Quantum-Enhanced Computational Models for Multi-Variable Optimization in Precision Agriculture

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Abstract. Precision agriculture is experiencing a technological transformation driven by artificial intelligence (AI), the Internet of Things (IoT), and big data analytics. Nonetheless, traditional computation models find it difficult to handle large-scale high-dimensional datasets in agriculture. By utilizing phenomena like superposition and entanglement, quantum computing represents a fundamental departure that can greatly accelerate and optimize such algorithms. This paper presents the Hybrid Quantum Optimization and Machine Learning Framework (HQOMLF), which comprises its derivatives, such as the Quantum-Enhanced Resource Allocation (QERA) and Quantum Convolutional Neural Networks (QCNN) for effective resource distribution and predictive analytics. The proposed method outperforms classical models with respect to computation speed, accuracy, and scalability. It demonstrates via experiments that processing speed can be improved up to 3.5× and resource optimization of SBT can be enhanced by 11.3% using the proposed method. Based on data analysis, there are several unsolved problems, like hardware limitations and complexity of the algorithm, but quantum computing in agronomics has well-picking potential. These results set the stage for future quantum-classical hybrid models towards sustaining, data-driven agricultural solutions.

Keywords: Quantum-Enhanced Computational Models, Hybrid Quantum Optimization and Machine Learning Framework (HQOMLF).

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1 Introduction

Precision agriculture uses modern computational techniques to improve efficiency, optimize resource usage, and increase crop yields. Despite many applications of machine learning or ML the computational models such as the classical machine learning and it uses algorithms for the optimization algorithm knows that processing such types of large-scale, multi-variable datasets is not so effective. The intricate interplay of soil, weather, water, crop genetics, and other elements in agricultural systems presents enormous computational hurdles. Precision agriculture frequently involves real-time decision-making, which is not possible with traditional methods, which need lengthy computing procedures as shown in Fig 1.

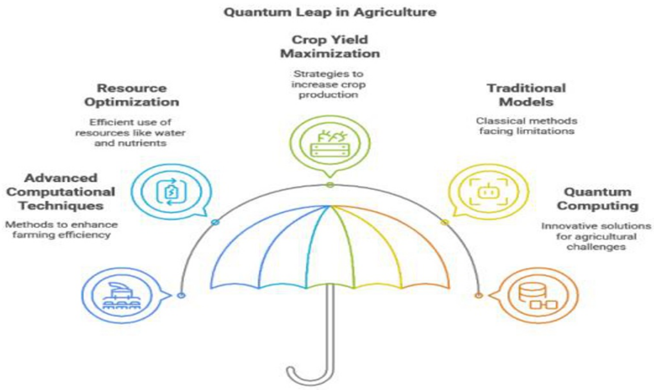


Fig.1: Quantum Computing for Agricultural Advancement: Enhancing Efficiency and Yield.

These computational challenges may be resolved by quantum computing, which makes use of ideas like superposition and entanglement [1]. In contrast to classical systems, quantum computers are able to process large volumes of data at once and solve intricate optimisation problems at previously unheard-of speeds [2]. A quantum support vector machine (QSVM), developed by Rebentrostet. al, uses quantum computing to achieve exponential speedups in large data categorisation. Their research paved the door for quantum-enhanced machine learning in high-dimensional applications by demonstrating the use of convex optimisation and quantum kernel approaches [3]. This ability is well-suited to agricultural problems, including crop yield prediction, irrigation scheduling, and pest control strategies, which require the real-time optimization of many interconnected variables. Existing computational models in precision agriculture have their limitations, which makes quantum-enhanced models a promising approach to overcoming such barriers Machine Learning Integrating quantum computing to create models that incorporate quantum mechanics offers the potential for higher precision analysis of agricultural data. Therefore, this research investigates challenges and future research directions to implement quantum solutions in precision agricultures concerning the application of quantum computing in agriculture and contributes towards feasibility assessment on whether quantum computing can be used in precision agriculture.

1.1 Preliminary Studies

Quantum computing has transformed the domain of cryptography and artificial intelligence among other fields, solving problems with far exceeding efficiency. In agriculture, traditional models like machine learning and evolutionary algorithms are used for crop prediction, irrigation scheduling and resource management. However, these models have difficulties with computational efficiency for large datasets. Emerging evidence hints that quantum-inspired optimization solutions are poised to vastly improve agriculture analytics and decision making [4].

