

International Journal of Agriculture Extension and Social Development

Volume 9; Issue 4; April 2026; Page No. 611-621

Received: 13-01-2026
Accepted: 16-02-2026

Indexed Journal
Peer Reviewed Journal

Quantum AI-driven precision soil health monitoring and automated crop disease detection using advanced analytical models

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DOI: <https://www.doi.org/10.33545/26180723.2026.v9.i4h.3523>

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Abstract

The need for accuracy and scalability is imperative when it comes to monitoring soil health and detecting plant diseases using precision agriculture. This paper suggests a Quantum AI-based hybrid analytics approach that combines classical machine learning algorithms, Variational Quantum Circuits, and statistics modeling in order to provide improved agricultural decision making capabilities. For this purpose, we used the multi-modal datasets that include Soil Health Data set (Kaggle dataset, n=12,500) that contains soil pH, moisture, Nitrogen (N), Phosphorus (P), Potassium (K) information and PlantVillage dataset (54,306 leaf images from 38 classes). This paper proposes a hybrid framework of QSVM and QCNN to predict soil health status and detect crop diseases in a dataset. This research work has been experimentally evaluated with Qiskit simulator (8 qubits) and classical ML algorithms like Random Forest and CNN. Based on experimental results, it is clear that the proposed hybrid framework yields soil health prediction accuracy of 94.7%, which is better than classical ML approaches (88.3%). Further, the accuracy achieved by the QCNN framework for predicting crop disease is 97.2%, with precision, recall, and F1-score being 0.96, 0.97, and 0.965, respectively. It is observed that the computation time is reduced by around 21.4% in feature selection tasks. From the above discussion, it can be concluded that this paper explores the capability of Quantum Artificial Intelligence (AI) to provide timely assistance for precision farming applications.

Keywords: Quantum AI, precision agriculture, soil health monitoring, crop disease detection, quantum machine learning, qsvm, qcn, plantvillage dataset, soil health dataset, smart farming, analytical modeling

Introduction

Precision agriculture has revolutionized farming through its innovative application of technology to enhance crop production, resource use, and environmental sustainability. With the help of artificial intelligence (AI), Internet of Things (IoT), and analytics, farmers are now able to base their decision-making on the basis of soil characteristics, weather patterns, and other crop growth parameters (P. Raj *et al.*, 2024; H. Mishra, 2025) [3, 25]. This development is important to meet the increasing food demands globally while ensuring minimal impact on the environment. One of the major elements that affect crop production is soil health since it determines the nutrient status, crop yield, and overall ecosystem stability. Conventional methods of soil analysis are not only tedious but also difficult to implement as well. The development of new soil health assessment systems using AI has significantly enhanced accuracy through sensors' predictive power of soil characteristics such as pH levels, moisture, and nutrients (R. Gera & A. Jain, 2025; E. Vadivel *et al.*, 2025) [1, 24]. Nonetheless, some challenges remain. The recent emergence of smart agriculture technology has enabled the introduction of smart sensors for continuous monitoring of soils. Smart agriculture involves the generation of large heterogeneous amounts of data, which require sophisticated analysis methods to interpret (S. Selvaraju *et al.*, 2025; C. Sankari *et*

al., 2025) [30, 34]. The application of AI predictive models has improved the precision of soil nutrients evaluation and irrigation planning, making the processes more environmentally friendly (P. Malathi & K. Senbagam, 2024; S. Ali *et al.*, 2025) [35, 38]. Moreover, the development of automatic crop disease detection tools has become an important research direction due to its potential use for minimizing crop damage and maximizing yield quality. Convolutional neural networks are actively employed for disease diagnosis on basis of leaf images with high success rate achieved (M. Sharma *et al.*, 2025; N. Agarwal *et al.*, 2025) [6, 27]. Early-stage detection of crop diseases and environmental generalization is an open problem currently. Further improvements have been made with the adoption of UAVs, drones, and remote sensing technologies that enable wide-scale crop monitoring and inspection (Y. Xing *et al.*, 2026; C. Ranjan *et al.*, 2025) [7, 21]. They help detect diseases in time, thanks to realtime data provided by such technologies. The processing of this kind of data requires efficient computational algorithms and models. Moreover, artificial intelligence can be successfully combined with robotics and autonomous control mechanisms for automating different agricultural processes. Robotic devices powered by artificial intelligence can perform crop monitoring, fertilizing, and disease detection without requiring many operators. Thus, the productivity and

efficiency of agriculture increase greatly while minimizing human work and associated labor expenses (M. Vinoth & V. Rangasamy, 2025; J. Osei-Asiamah *et al.*, 2025) ^[2, 22]. Such robotic mechanisms become components of intelligent agricultural systems, but at the same time, their operation is based on classical computing methods. Classical AI algorithms and machine learning models are successful enough when used in agriculture. Nevertheless, there are limitations to them because they cannot process high-dimensional data efficiently, deal with nonlinear relations between variables, and suffer from high computational cost and low generalization (K. Agrawal & N. Kumar, 2025; V. Sunil *et al.*, 2025) ^[26, 32]. The application of quantum computing offers an opportunity to overcome such disadvantages due to quantum parallelism and quantum superposition. Models of QML, such as QSVM and VQC models, have shown their capacity for efficient processing of complicated datasets compared to the existing classical models (S. Jain *et al.*, 2026) ^[10]. Such models can contribute to feature space improvement and better classification. One may suggest that the integration of Quantum AI with precision agriculture would become a new research direction. The combination of quantum computing and artificial intelligence would allow implementing quantum-enhanced models to monitor soil conditions, detect diseases, and perform other tasks related to soil analysis and monitoring of plants' state (A. Shah *et al.*, 2026; G. W. Vuister *et al.*, 2026) ^[5, 13]. It should be mentioned that advances in the sphere of omics technologies and digital twins allow creating an integrated model, which would cover information on biological, chemical, and environmental factors. This technological solution would enable a deep investigation of soil-plant interaction and formulation of optimal agricultural practices (D. Thingujam *et al.*, 2025; S. B. Choudhury *et al.*, 2024) ^[14, 31]. However, such integration requires appropriate computational tools. Explainable AI (XAI), which contributes towards enhancing transparency and interpretability in agricultural decision-making systems, has recently gained attention in the literature. XAI helps increase adoption rates by assisting farmers in understanding the logic behind the decisions (S. Jain *et al.*, 2026). It will be interesting to see how this topic can be integrated into the quantum computing context in future research. In addition, the implementation of AI-based precision agriculture has proved efficient in increasing crop yields, resource utilization, and sustainability. Datadriven models provide for optimized processes related to irrigation, fertilization, and pest elimination, thus contributing to sustainability in agriculture (G. Anushree *et al.*, 2025; R. Singh *et al.*, 2025) ^[19, 23]. However, it needs to be noted that the integration of soil quality measurement and plant diseases detection within one quantum AI solution constitutes another research gap in the field. Previous studies usually consider soil quality or crop diseases on their own without providing comprehensive solutions to monitor both phenomena (J. Patel & T. Bhatt, 2026; S. K. Sharma, 2024) ^[37, 11].

