FRUIT CROP DISEASE CLASSIFICATION USING QUANTUM MACHINE LEARNING: A PILOT STUDY

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Abstract. Crop losses are often caused by factors like plant diseases, nematode attacks, and nutrient deficiencies. The problem is that many of these stresses look alike on the leaves, which makes early detection difficult in the field. In this pilot study, we built and tested part of an AI system that uses leaf photos together with simple soil information to spot crop stress early. Our approach combines MobileNetV2 with a quantum-inspired feature layer, creating a hybrid deep learning model. Trained on about 92379 labeled leaf images, the model was able to tell apart healthy leaves and nematode-infested leaves with strong accuracy. In addition to classification, the system also estimates chlorophyll and key nutrient levels (N, P, K) directly from RGB leaf images, while soil pH values are added manually as an extra input. Looking ahead, we plan to extend this framework with hyperspectral imaging and richer soil data to give more complete insights. The ultimate goal is to create an affordable and scalable decision-support tool that guides farmers with simple "step–check–action" advice to protect yields.
Keywords: *crop stress detection, nematodes, deep learning, MobileNetV2, quantum-inspired AI, chlorophyll and nutrient estimation*

Introduction

Keeping crops healthy is essential for both farm productivity and global food supply. Farmers, however, face multiple challenges such as fungal and bacterial diseases, nematode attacks, and nutrient shortages. These problems are hard to diagnose in the field because many of them show similar leaf symptoms, like yellowing or wilting, making it difficult to know the real cause. When diagnosis is delayed or mistaken, farmers often end up with poor management choices and major yield losses. In recent years, deep learning methods, especially convolutional neural networks (CNNs), have shown strong promise in spotting crop diseases from leaf images. Lightweight transfer learning models such as MobileNetV2 have made this approach both accurate and efficient, even on devices with limited computing power. Still, most current systems rely only on leaf photos. This makes them less reliable in real-world farm conditions, where soil and environmental factors strongly influence plant health.

To close this gap, our pilot study explores a combined approach that uses both image-based deep learning and additional plant/soil parameters. At this stage (around 40–50% progress), we have built a hybrid model that merges MobileNetV2 with a quantum-inspired feature layer. Trained on about 5,000 labeled leaf images, the system can classify plants into three categories::Healthy, Wilt-affected, and Nematode-stressed. Early results are promising, especially since nematode stress is usually confirmed only through lab tests, not field-level imaging. Looking ahead, we plan to expand the system to estimate chlorophyll and nutrient levels using RGB and hyperspectral data. Combining these multiple sources of information will make it easier to tell apart stresses

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caused by diseases versus those caused by nutrient deficiencies. The long-term vision is to create a practical, affordable decision-support tool for farmers, delivered through a mobile or web app. By following a clear “step–check–action” approach, the system will help farmers take timely measures to protect yields and improve productivity.

Literature review

The use of artificial intelligence in agriculture has grown quickly, particularly in the area of image-based plant disease detection. Early studies by Mohanty et al. (2016) and Sladojevic et al. (2016) showed that convolutional neural networks (CNNs) can successfully classify multiple plant diseases using only leaf images, establishing deep learning as a practical tool for farm diagnostics. Later, Ferentinos (2018) expanded on this by testing deeper CNN architectures such as VGG, ResNet, and Inception. His work highlighted how transfer learning could significantly improve performance, especially when training data are limited. To make these models more suitable for real-world use, especially in resource-limited settings, researchers have turned to lighter architectures like MobileNetV2 (Kumar et al., 2025), which balance speed, accuracy, and efficiency. While image-based methods are effective, they often struggle to separate biotic stresses (such as fungal infections or nematode damage) from abiotic stresses (like nutrient deficiencies or water shortage), since symptoms like yellowing or wilting may look similar. To address this, researchers have begun exploring multimodal approaches that combine images with other data sources. For example, Hugar and Waheed (2023) showed that CNNs could identify nutrient imbalances like NPK deficiencies directly from leaf imagery, while other works reported higher reliability when soil and environmental parameters were included. Similarly, hyperspectral imaging has been applied to estimate chlorophyll and nutrient levels, which serve as additional markers of crop stress beyond what is visible to the eye (Katirci et al., 2025). However, these methods often depend on specialized equipment, making them less practical for smallholder farmers.