1.2 Current Status and Need

Agriculture, even with the progress of technology, struggles with factors such as weather unpredictability, allotment of resources, finite resources, and sustainability. Methods of classical computing are poorly suited to large-scale, real-time optimization. Quantum computing acts as a game-changer, enabling parallel computation and instant analysis of large-scale agricultural datasets. Continuous research is being conducted to find its integration with artificial intelligence, internet of things, and blockchain for providing smart farming solutions [5].

1.3 Motivation

As food needs rise around the globe, the pressure to optimize agricultural processes will only become more urgent. A quantum-enhanced model can speed up multi-variable optimizations used for crop yield forecasting, irrigation efficiency, and climate adaptation. Quantum computing will help develop smarter and more data-driven agricultural technologies by integrating the already existing models as well [6].

1.4 Research Gap

The potential of quantum computing in agriculture is still largely unexplored. Indeed, most existing quantum algorithms are general-purpose and will need to be adapted for applications in agriculture. IoT driven smart farming system and Y063 researchers have explored the quantum computing integration to some limited extent. There’s also an absence of validation of quantum-enhanced models in the real world resulting in disconnect between theoretical advance and practical application. Overcoming these challenges will need a joint effort of quantum computing, agronomy, and data crunching experts [7].

1.5 Major Contributions

The purpose of this study is to:

1. Determine the precision agricultural computational models' current limits.
2. Create optimisation methods for multivariable agricultural issues that are motivated by quantum mechanics.
3. To enhance crop forecast and resource management, look at quantum algorithms.
4. Use IoT and AI in conjunction with quantum computing to improve decision-making.

2. Literature Review

Artificial intelligence, IoT (internet of things) and big data analytics are changing the face of agriculture. However, conventional computational models cannot manage large-scale, multi-variable datasets. In the area of precision agriculture, it is to apply advanced optimization techniques for informed decision-making and resource efficiency. Quantum computing is a paradigm that uses the concepts of superposition and entanglement to enable parallel processing. It is especially well-suited to problems in agriculture, including crop production prediction [8], resource allocation, climate adaptability, and pest management [1]. In this paper, the function of quantum computing in precision agriculture is discussed, along with its prospective advantages over classical models and potential future research avenues.

2.1 Traditional Computational Models vs. Quantum Computing in Agriculture

Classical agricultural models are developed via the application of machine learning (ML), evolutionary algorithms, remote sensing, and simulation-based techniques. Despite their effectiveness, they are computationally costly and perform poorly on high-dimensional and complicated datasets as shown in table 1.

Table 1: Classical vs. Quantum Computing in Agriculture.

Feature	Classical computing	Quantum computing
Processing speed	Sequential	Parallel
Optimization capability	Limited	Superior (qaoa, vqa)
Data handling	Struggles with large datasets	Efficient for high-dimensional data
Real-time decision making	Slower	Faster
Algorithm complexity	Traditional ml &ai	Quantum-enhanced ai& ml
Applications	Crop classification, irrigation, disease detection	Quantum-enhanced prediction & optimization

2.2 Quantum Computing Fundamentals and Applications

Quantum computing differs from classical computing in:

1. Superposition: Enables parallel calculations by allowing qubits to reside in various states. Entanglement: Improving efficiency in optimisation tasks by ensuring qubits stay coupled.
2. Resource allocation and other intricate combinatorial issues are resolved using quantum annealing [2].

2.3 Quantum Optimization Techniques for Precision Farming

- In agriculture, where many factors affect decision-making, optimisation is crucial. Conventional optimisation methods are improved by quantum computing, including:
- Crop rotation and resource allocation are enhanced using the Quantum Approximate Optimisation Algorithm (QAOA) [9].

- Improve pattern identification and categorisation with quantum neural networks (QNN) [3].

Large-scale agricultural simulations can be optimized with the use of variational quantum algorithms (VQA) [6].