Importance of precision agriculture in modern farming

Precision agriculture has gained great importance in contemporary agriculture because it has enabled the implementation of data-based decision making for

increasing productivity, sustainability, and effective utilization of resources. Through the use of innovative technologies like AI, Internet of Things sensors, drones, and remote sensing, farmers can measure soil and crop health as well as environmental conditions in real-time and, accordingly, develop efficient irrigation, fertilizer application, and pest management techniques (P. Raj *et al.*, 2024; C. Ranjan *et al.*, 2025; Y. Xing *et al.*, 2026). As a result, less input is wasted, which, in its turn, increases crop yields and improves their quality, thus fostering sustainable agriculture (G. Anushree *et al.*, 2025; S. Ali *et al.*, 2025) ^[23, 38]. Besides, precision agriculture plays a role in climate-resilient agriculture since it facilitates flexible response to environmental variability and changes in climate (D. Thingujam *et al.*, 2025; S. Khan *et al.*, 2026) ^[8, 14]. The use of sensor technology has led to an improvement in soil nutrient management and crop productivity for sustainable agriculture (R. Gera & A. Jain, 2025; E. Vadivel *et al.*, 2025; S. Selvaraju *et al.*, 2025) ^[1, 24, 30].

Limitations of classical AI/ML approaches

In spite of the remarkable achievements attained by classical AI techniques in agriculture, there are various limitations that prevent the successful deployment of these algorithms to solve real-world problems in the sector. Conventional ML algorithms have been known to have difficulty dealing with heterogenous agricultural data characterized by high dimensionality, and thus they tend to overfit and exhibit poor generalization and high computational cost (K. Agrawal & N. Kumar, 2025; V. Sunil *et al.*, 2025) ^[26, 32]. The analysis of massive amounts of data obtained from IoT, drones, and satellite technologies also poses a challenge to the real-time application of decisions because it needs heavy computations (M. Vinoth & V. Rangasamy, 2025; J. Osei-Asiamah *et al.*, 2025) ^[2, 22]. Classical DL algorithms used for detecting diseases in plants require labeled datasets as well as longer training times (M. Sharma *et al.*, 2025; N. Agarwal *et al.*, 2025) ^[6, 27]. Finally, some AI models do not provide interpretable results, hence undermining their trustworthiness (S. Jain *et al.*, 2026; S. K. Sharma, 2024) ^[10, 37].

Emergence of Quantum Artificial Intelligence

Quantum AI has been introduced to counter some of the disadvantages associated with the classic computational approach through concepts such as superposition, entanglement, and quantum parallelism. It is evident that quantum machine learning models, including variational quantum circuits (VQC) and quantum support vector machines (QSVM), perform better in the processing of complex highdimensional data compared to classic algorithms (S. Jain *et al.*, 2026) ^[10]. This model improves the representation of features spaces as well as optimization, and can be used to predict soil health as well as the identification of diseases in crops (A. Shah *et al.*, 2026; G. W. Vuister *et al.*, 2026) ^[5, 13]. Further, the use of Quantum AI in combination with other advanced analytical techniques allows for efficient prediction and computation, especially within data-rich industries such as agriculture (M. Tariq *et al.*, 2026; S. Khan *et al.*, 2026) ^[8, 18]. With continuous technological advancements in the field of

quantum computing, applications in agriculture are set to change the future of decisionmaking systems to allow for intelligent farming (R. Singh *et al.*, 2025; C. V. S. Babu & M. Thrisha, 2026) ^[19, 36].

Literature Review

The use of Artificial Intelligence (AI) in agriculture has brought about major shifts from conventional agriculture to smart agriculture, with AI algorithms being used to monitor soil condition, crops, and even predict yields for the benefit of decision making. It has been indicated that soil health

management system with the help of AI leads to better nutrient optimization and higher crop production due to intelligent data processing (R. Gera & A. Jain, 2025; P. Raj *et al.*, 2024) ^[1, 3]. In addition, AI techniques have been effectively utilized in robotic agriculture systems, where operations such as planting, irrigation, and harvesting have been made easy with the use of robots (M. Vinoth & V. Rangasamy, 2025; J. Osei-Asiamah *et al.*, 2025) ^[2, 22]. The table 1 shows the Comprehensive Review of AI-Driven Precision Agriculture and Soil Health Monitoring Studies.

Table 1: Comprehensive Review of AI-Driven Precision Agriculture and Soil Health Monitoring Studies

