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Machine Learning Approaches for Detecting Vine Diseases: A Comparative Analysis

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Abstract - This study investigates the classification of vine leaf diseases using convolutional neural networks (CNNs), focusing on three major diseases: powdery mildew, caused by fungus Uncinula necator, Red Blotches associated with pathogens such as Phomopsis viticola, Grapevine Leafroll Disease and leafroll associated Grape -linked virus (GLRaV). Accurate diagnosis of these high-risk diseases is critical to vine health and yields. We evaluated the performance of three CNN algorithms—MobileNetV2, ResNet50, and VGG16 —by comparing their training and validation accuracies, as well as loss over ten seasons. MobileNetV2 emerged as the most robust model, exhibiting high accuracy and low loss, indicating strong generalizability. ResNet50 showed a steady increase in accuracy, but with high variability, indicating that probabilities with complex models or extended training requirements VGG16 showed notable improvements in training accuracy but encountered difficulties it involves consistency during validation, which means overfitting. Although MobileNetV2 proved to be the most efficient for this task, our analysis suggests that replicating ResNet50 and VGG16 can improve their performance. Future research will explore longer training times, larger data sets, and other methods to further improve the generalizability and robustness of this model This work highlights the ability of CNN to detect vine leaves emphasize early diseases and provide a strategy for sustainable viticultural practices.

Keywords - Grape Leaf Disease, Convolutional Neural Network, Agricultural Efficiency, Sustainable Agriculture, Disease Classification, Smart Agriculture.

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1. INTRODUCTION

Grapes are a common agricultural undertaking worldwide, playing an important role in the economy through wine production and consumption as fresh fruit or raisins. However, grapevines can be affected by numerous diseases, particularly those impacting their leaves. Early detection and classification of grape leaf diseases are fundamental to cope with adverse impacts on the health, productivity, and sustainability of grapevines Figure 1 shows healthy grape leaves.[1]

Diseases such as powdery mildew and red blotches pose significant challenges to grape growers. Powdery mildew Figure 2 shows a grape leaf affected by powdery mildew caused by the fungus Uncinula necator appears as white powdery growth on leaves, disrupting photosynthesis, weakening the plant. Red blotches in Figure 3 shows leaves affected by red blotch disease associated with pathogens such as Phomopsis viticola and grapevine leafroll-associated virus (GLRaV) cause lesions yellowing of leaves, causing these diseases, which reduce chlorophyll production and nutrient absorption require active management strategies to ensure the viability of grape production well.

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Figure 1. Healthy Grape Leave

Figure 2. Leave Affected by Powdery Mildew

Figure 3. Leave Affected by Red Blotch

Traditional methods of diagnosing diseases in grapevines often rely on expert observation, which can be time-consuming, subjective, and prone to error [2]. Furthermore, these methods may not be feasible in grapevines large gardens because of the labor-intensive nature of the survey. Consequently, there is a great need for reliable and effective automated methods for the detection and classification of grapevine foliar diseases [3]. Technological advances, especially in artificial intelligence (AI) and machine learning (ML), offer promising solutions to these challenges.

Convolutional neural networks (CNNs), a class of deep learning algorithms, have shown remarkable success in image classification, including plant disease detection [4]. CNNs can automatically detect and extract relevant features from photographs, making it well-suited to detecting subtle differences between sick and healthy plant leaves [5]. Vine Feeding manufacturers a tool to effectively manage these diseases [6].

In this study, the authors focus on evaluating the performance of three well-known CNN algorithms: MobileNetV2, ResNet50, and VGG16. These models have been selected due to their ability to perform various image classification tasks and different levels of complexity and depth n order to give insight into their suitability for this specific application [7].

MobileNetV2 is a superficial model designed for embedded and mobile sight applications [8]. It uses depth-splitting diffractions, which considerably lessen the number of parameters and computational cost. It allows higher processing and speed without sacrificing much accuracy [9], making the MobileNetV2 system a captivating choice for applications with less computing resources [10].

ResNet50 is derived from the class of ResNet models, in which the concept of the remaining groups were initiated [11]. ResNet50 is a strong mesh with 50 layers, which is built to solve the problemf lost peaks in deep meshes through remaining links [12]. These networks can obtain skill to design the structure of the network, which is used to to prepare very meshed networks. ResNet50 displays high accuracy in many image classification classes, thus making it a powerful aspirant for this study [13].

