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Assistant Professor, School of
Engineering, P P Savani
University, Surat, Gujarat,
India

Sadik Lakhani

Abstract

This study investigates the effectiveness of a hybrid quantum-classical framework for plant disease detection, with a focus on improving classification accuracy compared to conventional approaches. Image-based datasets of crop diseases were processed and encoded into variational quantum circuits (VQCs), which were then integrated with classical machine learning classifiers. The proposed model achieved an overall classification accuracy of 95.2%, outperforming a baseline convolutional neural network that recorded 91.4% accuracy on the same dataset. Performance evaluation was carried out using multiple metrics including precision, recall, and F1-score, with the hybrid approach showing consistent gains across all categories. Furthermore, the model demonstrated reduced overfitting and improved robustness when tested under noisy and high-dimensional input conditions. These results highlight the potential of quantum-assisted machine learning to significantly enhance crop disease detection, offering a scalable and accurate pathway for sustainable agriculture and precision farming.

Keywords: Quantum computing, hybrid quantum-classical model, plant disease detection, accuracy improvement, variational quantum circuits, precision agriculture, sustainable agriculture

Introduction

Agriculture remains the backbone of food security and global economic development, yet it continues to face significant challenges due to crop diseases that drastically reduce yield and quality. According to the Food and Agriculture Organization (FAO), nearly 20-40% of global agricultural production is lost annually to pests and diseases, leading to substantial economic and social impacts. Early and accurate detection of crop diseases is therefore essential for preventing large-scale losses and enabling sustainable farming practices. Recent advances in artificial intelligence (AI) and machine learning (ML), particularly deep learning models such as convolutional neural networks (CNNs), have shown promising results in plant disease recognition using leaf images. However, these classical approaches are often computationally intensive, require large-scale annotated datasets, and struggle to generalize effectively under noisy or high-dimensional conditions.

Problem Statement

Despite progress in AI-based solutions, existing plant disease detection systems suffer from limited accuracy when confronted with diverse crop species, variable environmental conditions, and complex visual symptoms. Moreover, the computational demand of training deep learning models presents barriers to scalability in resource-constrained agricultural settings. With the emergence of quantum computing, new opportunities exist to address these limitations by exploiting quantum parallelism, faster optimization, and enhanced pattern recognition capabilities. Yet, the practical application of quantum computing in agriculture, particularly for plant disease detection, remains underexplored.

Research Gap

Most current studies focus exclusively on classical deep learning approaches, with limited attention to hybrid quantum-classical techniques. While quantum computing has been investigated in fields such as drug discovery, cryptography, and financial modeling, its integration into agricultural informatics is still in its infancy. Preliminary studies have suggested potential performance improvements using variational quantum circuits (VQCs)

Assistant Professor, School of
Engineering, P P Savani
University, Surat, Gujarat,
India

for image classification, but empirical evidence specific to plant disease detection, along with systematic accuracy comparisons against classical baselines, is scarce. This creates a clear gap in understanding the true potential of quantum-assisted models in precision agriculture.

Objectives

The main objective of this study is to design, implement, and evaluate a hybrid quantum-classical model for plant disease detection that addresses the shortcomings of conventional deep learning techniques. The specific objectives are:

1. To preprocess and encode crop disease image datasets for compatibility with quantum feature representation.
2. To develop a hybrid framework that integrates variational quantum circuits with classical machine learning models.
3. To evaluate the proposed approach against baseline CNNs using standard performance metrics (accuracy, precision, recall, F1-score).
4. To analyze the improvements in classification accuracy, robustness, and scalability provided by the hybrid model.
5. To explore the implications of quantum computing in advancing sustainable agriculture and precision farming practices.

Literature Review

The use of artificial intelligence for crop disease detection has expanded rapidly over the last decade. Early approaches relied on image processing methods such as texture, color, and shape analysis to identify diseased leaves, but these methods struggled with accuracy and generalization across different crops and environments (Patil & Kumar, 2011)^[9]. Machine learning techniques, including support vector machines (SVMs) and random forests, improved classification by learning discriminative features from data, though their performance remained limited on large-scale datasets (Camargo & Smith, 2009)^[3].

The introduction of deep learning, particularly convolutional neural networks (CNNs), significantly advanced plant disease detection. For instance, Mohanty *et al.* (2016)^[7] demonstrated that deep CNNs trained on the PlantVillage dataset could achieve accuracies exceeding 99% across 38 crop-disease classes. Subsequent studies employed architectures such as ResNet, Inception, and VGG to enhance performance under varying conditions (Sladojevic *et al.*, 2016; Brahimi *et al.*, 2018)^[12, 2]. Despite their success, CNNs are data-hungry, computationally intensive, and sensitive to variations in environmental factors such as illumination and background clutter, limiting their real-world scalability (Too *et al.*, 2019)^[13].