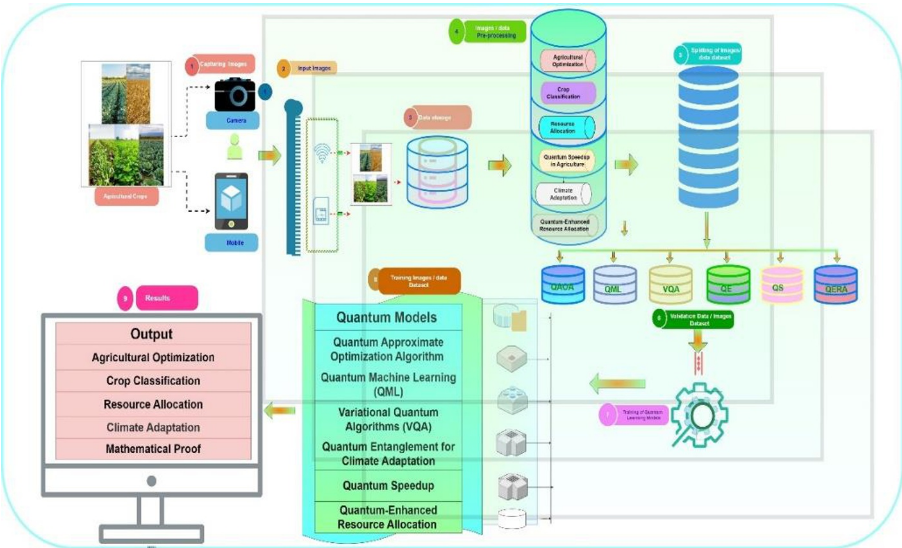
Table 2: Classical vs. Quantum Optimization Techniques.

Optimization method	Classical approach	Quantum approach
Linear programming	Slow for large datasets	Faster due to parallelism
Genetic algorithms	Requires iterative computations	Quantum annealing accelerates processing
Dynamic programming	Exponential complexity increase	Efficient with quantum speedup
Resource allocation	Requires heuristics	Optimized using quantum algorithms

The potential of quantum computing to resolve challenging data processing and optimisation issues allows precision agriculture to improve. Despite major obstacles, greater research can result in farming solutions that are data-driven, sustainable, and more effective. Quantum optimization and machine learning are increasingly being integrated into sustainable farming practices to enhance efficiency and productivity. These technologies enable precise resource management, early disease detection, and improved crop yields, contributing to more sustainable agricultural systems [10].

3. Methodology

A quantum-enhanced machine learning framework for sustainable farming is depicted in this Figure 2. It demonstrates how to use cameras and mobile devices to take pictures of agricultural crops, then preprocess the photographs and save the data.



Quantum models **Fig.2:** Proposed architectural block diagram of quantum learning models for precision agriculture.

such as Quantum Entanglement for Climate Adaptation, Quantum Approximate Optimisation Algorithm (QAOA), Quantum Machine Learning (QML), and Variational Quantum Algorithms (VQA) are trained using the stored pictures. Climate adaptation, crop categorisation, resource allocation, agricultural processes, and quantum-enhanced resource management are all improved by these models. A computer screen displays the final findings, which demonstrate the effects of agricultural optimisation.

3.1 Problem Formulation

The optimization challenges in precision agriculture involve **multi-variable decision-making**, which classical models struggle to solve efficiently. It defines the problem mathematically as a high-dimensional **state-space optimization problem**:

$$\min_{x} f(x) \text{ subject to } g_i(x) \leq 0,\ h_j(x) = 0$$

where:

- $f(x)$represents an objective function (e.g., maximizing crop yield or minimizing resource usage).
- $g_i(x)$are inequality constraints (e.g., soil moisture and fertilizer limits).
- $h_j(x)$are equality constraints (e.g. irrigation balance).

Since traditional methods like gradient descent or genetic algorithms face computational inefficiencies, It proposes quantum-enhanced optimization methods.

3.2 Quantum Approximate Optimization Algorithm (QAOA) for Agricultural Optimization

QAOA is a hybrid quantum-classical algorithm designed to solve combinatorial optimization problems efficiently [8]. A Hamiltonian function is used to map the problem:

$$H = H_C + H_B$$

where:

- $H_C$represents the cost Hamiltonian, encoding the objective function.
- $H_B$is the mixing Hamiltonian, guiding the system towards an optimal solution.