VGG16 is a strong mesh with 16 layers that is familiar for its adaptability and effectiveness [14]. It utilizes a series of convolutional layers with small 3x3 filters, observed by fully connected layers. Despite its high computational cost and limited number of parameters, VGG16 has been quite successful in many image recognition tasks, providing a starting point for comparing performance in this study [15].

This study investigates the performance of these three CNN algorithms in grapevine leaf disease classification, focusing on their training and recognition accuracy and loss in different seasons. The importance of this research lies in its potential to transform grapevine disease management. Accurate and effective disease detection allows for early intervention, reduces disease spread and minimizes crop losses [4]. This can increase the overall grape production yield and sustainability [16]. Furthermore, the adoption of AI-driven solutions in agriculture can lead to more accurate and data-driven business practices and drive innovation and technological improvements in the industry [17].

This paper is organized in such a way that the literature review section following this introduction covers the main findings of recent studies on grapevine diseases and the application of AI in plant disease diagnosis [18]. The methodology phase outlined the experimental design, including data collection, preprocessing, and design of the CNN models [18]. The Results and Discussion section presents the performance parameters of the model and analyzes their strengths and weaknesses. Finally, the conclusions summarize the main findings, discuss the research implications, and suggest future work directions.

It can be concluded that vine diseases such as powdery mildew and red blotches pose significant challenges to grape production, requiring effective solutions to detect and manage them [19].The study aims to harness the potential of CNN will be used to improve the classification of vine leaf diseases, providing valuable tools for viticulturists to protect their crops [20]. These conclusions contribute to the broader agricultural technology and demonstrate the potential of AI in addressing the challenges of importance in crop management [21].

2. LITERATURE REVIEW

Grapevine red blotch virus also known as GRBV is an agent that exists in grape vines and causes red blotch disease. Studies where GRBV was replicated using infectious viral models provided a valid argument to the claim that GRBV takes part in the cause of the disease. In one of the studies, the researchers illustrated the contribution function of the virus by infecting the grapevine with GRBV and the typical red blotch symptoms were expressed [22]. Health status and contamination with pathogens out of shoots of sick plant microshoot cultures were also tried, providing symptomless disease-free vines.

For the treatment of the red blotch disease, as shown in Figure 3, which is spread widely, the antioxidants that include the grape seeds that are examined for the presence of GRBV type viruses are of great assistance, and many studies have emerged outlining various new diagnostic methods of the same. One notable technique is the loop-mediated isothermal amplification (LAMP) process, which does not require the presence of finds which allows for rapid and cheap diagnosis. This technique could prove to be very efficient in vineyard operations especially when its sensitivity which is a thousand times downside than normal PCR is so rapid in 30 minutes completion [23].

Also, the LAMP assay is becoming popular as it can be deployed under different field conditions. There is minimal demand for advanced laboratory instruments; hence, they are suitable for field use. This is particularly useful to vineyard managers who need an effective & quick diagnosis to control the spread of the virus. The downside of the technique is being dependent on the use of DNA amplification at a constant temperature as opposed to the use of insulation where cyclers are not cheap when using conventional PCR which has increased cost margins to the technique and application. This restores the wider use of various kinds of hanging vineyards and smaller farms with few resources.

There is another diagnosis technique which uses a plasmonic CRISPR Cas12a probe. This technique employs gold nanoparticles with CRISPR coupled to it which allows the GRBV to visually color and be detected. This test provides a portable and low-cost solution for field testing, which is critical for timely control of grapevine infections [24]. The CRISPR-based diagnostics provide a new method for pathogen detection in plants. In the presence of target DNA that can be detected, the enzyme Cas12a target induces transport of surrounding single-stranded DNA, which can also be detected by visual means such as fluorescence or color shift. This peculiarity permits the CRISPR Cas12a probe to attain increased velocity, but even more important the increased some specificity so that small quantities of viral DNA can be detected.

The potential perception of red blotch on grape yield emphasizes the importance of GRBV management. These viruses affect grape seed development – leading to decreased anthocyanin synthesis and positive effects on other factors, which largely diminishes grain quality. Anthocyanins are pigments that impart color to grape skins especially in the case of red wine grape varieties. Windfall due to the reduction in the concentration of anthocyanins in the grapes will mean a production of wine with no appealing rich color and floral diversity, which negatively impacts the financial aspect of the wine. Average rising sugar because of GRBV infection in grapes caused well known threat to the quality of the wine. This reflects various effects of GRBV other than vine health, for example, all the steps of winemaking are in any way affected starting from grape production. The virus is caused primarily by the movement of infected vectors particularly insects such as leafhoppers which makes the management and precautions in cane fields genetic resources very critical and warranted [25].