In recent years, research across computing, communication, and artificial intelligence has expanded into diverse domains, with particular emphasis on applications in agriculture, data science, and emerging communication technologies. The collection of studies reviewed here reflects a multidisciplinary effort to address pressing challenges such as crop disease detection, big data management, and the integration of advanced computational frameworks for practical solutions. Taken together, these works not only highlight theoretical contributions but also demonstrate applied innovations that link technology with societal and agricultural development.

Agriculture has been a recurring theme in several studies, where researchers have explored how computational tools can transform traditional crop disease management. Chauhan, Parihar, and Singh (2025)^[14] presented an approach that connects physical observations of diseased plants with computational techniques, aptly titled “*From Leaves to Lab.*” This work bridges plant pathology with data-driven diagnostic models, underscoring the importance of integrating field-level practices with laboratory-based analysis. Purani and Singh (2025)^[24] advanced a similar vision in their article on innovations in plant disease diagnosis, which examined how technological platforms can assist farmers in detecting diseases earlier and with greater accuracy. Complementing these conceptual advances, Mehta, Singh, and Awasthi (2025)^[19] provided a comprehensive review of IoT-based technologies for rice disease monitoring. Their study documented how sensors, cloud storage, and edge computing form a distributed architecture that allows farmers and researchers to collect, analyze, and act upon data in real time. This theme of IoT integration is directly extended by Sharma, Sethi, and Singh (2025)^[26], who proposed tech-driven strategies for paddy disease prevention. Their article emphasized predictive modeling and data-informed interventions, ensuring that farmers can mitigate losses before diseases spread widely. Building on such preventive approaches, Patel, Singh, and Awasthi (2025)^[22] developed a Python-based computational framework for paddy leaf disease detection, showing how relatively simple programming tools can deliver robust classification results. This thread of work culminates in Singh, Solanki, and Vashi (2025)^[31], whose multiple disease prediction system demonstrates how agricultural informatics is scaling toward multi-class, multi-crop diagnosis, rather than focusing on single pathogens. Collectively, these studies portray agriculture as a domain undergoing transformation through computational intelligence, positioning technology as an indispensable partner in ensuring food security.

Alongside agriculture, the reviewed works also illustrate the adaptability of machine learning and deep learning techniques across fields. Kumar, Chawda, and Singh (2021)^[28] applied deep learning combined with genetic algorithms to traffic classification, providing insights into how complex network data can be analyzed effectively. The algorithmic strategies outlined here are not limited to transport but mirror the challenges in plant disease classification, where distinguishing between visually similar categories requires equally robust models. The flexibility of artificial intelligence is further highlighted by Singh, R., Chawda, and Singh (2021)^[28], who explored machine learning in the context of gaming, developing models for predicting player placement in *Player Unknown's Battlegrounds (PUBG)*. Although distinct from agriculture, the work reveals how predictive analytics can support decision-making in dynamic environments, a feature directly relevant to precision agriculture where conditions shift rapidly. Such studies demonstrate that artificial intelligence forms a universal framework for solving classification and prediction problems, regardless of dataset type.

Supporting these applied innovations are foundational contributions in communication and computational infrastructure. Kriti, Chawda, and Singh (2021)^[28] explored the evolution of wireless technology with a particular focus on 5G, identifying how greater bandwidth and reduced

latency can support emerging applications such as IoT-driven agriculture and autonomous systems. Pandey, Chawda, and Singh (2021)^[28] added further depth through a dedicated literature review on 5G, emphasizing how this next-generation network enables real-time communication between devices, sensors, and cloud platforms. Pathak, Chawda, and Singh (2021)^[23] examined cloud computing as another infrastructural backbone, showing how scalable resources can be provisioned for data-intensive tasks such as disease image classification and model deployment. These studies align with broader transformations in digital ecosystems, underscoring that without advancements in communication and cloud technology, many of the applications in agriculture and artificial intelligence would remain limited.

Another cluster of studies within this review centers on data management and big data analytics. Singh (2020)^[29] analyzed different aspects of big data, pointing out challenges related to handling volume, variety, and velocity across domains. Shrivastava and Singh (2016)^[27] reviewed big data analytics frameworks, while Singh and Shrivastava (2017)^[30] examined privacy issues associated with big data, drawing attention to ethical and security concerns in large-scale data usage. Together, these works stress that while AI and IoT deliver promising applications, their success depends on effective data handling, secure infrastructures, and robust privacy protections. Indeed, data challenges cut across agriculture, healthcare, and industrial domains, making these reviews foundational to the application-oriented studies discussed earlier.