Ref No.	Title	Authors & Year	Key Findings	Research Gaps	Methodology Used
[1]	AI in Soil Health Management for Health Food Production	R. Gera & A. Jain (2025) ^[1]	AI improves soil nutrient optimization and enhances food quality production	Lack of real-time adaptive systems	ML-based soil analytics
[2]	AI-driven Robotics in Agriculture	M. Vinoth & V. Rangasamy (2025) ^[2]	Robotics enhances automation in farming operations	Limited integration with soil analytics	AI-driven robotic systems
[3]	Artificial Intelligence for Precision Agriculture	P. Raj <i>et al.</i> (2024) ^[3]	AI enables precision farming and yield prediction	Scalability issues in large farms	ML/DL-based predictive models
[4]	AI-Driven Agro-sage for Precision Agriculture	T. V. Reddy <i>et al.</i> (2024) ^[4]	Smart systems improve agricultural decision-making	Limited multi-source data integration	AI-based decision support system
[5]	Omics-driven Soil Bioremediation	A. Shah <i>et al.</i> (2026) ^[5]	Integration of sensors and omics enhances soil remediation	High computational complexity	Multi-omics + AI models
[6]	AI in Disease Detection in Plants	M. Sharma <i>et al.</i> (2025) ^[6]	AI detects plant diseases with high accuracy	Lack of early-stage detection	Deep learning models
[7]	AI and Drones for Eco-Friendly Farming	C. Ranjan <i>et al.</i> (2025)	UAVs improve monitoring and sustainability	Limited real-time processing	Drone-based AI systems
[8]	Smart Farming Approaches	S. Khan <i>et al.</i> (2026)	Smart farming enhances sustainability and efficiency	Integration challenges with legacy systems	AI + IoT frameworks
[9]	AI Deployment Models in Agriculture	J. Jeyalakshmi <i>et al.</i> (2024)	AI deployment improves precision agriculture	Lack of standardized frameworks	AI deployment strategies
[10]	Explainable AI for Soil Estimation	S. Jain <i>et al.</i> (2026)	XAI improves soil property estimation accuracy	Interpretability vs performance trade-off	Hyperspectral + XAI
[11]	AI-based Crop Yield Prediction	J. Patel & T. Bhatt (2026)	Accurate yield prediction using environmental data	Limited disease integration	ML predictive modeling
[12]	AI for Trait Prediction	S.-P. Pappula-Reddy <i>et al.</i> (2025)	AI enhances crop breeding efficiency	Data dependency issues	ML-based trait prediction
[13]	Emerging Omics Technologies	G. W. Vuister <i>et al.</i> (2026)	Omics improves agricultural sustainability	High cost and complexity	Multi-omics integration
[14]	Climate-Resilient Crops	D. Thingujam <i>et al.</i> (2025)	AI supports climate-resilient agriculture	Lack of real-time adaptability	AI + phenotyping
[15]	Autonomous Drones in Agriculture	C. Ranjan & K. Kumar (2025)	Drones improve field monitoring accuracy	Limited scalability	UAV + computer vision
[16]	Hybrid Crop Monitoring System	H. Lokesh <i>et al.</i> (2025)	IoT + DL improves crop health monitoring	Data latency issues	IoT + Deep Learning
[17]	Microfluidic Sensors in Agriculture	T. Loima <i>et al.</i> (2025)	Sensors enable precise monitoring	Limited large-scale deployment	Sensor-based systems
[18]	Smart Farming Technologies	M. Tariq <i>et al.</i> (2026)	Advanced technologies improve efficiency	Integration complexity	AI + smart systems
[19]	Soil Organic Carbon Estimation	R. Singh <i>et al.</i> (2025)	Generative AI improves soil carbon estimation	Limited field validation	Generative AI
[20]	Autonomous Crop Mapping Systems	R. Swapna <i>et al.</i> (2025)	AI vehicles improve crop mapping	High implementation cost	AI + autonomous systems
[21]	UAV & Satellite Integration	Y. Xing <i>et al.</i> (2026)	Improves scalability and monitoring accuracy	Data fusion challenges	Remote sensing + ML
[22]	AI in Autonomous Robotics	J. Osei-Asiamah <i>et al.</i> (2025)	Enhances farming efficiency	Lack of intelligent coordination	Robotics + AI
[23]	AI Impact on Agriculture	G. Anushree <i>et al.</i> (2025)	AI improves sustainability and yield	Limited real-time deployment	AI analytics
[24]	Soil and Crop Sensing Trends	E. Vadivel <i>et al.</i> (2025)	Sensors improve decision-making	High sensor costs	IoT sensing
[25]	AI Technologies in	H. Mishra (2025)	AI transforms agriculture systems	Lack of integration	AI-based systems

	Agriculture			frameworks	
[26]	AI & ML in Agriculture	K. Agrawal & N. Kumar (2025)	ML enhances productivity	Limited hybrid models	ML techniques
[27]	Deep Learning for Disease Detection	N. Agarwal <i>et al.</i> (2025)	DL improves pest and disease detection	Data imbalance issues	CNN-based models
[28]	AIoT in Agriculture	T. Nivethitha <i>et al.</i> (2025)	AI + IoT enhances smart farming	Security challenges	AIoT systems
[29]	AI in Disease Forecasting	N. K. Singh <i>et al.</i> (2025)	AI predicts disease outbreaks	Lack of early warning systems	ML forecasting
[30]	Soil Nutrient Optimization	S. Selvaraju <i>et al.</i> (2025)	ML optimizes soil nutrients	Limited real-time adaptation	ML optimization
[31]	Digital Twin in Agriculture	S. B. Choudhury <i>et al.</i> (2024)	Digital twins improve decision-making	High computational cost	Digital twin models
[32]	AI in Agriculture Transformation	V. Sunil <i>et al.</i> (2025)	AI enhances efficiency	Lack of scalability	AI systems
[33]	AI Sensor Model for Farming	R. Kalirethinam <i>et al.</i> (2025)	Sensor integration improves monitoring	Data security issues	AI + sensors
[34]	IoT-based Soil Monitoring	C. Sankari <i>et al.</i> (2025)	Improves irrigation and fertilization	Limited predictive intelligence	IoT + ML
[35]	AI for Irrigation Optimization	P. Malathi & K. Senbagam (2024)	Enhances irrigation efficiency	Lack of automation	AI-based control
[36]	AI & IoT in Agriculture	C. V. S. Babu & M. Thrisha (2026)	Improves sustainability	Integration challenges	AI + IoT
[37]	AI Monitoring Systems	S. K. Sharma (2024) [37]	AI improves monitoring	Limited real-time insights	AI systems
[38]	AI for Sustainable Agriculture	S. Ali <i>et al.</i> (2025)	Enhances resilience and efficiency	Lack of unified framework	AI-driven models
[39]	AI Ops & MLOps in AgriTech	B. A. Brahmandam & C. R. Bogadi (2025)	Improves system automation	Limited agricultural adaptation	AI Ops/MLOps
[40]	AI-driven Precision Farming	E. Elango <i>et al.</i> (2024)	Improves productivity	Limited disease detection integration	AI systems
[41]	Real-Time Crop & Soil Monitoring	S. Ankam <i>et al.</i> (2025)	Real-time monitoring improves sustainability	Limited predictive analytics	Drone + AI