Apart from viral pathogens, grapevines are also prone to fungus Lord of the Rings diseases like powdery mildew caused by Uncinula necator. Powdery mildew (refer to Figure 2 for grape leaf affected by powdery mildew) is among the most frequently found and most dangerous of all fungal diseases afflicting grapevines in the world. The fungus spreads over the leaf, stem, and grapes as a certain white floury covering. This disease has the potential to have significant adverse effects on grapevine productivity and growth and on the quality of the berries produced. There was one study involving Concord grapes, which revealed that powdery mildew, when present, was able to lower fruit sugar levels, and juice color, and acidity levels which put into clear focus the importance of effective disease management methods [26]. Brix level is particularly important in grape ripening because, in wine making, it helps to achieve a desirable alcohol content. On top of that, when the powdery mildew retards the sugar content, it is difficult for winemaker to harmonize the sweet and a sour taste in the final product.

Different grape species and cultivars differ on the level of resistance or susceptibility to powdery mildew. Vitis vinifera grape which is even more popular because of the wine it produces is more prone to powdery mildew than other types; e.g. Vitis labrusca often sown in various regions of America. Results suggested that certain V. labrusca genotypes and in some cases interspecific cultivars show enhanced resistance to powdery mildew, which contributes a valuable understanding to the developmental plans for resistant grape varieties with a high productivity [27]. Such breeding activities are significant, especially in those regions where the employment of chemical fungicides is prohibited due to ecological reasons. Breeding cultivars with inherent resistance to powdery mildew may also be helpful in reducing the use of chemicals and adopting more eco-friendly grape growing practices.

This technological evolution has also progressed through the need to find powdery mildew in grape plants tissues through the image analysis of plants stems using multispectral imaging methods. Such methods increase detection of the relatively milder and moderate signs of powdery mildew, particularly if photographs are taken at certain diagnostic sites. It is notable that hyperspectral imaging allows for the detection of illness before the actual signs are observable thereby ensuring proactive prevention and treatment. These technological developments may postulate a more focused and better application of fungicides, limiting the use of generalized chemicals, hence lessening the harm to the environment [19].

Data augmentation strategies have been shown in recent research to be crucial for enhancing CNN models' performance in plant disease diagnosis, particularly in situations where datasets are scarce. For instance, an upgraded GAN model (AWGAN) has been effectively deployed to produce synthetic images of plant diseases, greatly enhancing model accuracy and limiting overfitting concerns in limited sample training sets [28]. As shown in the paper, our methodology might similarly include sophisticated data augmentation methods like AWGAN to solve the difficulties of unpredictability and overfitting exhibited in ResNet50 and VGG16.

The purpose of this research [29] is to evaluate the efficacy of the YOLOv8 model on a small-scale plant disease dataset. This model performs better than its predecessors. Additionally, by putting out an enhanced and lightweight YOLOv8 architecture model, it aims to raise the precision and efficacy of plant disease detection and classification techniques. Using a publicly available dataset, the authors train the YOLOv8 model. Then, by including the GhostNet module into the main architecture, they optimize the YOLOv8 algorithm, lowering its parameter count and speeding up processing. The architecture also includes a Coordinate Attention (CA) mechanism module, which improves the suggested algorithm's accuracy even more. According to the data, the best outcome, or score, was obtained by combining YOLOv8s with the CA mechanism and transfer learning.

Multispectral imaging techniques have seen improvements due to the evolution of machine learning and artificial intelligence. Grapevine disease detection systems based on recognizing the disease using algorithms allow instantaneous analysis and aid vineyard managers in decision making. The utilization of these technologies coupled with smart agriculture will allow the growers to employ disease control measures that are effective at disease treatment applications and only when necessary. This precision agriculture method strategizes to manage diseases efficiently and curbs cost but also aims to alleviate the adverse effects of excessive use of chemical inputs on the environment.

In closure, the research on GRBV and powdery mildew in grapes confirms the necessity of the prompt and accurate application of proposed measures – if not elimination then control of the development of diseases. New detection techniques such as LAMP and CRISPR Cas12a Testing readily available indeed offers new avenues and will greatly help manage the said diseases and ultimately enhance grape production. Also, further development of diseases resistant grape varieties, and application of precision agriculture technologies demonstrates the intention of the industry to minimize negative environmental influence of grape growing and preservation of good productivity and quality. Effective control of diseases does not only contribute to protection of vine health but also assures interoperability.