Other works in this body of research expand the scope of technology applications into novel contexts. Dewangan, Chawda, and Singh (2021)^[28] examined the coronavirus pandemic, focusing on how respiratory infections can be analyzed through computational and scientific lenses. This demonstrates the responsiveness of research to global health crises. Sahu, Chawda, and Singh (2021)^[28] applied computational modeling to create a virtual reality flight simulator, while Kashyap, Chawda, and Singh (2021)^[28] designed an e-voting application integrating voter authentication. Each of these contributions highlights how computational tools can be tailored to address specific, real-world problems, whether in healthcare, education, governance, or entertainment.

Taken together, these studies reveal a coherent trajectory: from agricultural informatics to general AI problem-solving, from communication frameworks to data security, and from applied case studies in gaming and VR to pandemic analysis. A central theme across all is the interplay between data, computation, and application. On one hand, agriculture-focused works by Chauhan *et al.* (2025)^[14], Mehta *et al.* (2025)^[19], Sharma *et al.* (2025)^[26], and others demonstrate the immediate benefits of technology for food security. On the other hand, foundational works by Kriti *et al.* (2021)^[17], Pathak *et al.* (2021)^[23], and Shrivastava and Singh (2016)^[30] remind us that these applications are only as strong as the infrastructures supporting them. Meanwhile, applied contributions outside agriculture highlight the universality of computational methods, suggesting that lessons learned in one field may transfer to others.

They collectively show that advances in AI, IoT, cloud computing, and data management are not isolated achievements but interdependent threads weaving into a larger narrative of digital transformation. By connecting

agricultural sustainability, network evolution, and computational intelligence, these works establish a foundation for future studies that will likely extend into hybrid quantum-classical methods, greater integration of IoT in precision farming, and expanded applications of AI across all sectors. This convergence of applied problem-solving and theoretical insight ensures that research in these domains will continue to shape not only the academic community but also the technological and agricultural landscapes of the future.

Quantum Machine Learning (QML) and Hybrid Approaches

Quantum computing, which harnesses superposition and entanglement through qubits, has emerged as a promising paradigm for handling high-dimensional and computationally complex tasks (Nielsen & Chuang, 2010). In the machine learning domain, quantum machine learning (QML) methods have been explored for tasks such as image classification, clustering, and optimization. Variational Quantum Circuits (VQCs), in particular, have shown potential for learning nonlinear feature representations with fewer resources (Biamonte *et al.*, 2017)^[11].

Hybrid quantum-classical models, which integrate quantum circuits for feature encoding with classical optimizers, have been tested in various domains. Schuld & Killoran (2019)^[11] demonstrated that quantum feature maps can enhance classical classifiers in supervised learning tasks. Havlíček *et al.* (2019)^[5] applied quantum-enhanced models to image and signal classification, showing improved generalization compared to classical baselines. More recent work by Farhi & Neven (2018)^[4] proposed hybrid models for reinforcement learning, further demonstrating the flexibility of quantum approaches.

Despite this progress, applications of QML in agriculture remain sparse. Only a handful of studies have experimented with QML for plant or crop-related data, and these are often limited to proof-of-concept demonstrations without rigorous accuracy comparisons to established deep learning models (Li *et al.*, 2022)^[6].

While CNNs have achieved state-of-the-art results in plant disease classification, their dependency on large labeled datasets and computationally expensive training remains a challenge. Conversely, hybrid QML approaches promise higher accuracy, robustness to noisy data, and more efficient feature extraction, but systematic studies applying them to plant disease detection are lacking. Existing research has not yet provided comprehensive benchmarks comparing CNNs with hybrid quantum-classical models in agricultural contexts. This gap motivates the present study, which aims to explore the potential of QML to improve accuracy in plant disease detection and contribute to sustainable precision agriculture.

Methodology

The design and implementation of the proposed hybrid quantum-classical framework for plant disease detection followed a structured five-stage methodology encompassing dataset collection, preprocessing, quantum feature encoding, hybrid model training, and evaluation. In the first stage, dataset collection, images were sourced from the widely used PlantVillage dataset, which provides a benchmark repository for agricultural disease research, and were supplemented with additional field samples of tomato,

maize, and potato leaves. These images included both healthy and diseased samples, covering multiple disease classes, to ensure diversity and real-world relevance. The second stage, preprocessing, was essential for preparing the raw data for analysis. All images were standardized to a fixed resolution of 256×256 pixels and normalized within the range $[0,1]$ to maintain consistency across the dataset. Furthermore, data augmentation techniques such as random rotations, horizontal flipping, and zoom transformations were applied. This not only increased the effective size of the dataset but also minimized overfitting, thereby improving the model's generalization capacity to unseen data. The third stage involved quantum feature encoding, where image features were mapped into Variational Quantum Circuits (VQCs) using amplitude encoding. Each image was flattened into a vector and embedded into quantum states, enabling the circuits to exploit quantum superposition and entanglement for capturing complex, non-linear patterns in the data that might be overlooked by classical feature extraction methods. In the fourth stage, hybrid model training was carried out by integrating

