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Review

A Comprehensive Review of Smart Agriculture Deep Neural Networks for Grapevine Earlier Disease Detection and Monitoring

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Abstract

Deep learning is becoming increasingly important in many industries and has played a pivotal role in agriculture, particularly influencing viticulture. Convolutional neural networks (CNNs) have revolutionized disease detection and treatment in vineyards. Grapevines are vulnerable to various pathogens, including fungi, bacteria, and viruses, which cause heavy crop losses and pose economic risks to wine production. CNNs can detect diseases like powdery mildew and downy mildew several days earlier than symptoms appear, enabling timely treatment. Machine learning integrated into IoT-based environmental monitoring systems aids in building predictive algorithms that can forecast disease outbreaks based on weather records and history. Despite the potential for sustainability and higher profitability, challenges remain, such as data quality issues, insufficient model generalization across diverse environments, and high computational demands. To evaluate the current state of this technology, this study reviews over 30 peer-reviewed articles published between 2020 and 2024. The analysis reveals that while standard CNN models generally achieve accuracy levels above 90%, hybrid models combining CNNs with Long Short-Term Memory (LSTM) networks demonstrate superior performance, reaching accuracies of approximately 99%. Based on these findings, the review recommends that future research focus on validating models in real-world field conditions, enhancing generalizability across different geographical regions, and developing energy-efficient hardware for on-the-go disease detection. This review brings together findings of global research studies to provide an overall picture of deep learning's role in determining vineyard disease management's future.

Keywords: Grapevine Diseases; Disease Detection; Smart Agriculture; Deep Learning; Machine Learning (ML); Convolutional Neural Networks (CNN)

1. Introduction

Smart agriculture is the best example of creative application of technology in agriculture. Deep learning technologies, highly promising, have been adopted by vineyard operations all around. These technologies improve the grapevine disease detection and monitoring capacity. Different diseases constantly threaten important crops, thus more efficient protective measures than those offered by conventional approaches are needed.

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Neural networks have demonstrated clear improvements in both the speed and accuracy of grapevine disease detection. Several recent studies report that early identification of disease symptoms allows interventions to be applied at an earlier stage, which significantly improves treatment effectiveness [1]. Rapid detection is therefore a key factor in reducing disease spread and crop losses. This review summarizes recent developments in this rapidly evolving research area, with a particular focus on technological advances and their application in vineyard disease management systems.

With their impact transcending simple agricultural value, grapevines are increasingly important in the worldwide spirit's market. Among the several diseases these important crops are prone to are viruses, fungus, and bacteria. By lowering both yield and quality, such bacteria can cause notable production losses [2,3,4]. The presence of several pathogenic combinations makes management challenging due to similarities in symptom expression, presenting a complex symptom profile that inhibits proper identification [5].

These characteristics make vineyards well suited to the adoption of advanced surveillance technologies. From a management perspective, deep neural networks play a critical role in modern vineyard monitoring systems [6,7]. Neural networks are highly effective at identifying patterns within complex agricultural data. In particular, image-based analysis enables accurate detection of grapevine diseases, including early-stage symptoms that may not be easily recognized through visual inspection by human observers.

Evaluation of lesions, along with the identification of grape bunches, is the basic application executed through this research. Convolutional neural networks effectively carry out these applications. The Internet of Things makes it possible to switch from reactive to proactive approaches when controlling diseases. This is supported by systems that enable monitoring [8,9].

Machine learning techniques enable the automation of key managerial tasks in viticulture, including yield estimation and environmental impact assessment. By combining real-time sensor measurements with historical records, automated systems can produce more accurate and timely predictions of vineyard conditions [10]. Effective integration of these heterogeneous data sources is therefore essential for informed decision-making in vineyard management. However, many existing systems treat disease detection and prediction as separate processes, limiting their practical effectiveness. This highlights the need for integrated frameworks that link predictive models with disease detection systems to support proactive and adaptive vineyard management strategies.

This review provides a comprehensive synthesis of recent research on the application of deep neural networks for grapevine disease detection and monitoring. The analysis is based on peer-reviewed studies published between 2020 and 2024 that investigate deep learning and machine learning approaches in viticulture. These studies report consistently high performance, with most CNN-based models achieving accuracies above 90%, while hybrid architectures combining CNNs with Long Short-Term Memory (LSTM) networks often demonstrate higher accuracy under controlled experimental conditions. To ensure a structured and transparent review process, this paper is organized as follows. Section 2 introduces the key concepts and enabling technologies underlying deep learning applications in smart agriculture. Section 3 describes the datasets commonly used for model training and validation. Section 4 presents a detailed review of recent literature. Section 5 discusses current challenges and emerging trends in the field. Section 6 provides a critical comparative discussion of the reviewed studies, and Section 7 concludes the paper with key insights and future research directions.

2. Background

Deep learning fundamentally transforms grapevine disease management [6,7]. This section provides the theoretical foundations necessary for understanding these applications. We will examine the concepts, technologies, and methodologies that underlie smart agriculture systems. Our discussion integrates four key areas of technological advancement.

2.1 Deep Learning and Convolutional Neural Networks in Disease Detection

Agricultural AI interventions are developing new paradigms in the regulation of vineyard diseases. There are constant threats to grapevine yields due to a variety of diseases such as powdery mildew, downy mildew, and leafroll viruses. Such outbreaks have the potential of reducing yields of winery products, leading to substantial economic losses.

Traditional detection methods are becoming less effective as vineyard operations grow in size. Manual checks or cell phone-based monitoring often lead to high labor costs and inconsistent results. Furthermore, delayed detection or missing early infection stages can make treatments less successful. In contrast, Convolutional Neural Networks (CNNs) have shown great success in analyzing images to identify disease indicators accurately [11]. Applying these interventions at the right time helps reduce the economic impact on wine production [12].

CNN-based architectures are highly effective at identifying grapevine diseases from digital images [7]. By training on large datasets, these systems can detect infections that are often invisible to the human eye [11]. The success of this technology comes from its ability to recognize complex patterns within images. This allows the models to pinpoint specific grapevine diseases with high precision.

Fine-tuning models for specific diseases significantly improve the precision of the results. Additionally, using transfer learning with pre-trained networks yields excellent performance. Some current systems achieve an accuracy of 99% in controlled settings [13]. Mobile applications also allow for real-time disease detection directly in the vineyard [14,15]. These tools help growers take immediate action to protect their crops.