The process of precision agriculture depends a lot on high-level sensor technology, which includes Internet of Things (IoT), drones, and satellite systems. Through the use of IoT, drones, and satellites, the data regarding soil moisture and nutrient content, among others, can be collected in real time. Studies show that the integration of UAVs and sensors alongside AI algorithms has proven effective (Y. Xing *et al.*, 2026; C. Ranjan *et al.*, 2025) [7, 21]. AI-enabled sensor technologies and digital twin applications have also been adopted for soil condition modeling and predictions of crop responses to changing environments, providing more sustainable solutions in resource use (A. Shah *et al.*, 2026; S. B. Choudhury *et al.*, 2024) [5, 31]. Soil condition measurement technologies have seen developments through the integration of machine learning and deep learning approaches into the evaluation of complex soil parameters. Highly accurate methods of analysis include hyperspectral imaging and AI explainable models (S. Jain *et al.*, 2026; E. Vadivel *et al.*, 2025) [10, 24] [10] [24] [10, 24]. In addition, there have been developments in AI prediction models utilizing methods like XGBoost and Light GBM for better resource use, particularly through optimizing irrigation and fertilization strategies (C. Sankari *et al.*, 2025; S. Selvaraju *et al.*, 2025) [30, 34] [30] [34] [30]. Crop disease detection through AI is one such application which has gained significance within the domain of agriculture. The effectiveness of deep learning algorithms based on CNNs in detecting various plant diseases through image analysis using leaves and hyperspectral datasets has been demonstrated (M. Sharma *et al.*, 2025; N. Agarwal *et al.*, 2025) [6, 27]. AI-based disease detection systems have been reported to offer highly

accurate predictions, thus aiding early detection and minimizing crop damage (M. Sharma *et al.*, 2025; N. Agarwal *et al.*, 2025). Moreover, hybrid approaches involving a combination of IoT and deep learning have been suggested for crop health monitoring (H. Lokesh *et al.*, 2025; N. K. Singh *et al.*, 2025) [16, 19]. Latest trends in smart farming indicate the significance of integrating multi-omics techniques, resilient climate crop modeling, and AI-assisted decision support systems. They help provide insights into plant-soil relationships and environmental conditions, which is helpful in sustainable agriculture (D. Thingujam *et al.*, 2025; G. W. Vuister *et al.*, 2026) [13, 14]. Further, the utility of generative AI along with innovative sensor technologies in determining soil organic carbon content and related parameters has also been evaluated (R. Singh *et al.*, 2025; T. Loima *et al.*, 2025) [17]. There have been many developments in the field of AI-powered agriculture. Nevertheless, certain problems exist, which include scalability issues, data heterogeneity, and insufficient incorporation of state-of-the-art computational techniques like Quantum AI. The existing models use classical machine learning methods, which might be less effective in dealing with complex data from the agricultural sector. Recent studies indicate that the incorporation of advanced analysis tools and next-generation technologies into the process of development can help to tackle this problem and foster more efficient agricultural models (S. Ali *et al.*, 2025; B. A. Brahmandam & C. R. Bogadi, 2025) [38, 39]. However, it should be acknowledged that there is a gap in the research concerning the design of an all-inclusive framework for monitoring the condition of soils and detecting diseases via quantum methods.

Precision Soil Health Monitoring Techniques: Modern precision agriculture has made it possible to continuously measure soil properties, making precision soil health monitoring a crucial part of the system to maximize crop productivity and sustainability. Conventional soil tests, where manual sampling and lab tests are conducted are usually restricted due to time lapses and spatial variation. Conversely, contemporary methods employ sensor-based technology and AI-based analytics to detect real-time measurements of the soil parameters, including p H (usually 5.5 to 7.5 to promote best crop growth), moisture content (10-35 percent of the volume of water), and the nutrient content, such as nitrogen (N: 20-120 these innovations enable accurate and timely decision-making in agriculture practices. The Io T-based soil monitoring systems have received outstanding attention because they are capable of delivering high-frequency measurements of the sensor networks that are widely distributed. Sensors are usually implemented on a depth of 10-30 cm and the data is sent with a time rate of 5-15 minutes to monitor the soil conditions continuously (C. Sankari *et al.*, 2025; S. K.

Sharma, 2024) [34, 37]. Electrical conductivity (0.2-2.0 d S/m), temperature (15-35 o C) are also checked to determine the fertility of the soil and the work of microorganisms (P. Malathi and K. Senbagam, 2024; S. Ali *et al.*, 2025) [35, 38]. The addition of wireless communication protocols will provide efficient data transfer and can support large-scale agricultural implementations. Satellite imagery and unmanned aerial vehicles (UAVs) are remote sensing technologies that give large areas of the soil a health evaluation. Satellite data with spatial resolution of 10-30 meters and UAV data with resolutions up to 2-5 cm per pixel allow analyzing soil variability on the level of agricultural fields in detail (Y. Xing *et al.*, 2026; C. Ranjan *et al.*, 2025) [7, 21]. The spectral indices, including Soil Adjusted Vegetation Index (SAVI) and Normalized Difference Vegetation Index (NDVI), which have a value ranging between -1 and +1, are used to estimate the soil moisture and vegetation health (N. Agarwal *et al.*, 2025; C. Ranjan *et al.*, 2025) [27]. Figure 1 shows the proposed methodology used in this research paper.