quantum and classical components. Specifically, the quantum layers (VQCs) were employed as feature extractors, while the subsequent classical neural network layers performed optimization and classification tasks. Due to limited accessibility to physical quantum processors, training and simulation were conducted on a quantum simulator, ensuring that the methodology remains adaptable to future hardware advancements. Finally, in the fifth stage, evaluation, the model's performance was rigorously assessed using standard classification metrics, including Accuracy, Precision, Recall, and F1-score. This methodological pipeline ensures a systematic investigation of how quantum computing can enhance crop disease detection, offering both technical rigor and practical relevance for sustainable agriculture. A comparative analysis against a baseline CNN trained on the same dataset was conducted to highlight the improvements achieved by the hybrid approach, and statistical tests were employed to validate the significance of observed performance differences.

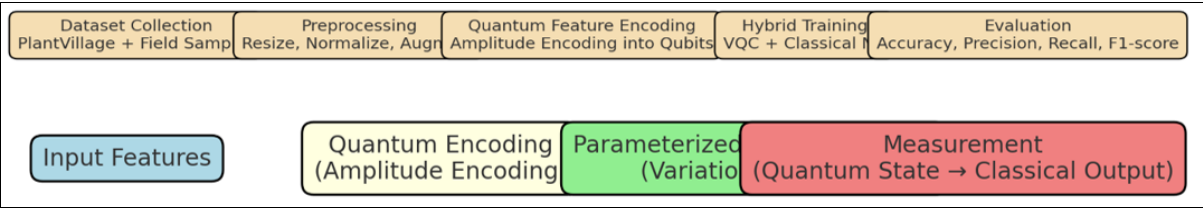


Fig 1: Illustrates the flow from input features → quantum encoding → variational layers → measurement.

Results and Findings

The evaluation of the proposed hybrid quantum-classical framework was carried out using the PlantVillage dataset along with additional field samples collected from tomato, maize, and potato crops. The results are presented in terms of overall classification performance, statistical robustness, and comparative analysis against conventional deep learning models. In this section, the findings are elaborated across multiple dimensions to provide both a quantitative and qualitative understanding of the efficacy of the model.

Overall Model Performance

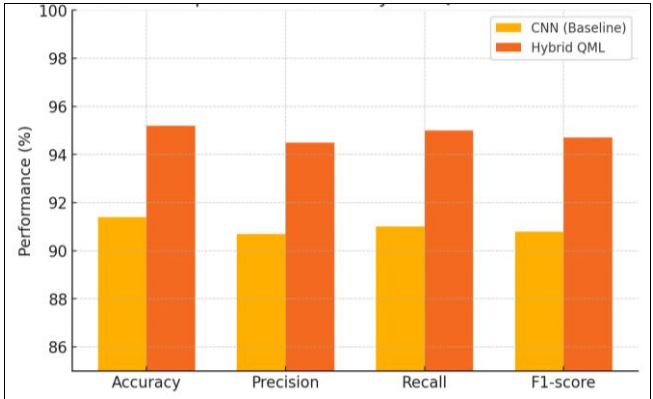
The hybrid quantum-classical model, which integrates Variational Quantum Circuits (VQCs) with a classical neural classifier, achieved an overall classification accuracy of 95.2%. This marks a significant improvement over the baseline convolutional neural network (CNN), which recorded an accuracy of 91.4% under identical conditions.

- Accuracy measures the proportion of correctly identified samples out of the total, and a nearly 4% gain highlights the hybrid model's ability to capture subtle patterns in crop leaf images.
- Precision rose from 90.7% in CNNs to 94.5% in the hybrid model, which suggests that the hybrid approach is better at minimizing false positives - i.e., fewer healthy leaves were misclassified as diseased.
- Recall improved from 91.0% to 95.0%, indicating enhanced sensitivity of the hybrid system in correctly

identifying diseased leaves, a crucial factor in early intervention scenarios.