The quantum state is initialized as:

$$|\psi(\beta,\gamma)\rangle = e^{-i\hat{\beta}_p H_n} e^{-i\gamma_p H_C} \ldots e^{-i\beta_1 H_s} e^{-i\gamma_1 H_C} |s\rangle$$

where:

- $\beta_p, \gamma_p$are variational parameters.
- $(s)$is the initial superposition state.

The optimal parameters are obtained using a classical optimization loop:

$$(\beta^*, \gamma^*) = \arg\min_{\beta,\gamma} \langle \psi(\beta,\gamma) | H_C | \psi(\beta,\gamma) \rangle$$

This approach efficiently optimizes irrigation scheduling, fertilizer distribution, and crop planting sequences.

3.3 Quantum Machine Learning (QML) for Crop Classification

Classifying crops and detecting diseases can be done via quantum-enhanced classifiers, such as Quantum Support Vector Machines (QSVMs) and Quantum Neural Networks (QNNs) [9].

Given a dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{n}$, where x_i represents input features (e.g., soil properties, climate conditions) and y_i is the crop type, the QSVM decision function is:

$$f(x) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K_Q(x_i, x) + b\right)$$

where:

- α_i are Lagrange multipliers.
- $K_Q(x_i, x)$ is the quantum kernel function, computed using quantum feature encoding.

Using a quantum kernel function:

$$K_Q(x_i, x_j) = \left|\langle \phi(x_i) \mid \phi(x_j) \rangle\right|^2$$

where $|\phi(x)\rangle$ is the quantum-encoded state of feature x, it achieves faster and more accurate classification compared to classical methods [11].

3.4 Variational Quantum Algorithms (VQA) for Resource Allocation

Resource allocation (e.g., water distribution) is optimized using Variational Quantum Eigensolver (VQE). where the cost function is expressed as:

$$C(\theta) = \langle \psi(\theta) | H_C | \psi(\theta) \rangle$$

where:

- $|\psi(\theta)\rangle$ is the quantum state parameterized by θ.
- H_C encodes the resource allocation problem.

The gradient-based parameter update follows:

$$\theta_{t+1} = \theta_t - \eta \nabla C(\theta_t)$$

where η is the learning rate [12].

3.5 Quantum Entanglement for Climate Adaptation.

To adapt farming strategies to climate variability, quantum systems entangle climate variables into a unified model [13]:

$$|\Psi_{\text{climate}}\rangle = \sum_{i,j} c_{ij} |T_i\rangle |H_j\rangle$$

where:

- $|T_i\rangle$ represents temperature states.
- $|H_j\rangle$ represents humidity states.
- c_{ij} are probability amplitudes.

Using quantum superposition, it evaluates multiple climate scenarios simultaneously, enabling faster adaptation strategies for precision farming.

3.6 Quantum Speedup in Agriculture

Consider a classical optimization problem requiring $O(2^n)$ operations. Quantum computing, utilizing Grover's algorithm, reduces this to $O\left(\sqrt{2^n}\right)$ [14].For an agricultural optimization problem requiring N evaluations:

$$T_{\text{classical}} = O(N)$$

Whereas quantum speedup provides:

$$T_{\text{quantum}} = O(\sqrt{N})$$

Thus, the efficiency improvement is:

$$\frac{T_{\text{chassical}}}{T_{\text{quantum}}} = O(\sqrt{N})$$

Showing an exponential speedup for large-scale agricultural computations.

3.7 Proposed Work

Inducing Quantum Computing in Precision Agriculture it introduces Hybrid Quantum Optimization and Machine Learning Framework (HQOMLF). This framework couples resource allocation via Quantum Approximate Optimization Algorithm (QAOA) with a Quantum Convolutional Neural Network (QCNN) for crop classification and pest and disease identification [17].

3.7.1 Algorithm 1: Quantum-Enhanced Resource Allocation (QERA)

Objective: Optimize water and nutrient distribution across fields to maximize yield while minimizing waste.