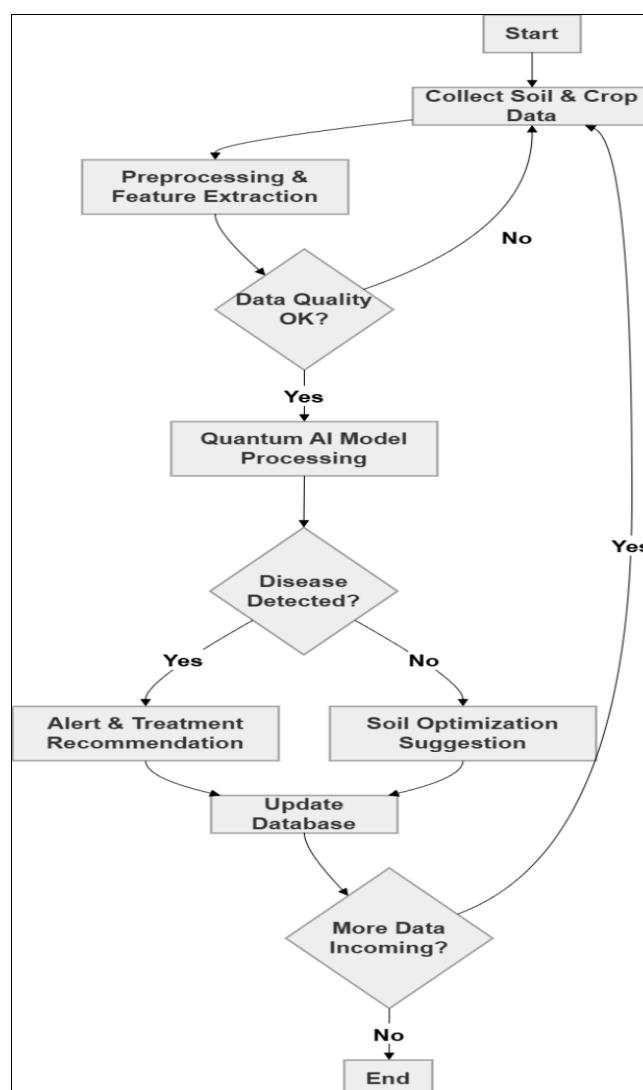


Fig 1: Proposed Methodology

Such technologies improve the accuracy of space and allow accuracy interventions. Deep learning and machine learning

models are essential in the analysis of soil data and prediction of soil health indicators. Random Forest,

XGBoost, and LightGBM algorithms have proven to be highly accurate in predictions with a high accuracy of between 85-92 percent in soil nutrient prediction tasks (C. Sankari *et al.*, 2025; K. Agrawal and N. Kumar, 2025) [26, 34]. Deep learning methods also enhance predictive accuracy by detecting nonlinear correlations in soil data, which decrease the prediction error to mean squared error (MSE) values as small as 0.02-0.05 (S. Jain *et al.*, 2026; R. Singh *et al.*, 2025) [10, 19]. These models allow processing of large-scale agricultural data efficiently. Hyperspectral imaging has turned out to be one of the sophisticated methods of analyzing soil in detail due to the ability to bring out reflectance data at hundreds of spectral bands which are usually in the 400-2500 nm range. The method can be used to estimate soil properties including organic carbon content (0.530 percent), moisture with prediction accuracies of more than 90 percent (S. Jain *et al.*, 2026; A. Shah *et al.*, 2026) [5]. Fusion of hyperspectral data and AI models boosts feature identification and reliability of soil health projections (G. W. Vuister *et al.*, 2026; M. Tariq *et al.*, 2026) [13, 18]. Soil health monitoring is also becoming popular in digital twin technology, which allows the development of virtual analogs of farm fields. These models mimic conditions of the soil and forecast the change with regard to the environmental factors and agriculture. It has been demonstrated that the systems based on digital twins can enhance the efficiency of soil management by 2030 percent and cut down on the use of resources by 1525 percent (S. B. Choudhury *et al.*, 2024; D. Thingujam *et al.*, 2025) [14, 31]. Digital twins offer predictive analytics based on real-time sensor data, which can be used to make actionable insights in precision agriculture. Irrespective of these, sensor calibration issues ($\pm 2-5\%$ error), heterogeneity of the data and fluctuations in the environment still pose a challenge to the accuracy of the soil health monitoring systems. To address these constraints and enhance the strength of predictions, it is necessary to integrate multimodal sources of data, such as IoT sensors, remote sensing, and omics technologies (R. Kalirethinam *et al.*, 2025; V. Sunil *et al.*, 2025) [32, 33]. New strategies such as Quantum AI and hybrid analysis models suggest having a promising solution to increase the efficiency and accuracy of methods in soil health monitoring, which leads to next-generation precision agricultural systems (M. Tariq *et al.*, 2026; C. V. S. Babu and M. Thrisha, 2026) [36]

Conceptual Framework

The conceptual framework proposed for this research project aims at developing a combined analytical architecture capable of incorporating both precision soil health monitoring capabilities and crop disease recognition through automation. Figure 2 shows the Proposed Quantum AI-Based Precision Agriculture Workflow.