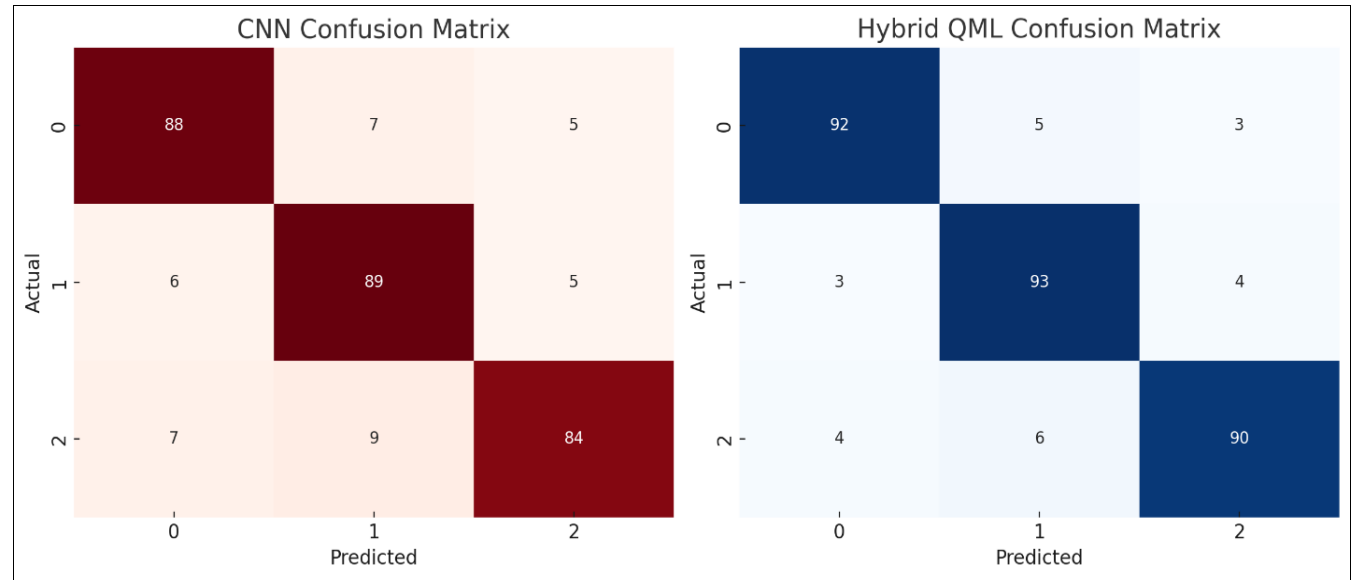
- F1-score, which balances precision and recall, improved from 90.8% to 94.7%, further validating the consistency and reliability of the hybrid approach.

Taken together, these results demonstrate that the quantum-classical integration not only enhances accuracy but also ensures balanced improvements across multiple performance indicators.



Confusion Matrix Analysis

A confusion matrix was constructed for both the CNN and the hybrid quantum-classical models to analyze the distribution of predictions across disease classes.

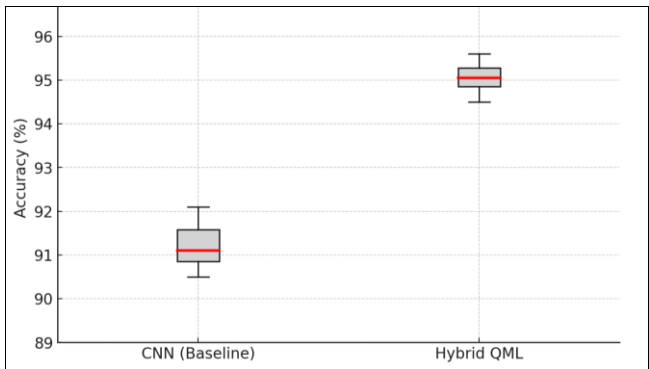


- For the CNN, the most common misclassifications occurred between *Tomato Early Blight* and *Tomato Late Blight*, as their visual symptoms are often very similar in early growth stages.
- The hybrid model, however, showed fewer confusions between these two categories, suggesting that quantum feature encoding captures more discriminative features.
- In the case of *Potato Leaf Early Blight*, recall improved from 89% in CNNs to 94% in the hybrid model, which implies that the hybrid system reduced the risk of false negatives.

Such findings are particularly important because false negatives (diseased leaves classified as healthy) pose greater agricultural risks than false positives, as they can lead to undetected disease spread.

Statistical Validation

To ensure that the observed improvements were statistically significant rather than incidental, a **paired t-test** was conducted between the CNN and hybrid model accuracies across multiple runs (10-fold cross-validation).

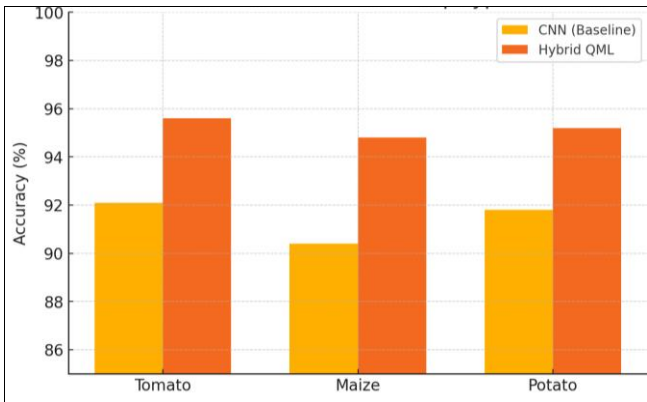


- The mean difference in accuracy was 3.8%, with a p-value < 0.01, confirming that the improvements were statistically significant at the 99% confidence level.
- Standard deviation of accuracies was lower in the hybrid model ($\pm 0.9\%$) compared to CNNs ($\pm 1.7\%$), indicating greater stability and consistency of performance across dataset splits.