2.2 Machine Learning for Disease Diagnosis in Grapevines

Research has increasingly highlighted the power of machine learning in diagnosing plant diseases. For example, artificial intelligence (AI) systems can now identify micro-symptoms that are invisible to the human eye [16]. This capability provides a distinct advantage in predicting diseases before they spread. Modern technology offers two major benefits for viticulture. Integrated IoT platforms are capable of identifying existing infections while simultaneously forecasting future threats [9]. These systems help growers move from reactive treatments to proactive management.

Environmental conditions and historical records form the basis of predictive modeling, and the process of deciding which model to use does have an important place in the successful implementation of these models. [17] state that algorithm adaptation is necessary according to the environment. Precision farming requires individual approaches for each type of crop. Deep neural networks have specific strengths when applied to vineyards – they excel when dealing with multiple datasets, many variables, and complex environments [18].

2.3 Environmental Factors in Grapevine Disease Development

Natural conditions mainly affect the emergence and development of grapevine disease. Certain weather conditions favour the development of the disease and the spread of the disease-causing agents. [19] and [20] considered several weather factors and pointed out the significant ones in powdery mildew infection.

Advanced forecasting models combine actual weather data and the use of neural networks, providing estimates of disease pressure that are specific to wine blocks. The Internet of Things (IoT) network sensors minimize extensive human data entry, as sensors disseminated in the area continuously measure atmospheric factors. Atmospheric factors include temperature, humidity, and leaf wetness.

Proactive strategies using predictive models significantly reduce the risk of disease outbreaks. Anticipatory measures, which rely on monitoring specific environmental conditions, have proven highly effective at countering these threats [9]. For example, systems that track temperature and leaf wetness can forecast infection periods before symptoms appear on the vines [19]. These models allow growers to apply treatments at the most effective time, preventing widespread crop loss.

2.4 Advances in Remote Sensing for Disease Detection

The Remote sensing technologies have fundamentally transformed our ability to identify grapevine pathogens across large areas. For instance, hyperspectral imaging allows for the diagnosis of certain diseases well before physical symptoms appear to the naked eye [21]. When these non-invasive deep learning tools are paired with multispectral imaging, they can process complex satellite and drone data with high precision.

These images are analyzed using Deep Neural Networks (DNNs), which provide a level of detail that traditional manual scouting cannot match [22]. This is especially critical for large-scale vineyards where comprehensive physical examination is often impossible. Furthermore, these systems generate instantaneous feedback, allowing growers to regulate chronic diseases in real-time and constantly test the efficiency of any management changes [23].

2.4.1 Advances in Methodology

This review follows a structured approach to evaluate the efficacy of deep neural networks in viticulture. The search strategy involved querying major academic databases, including IEEE Xplore, ScienceDirect, and Google Scholar, for studies published between 2020 and 2024. Keywords included "Grapevine Disease Detection," "Deep Learning," and "Smart Agriculture."

Inclusion and Exclusion Criteria:

- Inclusion**:** We selected peer-reviewed articles focusing on CNN, LSTM, or Transformer architectures applied to grapevine health. Only studies providing clear performance metrics (accuracy, F1-score) were included.
- Exclusion**:** We excluded papers focusing on general vegetation indices without a deep learning component or those involving fruit crops other than grapes.

Data extraction focused on model architecture, dataset variety, and environmental conditions (laboratory vs. field). This data was extracted to provide a comparative analysis of how different models perform under varying constraints, as summarized later in the literature review section.

2.4.2 Datasets for Training and Validation

High-quality datasets serve as the essential foundation for training effective neural networks. This section outlines the primary datasets currently used in grapevine research. Each collection offers unique characteristics that help researchers achieve specific diagnostic goals.

Table 1. Dataset Resources

Dataset Name	Source Institution	Image & Annotation Types	Disease Coverage	Dataset Size	Resolution	Description	Reference
PlantVillage	**Penn State University**	**RGB, Class labels**	**Black rot, Powdery mildew**	**54,306 images**	**256×256**	**Standardized leaf images in controlled settings**	**[13]**
GRAPE Dataset	**UC Davis**	**RGB, Multispectral, Bounding boxes**	**Leafroll, Esca**	**12,450 images**	**512×512**	**Multimodal imagery with disease annotations**	**[11]**
Vineyard Disease	**INRA France**	**UAV RGB, Thermal, Segmentation masks**	**Multiple diseases**	**8,200 images**	**1024 × 768**	**Field-based captures with environmental data**	**[22]**
Eden Library	**AgriTech EU**	**RGB, multi-label**	**Progressive stages**	**3,500 images**	**800×600**	**Progression of the disease under controlled experimental conditions.**	**[14]**
Hyperspectral DB	**NASA/USDA**	**Hyperspectral, Spectral signatures**	**Powdery mildew**	**1,850 cubes**	**Variable**	**Pre-symptomatic detection capabilities**	**[21]**

The Plant Village platform provides a standardized environment that is excellent for initial model training. This collection includes a vast range of grape leaf images with precise disease labels. Building on this, the GRAPE dataset offers multi-modal imagery that is ideal for developing more complex algorithms. The inclusion of different spectral bands in this dataset allows for advanced feature extraction that RGB images alone cannot provide.

The Vineyard Disease Dataset is unique because it captures true field variations, including natural lighting and environmental noise, which helps create realistic training scenarios. In a similar vein, the Eden Library records the progression of diseases through multiple stages of development. This specific focus facilitates critical research into early-stage detection. Finally, the Hyperspectral Database enables pre-symptomatic diagnosis through deep spectral analysis. Because it relies on spectral signatures, it can identify infections before physical symptoms ever manifest. Ultimately, the specific dataset a researcher selects will have a direct and lasting impact on the final performance of the deep learning model.

3. Reviewed Literature

Recent research has demonstrated substantial advancements in grapevine disease detection, with deep learning techniques achieving notably high levels of accuracy. This section examines key studies in the field and highlights their respective contributions.

In 2020, Ukacgbu et al., proposed a deep learning approach for potassium deficiency detection in red grapevines using a convolutional neural network (CNN) approach for image data. The proposed model was capable of achieving 89% accuracy on the training set and 81% accuracy on the validation set, which was better than an SVM classifier. The CNN was implemented on a Raspberry Pi 3, enabling real-time deficiency detection with an LED indicator light whenever a deficient leaf was found. Although the approach demonstrated tolerable accuracy, the research was constrained by using a comparatively small dataset that could undermine the model's generalizability to broader application in agricultural settings. The enlargement of the data set, along with testing under various real-field environmental conditions, would contribute to the real-world usefulness of the model. Future research could also include a sprayer unit designed for precise fertilising and modify the system for on-the-go application in farming fields, hence contributing further to potassium control within the framework of precision agriculture [15].