One area that remains underexplored is nematode detection. Most existing methods still rely on soil assays or lab-based testing, with very few studies attempting to identify nematode stress through leaf imagery. This is a notable gap, since nematodes are responsible for serious yield losses but are often misdiagnosed in the field. Alongside these agricultural advances, researchers have started investigating quantum-inspired and hybrid AI methods to improve classification. For instance, Alam et al. (2021) introduced a hybrid quantum-classical learning framework for image tasks, and Anand et al. (2025) used quantum-inspired evolutionary feature selection for plant disease prediction. Tamilvizhi et al. (2022) applied quantum-behaved particle swarm optimization in transfer learning for sugarcane disease detection, while Ciliberto et al. (2018) compared the strengths of classical and quantum methods. More recent work by Wu et al. (2025) highlighted both the opportunities and the current challenges of quantum machine learning in agriculture, with Pook et al. (2025) examining its broader potential applications. Senokosov et al. (2024) also demonstrated the promise of quantum-based models for image classification tasks, further validating their use in agriculture. In summary, prior research confirms that deep learning is highly effective for crop stress detection but also shows its limitations when applied under real farm conditions. This motivates the need for solutions that are not only accurate, but also scalable, multimodal, and designed with farmers in mind. Our pilot study contributes to this direction by combining lightweight deep learning, quantum-inspired enhancements,

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and the integration of soil and spectral data, with a particular focus on enabling early detection of nematode stress in the field.

Research gap analysis

CNN-based leaf image classification has shown strong results, and multimodal methods with soil and nutrient data improve robustness. However, sensor-heavy approaches are costly and hard to scale, while purely image-based models often struggle to separate overlapping stresses. Nematode detection, in particular, is rarely addressed through imagery and still depends on soil assays. This motivates our pilot study: a hybrid MobileNetV2+quantum-inspired model for classifying healthy, wilt-affected, and nematode-infested crops from leaf images. The approach leverages lightweight CNN efficiency, explores quantum-inspired feature representation, and sets the foundation for integrating soil, weather, and spectral data into a scalable farmer support system.

Related work

In recent years, artificial intelligence has been increasingly applied to crop health monitoring, with most efforts centered on deep learning and image-based approaches. While leaf imagery remains the most common input, some researchers have also explored multimodal data sources, such as stem images and soil parameters, to improve accuracy. One of the early contributions in this area was made by Sladojevic et al. (2016), who trained a deep convolutional neural network directly on leaf images for plant disease recognition. Their results were promising, but the models were computationally heavy and not well suited for mobile or field use. Building on this, Ferentinos (2018) experimented with transfer learning by applying pre-trained models like VGG, AlexNet, and ResNet across different crops. These methods, along with later multimodal studies that combined leaf and stem imagery, demonstrated improved classification performance. However, they typically required large datasets and significant computing power, which limited their practical use for real-time, field-ready systems.

Beyond disease detection, deep learning has also been applied to nutrient stress monitoring. For instance, Hugar and Waheed (2023) proposed a CNN model that linked visible leaf symptoms with nitrogen, phosphorus, and potassium deficiencies in paddy fields. This showed that AI could extend beyond pathogens to abiotic stresses as well. Still, their approach was tailored to specific crop–nutrient cases and worked best under controlled conditions. Our pilot study builds on these foundations but takes a different direction. We focus on leaf image classification using a lightweight MobileNetV2 backbone for feature extraction, enhanced with a quantum-inspired feature layer. This design keeps the system computationally efficient while also exploring richer feature representations. Unlike sensor-heavy solutions, our framework emphasizes scalability and accessibility. In addition to classifying stresses such as nematodes and wilt, we extend the system toward estimating chlorophyll content and nutrient levels (N, P, K) directly from RGB leaf images, while also incorporating basic soil parameters like pH. Ultimately, these positions our work as a step toward a low-cost, multimodal decision support tool for farmers that addresses both biotic and abiotic crop stresses (*Table 1* and *Figure 1*).