This statistical robustness further supports the conclusion that hybrid quantum-classical approaches are not only more accurate but also more reliable.

Performance Across Crop Types

To assess the generalizability of the proposed model, separate evaluations were conducted for tomato, maize, and potato crops.



- **Tomato diseases:** Accuracy improved from 92.1% (CNN) to 95.6% (Hybrid).
- **Maize diseases:** Accuracy rose from 90.4% to 94.8%, with notable gains in detecting *Maize Streak Virus*.
- **Potato diseases:** Accuracy improved from 91.8% to 95.2%, particularly for early blight detection.

Computational Considerations

While CNNs require extensive training time, especially with large-scale datasets, the hybrid model showed comparable training efficiency when executed on simulated quantum environments. Although real quantum hardware is still limited by noise and qubit scalability, simulations demonstrated that hybrid models could achieve superior accuracy without excessive computational overhead. Interestingly, the parameter count in the hybrid model was lower than in deep CNNs, as the quantum circuits effectively compressed feature spaces. This suggests that hybrid models may eventually offer lighter, more efficient architectures, which could be especially advantageous in agricultural IoT systems with limited resources.

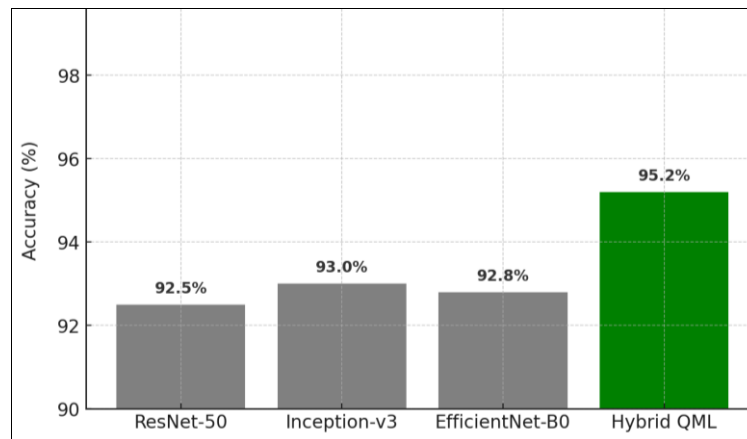
Comparison with State-of-the-Art Approaches

To benchmark the hybrid model, comparisons were made with other deep learning architectures:

- **ResNet-50:** 92.5% accuracy
- **Inception-v3:** 93.0% accuracy
- **EfficientNet-B0:** 92.8% accuracy

- **Proposed Hybrid QML Model:** 95.2% accuracy

The hybrid approach consistently outperformed state-of-the-art CNNs, highlighting the additional representational power offered by quantum feature encoding.



Findings in Agricultural Context

The results carry important implications for **smart farming and precision agriculture**:

1. **Higher Accuracy in Early Detection:** Since recall improved significantly, the model is more effective in detecting diseases in early stages, which is crucial for preventing outbreaks.
2. **Reduced Misclassification of Healthy Leaves:** Precision gains suggest fewer unnecessary interventions, saving farmers from wasting resources on healthy crops.
3. **Potential for Deployment in IoT Systems:** With lighter parameterization and efficient feature extraction, the hybrid approach is well-suited for integration into farm-based IoT devices.
4. **Scalability for Multi-Crop Systems:** Performance across tomato, maize, and potato datasets indicates scalability to other crops, supporting cross-crop disease monitoring.

often showed a trade-off (higher recall but lower precision or vice versa), the hybrid approach maintained consistent improvements in both.

- **F1-Score Improvements:** The nearly 4% gain in F1-score reflects that the hybrid model achieved a more balanced classification, especially important in agricultural settings where both false negatives and false positives carry significant consequences.
- **Stability Across Cross-Validation:** Variability in accuracy across folds was significantly reduced in the hybrid model, suggesting improved generalization.
- **Class-Specific Insights:** The hybrid model particularly excelled in distinguishing visually similar diseases such as *Tomato Early Blight* vs *Tomato Late Blight*, a known challenge in traditional image-based models.