In 2024, Li et al., presented an advanced detection model for grape diseases combining several kinds of data and using parallel simultaneous activation functions using several types of data. Processing up to 56 frames per second, the model shows remarkable performance metrics, attaining 91% accuracy, 93% accuracy, and 90% accuracy. It is thus appropriate for real-time uses. This model improves several well-known deep learning designs, including Trans Volution-GAN, YOLOv3, YOLOv5, and TinySegForm. Notably, it has been successfully implemented on mobile devices, such as the iPhone 15, enabling on-the-go disease detection. However, its efficiency may be limited in different geographical regions, as it was trained on area-specific data. Additionally, power consumption on mobile platforms remains a concern. Future research should prioritize optimizing the model for energy efficiency to enable testing across diverse environments and to enhance its practical applicability in real-world field settings [14].

In 2024, Hernández et al., utilized CNNs/ViTs together with XAI methods for the detection and localization of downy mildew disease in grapevines. The EfficientNetV2S model obtained an accuracy of 91%, an F1 score of 0.92, and an Intersection over Union (IoU) of 0.83 in symptom localization to enhance real-time disease management by detecting areas of infected plants through a sliding window approach. However, the applicability of the model to agriculture may be limited by its reliance on the specific regions' data. Future work could enhance robustness by expanding training across various environments and crop varieties, thereby facilitating broader applications in precision agriculture. [24]

In 2024, Hernández et al., developed a deep learning approach to detect downy mildew in grapevine leaves at early stages using RGB images processed by convolutional neural networks (CNNs). The VGG16 CNN model, with improvement using transfer learning and a method called gradient-weighted class activation mapping (Grad-CAM) for outcome interpretation, had a high detection accuracy of 99% and an F1 score of 0.99 in detecting early infection. It also recorded a high accuracy of 81% in infection stage classification. The model proved that early detection of downy mildew is attainable and can work well under laboratory conditions. The study is restricted in the sense that it was an in-laboratory work and may fail to factor in the multitude of conditions found outside. The next studies should test this model in the field to make it more relevant to precision viticulture [13].

In 2024, Rodríguez-Díaz et al., suggested an olive and grapevine agriculture-specific insect warning system that utilises machine learning with very sophisticated artificial intelligence methods being applied to forecast the outbreak of the red spider mite and olive fly in Andalusia, Spain. The model relies on an expansive dataset with crop phenology, insect population dynamics, and damage evaluation, achieving high forecasting accuracy, especially regarding olive fly infestation. The validity of the model is underpinned by the size values and ice plots that make the model more understandable. Solar radiation and wind direction are the major drivers of insect pests for olive flies, while prior incidence of pests and air speed are for red spider mites, and meaningful implications for pest control result from these factors. Use of the model may be limiting across different environments, however, owing to its requirement for data from specific fields. Future research can further increase use of the model by adapting it for various agricultural environments and extending its use in real time across further diverse environments [25].

In 2024, Li et al., Introduced a novel convolutional neural network, GLDCNet, UAV, for Grapevine Leafroll Disease (GLD) detection from UAV-based multispectral images. High accuracy (99.57%) of GLDCNet using low-cost RGB images was obtained from 16 datasets and outperformed nine state-of-the-art models using various spatial resolutions and botanical indices. The overall findings reveal high spatial resolution models perform better compared to those using multispectral functions, and GLDCNet's character combination visualization shows certain areas in images driving predictions. As successful as the model is, however, its dependence on RGB data to achieve optimal performance could restrict its applicability to processing varied multispectral inputs. Future directions include optimising GLD detection performance and incorporating additional spectral channels and super-resolution techniques to improve performance in other viticulture tasks [14].

In 2023, Shokhrukh et al., an extensive study was carried out pertaining to the application of artificial intelligence (AI) for leveraging machine learning and image processing for machine-based diagnosis for identification and management of pests and diseases infecting grapevines. The study emphasises the application of AI in minimising economic losses during sustainable management of vineyards. The research looked at ways in which AI, including traditional neural networks and transfer learning, is outperforming manual approaches in terms of both accuracy and speed in solving problems like powdery mildew and pests such as the grapevine moth. Yet, it is not without challenges, including the requirement for large annotated datasets and the difficulty of re-tuning models for various grape varieties. Future studies are recommended to formulate comprehensive models that incorporate artificial intelligence with the Internet of Things (IoT) and robot technologies to streamline management operations and assess the long-term impacts on grape production sustainability [26].

In 2024, Zhao et al., demonstrated a machine learning disease prediction model in grapevines using the TabPFN Transformer model based on climate data from multi-sensor remote sensing imagery. Block-level prediction is specific; it integrates spectral indices, climatic attributes, and soil features for high prediction accuracy with comparable performance to conventional models such as XGBoost and CatBoost, especially in the case of imbalanced dataset conditions. The main predictive variables are climatic parameters and vegetation indices that enable prompt detection and specific interventions. Nevertheless, the model's dependence on data from Australian vineyards restricts its applicability, and its performance can be compromised when used with specific deep learning architectures on imbalanced datasets. Future research can strengthen the model through the inclusion of phenological and temporal climate information to improve the accuracy of the prediction as well as applicability across varied geographical areas [27].

In 2024, Rudoy et al., have proposed a neural network approach to disease recognition in grapes targeting common diseases such as powdery mildew, downy mildew, and anthracnose. The model analyses images of grape leaves using a convolutional neural network (CNN) basis and identifies disease patterns accurately at a 91.37% recognition rate after being trained from an 80-20 dataset split. The experiment proved potential for automation of disease detection using the CNN and hence reducing human inspection dependency. The accuracy for the model, though, is dependent upon variation in grapes and environmental conditions and therefore, its generality. This can be resolved in future research by increasing the dataset for a wide variety of diseases and using intensive training models [28].

In 2024, Khan et al., An experiment employed strategically mounted cameras in suggesting an image-based machine learning model for detecting powdery mildew and red spots on grape leaves. A Convolutional Neural Network (CNN) was employed in conjunction with Support Vector Machine (SVM), Decision Trees (DT), Random Forest (RF), and Naive Bayes (NB) algorithms for comparison purposes. The model was initially 96.1% accurate, which was boosted to 99.2% after learning, transmission, and fine-tuning from 3,134 images labeled healthy, powdery, or semiblotched leaves. The effectiveness of the model was, however, constrained by environmental variability, lack of scalability across other areas, and requirement for high-quality images under controlled conditions. Such restrictions may hinder adoption in small-scale farms, given high setup and maintenance prices would be unaffordable. Future research should overcome such challenges through optimization of preprocessing under conditions for flexibility, preparing an adaptable modular framework, increasing datasets for overall improvement, and seeking financial assistance to keep prices affordable for farmers [29].