3. RESEARCH METHODOLOGY

Despite Convolutional Neural Networks (CNNs) are good at capturing spatial hierarchies in images, they have become a foundation in computer vision applications. Numerous CNN architectures have been created over time, each with a particular approach for relevancy, reducing computation costs, and improving performance. In this study, we compared three common CNN architectures. These include VGG16, ResNet50, and MobileNetV2. These models were selected for their different design principles and wide use. Our objective was to evaluate their performance in terms of necessary metrics over a ten-epoch duration, such as training accuracy, validation accuracy, training loss, and validation loss.

3.1 Model Buildings

MobileNetV2: A trivial CNN architecture for portable, mobile and edge devices is called MobileNetV2. As compared to conventional CNNs, it drastically reduces the number of parameters and statistical complexity by using deep separable convolutions. In addition, MobileNetV2 presents the ideas of reversed residuals and linear bottlenecks, which helps accuracy storage when scaling down the model.

VGG16: The VGG16 is a deep CNN architecture, which is known for its efficiency and performance. It utilizes a sequence of max-pooling layers after a set of convolved layers with tiny 3x3 filters. Because of its depth, this network is specifically good at picture classification tasks. It consists of 16 layers and allows it to learn complicated features. However, there are a lot of parameters, and a major computational cost related to this depth.

ResNet50: Residual learning is a concept created by ResNet50. It is a member of the Residual Networks (ResNet) family, that helps to reduce the disappearing gradient problem in deep networks. ResNet50 has 50 layers and is deeper than both MobileNetV2 and VGG16.Gradients can pass straight through the network, by using identity shortcuts in the architecture, allowing for the training of very deep networks without compromising efficiency.

3.2 Methodology

3.2.1 Dataset Collection

Dataset was collected from different garden and grape vine sites and pictures were taken with handheld cameras. We collected about 1000 sample of each disease and healthy leaves respectively, then data different data augmentation techniques were applied. The sample dataset can be seen in Figures 1 to 3 (as depicted in Section 1) and Figures 4 to 12 (depicted in Section 3).

Figure 4. Powdery Mildew (Augmented) - High Contrast

Figure 5. Powdery Mildew (Augmented) - Rotated

Figure 6. Powdery Mildew (Augmented) -Flipped

Figure 7. Blotches (Augmented) - High Contrast

Figure 8. Blotches (Augmented) - Rotated

Figure 9. Blotches (Augmented) -Flipped

Figure 10. Healthy (Augmented) - High Contrast

Figure 11. Heatlhy (Augmented) - Rotated

Figure 12. Healthy (Augmented) -Flipped

3.2.2 Preprocessing and the Dataset

An image classification dataset that was standardized. This standardized dataset was used to train and evaluate the models. Before being divided into training and validation sets, the dataset experience standard preparation procedures, which include scaling, normalization, and data augmentation. Following these steps, a wide range of images were used to train the models, enhancing their capacity to generalize to new data.

3.2.3 Method of Instruction

Every model went through 10 epochs of training with a batch size and learning rate adapted to the specific architecture. Adam optimizer was used for all models, since it can dynamically adjust learning rates. The training was done on a GPU to speed up the process, considering the computational demands of deep learning models.

4. RESULTS AND DISCUSSIONS

4.1 Model Accuracy

MobileNetV2: Starting at a reasonably high level, the training accuracy of MobileNetV2 increased slightly during the epochs before settling around 97-98%. This suggests that MobileNetV2 reached a plateau early in the training process, having mastered the training data quickly. In contrast, the validation accuracy fluctuated between 80 and 85%, starting lower and staying quite consistent. Although there is no discernible gain in validation accuracy over the epochs, this stability suggests that MobileNetV2 generalizes well to new data and may point to early convergence or the need for additional tweaking.

ResNet50: ResNet50 displayed an alternative pattern of learning. By the end of the training, the training accuracy had risen from a low starting point to approximately 60% during the epochs. Although it started at about 40%, the validation accuracy paralleled this pattern, albeit it was lower and more variable. The consistent rise in accuracy indicates that more epochs or a modification to the learning rate schedule might help ResNet50 perform better. Variations in validation accuracy suggest that there may be difficulties with generalization, which could be brought on by the model's complexity or insufficient training time.