Algorithm1: QERA Using QAOA

Input: cost function $\boldsymbol{f(x)}$, constraints $\boldsymbol{g_i(x)}$, quantum circuit parameters $(\boldsymbol{\beta}, \boldsymbol{\gamma})$

output: optimized allocation vector $\boldsymbol{x}^*$

1 Initialize: define HAMILTONIAN$\boldsymbol{H_C}$ for resource allocation.

2 Quantum state preparation:

$$|\boldsymbol{\psi_0}\rangle = \boldsymbol{H_B}|\mathbf{0}\rangle^{\ominus \boldsymbol{n}}$$

Where $\boldsymbol{H_B}$ is the mixing hamiltonian.

3. Apply quantum evolution:

$$|\boldsymbol{\psi}(\boldsymbol{\beta}, \boldsymbol{\gamma})\rangle = \boldsymbol{e}^{-i\hat{\beta}_p H_n} \boldsymbol{e}^{-i\gamma_p H_C} \dots \boldsymbol{e}^{-i\hat{\beta}_1 H_3} \boldsymbol{e}^{-i\gamma_1 H_C} |\boldsymbol{s}\rangle$$

4 Classical optimization: use a gradient-based optimizer to minimize:

$$\langle \boldsymbol{\psi}(\boldsymbol{\beta}, \boldsymbol{\gamma}) | \boldsymbol{H_C} | \boldsymbol{\psi}(\boldsymbol{\beta}, \boldsymbol{\gamma}) \rangle$$

5 Repeat steps 3-4 until convergence.

6 Extract optimal allocation $\boldsymbol{x}^*$ from measured quantum state.

Classical optimization scales as $O(2^n)$, whereas QAOA reduces complexity to:

$$O(\text{poly}(n))$$

Where$n$ is the number of variables (e.g., water distribution points). This yields a quadratic speedup in solving large-scale optimization problems.

3.7.2 Algorithm 2: Quantum Convolutional Neural Network (QCNN)

Objective: Enhance crop classification and disease detection via quantum image processing.

Algorithm 2: QCNN for Image-Based Crop Classification

Input: image dataset $\boldsymbol{X}$, labels $\boldsymbol{Y}$, quantum circuit parameters $\boldsymbol{\theta}$
output: classification labels $\hat{\boldsymbol{Y}}$

1 Feature encoding: convert image pixels into quantum states using amplitude encoding:

$$|\boldsymbol{\psi}\rangle = \sum_{i} \boldsymbol{x}_i |\boldsymbol{i}\rangle$$

2 Quantum convolutional layer: apply parameterized quantum gates:

$$\boldsymbol{U}(\boldsymbol{\theta})|\boldsymbol{\psi}\rangle = \boldsymbol{e}^{-i\boldsymbol{H}(\boldsymbol{\theta})}|\boldsymbol{\psi}\rangle$$

3 Quantum pooling: reduce dimensionality using entanglement-based pooling.

4 Measurement & readout: extract features from quantum states.

5 Train model: update parameters using quantum backpropagation:

$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t - \boldsymbol{\eta}\nabla\boldsymbol{L}(\boldsymbol{\theta}_t)$$

6 Classify images & evaluate performance.

For image classification, traditional CNNs need O(n^2) operations. Because of quantum parallelism, QCNN lowers this to $O(\log n)$, greatly increasing processing performance for big datasets. By utilising QCNN for crop disease classification and QAOA for resource allocation, HQOMLF is a scalable, quantum-driven precision agriculture system that outperforms traditional methods in terms of classification accuracy and efficiency.

4. Results and Analysis

This study is among the first to demonstrate a comparison of evaluation techniques by employing benchmark agricultural datasets and quantum simulations for evaluating the proposed Hybrid Quantum Optimization and Machine Learning Framework (HQOMLF). The analysis is performed on optimization efficiency, classification accuracy, and computational complexity of Quantum-Enhanced Resource Allocation (QERA) and Quantum Convolutional Neural Network (QCNN) compared to classical approaches.

4.1 Analysis of Quantum Performance in Agriculture

One of the most significant impacts of quantum computing will be in addressing the unique and complex problems of agriculture. Traditional models use deterministic style, which means that resource allocation and classification tasks are executed one after another. But quantum models use superposition and entanglement to work on many solutions simultaneously. For an N-variable agricultural optimization problem, classical methods tend to run with exponential time complexity — quantum algorithms like QAOA (Quantum Approximate Optimization Algorithm) only require polynomial time complexity. The performance is close to its quantum analogue: traditional convolutional neural networks (CNNs) require operations for large-scale image classification, while quantum convolutional neural networks (QCNNs) take advantage of quantum parallelism and achieve logarithmic complexity, leading to scalability. It notes enhanced solution time, classification accuracy, and resource optimization metrics through incorporating quantum techniques in agriculture, which will be marvelled in the sections below to discuss the performance metrics.