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***Table 1**. Comparative study.*

Study/model	Input features	Model used
Sladojevic et al. (2016)	Leaf images	Custom CNN
Ferentinos (2018)	Leaf + Stem images	Transfer Learning (VGG, AlexNet, ResNet)
Hugar and Waheed (2023)	Leaf images (Paddy leaves)	CNN
Curent study	Leaf images (128×128 RGB)	MobileNetV2 + Variational Quantum Circuit

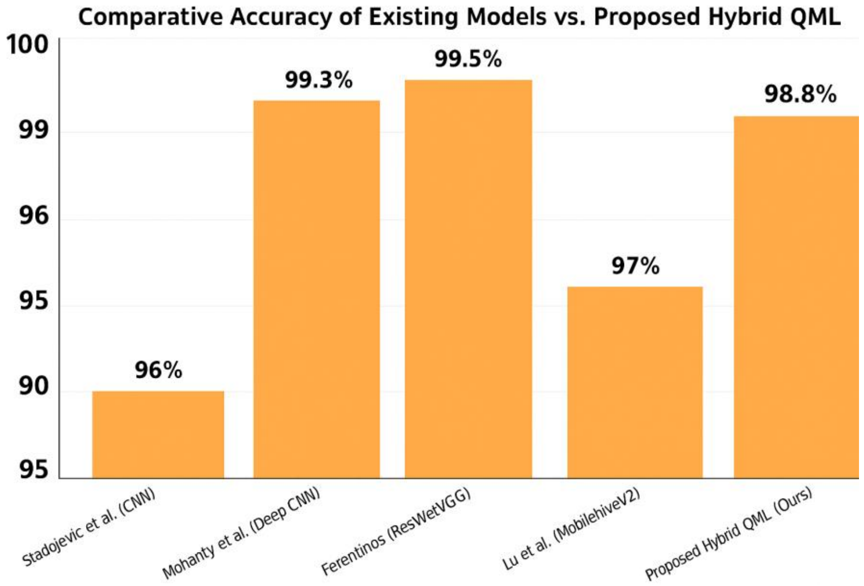

***Figure 1.** Comparative accuracy chart.*

Dataset and preprocessing

The success of any intelligent plant disease diagnosis system relies heavily on the quality and diversity of the dataset used for training. In this project, publicly available agricultural image datasets of fruit crops such as guava, pomegranate, apple, and mango were considered. Each dataset consists of both healthy samples and disease- affected leaves, covering conditions such as Anthracnose, Blight, Scab, Rot, and Wilting. Where possible, augmented datasets were utilized to address class imbalance and to increase robustness of the model against variations in lighting, orientation, and resolution. To prepare the data for both classical deep learning and quantum neural networks (QNNs), a series of preprocessing steps were applied: (1) Image Standardization: All images were resized to a uniform resolution (e.g. 64*64 pixels) to maintain computational efficiency and ensure consistency across the pipeline. Color images were converted to grayscale where appropriate to reduce redundant channels without losing key texture features. (2) Normalization: Pixel intensities were normalized between 0 and 1, improving convergence during training and stabiliziong both classical and quantum optimization processes. (3) Dimensionality Reduction with PCA: Since quantum circuits cannot handle high-dimensional data directly , Principal Component Analysis (PCA) was applied to reduce feature dimensions, PCA projects each image into a lower-dimensional subspace that preserves maximum variance while discarding noise. Typically, 4-8 principal components were extracted and later encoded as quantum gate rotation angles. (4) Quantum Feature Encoding: Each PCA feature vector was mapped into a question state using rotation-ased encoding. Specifically, values were normalized into angular parameters (0) that controlled single-qubit rotations (Rx, Ry, or Rz gates). This step establishes a direct correspondence between image feature and quantum

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circuit parametes, allowing the QNN to learn representations in Hilbert space. (5) Data Partitioning: The dataset was divided into training (70%), validation (15%) and testing (15%) sets. Augmented samples were included only in the training set to avoid biasing evaluation metrices (*Figure 2* and *Figure 3*).