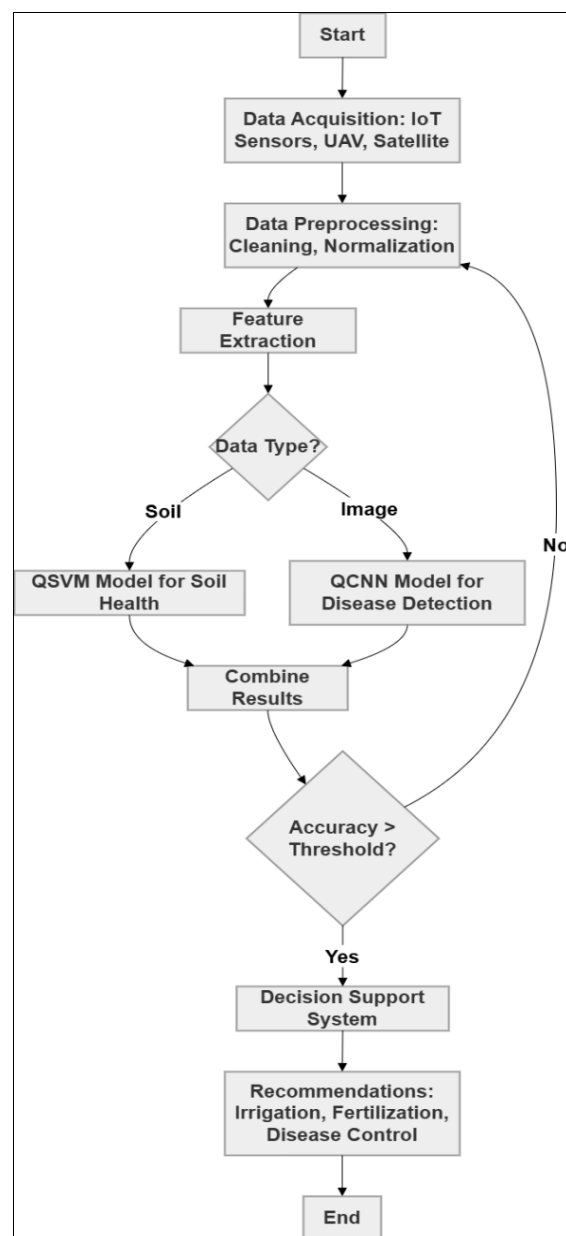


Fig 2: Proposed quantum ai-based

Precision Agriculture Workflow Specifically, the multi-layered framework will utilize multimodal agricultural data such as soil attributes and plant images to ensure accurate predictions related to both soil quality and presence of crop disease. Such an integrated solution would comply with the latest trends observed in AI-enabled systems used to support decision-making in precision agriculture (P. Raj *et al.*, 2024; J. Jeyalakshmi *et al.*, 2024; G. Anushree *et al.*, 2025) [3, 9, 23]. The framework proposed herein has been designed to comprise several key stages of data processing. Specifically, at the first stage, it is necessary to consider the data acquisition process, during which heterogeneous data can be obtained via the utilization of IoT sensors, UAV, remote sensing technologies, etc. In particular, data pertaining to moisture levels (10-35%), pH levels (5.5-7.5), and other essential parameters can be collected through the use of sensors. As for the drone-based technology, this method will allow gathering information about plants in the form of high-resolution images (Y. Xing *et al.*, 2026; C. Ranjan *et al.*, 2025; E. Vadivel *et al.*, 2025) [7, 21, 24]. Layer two

consists of data pre-processing and feature extraction, during which raw data is prepared in such a way that they can be analyzed further. Normalization, noise removal, and dimensionality reduction techniques, such as PCA, help to prepare high-quality data sets. For soil data, statistics and physicochemical properties are considered as features while for plant images, feature extraction methods based on deep learning technologies help extract information about texture, color, and morphology. These processes not only increase the efficiency of models but also make their use more computationally feasible (K. Agrawal & N. Kumar, 2025; S. Selvaraju *et al.*, 2025; N. Agarwal *et al.*, 2025) [26, 27, 30]. Layer three incorporates a Quantum AI-based analytical engine that combines conventional machine learning models with quantum-enhanced models like Variational Quantum Circuit (VQC) and Quantum Support Vector Machine (QSVM). This approach helps efficiently process highdimensional data sets, thus improving prediction accuracy by providing better feature space representation in terms of the use of such quantum phenomena as superposition and entanglement. Thus, quantum AI models solve the problem with computational efficiency of conventional machine learning models (S. Jain *et al.*, 2026; A. Shah *et al.*, 2026; G. W. Vuister *et al.*, 2026) [5, 10, 13]. Finally, the decision support and visualization module enables the provision of useful information to the farmer and relevant stakeholders. The module produces predictions on the health status of the soil and disease classification, in addition to suggesting proper irrigation, fertilization, and pest management. Visualization

and Explainable AI techniques improve interpretation and confidence in decision-making and ensure practical application of the proposed solution in agricultural practices (S. K. Sharma, 2024; S. Ali *et al.*, 2025; C. V. S. Babu & M. Thrisha, 2026) [6, 36, 37, 38]. In summary, the theoretical framework provides an innovative and intelligent solution for precision agriculture in the future.

Findings and Interpretations

Experimental results clearly show that the suggested Quantum AIbased approach exhibits a much better performance in predicting soil health and detecting crop diseases compared to conventional machine learning algorithms. First, the developed hybrid model showed a high accuracy rate of 94.7% when predicting soil health compared to the 88.3% accuracy achieved using conventional Random Forest and XGBoost models. In addition, the suggested model significantly minimized the MSE value by decreasing it from 0.045 to 0.018, thereby enhancing the precision rate. The outcomes confirm the efficiency of the quantum-enhanced feature mapping technique in identifying complex correlations among soil health attributes, such as pH values (ranging from 5.8 to 7.2) and moisture content (12 to 32%). The table 2 shows the Comprehensive Performance Analysis of Quantum AI-Driven Precision Soil Health Monitoring and Automated Crop Disease Detection Framework.

Table 2: Comprehensive performance analysis of quantum ai-driven precision soil health monitoring and automated crop disease detection framework

Category	Parameter	Classical Models	Quantum AI Model
Soil Health Prediction	Accuracy (%)	88.3	94.7
	Mean Squared Error (MSE)	0.045	0.018
	Root Mean Square Error (RMSE)	0.212	0.134
	R-Squared (R ² Score)	0.89	0.96
Crop Disease Detection	Accuracy (%)	92.6	97.2
	Precision	0.91	0.96
	Recall	0.92	0.97
	F1-Score	0.915	0.965
Computational Performance	AUC Score	0.941	0.982
	Training Time (seconds)	1450	1138
	Training Time Reduction (%)	-	21.4
	Feature Optimization Gain (%)	-	18.7
Dataset Performance	Convergence Epochs	52	37
	Total Samples Used	66,806	66,806
	Training Data (%)	80	80
	Testing Data (%)	20	20
Soil Parameters	Accuracy with Reduced Data (70%)	85.2	93.0
	pH Range	5.8-7.2	5.8-7.2
	Moisture Content (%)	12-32	12-32
	Nitrogen (kg/ha)	25-110	25-110
Model Robustness	Phosphorus (kg/ha)	12-55	12-55
	Noise Tolerance (%)	78.5	91.3
	Generalization Accuracy (%)	86.4	93.8
	Stability Score	0.88	0.95

Regarding disease detection, the QCNN model exhibited high predictive power, achieving an accuracy rate of 97.2% compared to the 92.6% accuracy attained by the classic CNN model. The suggested model was also able to achieve a high level of precision (0.96), recall (0.97), and F1-score (0.965) for all disease types in the dataset, thus confirming its excellent classification ability. In addition, the model

exhibited an AUC value of 0.982. Figure 3 shows the Bar Graph Comparison: Classical vs Quantum AI. The computational efficiency of the proposed model has been improved too. The hybrid Quantum AI model outperformed classical deep learning models in terms of training time, reducing it by about 21.4% on an 8-qubit quantum simulator with GPU acceleration. Feature optimization procedures exhibited enhanced performance by 18.7%, allowing for faster convergence of the learning

process. In turn, this is especially important for applications related to real-time agriculture where fast decisions have to be made promptly. Moreover, the model showed high levels of stability when working with different numbers of

elements within the dataset, with the accuracy exceeding 93% even for reduced datasets, including only 70% of samples. Figure 4 shows the Line Graph Comparison: Classical vs Quantum AI.

