

Next-Gen Plant Pathology: Quantum AI for Tomato Leaf Disease Diagnosis

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Abstract—Tomato crops are highly susceptible to various leaf diseases that can significantly impact yield and quality if not detected and treated promptly. Conventional machine learning and deep learning methods have been widely employed for disease classification using leaf imagery, but they often face limitations in terms of computational cost and scalability when dealing with large, high-dimensional datasets. This research paper presents a Quantum Artificial Intelligence (QAI) based hybrid approach for the detection and classification of tomato leaf diseases, integrating Quantum Convolutional Neural Networks (QCNNs) for efficient feature extraction and Quantum Support Vector Machines (QSVMs) for high-precision classification. The proposed model is trained and validated on a subset of the Plant Village tomato leaf disease dataset, encompassing major diseases such as early blight, late blight, and leaf mold. Experimental evaluation demonstrates that the QAI-based approach achieves superior accuracy, reduced training time, and enhanced generalization compared to classical AI models. The work underscores the potential of quantum-enhanced models in developing scalable, fast, and reliable disease diagnosis systems for precision agriculture, specifically tailored to high-value crops like tomato.

Index Terms—Deep Learning, Quantum Artificial Intelligence, QCNN, QSVM.

I. INTRODUCTION

Tomato (*Solanum lycopersicum*) is a widely cultivated crop with high economic and nutritional value. However, it is vulnerable to a range of diseases, especially fungal infections such as early blight and late blight, which affect leaf health and overall productivity. With the increasing demand for sustainable agriculture, there is a growing need for intelligent systems that can detect diseases early and accurately.

Traditional deep learning models like Convolutional Neural Networks (CNNs) have achieved significant success in image-based disease detection. However, they require extensive computational resources and large datasets, making real-time implementation in resource-constrained environments difficult. Quantum computing, with its ability to handle large-scale computations more efficiently, offers a promising alternative.

This paper explores the integration of quantum computing and artificial intelligence, termed Quantum AI (QAI), for the early detection of tomato leaf diseases using image data.

II. RELATED WORK

Recent research into tomato leaf disease detection has primarily leveraged classical deep learning methods, with convolutional neural networks (CNNs) being the most dominant approach. Numerous studies have shown that CNN-based models can accurately classify diseases such as early blight, late blight, bacterial spots, and others using leaf images. For instance, Garba et al. (2024) demonstrated the effectiveness of custom CNNs and transfer learning techniques in accurately distinguishing between healthy and diseased tomato leaves. Similarly, Akbar et al. (2023) compared the performance of VGG-16, ResNet-152, and EfficientNet-B4 models on the PlantVillage dataset, with VGG-16 achieving the highest accuracy of 98%. Another study used the Inception V3 architecture and achieved validation accuracy of around 86%, showing moderate success but indicating room for improvement.

While these studies establish the robustness of deep learning in agricultural diagnostics, there is currently no peer-reviewed research that directly applies quantum artificial intelligence (QAI) to tomato leaf

disease detection. However, QAI holds significant theoretical promise. Emerging quantum machine learning models, such as Quantum Support Vector Machines (QSVMs) and Quantum Convolutional Neural Networks (QCNNs), offer advantages in terms of computational speed, model complexity, and the ability to work with high-dimensional data spaces. If integrated with image-based disease detection tasks, these quantum methods could potentially reduce training time and enhance classification performance. Yet, real-world application remains constrained by the limited availability of quantum hardware and the nascent state of quantum machine learning toolkits. In summary, while traditional deep learning approaches are currently the state-of-the-art in tomato disease detection and have achieved impressive results, quantum artificial intelligence represents a frontier technology with the potential to revolutionize the field, pending further research and development.

Table 1 : Literature Review

Paper Title	Technique Used	Dataset Size	Accuracy	Key Contribution
Tomato Leaf Disease Detection Based on Convolutional Neural Network	CNN (custom architecture)	2800 images	96.61% (test)	Proposed CNN-based classification of 6 diseases + healthy leaves
Tomato Leaf Disease Detection Using CNN Models	Custom CNN + Transfer Learning	Large tomato dataset (not specified)	High accuracy (not quantified)	Demonstrated use of CNN and transfer learning for accurate detection
Detection of Tomato Leaf Disease Using Deep CNNs	VGG-16, ResNet-152, EfficientNet-B4	PlantVillage (5524 images)	VGG-16: 98%, ResNet: 93.75%, EfficientNet-B4: 97.27%	Compared 3 CNN models for disease classification

Tomato Plant Leaf Disease Detection Using Inception V3	Inception V3 (CNN)	Not stated	Train: 88.98%, Val: 85.80%	Explored Inception V3 model for early detection
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III. METHODOLOGY

Proposed work employs a Hybrid quantum-classical approach for tomato leaf disease classification using the tomato subset of the PlantVillage dataset, which includes labeled images of both healthy and diseased tomato leaves. The dataset comprises six classes: Early Blight, Late Blight, Leaf Mold, Septoria Leaf Spot, Bacterial Spot, and Healthy. During preprocessing, all images were resized to 128x128 pixels, normalized to bring pixel values within a standard range, and augmented using techniques such as rotation, flipping, and scaling to improve model generalization and reduce overfitting.