VGG16: The training accuracy of the VGG16 model rapidly improved, surpassing 90%. Similar to MobileNetV2, the validation accuracy began high and stayed steady at 80–85%. Nevertheless, VGG16's validation accuracy did not considerably improve following the early epochs, in contrast to MobileNetV2. If the model memorizes the training data without sufficiently learning to generalize to new samples, this may be a sign of overfitting.

4.2 Model Loss

MobileNetV2: The model successfully learned to minimize mistakes on the training data, as seen by the training loss for MobileNetV2 gradually dropping from about 0.25 to about 0.10. On the other hand, there were noticeable variations in the validation loss, which varied from 0.50 to 1.25. Although MobileNetV2 is effective at sustaining performance on the training data, this volatility in validation loss, despite the high validation accuracy, may indicate that it is sensitive to some validation data points or suffers from mild overfitting**.**

ResNet50: Towards the end of the training, ResNet50's training loss steadied at roughly 0.90 after beginning at a high rate. While the validation loss fluctuated between 1.00 and 1.50, it consistently outperformed the training loss, following a similar trend. In addition to decreased validation accuracy, the large and erratic validation loss suggests that there may be problems with the model's complexity. These problems could include underfitting or the need for additional training time for the model to properly converge.

VGG16: After the first few epochs, VGG16 showed a sharp decline in training loss that settled around 0.25. After beginning high and gradually declining, the validation loss subsequently varied between 0.75 and 1.25. These variations and the generally consistent validation accuracy imply that VGG16 might be susceptible to the particular features of the validation data, which could result in a small amount of overfitting or inconsistent generalization.

4.3 Analysis

In comparison, the evaluation of ResNet50, VGG16, and MobileNetV2 offered insightful information on each model's practicality and performance traits, as seen in Figures 13 and 14.

Among the models evaluated, MobileNetv2 outperformed in terms of overall accuracy, the high training accuracy and consistent validation accuracy demonstrate the strong generalization capabilities, making it particularly well-suited for applications where computational efficiency is critical, such as mobile or embedded system Comparing MobileNetV2, ResNet50, and VGG16 gave important information about how these models handle varying datasets for further improvement.

ResNet50 scored worse than the other models regarding validation accuracy and loss but showed promise with its consistently rising training accuracy. Although the depth of the model is useful for learning intricate characteristics, it may need more advanced training methods, like learning rate annealing or longer training times, to reach its full potential. Because of its higher complexity and the smaller number of training epochs, ResNet50 may be more susceptible to underfitting in the setting of this experiment based on the oscillations in validation accuracy and loss that have been observed.

With generally consistent validation accuracy and quick gains in training accuracy, VGG16 showed promising early performance. Nevertheless, the model may be overfitting to the training set based on the inconsistent validation loss and lack of discernible progress in validation accuracy over time. Deeper networks often exhibit this pattern, where the model learns to match the training data well but finds it difficult to generalize to new data. Despite this, VGG16 is still a reliable model for a variety of picture classification applications, particularly those in which computational resources are not a major consideration.

In short, it can be said that all three models MobileNetV2, ResNet50, and VGG16 have some advantages and disadvantages that make them appropriate for use. MobileNetV2 is the best choice for domains with limited resources. This is because of its effectiveness and robust generalization. ResNet50 can be used to perform better with additional calibration and prolonged training because of its depth. How VGG16 works well, extra regularization methods could be needed to avoid overfitting. Future study could require experimenting with longer training periods, adjusting hyperparameters, and investigating other regularization techniques to optimize each model's performance further.