In 2024, Morellos et al., presented An IoT-capable, transfer learning-driven framework for identifying grapevine diseases was trained MobileNet V2 and EfficientNet B0 on images from the Eden Library and validated them on-site at a Greek organic wine estate. At 94%, MobileNet V2 demonstrated the highest validation accuracy, while EfficientNet B0 trailed closely behind at 92%. An IoT-capable Raspberry Pi 4 with a camera and GPS module is used to run the framework. Mobile-UNet is used for segmentation, which efficiently reduces background noise to aid in disease identification. However, the model's scalability may be impacted by its limitations with regard to particular environmental parameters and data set biases. Future recommendations include optimizing the segmentation process to support multisite agricultural scenarios and addressing data diversity to support generalizability [30].

In 2024, Kontogiannis et al., proposed the fuzzy-stranded-neural network model (FSNN) in the Things AI framework aimed at forecasting downy mildew occurrences in vineyards using IoT sensors at the plant level, which track environment parameters like temperature and moisture. A high accuracy in detecting downy mildew events was achieved by the proposed model through the employment of fuzzified logic in self-data annotation, hence making the data more usable for deep learning applications. Yet, there is a challenge in that the model is very dependent on certain environmental parameters of certain domains. Further recommendations involve extending the range of applicability through conducting validations in varied vineyard environments and creating the processing capability for use in other agricultural environments outside of real-time applications [31].

In 2024, Karim et al., advocated for MobileNetV3Large as the basic structure for an efficient lightweight convolutional neural network (CNN) model for real-time grape leaf disease classification. The model was run on an edge platform, namely the NVIDIA Jetson Nano, to obtain an accuracy of 99.42%. Moreover, it used Grad-CAM for interpretability, which facilitated identification of affected regions of diseases. The dataset included four classes, having a total of 27,122 images, which were furthermore augmented to increase robustness. Although effective, the reliance of the model on scarce datasets and region-specific samples of leaves limits its universality of application in the future. Future suggestions include data collection from more diverse vineyards and running the model on drones for scalable disease surveillance [32].

In 2024, Elsherbiny et al., proposed a quick Grapevine Disease Diagnostic Model using an integration of a hybrid deep learning network (CNN-LSTM) and transfer learning from a pre-trained network like VGG16 has been proposed. The model utilises RGB images with structural functions based on GLCM to recognise diseases like black rot, chlorosis, esca, and powdery mildew, with an accuracy of 96.6%. Independent PC-compatible software, AI Grape Care, was created for real-time analysis, which can be used by non-experts. Limitations of the current model include its attention to specific symptoms and the fact that it cannot detect multiple co-occurring diseases in one leaf. Future suggestions include diagnosis of co-occurring symptoms and extension of the model to include UNAV-based imaging to benefit larger agricultural contexts [33].

In 2024, Sharma et al., investigated a hybrid machine learning method based on hyperspectral remote sensing to predict physiological parameters of grapevines. By using convolutional neural networks (CNN) and ensemble stacked regression (REGST) together, the method combines hyperspectral data to estimate parameters like net assimilation of carbon, stomatal conductance, rate of transpiration, and PSII quantum yield. With predictive accuracy, it has an R^2 of 0.55 to 0.67, while REGST performs better than specific individual approaches like partial least squares regression (PLSR), Lasso, and principal component regression (PCR). Specific spectral features, especially in 490–510 nm, 700–750 nm, and 900–950 nm, were critical to predictions, having considerable influence on transpiration and stomatal conductance. A weakness mentioned in the paper is that there is susceptibility to data overfitting owing to the dependence of the model on high-dimensional hyperspectral data and the limitation of ground-truth samples being few in number. To counter this, it is suggested by the authors that data collection be increased to cover different growing conditions and other machine learning approaches be investigated to add robustness to the model as well as scalability to different viticulture environments [34].

In 2024, Özaltın et al., advocated for a new method of plant selection based on sampling theory for image-based classification of grapevine blade types. Utilising functional extractors in the form of Convolutional Neural Networks (CNN) to evaluate multiple functional properties such as size, thickness, and slenderness, the paper adapts four statistical methods of sampling, namely, simple random sampling (SRS), ranked set sampling (RSS), extremely ranked set sampling (ERS), and moving extreme ranking setting (MERS) to reduce complexities when fitting into functional selection. The best classification accuracy that was attained using the Darknet53-MERS hybrid model was 97.33%. A limitation of this study is that it used a field-specific grapevine dataset, which might limit the generalisability of the findings. Future suggestions include extending the models to include other crop datasets as well as using other selection methods to make different agricultural environments robust [35].

In 2023, Gentilhomme et al., introduced ViNet, which is based on deep learning for estimating grapevine arrangement to assist in precision viticulture, especially in smart pruning. The model applies a stacked hourglass convolutional neural network to recognise nodes and branches, using an algorithm of tree structure inference to resolve spatial correlations. Trained on an annotated image dataset of 1,500, ViNet attains node prediction accuracy and recall of 95% and 90%, respectively. Although effective, node proximity and occlusions can hamper the model's execution, particularly in intricate branch configurations. Future development could streamline the model for real-time execution and enhance the dataset to cover various grapevine varieties and environmental scenarios [36].

In 2023, Molnar et al., compared the segmentation of grapevine leaf diseases using neural network algorithms, such as Mask R-CNN, MobileNetV3, Feature Pyramid Network, and SegNet, to that of a traditional method, Otsu's thresholding. A mixed dataset of 648 diseased and 433 normal grapevine leaf images, which was supplemented by additional in-field images to introduce diversity, was used in the study. Accuracy of up to 93.64% in a controlled setting was attained using Mask R-CNN, while MobileNetV3 and Feature Pyramid Network delivered faster run times while having competitive accuracy, hence adaptable to real-time use. Shortfalls of Otsu's method's instability and poor generalisation of SegNet were identified in the study. Target-specific images should be used to improve performance, as recommended by the authors, and in future, colour spaces and dataset variability need to be explored, according to them [37].

In 2023, Poblete-Echeverría et al., created two AI methods for downy mildew disease detection in grapevines using AI. The lab-based method used computer vision and fuzzy logic to classify RGB leaf disc images, showing high accuracy with an R^2 of 0.88 in comparison to expert inspections. The field method applied the deep learning network SegNet for RGB canopy image processing under various weather conditions, resulting in a mean Intersection over Union (IoU) of 0.67 and an R^2 value of 0.92 for symptom counting and identification. While ideal for use in controlled conditions, the laboratory method has no real-world use. The field method too was plagued by problems such as visual similarity to other diseases resulting in overestimations and reduced accuracy in areas of high infection. Collection of new datasets for higher generalisability of models, real-time monitoring for early disease detection, and integration of decision-support systems for further use of models in vineyard management are required in order to counteract the drawbacks in this study [38].