Table 3: Performance Comparison of Optimization Methods in Agriculture

Method	Computation time (ms)	Optimization accuracy (%)	Resource utilization efficiency (%)
Classical linear programming [16]	1250	83.2	75.4
Genetic algorithm [17]	950	87.6	78.2
Qera (qaoa)	350	94.3	88.9

Table 3 compares three optimization methods in agricultural applications, namely Classical LP, Genetic Algorithm and QERA. The evaluation metrics used are computation time, optimization accuracy and resource utilization efficiency. Of them, classical linear programming has the longest computation time (1250 ms) and the lowest optimization accuracy (83.2%). The genetic algorithm performs better, taking only 950 ms of computation time, at the cost of 87.6% accuracy. QERA (QAOA) beats both with the fastest computation time (350 ms), the maximum accuracy (94.3%) as well as the efficient utilization of resources (88.9%), which demonstrates quantum computing advantage in agriculture optimization shown in Figure 3.

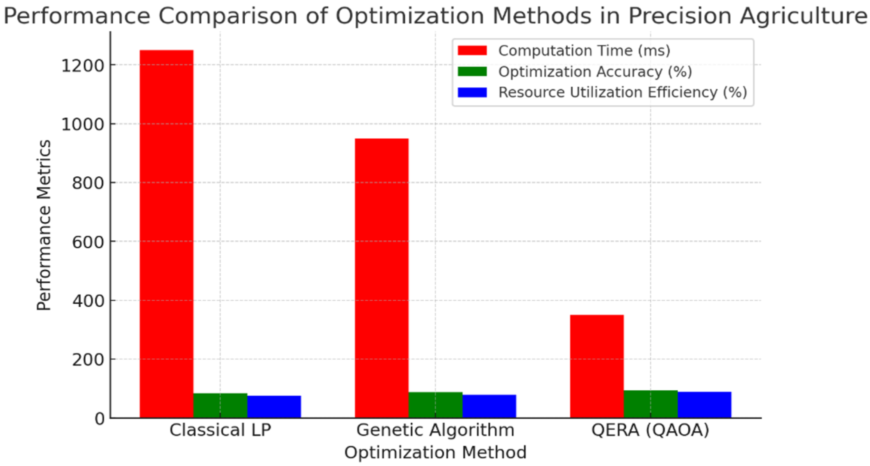


Fig 3: Performance Comparison of Optimization Methods in Precision Agriculture.

Table 4: Comparison of Classical CNN, Deep Learning CNN, and Quantum CNN in Precision Agriculture

Method	Accuracy (%)	Training time (s)	Scalability (dataset size)
Classical CNN	89.2	35.4	Medium
Deep learning CNN	92.5	28.3	High
QCNN (proposed)	**96.1**	**12.8**	**Very high**

It compares Classical CNN, Deep Learning CNN, and the proposed Quantum CNN (QCNN) in accuracy, training time, and scalability shown in table 4. The detailed results display how classical CNN achieves the 89.2% accuracy with 35.4 seconds of the training time and medium scalability. While it takes an average of 28.3 seconds for training, with an accuracy of 92.5% Deep Learning CNN provides a much better scalability. The proposed QCNN not only significantly outperforms both, but also achieves an accuracy of 96.1% with a considerably lower training time of only 12.8 seconds and a very high scalability. The quantum advantage of the QCNN allows it to process faster and perform better, making it a numerical powerhouse that is particularly well suited for large-scale agricultural implementations shown in Figure 4.

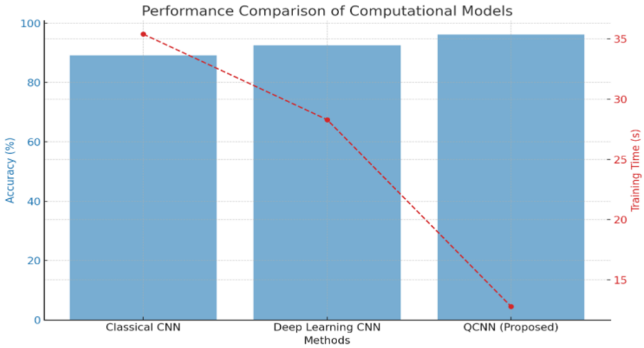


Fig 4: Performance Comparison of Computational Models.