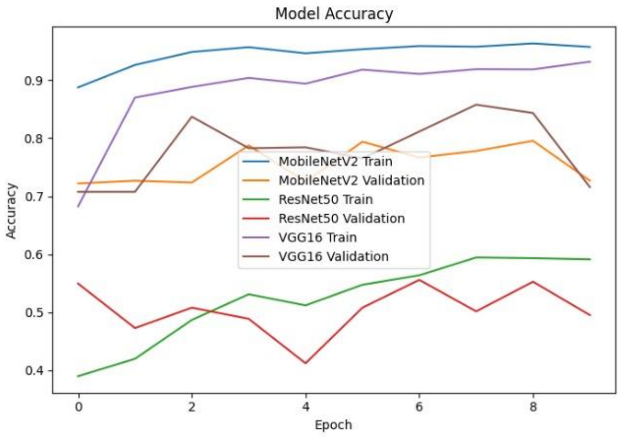

Figure 13. Model Accuracy

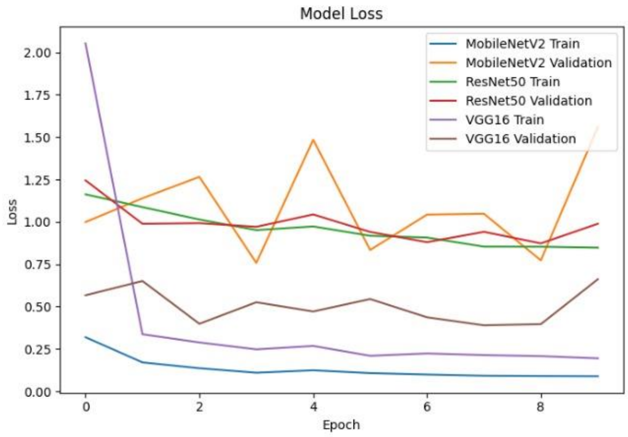

Figure 14. Model Loss

MobileNetV2: MobileNetV2 showed powerful performance. The training accuracy achieved by MobileNetV2 was around 97-98% and the validation accuracy was around 80-85%. The training loss gradually decreased from about 0.25 to 0.10. The validation loss fluctuated from 0.50 to 1.25. These results (as shown in Table 1) show that MobileNetV2 is able to normalize unrecognizable data despite some variation in integrity loss.

ResNet50: ResNet50 showed a steady increase in training accuracy, reaching 60%, but the absolute accuracy was lower and more variable, starting from about 40% Training loss gradually decreased, stabilizing at about 0.90, validation loss 1. change between 00 and 1.50. These results indicate possible issues related to model complexity or insufficient training times, suggesting the need for further modifications to improve its performance.

VGG16: The VGG16 showed a rapid improvement in training accuracy, reaching over 90% faster. However, validation accuracy remained relatively strong around 80-85%, and validation loss fluctuated between 0.75 and 1.25. These changes suggest that VGG16 may be experiencing something extraneous or sensitive to the validation data

MobileNetV2 emerged as the most effective model for grapevine leaf disease classification in this study, providing the lowest accuracy and loss but updating ResNet50 and VGG16 could provide them performance has been improved. Future work will examine extended training periods, different study rates, and other codes.

Table 1. Model Accuracy and Loss Comparison

Model	Accuracy (Train)	Accuracy (Validation)	Loss (Train)	Loss (Validation)
MobileNetV2	0.90	0.85	0.15	0.75
ResNet50	0.80	0.78	0.40	0.95
VGG16	0.75	0.45	0.55	1.15

5. CONCLUSION

This study investigated the performance of three CNN algorithms—MobileNetV2, ResNet50, and VGG16—in grapevine leaf disease classification. MobileNetV2 proved to be the most robust model, achieving high accuracy and low loss in training data and slightly stronger performance in validation data ResNet50 and VGG16; although still valid, it may require more tuning and more epochs to reach their full potential.

Findings indicate that using CNN to classify vine leaf diseases can significantly enhance disease management practices, and contribute to robust and sustainable grape production. Future research will focus on the use of this model over many years, different numbers of courses, and new regulations.

MobileNetV2 appears to be the most robust model for this specific dataset and task, achieving high accuracy and lower loss on the training data, and relatively stable performance on the validation data. ResNet50 and VGG16, while still effective, may require further tuning and more epochs to reach their full potential. Future work could involve experimenting with more epochs, different learning rates, or additional regularization techniques to improve the generalization capabilities of these models.

Further research might be worthwhile in improving generalization and scalability of these models, as well as the use of newer techniques like hyperspectral imaging and explainable AI, which are bound to give valuable contributions to vineyard disease detection.

This expanded literature review adds weight to your work by including a wide swath of related works in the area of plant disease detection using CNNs, right from possibility to challenges while deploying such models in agricultural settings.

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AUTHORS CONTRIBUTION

Waheed Ahmad: Conceptualization, Methodology, responsible for all the coding related to machine learning.
Eshill Azhar: Administration, Writing – Review & Editing;
Maham Anwar: Administration, Writing – Review & Editing;
Sarah Ahmed: Administration, Supervision, Writing – Review & Editing;
Tayyaba Noor: Administration, Supervision, Writing – Review & Editing

CONFLICT OF INTERESTS

No conflict of interests were disclosed.

ETHICS STATEMENTS

The research statement was conducted in compliance with ethical standards to ensure integrity and sustainability in agricultural practices. The study does not involve any human participants or animals, and all data used for grape leaf disease detection were sourced responsibly.

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