.57%**	Black rot, Esca, Isariopsis, Healthy
[5]	Real Vineyards (62,286 images)	Faster DR-IACNN	**99.47%**	Black rot, Black measles, Leaf blight, Mites
[6]	Field + public datasets	DICNN (Improved CNN)	**97.22%**	Brown spot, Mites, Black rot,

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				Downy mildew, Leaf blight, Healthy
[7]	Kaggle (1000 images)	Keras-based CNN framework	**91.37%**	Black rot, Esca, Leaf blight, Healthy
[8]	Kaggle (900 images)	AlexNet	**95.65%**	Black rot, Black measles, Isariopsis, Healthy, Powdery mildew, Downy mildew, Rust, Bacterial spot
[9]	PlantVillage grape (222 images)	AlexNet (Transfer Learning)	**99.03%**	Black rot, Esca, Leaf blight, Isariopsis, Healthy
[10]	Kaggle + PlantVillage (4040 images)	Ensemble (VGG16, InceptionV3, Xception, ResNet50 + RF)	**95.34%**	Black rot, Esca, Leaf blight, Healthy
[11]	Kaggle (1200 images)	MHDI-DETR	**96.3%**	Black rot, Black measles (Esca)
[12]	PlantVillage grape (4062 images)	InceptionV3 + Logistic Regression	**99.4% (0.994)**	Black rot, Black measles, Leaf blight, Mites, Anthracnose, Brown spot, Downy mildew, Healthy, Isariopsis, Nutrient deficiency
[13]	Roboflow (1598 images)	YOLOv5	Accuracy not reported	Black measles, Black rot, Blight fungus, Healthy
[14]	Aggregated public datasets (~14.6k images)	SwinGNet (Swin Transformer + GoogLeNet)	**99.8%**	Black rot, Black measles, Leaf blight, Mites
[15]	Kaggle (800 images)	DenseNet201	**96.67%**	Black measles, Black rot, Isariopsis leaf spot, Healthy

7. CHALLENGES

Despite tremendous advancements in the detection of grape leaf diseases, several obstacles prevent the widespread use of current techniques. Data availability and quality are major problems. Grape leaf disease datasets frequently suffer from small sample sizes and class imbalances, where certain disease categories are underrepresented. Deep learning models typically require large and balanced datasets. The reliability of the predictions and model learning is adversely affected by this disparity.

The visual appearance of disease symptoms can vary significantly between stages of infection, which presents another challenge. Models have difficulty accurately capturing consistent disease patterns because of this variation. The detection process is made more difficult by environmental variability because real vineyard conditions include a variety of lighting conditions, complicated backgrounds, and different leaf orientations, none of which are sufficiently represented in controlled datasets.

Additionally, many deep learning models that perform well have high computational complexity. However, these models frequently lack the scalability, low latency, and efficiency required for real-time deployment on mobile or edge devices used in agricultural settings. Finally, similar color and texture patterns can result in misclassification, especially in conventional machine learning techniques, making overlapping visual symptoms among various grape leaf diseases a major challenge.

8. FUTURE SCOPE

Future studies on grape leaf disease detection should concentrate on creating scalable, reliable solutions that function well in actual vineyard settings. The development of sizable, region-specific, and thoroughly annotated datasets that capture variations in disease stages, grape varieties, and environmental conditions is one crucial direction. Model generalization can be further enhanced by addressing class imbalance through sophisticated data augmentation techniques and the creation of synthetic data.

The development of lightweight and optimized deep learning architectures that strike a balance between computational efficiency and accuracy, allowing for real-time deployment on smartphones and edge devices, is another exciting area. In addition, hybrid frameworks that integrate deep learning and machine learning methods could improve robustness and lessen reliance on big datasets. Additionally, by offering visual explanations of model predictions, explainable artificial intelligence (XAI) techniques can enhance transparency and trust. When taken as a whole, these approaches can promote early disease detection, lower crop losses, and make automated grape leaf disease detection systems more widely used.

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9. CONCLUSION:

Future research should also investigate real-time processing capabilities to facilities immediate decision- making under field conditions. Emphasizing explainability and transparency in model predictions is essential to gain the trust of end users such as farmers and agronomists. Finally establishing open access platforms for sharing models and datasets can adoptive collaboration and accelerate innovation in this domain, and integrating user feedback mechanisms will further enhance model adaptability and relevance in practical applications. Additionally, addressing data privacy and security concerns is vital for ensuring ethical deployment. Continued investment in interdisciplinary training programs will equip researchers with the necessary skills to drive innovation in this rapidly evolving field. Collaborative efforts between academia, industry and representatives are crucial for establishing standardized protocols and best practices. Emphasizing transparency in data collection and model development can help mitigate bias and improve overall reliability. Furthermore leveraging advances in Explainable AI (XAI) will empower users to make informed decisions based on model outputs.

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