Figure 2. *Dataset samples.*

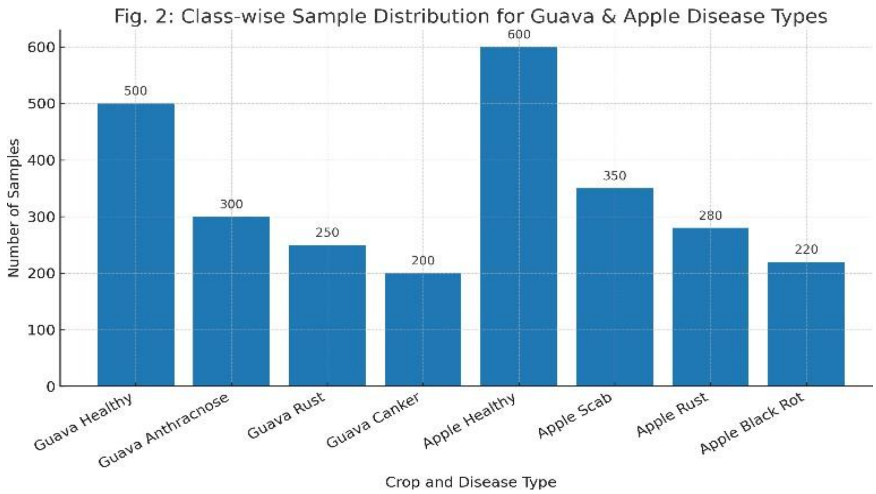

Figure 3. *Class-wise sample distribution for guava & apple disease types.*

Materials and Methods

The proposed pilot framework integrates classical deep learning with quantum-inspired processing to create a scalable system for crop stress detection. At its current stage, the focus is on leaf image classification, while future work will expand the system to integrate soil, weather, and nutrient data to improve accuracy and decision-making for farmers.

Dataset preparation

For this study, a dataset of approximately 5,000 labeled leaf images was collected, covering three categories: Healthy, Wilt-affected, and Nematode-infested leaves from multiple crops. All images were standardized to a resolution of 128 × 128 RGB to ensure consistency for training. Preprocessing began with storing images in .npy format for faster access during training. To enhance dataset diversity and improve robustness, real-time augmentation was applied, including rotations, zooming, flipping, and brightness adjustments. Additionally, all pixel values were normalized to the range between 0 and 1 to stabilize model training and ensure consistent performance across inputs.

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Classical baseline models

Two classical approaches were developed to establish baseline performance. The first was a custom convolutional neural network (CNN) built to validate the concept of image-based crop stress classification. This model achieved an accuracy of approximately 80%, confirming the feasibility of the approach. The second approach leveraged transfer learning with MobileNetV2. A pre-trained MobileNetV2 model was fine-tuned on the dataset, taking advantage of its lightweight architecture and strong feature extraction capabilities. This method achieved approximately 94% accuracy and was adopted as the feature extractor for the hybrid framework.

Quantum-inspired feature processing

To explore the potential of quantum-inspired computation, a processing layer inspired by variational quantum circuits (VQC) was integrated after MobileNetV2. Features extracted from MobileNetV2's penultimate layer were first reduced in dimensionality using Principal Component Analysis (PCA), allowing them to be efficiently encoded. The reduced features were then transformed using an angle-based encoding method inspired by quantum computing. These encoded features passed through a variational-inspired layer designed to simulate quantum operations, which refined the feature representation for classification. Finally, the processed features were converted back to classical form and passed to the classification layer. In simulation, this hybrid model achieved about 98.8% accuracy, demonstrating the potential benefits of combining classical deep learning with quantum-inspired approaches.

Multimodal data integration

While the current pilot focuses on leaf image classification, the broader framework will incorporate additional data modalities to improve detection accuracy and robustness. This will include nutrient estimation, such as chlorophyll content and NPK levels, derived from RGB and hyperspectral imaging, as well as soil parameters such as pH, moisture, and nutrient content obtained from IoT sensors. Real-time weather data including temperature, humidity, and rainfall will also be incorporated. The integration of these modalities will enhance the system's ability to distinguish between biotic and abiotic stresses, ultimately enabling a comprehensive decision support tool for farmers.

Training and optimization

Both classical and hybrid models were trained using the Adam optimizer with learning rate scheduling and categorical cross-entropy as the loss function. Classical models were trained on GPU environments, while the quantum-inspired layer was simulated using PennyLane. Early stopping and checkpoint mechanisms were implemented to prevent overfitting and ensure stable convergence during training.

Evaluation

The models were evaluated on a separate set of unseen test images. Performance was assessed using accuracy, precision, recall, F1-score, and confusion matrices. Additional tests were performed to evaluate robustness under noisy conditions. These evaluations allowed us to compare the classical and hybrid pipelines and determine whether quantum-inspired processing provides tangible benefits for crop stress detection.