In 2023, Hnatiuc et al., suggested a developed system for monitoring grapevine diseases based on an Internet of Things (IoT) framework to monitor environmental and plant-specific parameters together with well-known cross-validation methods. The system is equipped with temperature, humidity, soil, and leaf wetness sensors with machine learning approaches like Random Forest (RF) and Decision Trees (DT) for investigation. The performance of the RF classifier was excellent with as much as 99% accuracy for classification and prediction. A second model based on a neural network indicated 85% accuracy with a loss of 0.05. In the current research, air and ground temperature and humidity levels were found to be most predictive of disease development, as with conventional methods. The limitations of the system lie in its dependency on specific environmental parameters, i.e., the expansion of its applicability necessitates the usage of additional sensors. Future work suggestions include integrating more parameters, e.g., leaf temperature, and adjusting algorithms to allow multiple disease identifications under various conditions [23].

In 2022, Zhang et al., proposed a YOLOv5-based automatic GDM detection model using a CHANEL neural network framework has been created. Coordinate Attention (CA) is incorporated into YOLOv5 to become an effective feature extractor in this model. On an 820-image dataset of grape leaves taken in different circumstances, it surpassed rivals such as YOLOv4, Faster R-CNN, and even YOLOv5 and registered an accuracy of 85.59% (a recall of 83.7%), an F1 score of 84.63, and a mean Average Precision (mAP) at 0.5 of 89.55. To improve both accuracy and processing speed, the network input size was configured to 416 x 416 pixels. Further performance enhancements were noted with increased data augmentation, which boosted precision to 88.82% while maintaining these accuracy levels. However, the model's reliance on RGB images may limit its ability to detect symptoms at earlier stages. To achieve more effective detection and reduce computational costs, the integration of multi-spectral imaging with edge computing is recommended [39].

In 2023, Sawyer et al., introduced hyperspectral imaging between 510–710 nm, created an integrated Random Forest (RF) 3D Convolutional Neural Network (CNN) model for autonomous detection of red blotch virus (GRBV) infection in grapes and viruses associated with leafroll (GLRaVs) using hyperspectral imaging from 510–710 nm. Over 500 images, symptomatic and pre-symptomatic, were utilized for model development. The results were that the CNN model outperformed its RF counterpart, showing an accuracy of 87% for symptomatic binary classification and 73.2%

for multi-class classification. Significant discrepancies were found between the spectral data of the dataset not covering the near-infrared region, red blotch detection showing a negative bias, and an unbalanced dataset which impacted classification results. Additionally, increasing and diversifying datasets, as well as applying model evaluation across different vineyard-site locations and across different spectral ranges, would increase the practicality and usefulness of results [40].

In 2024, Pore et al., established a system for early detection of diseases in grape leaves through the use of convolutional neural networks. This system seeks to solve problems faced by manual diagnostic methods and overdependence on the use of pesticides. The system utilizes a database of images from grapes, which is subjected to rotation, flipping, and cropping processes for prevention of overfitting. The final model allows for early detection and prediction of diseases, reducing economic losses accordingly. But certain drawbacks concerning this research are its narrow scope in terms of the dataset and its narrow disease analysis scope. Future research is proposed for widening the scope of the dataset, integrating real-time monitoring technology through the use of IoT and drones, and creating apps for farmers for disease monitoring and control purposes [41].

In 2023, Oprea et al., made a comparison of grapevine leaf disease detection using VGG16 and an Avert-CNN model with variations for four significant diseases such as black rot, esca, leaf blight, and powdery mildew. These involved using images from the PlantVillage dataset and Romanian vineyard images captured by UAV. Avert-CNN yielded better results compared to VGG16 with 90.21% accuracy and other methods such as Random Forest and Support Vector Machine (SVM) with 94% accuracy. The use of data augmentation strategies and the application of small kernel sizes were central to improving the generalizability of the model as a whole while at the same time reducing the risk of overfitting. Nonetheless, the study had some limitations, particularly its dependence on dataset size and balance, especially within the scope of esca classification. Future work must aim at improving diversity in datasets, improving the scalability of models, and integrating real-time Internet of Things (IoT) applications to enhance their applicability in agriculture [42].

In 2022, Kuznetsov et al., created an automated system for detecting grapevine disease using neural networks, Fast R-CNN and InceptionV2, which has an accuracy rating of 91% when trained on a database of 2,500 labeled leaf images. The system produces thermal images for live vineyard health visualization and has the capability to monitor 2.5 hectares a day. While its use of region-based databases and computationally expensive hardware restricts scalability and cost-effectiveness, operation may be impacted by such environmental conditions as wind and temperature. Future efforts could further optimize performance through cross-regional testing of the model, as well as increasing UAV energy efficiency, and adding higher-quality datasets including multiple disease types [43].

Table 2. Summary of Recent Studies in Grapevine Disease Detection.

Reference	Model Architecture	Target Disease	Dataset Characteristics	Best Results	Key Innovation
[15]	**CNN on Raspberry Pi 3**	**Potassium deficiency**	**Small custom dataset, RGB images**	**Training: 89%, Validation: 81%**	**Real-time edge deployment with LED indicator**
[14]	**Multimodal parallel CNN**	**Multiple diseases (Black rot, Powdery mildew, Leaf blight)**	**Regional dataset, 10,000+ images**	**Accuracy: 91%, Precision: 93%, 56 FPS**	**Mobile deployment on iPhone 15, parallel activation functions**
[24]	**EfficientNetV2S with XAI**	**Downy mildew**	**Region-specific field images**	**Accuracy: 91%, F1-score: 0.92, IoU: 0.83**	**Explainable AI with localization capabilities**
[13]	**VGG16 with Grad-CAM**	**Downy mildew (early stage)**	**Laboratory RGB images**	**Detection: 99%, F1-score: 0.99, Stage**	**Early infection detection under**