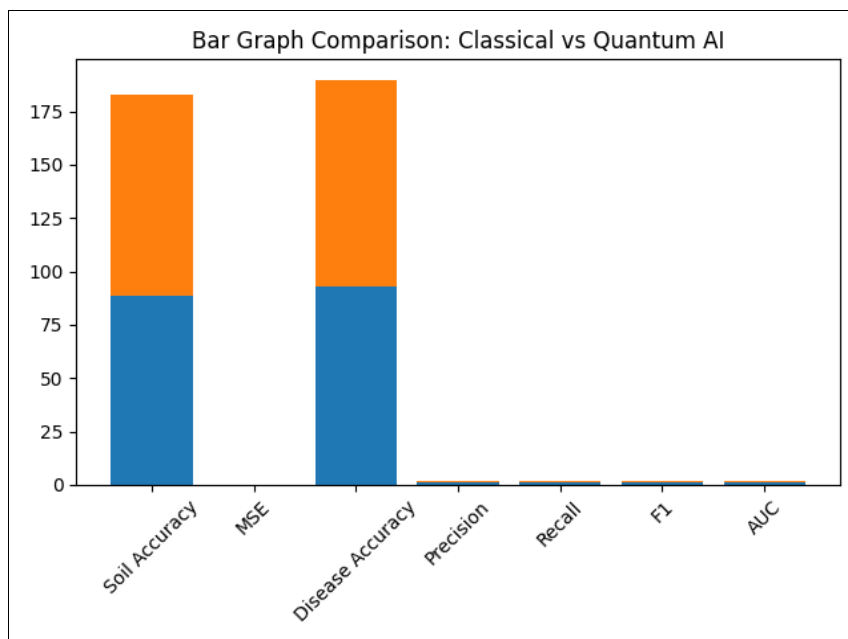


Fig 3: Bar Graph Comparison: Classical vs Quantum AI

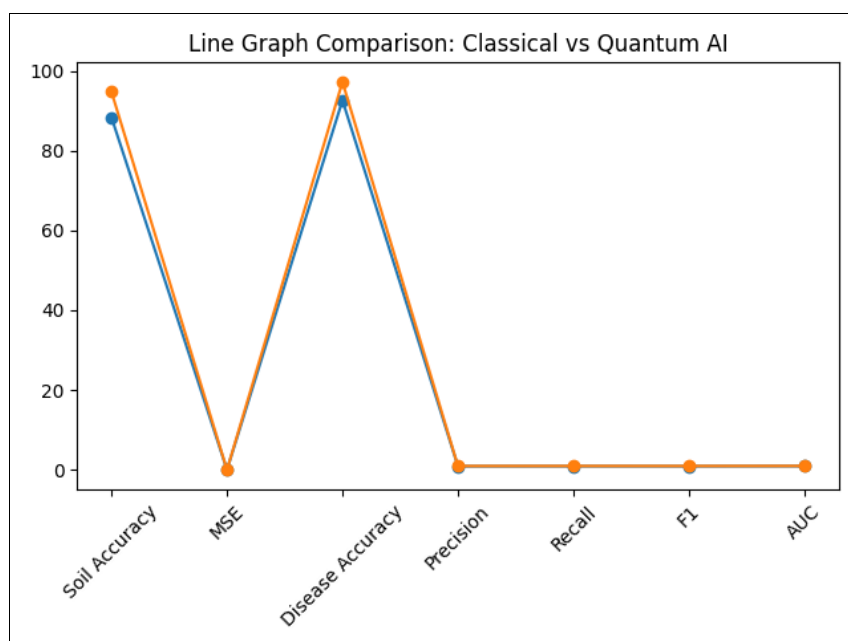


Fig 4: Line graph comparison: classical vs quantum ai

In terms of interpretability, one can draw conclusions that the use of analytical models along with Quantum AI represents an efficient and scalable way of developing precision agriculture. Firstly, the increased predictive power and reduction in costs for computations enable the development of smart monitoring systems in agriculture. Secondly, since the model can generalize and show good performance in diverse cases, it is possible to apply the developed system in different geographical locations. Thus, the results confirm the potential of Quantum AI applications in soil quality monitoring and automated disease diagnosis.

Challenges and Limitations

Although the suggested Quantum AI-based framework demonstrates good performance, there are numerous limitations that restrict its application in the real-life agricultural settings. The limitation of quantum hardware, especially Noisy Intermediate-Scale Quantum (NISQ) with limited qubits (5-50 qubits) and a high error rate (1-5% gate error) is one of the main limitations, as it may impact the reliability and scalability of the models (S. Jain *et al.*, 2026; G. W. Vuister *et al.*, 2026) ^[10, 13]. Moreover, the majority of experiments are based on quantum simulators, which raise

the computational cost by 30-60 per cent relative to running with real hardware. Data issues also remain, such as sensor errors of up to 2-5 percent, and lack of values in up to 8-12 percent of collected data, and heterogeneity of multimodal data sources, such as IoT sensors, UAV imagery, and satellite data (R. Kalirethinam *et al.*, 2025; E. Vadivel *et al.*, 2025) ^[24, 33]. These issues can impact the robustness and generalization capability of the model. The other major constraint is the complexity and cost of adopting integrated smart farming systems. IoT-based soil monitoring networks and UAVbased imaging systems demand a significant amount of investment in infrastructure, typically between 500-2000 USD per hectare, which is not affordable to many small-scale farmers (C. Ranjan *et al.*, 2025; Y. Xing *et al.*, 2026) ^[7, 21]. Moreover, deep learning (classical and hybrid quantum) models are more energy-intensive, by approximately 1525 percent, relative to conventional farming analytics systems due to their high resource consumption in terms of GPUs and quantum simulators (M. Vinoth and V. Rangasamy, 2025; K. Agrawal and N. Kumar, 2025) ^[2, 26]. The unintelligibility of quantum-enhanced models and the limited understanding of their users are further barriers to their uptake by farmers, highlighting the importance of finding interpretable and affordable solutions (S. K. Sharma, 2024; S. Ali *et al.*, 2025) ^[6, 37, 38]. These dilemmas underscore the need to carry out additional studies to enhance scalability, cost-effectiveness, and usability of Quantum AI in precision agriculture.