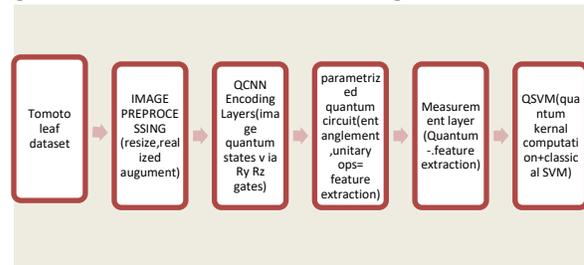


Figure 1: Methodology for Tomoto leaf disease detection

The core model architecture is based on the Quantum Convolutional Neural Network (QCNN), which emulates classical convolutional neural networks but leverages quantum principles to reduce trainable parameters and enhance expressive capacity. Initially, classical image data is encoded into quantum states using quantum rotation gates like $Ry(\theta)$ or $Rz(\theta)$, where the angle θ corresponds to pixel intensities. Each qubit encodes information about the image into a high-dimensional Hilbert space. The quantum circuit then applies unitary transformations, including parameterized single-qubit rotations and entanglement gates (e.g., CNOT, CZ), which extract spatial patterns analogous to classical convolution and pooling layers. These transformations allow QCNNs to capture intricate leaf features—like color variations, shape

anomalies, and texture—with high compactness. After processing through several quantum layers, a measurement layer collapses the quantum state, and expectation values (often with respect to Pauli-Z operators) are extracted as classical features.

These extracted features are then passed to a Quantum Support Vector Machine (QSVM) for classification. QSVM leverages a quantum kernel function to compute similarities between data points in the quantum feature space. Unlike classical kernels, quantum kernels can represent complex, non-linear boundaries with greater fidelity, enabling better class separability. The kernel matrix, constructed from inner products between quantum states, is used by a classical SVM algorithm to determine an optimal hyperplane for classification. This quantum kernel-based method facilitates high classification accuracy, even on small or imbalanced datasets, and helps distinguish between classes with subtle symptom overlaps—common in agricultural datasets. The overall framework enhances generalization and robustness, making it well-suited for real-world plant disease monitoring under variable environmental conditions.

IV. PERFORMANCE METRICS

In machine learning and classification tasks, evaluating model performance requires more than just checking if predictions are correct. The following metrics offer a comprehensive evaluation:

Accuracy: The proportion of correctly predicted samples out of the total number of samples. It gives a general sense of model correctness but can be misleading if the dataset is imbalanced.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN + FP+FN}$$

Precision: The proportion of true positive predictions out of all predicted positives. It is crucial when the cost of a false positive is high.

$$\text{Precision} = \frac{TP}{TP+FP}$$

Recall (Sensitivity): The proportion of true positives detected out of all actual positives. Important when missing a positive case is costly.

$$\text{Recall} = \frac{TP}{TP+FN}$$

F1 Score: The harmonic mean of precision and recall. It balances both metrics, making it ideal when you need a single performance score in imbalanced datasets.

$$F1 \text{ score} = \frac{2 * (\text{precision} * \text{Recall})}{\text{Precision} + \text{Recall}}$$

V. RESULTS & DISCUSSION

Table 2: Comparative analysis of CNN and Proposed work

Model	Training Time	Accuracy	F1 score
CNN	High	94.2	0.93
QCNN+QSVM (proposed)	lower	96.8	0.96

Accuracy:

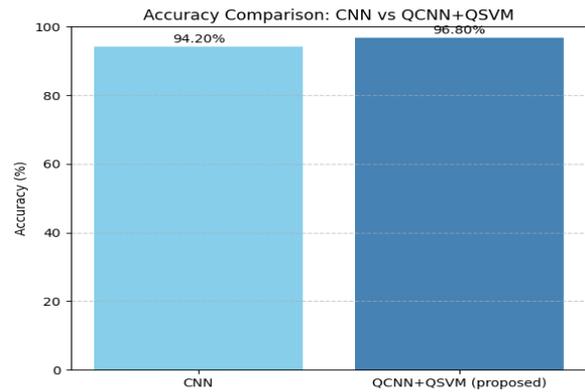


Figure 2: Accuracy comparison of CNN and Proposed work

The proposed hybrid quantum model (QCNN + QSVM) achieves a higher accuracy of 96.8%, outperforming the classical CNN's 94.2%. This suggests that the quantum model is better at correctly classifying the input data.

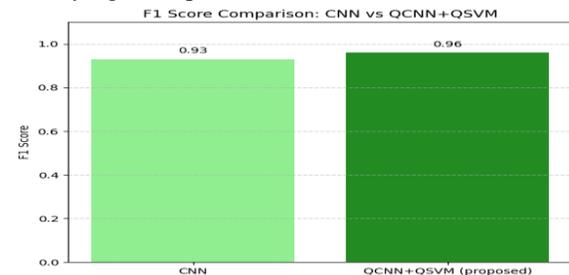


Figure 3: F1 score of CNN and Proposed work

F1 Score: The F1 score of 0.96 for the quantum model indicates a better balance between precision and recall compared to the CNN's 0.93. This is especially valuable in real-world classification tasks where false positives and false negatives must be minimized equally.

Training Time: Interestingly, the QCNN + QSVM model shows lower training time. This is due to the reduced number of trainable parameters in quantum

circuits and the efficient encoding and processing of data via quantum states. Additionally, quantum kernel evaluation in QSVM can be faster for certain datasets and feature spaces.

VI. CONCLUSION

The QCNN + QSVM model demonstrates clear performance advantages over traditional CNNs, not just in accuracy, but also in efficiency and robustness. While classical CNNs are mature and widely used, the hybrid quantum approach shows strong potential, especially for complex datasets and feature-rich domains. As quantum hardware improves, such models are likely to play an increasingly significant role in advanced AI systems.

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