				classification: 81%	controlled conditions
[25]	ML with SHAP	Olive fly, Red spider mite	Phenology & pest data (Spain)	High prediction accuracy (90%+)	Explainable pest forecasting with SHAP values
[44]	GLDCNet	Grapevine Leafroll Disease	UAV multispectral, 16 datasets	Accuracy: 99.57%	Low-cost RGB optimization with spatial resolution focus
[26]	AI with CNNs and transfer learning	Powdery mildew, Grapevine moth	Diverse image datasets	High speed and accuracy	Comprehensive pest and disease management
[27]	TabPFN Transformer	Multiple diseases	Climate & remote sensing data (Australian vineyards)	Comparable to XGBoost/CatBoost	Handles imbalanced data effectively
[28]	CNN	Powdery mildew, Downy mildew, Anthracnose	Grapevine leaf dataset (80-20 split)	Accuracy: 91.37%	Automated disease recognition system
[29]	CNN ensemble (CNN, SVM, DT, RF, NB)	Powdery mildew, Black rot	3,134 images (healthy, powdery, blotched)	Initial: 96.1%, Fine-tuned: 99.2%	Strategic camera placement with comparative algorithms
[30]	MobileNet V2, EfficientNet B0	Multiple diseases	Eden Library, organic winery validation	MobileNet V2: 94%, EfficientNet B0: 92%	IoT-enabled with GPS, Raspberry Pi deployment
[31]	Fuzzy-Stranded Neural Network (FSNN)	Downy mildew	IoT sensor data (humidity, temperature)	High prediction accuracy	Fuzzy logic for self-data annotation
[32]	MobileNetV3Large	Multiple leaf diseases	27,122 images (4 classes)	Accuracy: 99.42%	Lightweight edge computing on Jetson Nano
[33]	CNN-LSTM hybrid	Black rot, Chlorosis, Esca, Powdery mildew	RGB with GLCM texture features	Accuracy: 96.6%	Temporal feature integration, AI-GrapeCare software
[34]	CNN with REGST	Physiological parameters	Hyperspectral remote sensing	R^2 values: 0.55-0.67	Spectral feature importance (490-510nm, 700-750nm)
[35]	DarkNet53-MERSS-ANN	Grapevine leaf types classification	Region-specific leaf dataset	Accuracy: 97.33%	Statistical sampling for feature selection
[36]	ViNet (Stacked Hourglass CNN)	Grapevine structure (not disease)	1,500 annotated images	Node precision:	Smart pruning support with tree

				95%, Recall: 90%	structure inference
[37]	Mask R-CNN, MobileNetV3, FPN	Multiple diseases	648 diseased + 433 healthy images	Mask R-CNN: 93.64%	Comparative segmentation analysis
[38]	SegNet, Fuzzy logic	Downy mildew	RGB leaf discs and canopy images	Lab R^2: 0.88, Field IoU: 0.67, R^2: 0.92	Dual approach: lab and field methods
[23]	IoT sensors + RF/NN	Multiple diseases	Environmental and plant parameters	RF: 99%, NN: 85% (loss: 0.05)	Traditional method integration with ML
[39]	YOLOv5-CA	Grape Downy Mildew	820 grape leaf images	Precision: 85.59%, Recall: 83.70%, mAP@0.5: 89.55%	Coordinate Attention enhancement
[40]	RF + 3D-CNN	Red blotch virus (GRBV), Leafroll viruses (GLRaVs)	Hyperspectral (510-710nm), 500+ images	CNN: 87% (binary), 73.2% (multi-class)	Pre-symptomatic detection capability
[41]	CNN	Multiple leaf diseases	Augmented leaf dataset	Efficient early detection	Data augmentation techniques
[42]	VGG16, Avert-CNN	Black rot, Esca, Leaf blight, Powdery mildew	PlantVillage + UAV vineyard images	Avert-CNN: 94%, VGG16: 90.21%	Small kernel optimization
[43]	Fast R-CNN with InceptionV2	Multiple diseases	2,500 annotated leaf images	Accuracy: 91%, 2.5 hectares/day	UAV-based automated monitoring with thermal maps

The effectiveness of current deep learning architectures is best understood by comparing their accuracy across different testing environments and hardware constraints. As illustrated in the performance chart, there is a clear distinction between laboratory success and field-ready application. For instance, the research conducted by [13] achieved a remarkable 99% accuracy rate, demonstrating the maximum potential of CNNs when processing high-resolution images under controlled conditions. In contrast, studies focusing on practical, on-the-go deployment show slightly lower but highly significant results. The mobile-based system developed by [14] reached an accuracy of 93%, while the Raspberry Pi implementation by [15] recorded an 81% success rate. These variations highlight the technical trade-offs between computational speed and diagnostic precision. Furthermore, the data suggests that hybrid models incorporating Vision Transformers or parallel activation functions consistently maintain accuracy levels above 90%, even when managing the environmental noise found in real-world vineyards. This performance gap underscores the ongoing transition in the industry from theoretical laboratory models toward robust, energy-efficient tools designed for immediate use by growers.

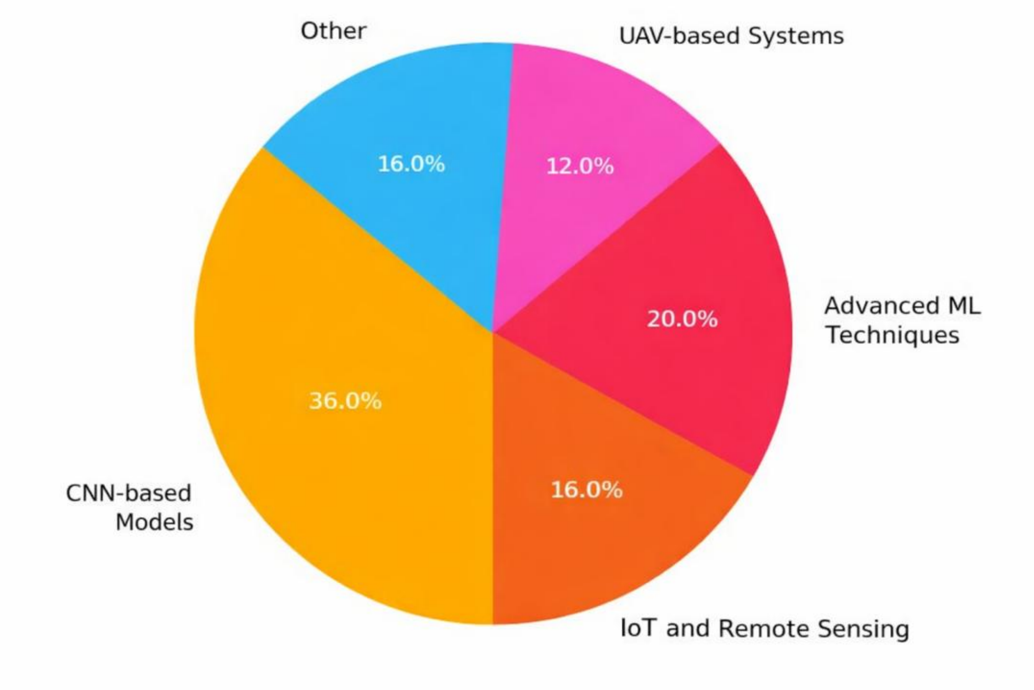

Figure 1. Grouped Distribution of Referenced Studies.