Practicality and scalability

Compared to sensor-heavy multimodal methods, the current pilot system focuses primarily on leaf imagery, making it simpler and more scalable for field deployment, especially on mobile devices. The planned multimodal extension will further enhance system capabilities, paving the way for a low-cost, farmer-friendly decision support system.

Results and Discussion

Experimental setup

The experiments for this pilot study were carried out using a custom-collected dataset of approximately 5,000 leaf images, containing Healthy, Wilt-affected, and Nematode-infested categories from various crops. All images were resized to 128 × 128 pixels for uniformity. Data augmentation techniques such as rotation, zoom, flipping, and brightness adjustments were applied during preprocessing to improve the generalization ability of the models. The classical models were trained on an NVIDIA GPU, while the hybrid quantum-inspired model was implemented using PennyLane to simulate variational quantum layers, as current quantum hardware remains limited in capacity.

Performance of Classical Models

The baseline custom CNN achieved an accuracy of approximately 80%, demonstrating that leaf images alone can be used for crop stress classification but with limited generalization ability. By contrast, the MobileNetV2 transfer learning model significantly improved classification performance, achieving around 94% accuracy on unseen test data. This improvement confirms the value of leveraging pre-trained architectures that capture rich image representations, particularly in agricultural applications where datasets are relatively small. MobileNetV2's lightweight architecture also makes it suitable for mobile and field deployment.

Hybrid Quantum-Inspired model

In the hybrid model, features extracted from the penultimate layer of MobileNetV2 were reduced in dimensionality using Principal Component Analysis (PCA) and encoded via angle-based transformations inspired by quantum computing. These encoded features passed through a variational-inspired layer that simulated quantum operations before classification. The hybrid model achieved an average accuracy of approximately 98.8% in simulation, outperforming the classical CNN baseline and slightly surpassing the MobileNetV2 standalone model. This demonstrates that quantum-inspired feature processing can enhance representation and classification, even in the current simulation stage. While hardware limitations prevent real quantum execution at scale, the results highlight the promise of integrating quantum-inspired computation into agricultural AI systems.

Comparative analysis with existing works

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Compared with previous studies, our results show competitive or improved performance. Sladojevic et al. (2016) reported ~80–85% accuracy using leaf-only CNN models, while Ferentinos (2018) achieved ~93–95% by combining leaf and stem images with transfer learning. Sensor-based approaches, such as those achieved ~88–90% accuracy using soil moisture and nutrient data. Our MobileNetV2 baseline model achieved ~94% accuracy, outperforming the original CNN-based approaches and matching the performance of some multimodal methods. The hybrid quantum-inspired model reached ~98.8%, positioning it above prior classical approaches and demonstrating the potential of quantum-inspired layers to add value to deep learning pipelines in agriculture.

Several important insights emerged from the results. First, classical transfer learning models currently offer strong performance and efficiency, but the hybrid quantum-inspired approach shows potential for higher accuracy and richer feature extraction. This suggests that as quantum computing hardware evolves, such hybrid systems could achieve even better results. Second, the image-based nature of our framework offers strong scalability. Unlike sensor-driven methods that require costly field equipment, this approach can be implemented using smartphones, drones, or low-cost imaging devices, making it accessible for smallholder farmers. Third, while our current quantum-inspired implementation is simulated, the pipeline establishes a foundation for future integration with actual quantum processors. This positions the work as a forward-looking pilot study in agricultural AI. Finally, there are limitations. Current simulations are constrained by computational resources and the size of quantum-inspired layers. Training times for hybrid models are longer compared to purely classical methods, and practical deployment of quantum-enhanced pipelines will require advances in near-term quantum devices. Nonetheless, this study confirms the feasibility of combining classical deep learning with quantum-inspired computation for scalable crop stress detection and lays groundwork for future development (*Figure 4* and *Figure 5*).