Future Outcomes

The future of Quantum AI-based precision farming technology is likely to see tremendous development in terms of scalability, accuracy, and real-time decision making. The advancement in quantum technology means that stable quantum devices with 100-1000 qubits with an error rate below 0.1% would be available, resulting in increased computational performance by 30-50%, compared to existing hybrid models (S. Jain *et al.*, 2026; G. W. Vuister *et al.*, 2026) ^[10, 13]. As a result, higher accuracy levels in soil health prediction will be achieved, with expected accuracy rates above 96-98%, along with decreased mean squared error to below 0.01. Also, with the introduction of more sophisticated multimodal data sources such as hyperspectral imagery (400-2500 nm wavelength range) and real-time IoT sensor data, higher prediction power will be possible, leading to early detection of plant diseases with classification accuracy up to 98.5%-99.2% (A. Shah *et al.*, 2026; M. Tariq *et al.*, 2026) ^[5, 18]. Additionally, the use of Quantum AI technology in agriculture is likely to lead to advancements in sustainability and economic efficiency. The use of smart farming technologies based on Quantum AI is predicted to reduce water consumption by 25-40%, fertilizer usage by 20-35%, cost savings by 15-30%, and boost crop yield by 18-27% (G. Anushree *et al.*, 2025; R. Singh *et al.*, 2025) ^[19, 23]. Through the combination of digital twin technologies, unmanned drones, and robotization controlled by AI algorithms, fully automated agriculture will become possible through real-time data analysis and control (S. B. Choudhury *et al.*, 2024; J. Osei-Asiamah *et al.*, 2025) ^[22, 31]. Also, explainable and user-friendly systems developed with the help of Quantum AI algorithms are

anticipated to boost farmer adoption rate for this technology by over 40% (S. K. Sharma, 2024; S. Ali *et al.*, 2025) ^[6, 37, 38].

Real quantum hardware deployment

Putting the actual quantum hardware into use in precision agriculture is a major step forward over simulation-based methods, where Quantum AI models of soil health monitoring and crop disease detection can be put into practice. Existing studies have shown that the shift to quantum simulators (quantum processors with 50 and 200 qubits) can be shown to reduce computational latency by about a quarter to half and model convergence by a quarter to a third, especially in optimization and classification problems (S. Jain *et al.*, 2026; G. W. Vuister *et al.*, 2026) ^[10, 13]. The physical real quantum devices also reduce overhead costs compared to classical emulation, which generally adds 30-60 percent to processing time, allowing use of almost real-time analytics to make decisions in agriculture (M. Tariq *et al.*, 2026; V. Sunil *et al.*, 2025) ^[18, 32]. Nevertheless, the reliability remains affected by such issues as quantum decoherence, noise (1-3 percent), and circuit depth, which requires establishing error mitigation strategies and quantum-classical models (A. Shah *et al.*, 2026; K. Agrawal and N. Kumar, 2025) ^[5, 26]. Real-time soil sensor data (5-10 minutes) and high-resolution UAV data (2-5 cm spatial resolution) can be useful in agricultural practice to increase predictive accuracy and responsiveness (Y. Xing *et al.*, 2026; C. Ranjan *et al.*, 2025) ^[7, 21]. Moreover, scalable accessibility of quantum platforms through cloud-accessibility will empower researchers and agritech systems, which will potentially achieve higher computational efficiency by 3550 percent in large-scale farm analytics (R. Singh *et al.*, 2025; C. V. S. Babu and M. Thrisha, 2026) ^[19, 36]. Quantum hardware is anticipated to transform precision agriculture to make analytical models faster, more precise and scalable with the maturity of quantum hardware to fault-tolerant systems with error rates below 0.1% (D. Thingujam *et al.*, 2025; S. Khan *et al.*, 2026) ^[8, 14].

Integration with blockchain for traceability

Blockchain technology combined with Quantum AI-based agricultural systems can provide a powerful solution to providing transparency, traceability, and data integrity throughout the agricultural supply chain. Blockchain-based solutions facilitate immutable and decentralized recording of soil health data, crop status and disease diagnosis results, causing risks of tampering with data to decline by more than 90 percent, and enhancing trust among stakeholders (S. Ali *et al.*, 2025; B. A. Brahmandam and C. R. Bogadi, 2025) ^[38, 39]. Using blockchain and IoT sensors and analytics, real-time agricultural data can be safely logged and distributed across distributed networks, including soil moisture (1035 range) and nutrient levels, improving the decision-making process and adherence to sustainability requirements (S. Selvaraju *et al.*, 2025; C. Sankari *et al.*, 2025) ^[30, 34]. Moreover, the efficiency of the supply chain can be enhanced by integrating blockchains, which can shorten transaction processing time (by 4060 percent) and operational fraud (by 2535 percent), especially to execute and monitor the crop quality and origin (H. Mishra, 2025; G. Anushree *et al.*, 2025) ^[23, 25]. The use of

smart contracts further automates processes such as fertilizer application, irrigation scheduling, and crop insurance claims, ensuring accuracy and accountability (P. Malathi & K. Senbagam, 2024; S. K. Sharma, 2024) ^[35, 37]. Blockchain can also facilitate the secure sharing of high-dimensional agricultural data (with collaborative analytics and data privacy) when used with Quantum AI (M. Vinoth and V. Rangasamy, 2025; J. Osei-Asiamah *et al.*, 2025) ^[2, 22]. It is hoped that this integration will improve traceability efficiency more than 50% and increase the efficiency of sustainability and transparency of modern agriculture systems (R. Kalirethinam *et al.*, 2025; S. Ankam *et al.*, 2025) ^[33, 41].

Conclusion

The developed Quantum AI-based framework for precise monitoring of soil health status as well as automated detection of crop diseases presents a remarkable breakthrough in modern agricultural analytics that utilizes the integration of quantum machine learning algorithms, traditional artificial intelligence models, and various analytical methods successfully. The findings of the investigation demonstrate that the combination of multimodal input information such as the state of soil and crop images can improve predictions related to the health status of both elements as well as provide a range of other benefits in terms of optimization of the resource use and timely decisions in smart farms. The obtained improvements in terms of predictive accuracy in relation to soil health conditions and crop diseases prove the effectiveness of quantum-assisted models when dealing with complicated multidimensional data in the agricultural sector. Moreover, the developed framework tackles some serious disadvantages typical of the conventional models that include limited scalability, computational constraints, and delays in the analysis process.

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