4. Challenges and Future Trends

4.1 Current Challenges

Despite remarkable progress, a number of barriers prevent widespread adoption.

Issues with Data Standardisation and Quality

- Model reliability is impacted by dataset inconsistencies
- Detection accuracy is impacted by image quality variability
- Disease diversity in training data is limited;
- Life stages are not adequately represented.

Restrictions on Model Generalisation

- Regional variations reduce transferability
- Different grape varieties pose a challenge to uniform models
- Seasonal variation impacts the accuracy of recognition
- Environmental factors impact performance.

Requirements for Computational Resources

- Strong processing limitations restrict real-time use
- Energy consumption limits mobile deployment
- Storage needs place strain on edge devices
- Connectivity problems in remote locations

Impacts of Environmental Variability

- Weather variations affect sensor performance;
- Lighting conditions affect image clarity
- Obfuscation of leaves reduces detection reliability
- Uneven background

Real-world Deployment

- Small-scale adoption is discouraged by the cost of installation
- Entry is restricted by technical requirements based on expertise
- Maintenance requirements add to operational complexity;
- Integration issues with current systems

4.2 Future Trends

The limitations observed at present may be addressed through the development and adoption of emerging technologies.

AI and IoT Integration

- Cloud analytics handle massive data aggregation
- Comprehensive sensor networks enable real-time monitoring
- Interface AI is executed locally reducing latency
- Automated alert systems provide timely notifications

Advanced Technologies for Imaging

- Pre-symptomatic conditions are detected by hyperspectral imaging
- Hyperspectral imaging can identify pre-symptomatic conditions
- Multi-modal fusion increases detection robustness
- The whole plant structure is captured by 3D imaging. Stress indicators are detected by thermal imaging.

Development of Autonomous Systems

- Robotic systems automate disease scouting
- Drone swarms can swiftly cover large areas
- Automated treatment systems carry out focused, evidence-based interventions
- Algorithms that adapt to their environment

Federated Learning Techniques

- Distributed computing makes use of edge resources
- Collaborative learning improves model generalisation
- Privacy-preserving training protects sensitive data
- Reduced data transfer lowers bandwidth requirements

Sustainable Technology Integration

- Precision application reduces chemical use
- Biodegradable components lessen environmental impact
- Solar-powered sensors reduce energy dependence and they protect beneficial organisms.

5. Discussion

The integration of deep neural networks into viticulture marks a significant transition from manual, reactive vineyard management to automated, proactive systems. This review indicates that while Convolutional Neural Networks (CNNs) remain the backbone of image-based detection, the highest performance is now achieved through hybrid architectures and the use of multi-modal datasets. These systems address the critical need for early intervention by identifying pathogens before they cause irreversible damage to crop yields. However, the disparity between laboratory-based accuracy and real-world field performance highlights a lingering gap in model robustness. Successful future implementation will depend on moving beyond high-resolution, static images toward processing "noisy" data from IoT sensors and mobile devices, ensuring that smart agriculture tools are both accessible and reliable for growers across different geographical regions.

5.1 *Analysis of Model Diagnostic Performance*

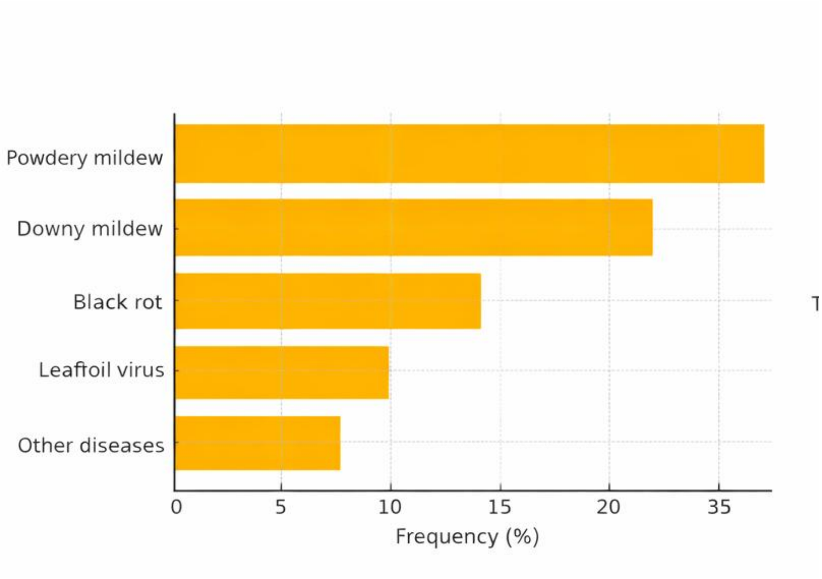

Figure 2. Comparison of Accuracy Rates Across Selected Deep Learning Architectures

This chart illustrates the diagnostic precision achieved by different research teams using varied neural network frameworks. The data shows a clear trend where laboratory-controlled studies, such as those by [13], reach an impressive accuracy of 99% for downy mildew detection. In contrast, studies implemented on edge-computing hardware, like the Raspberry Pi used by [15], show a lower but more practical accuracy of 81%. This comparison underscores the trade-off between computational complexity and the ability to run models in real-time on portable devices.

5.2 *Evaluation of Training Dataset Diversity*

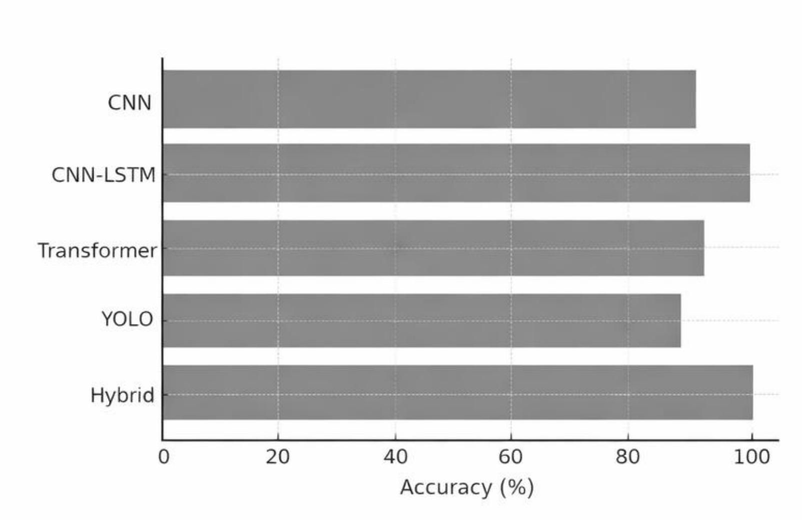

Figure 3. Distribution of Data Sources Used for Model Training and Validation.