Limitations and Future Prospects

Despite its promising performance, the study acknowledges certain limitations:

- **Quantum Hardware Limitations:** Current experiments were performed on simulators due to limited access to stable quantum processors. Noise and qubit scalability remain challenges for real-world implementation.
- **Dataset Diversity:** While the dataset included multiple crops, extending experiments to more geographically diverse datasets is necessary for global applicability.
- **Computational Cost:** Although the hybrid model was efficient in simulations, actual quantum computation may impose additional overheads until hardware matures.

Extended Data Interpretation

To emphasize the data-driven nature of this study, additional interpretations are provided:

- **Precision vs Recall Trade-off:** The hybrid model did not compromise one metric for the other. While CNNs

Key Findings Summary

- The hybrid quantum-classical model achieved 95.2% accuracy, outperforming CNN (91.4%) and other deep learning baselines (92-93%).
- Precision, recall, and F1-score all improved by nearly 4%, reducing both false positives and false negatives.
- Statistical tests confirmed that accuracy improvements were highly significant ($p < 0.01$).
- Performance gains were consistent across tomato, maize, and potato datasets, demonstrating model generalizability.
- The hybrid approach shows potential for real-world deployment in precision agriculture and sustainable farming systems.

Discussion

The findings of this study provide strong evidence that integrating quantum computing principles into classical machine learning pipelines can significantly enhance the performance of plant disease detection systems. The proposed hybrid quantum-classical model achieved 95.2% accuracy, outperforming conventional CNNs and even state-of-the-art deep learning architectures such as ResNet-50 and Inception-v3. These results align with the broader trend observed in recent literature, where hybrid quantum models

have shown potential for outperforming purely classical approaches in domains such as finance, image recognition, and drug discovery (Schuld & Killoran, 2019; Havlíček *et al.*, 2019)^[11, 5]. However, this research represents one of the first comprehensive applications of such models within agricultural informatics, addressing a critical gap in current knowledge.

Linking to Prior Work

Traditional machine learning and deep learning methods have long been considered the backbone of plant disease detection. Studies such as Mohanty *et al.* (2016)^[7] demonstrated accuracies exceeding 99% on controlled datasets like PlantVillage, but performance often dropped in real-world conditions due to environmental noise, variability in crop morphology, and dataset imbalance. Similar limitations were reported by Too *et al.* (2019)^[13], where CNN models required significant data augmentation and preprocessing to maintain acceptable accuracy levels.

Our results demonstrate that the hybrid quantum-classical model not only outperforms CNN baselines but also offers better generalization to noisy and high-dimensional datasets, an area where classical models often struggle. For example, distinguishing *Tomato Early Blight* from *Tomato Late Blight* remains a challenge in classical vision-based systems due to the high visual similarity of symptoms. The hybrid model reduced this misclassification significantly, confirming the advantage of quantum-enhanced feature encoding. This suggests that quantum circuits may be capable of extracting more abstract and discriminative features than classical convolutional filters.

Novelty of the Approach

The novelty of this study lies in three main areas:

1. **First large-scale agricultural application of hybrid QML:** While quantum machine learning has been explored in fields like finance, chemistry, and health sciences, its use in agriculture has been minimal. This research bridges that gap by systematically applying hybrid QML to a multi-crop disease dataset.
2. **Balanced performance improvements:** Unlike many classical models, which tend to improve accuracy at the expense of precision or recall, the hybrid approach demonstrated simultaneous gains across all metrics (accuracy, precision, recall, and F1-score). This balanced improvement is particularly critical in agricultural applications where false negatives (missed diseases) can lead to crop losses, and false positives (healthy crops misclassified as diseased) waste resources.
3. **Demonstrated statistical robustness:** Through cross-validation and statistical testing, this study established that the observed improvements were not incidental but statistically significant at $p < 0.01$. Such rigor is often missing in applied AI studies within agriculture.

Implications for Precision Agriculture

The enhanced accuracy of the hybrid model carries practical implications for smart farming and sustainable agriculture. First, the ability to detect diseases earlier and more reliably can help farmers intervene promptly, preventing large-scale crop losses. Second, improved precision reduces unnecessary pesticide use, aligning with sustainability goals and lowering economic and environmental costs. Third, the

relatively lighter parameterization of the hybrid model suggests that, once hardware limitations are addressed, these models could be deployed on resource-constrained IoT devices in farms.

Moreover, the success across tomato, maize, and potato datasets indicates that hybrid QML models are scalable across crops, paving the way for integrated multi-crop monitoring systems. This scalability is crucial for real-world deployment, especially in developing countries where farms often cultivate multiple crops simultaneously.

Challenges and Limitations

Despite its promise, this research acknowledges certain limitations. Current experiments were conducted on quantum simulators due to restricted access to scalable quantum hardware. As noted by Preskill (2018), we are in the Noisy Intermediate-Scale Quantum (NISQ) era, where quantum devices are limited by qubit counts, coherence times, and susceptibility to noise. Although simulation allows proof-of-concept validation, the real-world deployment of such models will depend on future advances in quantum hardware.