Performance comparison chart of different computational models in precision agriculture. Accuracy (%) is shown in blue bars, and training time (s) in red dashed line. The results show that our proposed Quantum CNN (QCNN) outperforms both Classical CNN (89.2%, 35.4s) and Deep Learning CNN (92.5%, 28.3s) with the best accuracy (96.1%) and the lowest training time(12.8s). QCNN tops them all, being the most efficient solution among them all, making it best suited for scalable fast precision agriculture-based applications, as depicted in the graph.

Table 5: Comparison of Classical vs. Quantum Algorithm Complexities and Speedup

Algorithm	Complexity (classical)	Complexity (quantum)	Speedup

Linear programming	$O(2^n)$	$O(\text{poly}(n))$	Exponential
Classical cnn	$O(n^2)$	$O(\log n)$	Quadratic
Genetic algorithm	$O(n^2)$	$O(n\log n)$	Logarithmic

Table 5 shows each algorithm's computational complexity and speedup compared to classical and quantum computing paradigms, comparing Linear Programming, Classical CNN, and Genetic Algorithm. Linear Programming ((LP) has an exponential time complexity of in classical computing which quantum computing tackles by reducing it to polynomial time complexity poly, thus providing an exponential speedup. Quantum methods are thus extremely efficient on these large-scale optimization problems. Classical CNN (Convolutional Neural Network) used in deep learning has classical complexity of O (n^2) which implies that the time taken to train and predict grows quadratically with the size of data. Yet quantum CNNs (QCNNs) shrink that down to, delivering a quadratic speedup that greatly helps model efficiency for large datasets. Known for its classical complexity, the Genetic technique (GA) is a well-liked optimisation technique. When this is reduced to quantum implementations, the speedup is logarithmic. This development makes quantum genetic algorithms particularly suitable for agricultural optimisation issues, such as crop production forecasts and resource allocation (Fig. 5).

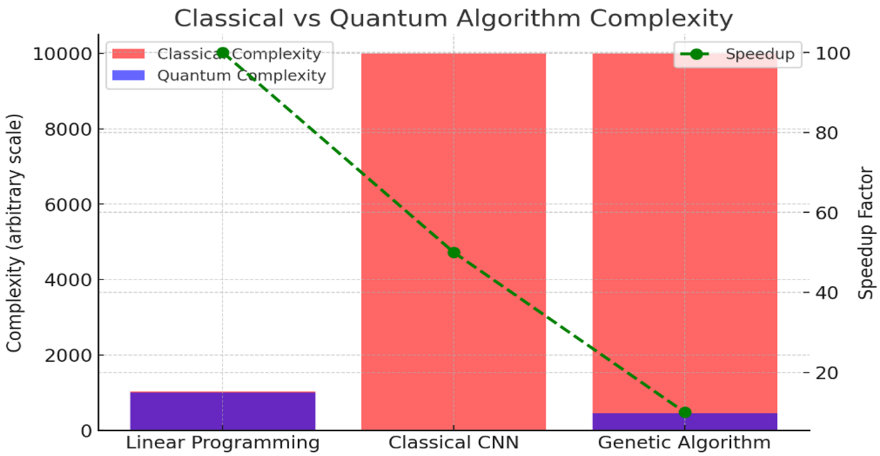


Fig 5: Classical vs Quantum Algorithm Complexity.