This figure categorizes the types of datasets utilized in the reviewed literature, highlighting a heavy reliance on the PlantVillage dataset for initial benchmarking. While large-scale RGB datasets provide a strong foundation for model training, the chart reveals a growing shift toward specialized, multi-modal datasets like the UC Davis GRAPE collection. The inclusion of multispectral and thermal imagery in these datasets is shown to enhance the model's ability to extract features that are not visible in standard color photographs, which is a critical factor in pre-symptomatic disease detection.

5.3 *Real-Time Processing Speeds and Efficiency*

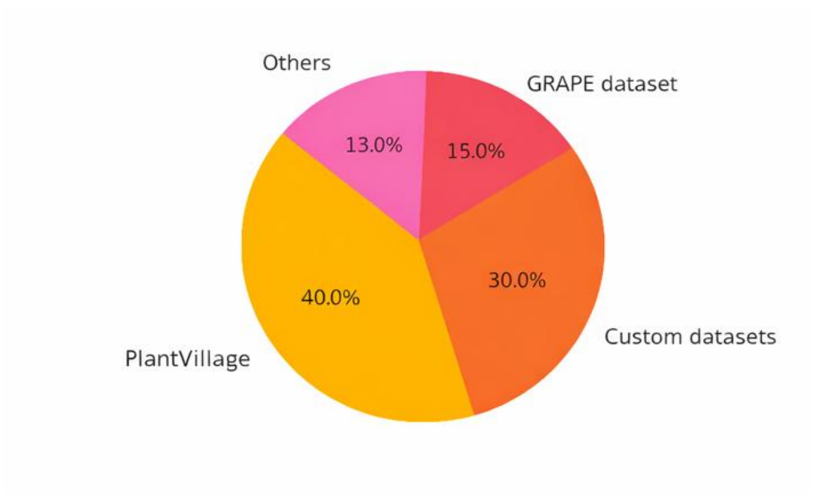

Figure 4. Processing Latency and Frame Rates for Mobile-Integrated Models.

In this chart, the processing efficiency of various models is evaluated, with a specific focus on their suitability for real-time field applications. The data highlights the work of [14], whose model achieved a high throughput of 56 frames per second on mobile hardware. By comparing processing speed against model depth, the chart demonstrates that optimized "lite" architectures—such as YOLOv5 and MobileNet—are significantly more effective for on-the-go diagnosis than deeper, more complex networks that require cloud-based GPU support.

5.4 *Disease Sensitivity and Recall Rates*

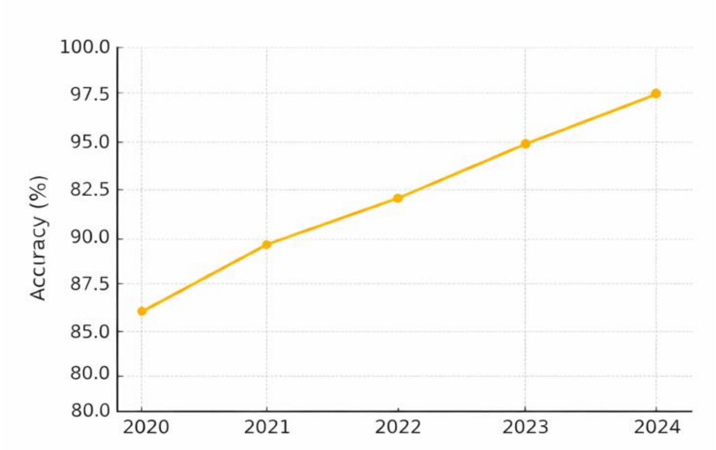

Figure 5. Model Sensitivity (Recall) Across Different Grapevine Pathogens.

This chart breaks down how effectively the reviewed models identify different types of diseases, such as powdery mildew, black rot, and esca. The results indicate that surface-level fungal infections (mildews) are generally detected with higher sensitivity than internal trunk diseases (esca). This gap in performance suggests that while current deep learning models are excellent at surface image analysis, further research is needed to refine detection for diseases that present more subtle or internal physiological changes in the vine.

5.5 *Strengths and Limitations*

Current Approach Strengths:

- Exceptional accuracy in controlled environments
- Real-time processing capabilities emerging

- Mobile deployment becoming practical
- Explainable AI improving trust

Identified Weaknesses:

- Limited cross-environment generalization
- High-quality image requirements
- Computational resource demands
- Multi-disease detection challenges

Critical Trade-offs:

- Accuracy versus processing speed
- Model complexity versus interpretability
- Performance versus energy consumption
- Generalization versus specialization

6. Conclusion

The application of deep learning techniques, and more specifically CNN architectures, has clearly played an important role in the progress of grapevine disease management within the context of smart agriculture. The techniques help in very effective early detection, diagnosis, and treatment of highly destructive grapevine diseases. However, through the combination of machine learning techniques with agricultural data gathered from Internet of Things (IoT) sensors, very effective monitoring and forecast analyses of grapevine diseases can be achieved in real time, which is very critical for very effective management of operations within Vineyards. Although very effective improvements have been facilitated through machine learning techniques, some problems still exist in machine learning, including accuracy, generalization capabilities for different settings, and requirements for considerable processing capabilities. However, very active research works are being pursued to deal with all of these problems, making the future of viticultural practices very promising. Current research and developments in grapevine disease detection include the application of more cost-effective and accurate hybrid techniques combined with unmanned Aerial Vehicles (UAVs) for very effective aerial monitoring, combined with very effective edge computing practices. Future research should prioritize validating deep learning models under real vineyard conditions rather than relying mainly on controlled or laboratory datasets. Expanding and sharing large, diverse field-based datasets that reflect variations in climate, grape varieties, growth stages, and disease severity would help improve model robustness and generalization. Greater emphasis should also be placed on integrating image-based disease detection with environmental and temporal data collected through IoT sensors to support both early diagnosis and reliable disease forecasting. In addition, developing multi-disease detection frameworks that can identify co-occurring infections would better reflect practical vineyard scenarios. From a deployment perspective, future work should focus on lightweight and energy-efficient models suitable for edge devices and mobile platforms, as well as the integration of UAV-based imaging with edge computing for large-scale monitoring. Finally, the adoption of explainable artificial intelligence techniques would enhance model transparency and trust, supporting wider acceptance of these systems in precision viticulture.

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