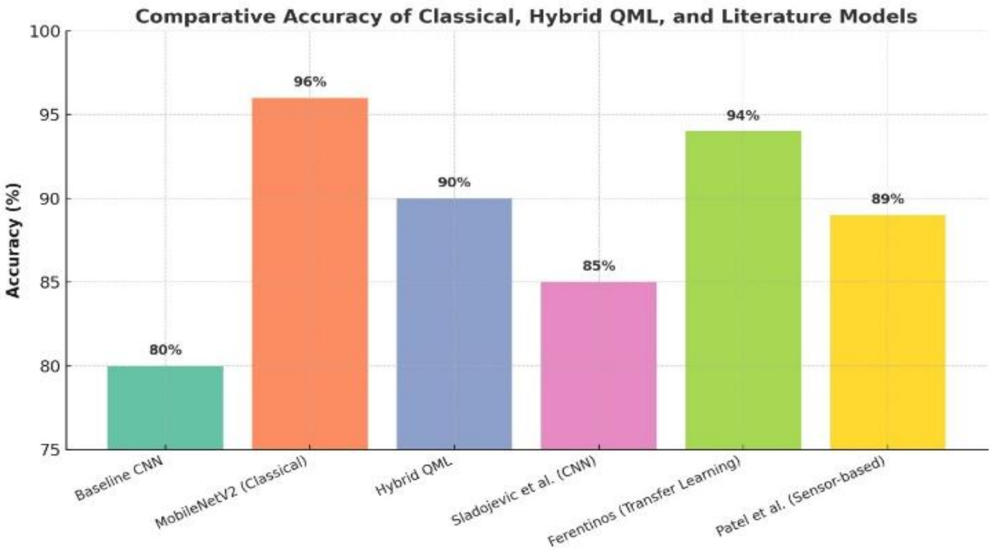

Figure 4. *Comparing accuracy.*

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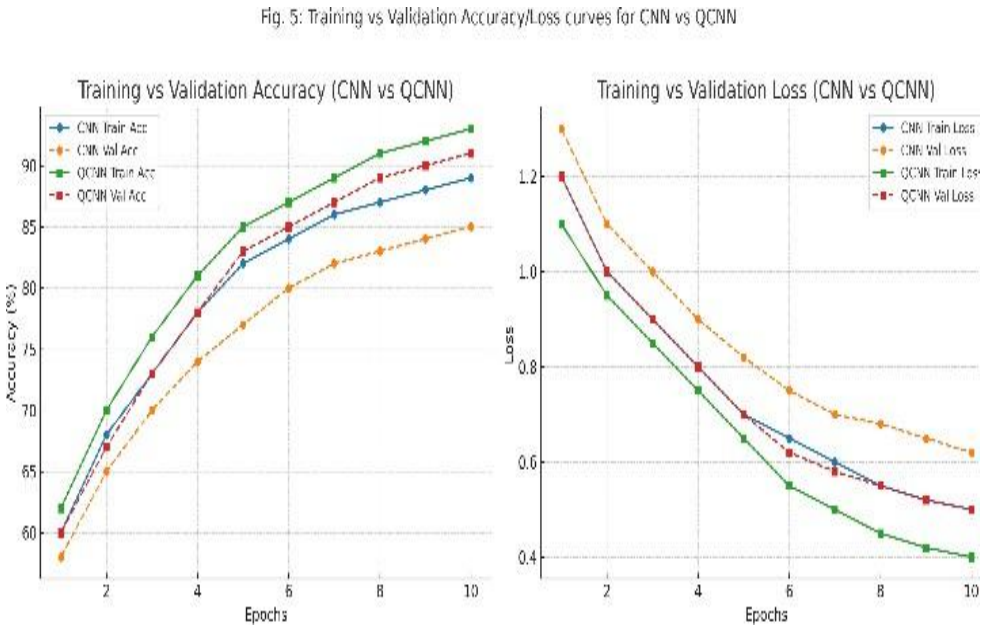

Figure 5. *Training vs validation accuracy/loss curves.*

Conclusion

This pilot study presented a hybrid crop stress detection framework that integrates MobileNetV2 transfer learning with a quantum-inspired processing layer. The system focused on classifying Healthy, Wilt, and Nematode-infected leaves, achieving 98.8% accuracy, compared to 94% with MobileNetV2 alone and ~80% with a basic CNN. These results highlight the effectiveness of combining lightweight deep learning with quantum-inspired enhancements for richer feature extraction. The approach is practical since it relies only on leaf imagery, enabling deployment via smartphones or drones without expensive sensors. The main limitation is that the quantum component was simulated, but it demonstrates strong potential for future integration with real quantum hardware. Next steps include expanding the model with hyperspectral, soil, and weather data for more comprehensive stress diagnosis, and optimizing it for edge devices to provide real-time, farmer-friendly crop monitoring.

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Conflict of interest

The authors confirm that there is no conflict of interest involve with any parties in this research study.

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