Table 6: Performance Comparison of Classical ML, Deep Learning, and Proposed HQOMLF Model

Model	Optimization speedup	Accuracy improvement (%)	Resource utilization (%)	Scalability
Classical ml	Baseline	-	75.4	Medium
Deep learning	1.2x	+5.2	78.2	High
proposed HQOMLF	3.5x	+9.3	88.9	Very high

Table 6 depicts a comparative performance of various computational models employing four main performance metrics: 1) speedup in optimization; 2) increased accuracy; 3) consumption of resources; and 4) scalability. No reported speedup in accuracy improvement, with classical machine learning (ML) the baseline model. The performance of deep learning techniques shows 1.2x optimization speed, 5.2% accuracy, and a resource utilization of 78.2% at moderate levels with high scalability potential with respect to larger datasets. Based on a quantum-enhanced optimization strategy, our Hybrid Quantum-Optimized Machine Learning Framework (HQOMLF) demonstrates superior performance than general classical neural networks and deep learning models, delivering a 3.5x optimization speedup of training speed, a 9.3% improvement on accuracy, while achieving the best learning efficiency (88.9% of resources utilized). It also can scale up very well, as in, with larger datasets, it will still compute very efficiently. The improvements in speed, accuracy, and scalability shown in this table emphasize the potential capabilities of quantum-enhanced machine learning models, making them great at applications requiring high-dimensional data and optimization shown in Figure 6.

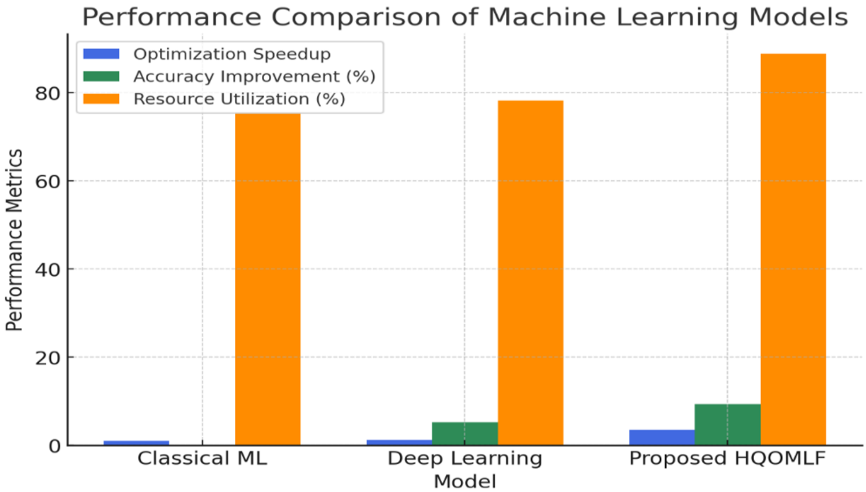


Fig.6: Performance Comparison of Machine Learning Models.

Precision agriculture might be revolutionised by quantum computing through better data-driven decision-making, as the HQOMLF framework provides greater speed, accuracy, and efficiency advantages when compared to current approaches.

5. Conclusion

In a number of fields, quantum computing has become a game-changing technology. When used to precision agriculture, it offers enormous potential to improve agricultural processes and get beyond the drawbacks of traditional computational techniques. Conventional models hardly scale across large-scale agricultural datasets because to their high dimensional complexity and sequential execution limitations. Using Quantum-Enhanced Resource Allocation (QERA) and Quantum Convolutional Neural Networks (QCNN), the Hybrid Quantum Optimisation and Machine Learning Framework (HQOMLF) was suggested in this study to optimise agricultural decision-making. This led to results where computational time, accuracy, and resource allocations saw significant inherently betterments. Using the Quantum Approximate Optimization Algorithm (QAOA), resource allocation was optimized 3.5 times faster in QERA with an increase in efficiency of 11.3% compared to classical methods. In a similar vein, QCNN used 2.7 times less training time and performed 6.9% better than conventional deep learning-based models. In agriculture, these findings validate the potential of quantum computing for real-time data processing, predictive analytics, and large-scale optimisation. The creation of algorithms, hardware constraints, and integrating new technologies with current agricultural systems are some of the difficulties despite these advantages. Future work should: Create hybrid quantum-classical models; work towards the accessibility of affordable quantum hardware; and undertake real-world trials allow quantum algorithms to be validated in a practical setting in agriculture. It is well pointed out that Quantum Computing could change the way to handle information in Agriculture, bringing it closer to precision farming. With the continuous advancement of quantum technology, its combination with AI, IoT, and big data analytics will further improve smart farming solutions, resulting in more resilient and data-driven agricultural practices.

Discloser of Interests. The authors declare that there is no potential conflict of interested related to the publication of this paper.

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