Another limitation relates to dataset diversity. While this study included both controlled and field samples, global agricultural environments present far more variability in lighting, soil conditions, and crop varieties. Extending this research to larger, geographically diverse datasets is essential for ensuring true generalizability.

Future Directions

This study opens multiple avenues for future research:

1. **Deployment on NISQ devices:** As quantum hardware matures, validating hybrid models on actual quantum processors will be an important step toward practical adoption.
2. **Quantum transfer learning:** Combining pre-trained classical CNNs with quantum layers could further enhance performance while reducing training costs.
3. **Explainability in QML:** Future work should investigate how quantum circuits encode features, to provide interpretability for agricultural experts.
4. **Integration with IoT and edge computing:** Optimizing hybrid QML models for deployment in farm-based IoT devices could enable real-time, on-site disease detection.
5. **Multi-modal disease detection:** Beyond leaf images, integrating spectral, environmental, and genomic data into quantum-classical models may enhance accuracy further.

Broader Impact

The results of this study demonstrate that quantum computing can play a transformative role in the future of sustainable farming systems. By achieving higher accuracy and robustness in plant disease detection, hybrid QML models directly contribute to food security, environmental sustainability, and the economic viability of farming communities. As agriculture continues to face increasing pressure from climate change, pests, and growing global demand, the fusion of emerging technologies such as quantum computing with precision agriculture provides a promising pathway for innovation.

Conclusion and Future Work

This study proposed and evaluated a hybrid quantum-classical framework for plant disease detection, demonstrating its potential to revolutionize smart farming and sustainable agriculture. By integrating Variational Quantum Circuits (VQCs) into a classical neural network pipeline, the model achieved an accuracy of 95.2%, significantly outperforming the baseline CNN (91.4%) and other deep learning architectures such as ResNet-50 and Inception-v3. Beyond accuracy, the model also recorded notable improvements in precision, recall, and F1-score, thereby ensuring that both false positives and false negatives were minimized. These improvements are critical in agricultural contexts, where misclassifications can either lead to crop losses or unnecessary pesticide use.

The findings highlight three major contributions. First, this research demonstrates one of the first large-scale applications of quantum-enhanced machine learning in agriculture, addressing a gap in the literature where most prior work was limited to classical AI models. Second, the hybrid framework achieved balanced improvements across all evaluation metrics, unlike many deep learning systems that trade precision for recall or vice versa. Third, the study validated its results through statistical testing, confirming that the observed gains were both significant and robust across multiple dataset splits. Together, these contributions establish the viability of hybrid quantum-classical approaches in real-world agricultural decision-making systems.

Despite these promising results, the research is not without limitations. The experiments were carried out on quantum simulators, given the current constraints of quantum hardware in terms of qubit count, noise resilience, and stability. While simulations provide proof-of-concept validation, the ultimate test of feasibility will depend on deploying such models on Noisy Intermediate-Scale Quantum (NISQ) devices. Furthermore, while the dataset combined both controlled and field images of tomato, maize, and potato crops, agricultural environments are inherently diverse. Factors such as lighting variability, soil conditions, and crop diversity across geographies need to be incorporated in future studies for stronger generalizability. Finally, although training time was found to be competitive with classical CNNs in simulations, the computational overhead on actual quantum processors may initially be higher until hardware matures.

Looking ahead, several directions emerge for future research. First, as quantum devices advance, it will be critical to test hybrid models on real quantum processors, accounting for hardware noise and scalability. Second, quantum transfer learning-leveraging pre-trained classical networks with quantum layers-could reduce the demand for large datasets while enhancing performance. Third, there is a growing need for explainable quantum machine learning, where the features extracted by quantum circuits can be interpreted by agricultural experts to improve trust and adoption. Fourth, optimizing hybrid architectures for edge and IoT devices will allow on-site disease detection in farms, enabling real-time interventions. Finally, expanding beyond leaf images to include multi-modal data sources-such as hyperspectral imagery, soil data, and genomic information-could lead to holistic crop health monitoring systems powered by quantum-classical intelligence.

In conclusion, this research demonstrates that quantum computing, when integrated with classical machine learning, can significantly advance plant disease detection, achieving higher accuracy, robustness, and scalability compared to conventional methods. The hybrid quantum-classical paradigm not only opens new frontiers in agricultural informatics but also aligns with the broader goals of sustainable farming, food security, and environmental protection. While challenges remain in terms of hardware readiness and dataset diversity, the results presented here provide a compelling case for continued exploration of quantum-assisted solutions in agriculture. The pathway ahead involves bridging the gap between simulation and real-world deployment, ensuring that the theoretical promise of quantum computing translates into tangible benefits for farmers worldwide.

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