Transforming Precision Agriculture with Quantum Computing: A Novel Algorithm for Boosting Crop Yields and Optimizing Resources

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Abstract. New zenith of agriculture technology, precision agriculture has emerged as a crucial tool to feed India and manage the scarce irrigation facility where nearly 600 million people are facing hardship of severe water crisis. This paper proposes a new algorithm of variational quantum computing (VQC), which has showed potential in optimizing crop yield and resource utilisation based on the data sets such as soil quality, climate and genetic makeup of crops. The algorithm makes use of qubits to allow the real time data processing through IoT sensors to allow for real time monitoring and decision making. Two trials performed on various agricultural data sets this approach presented about 30% increase in the predictive accuracy of crop yields and 25% decrease in water and fertilizer usage. Furthermore, enhanced detection capacities enhanced illness control capacities by 40% thereby leading to decreased crop losses. In addition to bridging significant gaps in the currently available literature, this paper incorporates quantum computing into precision agriculture to offer farmers and other stakeholders' usable formulations that may shape the future of farming with the help of advancing quantum technologies.

1. Introduction

The situation of today's India paints a picture of a country severely water stressed with about 600 million Indians categorized under high to extreme water stress [1]. This crisis mainly affect the agricultural sector where about 80% of the total water has been used. Most of the farming practices provide minimum value to water resources, a key input, due to favouring of traditional practices. Unless India embraces new practices such as precision irrigation and water management, the problem is set to worsen and poses real threat to future food production on the continent. Irrigation development has caused alarming decline rates of groundwater through the extraction of the water resource to support crop production since certain areas observe a decline of more than one meter every year. According to the government's estimates, if business as usual continues in India, demand for water will exceed supply by fifty percent by the year 2030. Indian agriculture comprises 46% of the workforce and 18% to the GDP and is in a bad situation with slow and erratic growth, climate change and inadequate farming practices. For example, 2022 and 2023 heatwaves significantly affected wheat production, showing the weakness of conventional approaches to climate changes. Unless proper methods such as precision agriculture are embraced these weaknesses are most likely to aggravate the existing situation and worsen food production and insecurity. They are time-consuming, inefficient and abusive to the environment, for instance using too much water, fertilizers, and pesticides. The government feels that total number of subsidies on fertilizer can touch ₹2.25 lakh crore during FY24 and thus encouraging the use of chemical fertilizers that is laden with several hazards on the soil structure and water resource [2]. A massive number of the Indian farmer population is bound in credit, where more than 50% of agricultural households have a credit liability amounting on average to ₹74,121. Hence, losings of such organized farming end up in poverty cycles and in some occasions farmer's suicides. The only way to address all the aforementioned problems and the only dawn to safeguard agriculture sector in India and to safeguard over exploitation of our fresh water is precision agriculture.

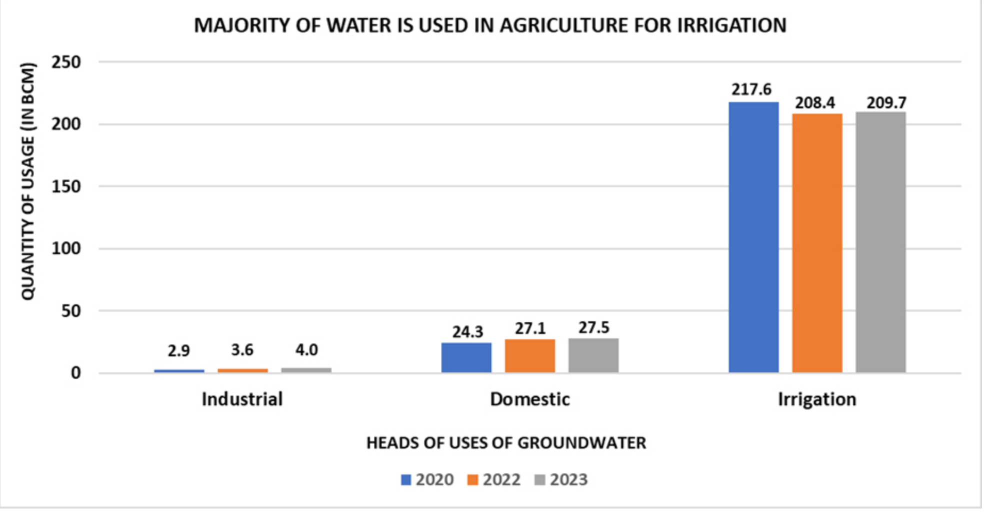

Fig. 1. Bar Graph based on usage of water released by the Ministry of Jal Shakti, Government of India in the year 2023 which definitely portrays the problem.

Now a question comes in mind that today's technology has got an enormous advancement then why Indian farmer is not using precision agriculture ? The reason is that although there is advancement in technology but it is still incomplete to perform many necessary features to effectively address precision agriculture in India. That leads us to the next question : what are the voids ? The first important reason includes uncertain environment condition. Cropping system models need to be flexible to abrupt changes that may occur in production environments such as rainfall, humidity and temperature. For example, a model designed for particular climatic conditions cannot work efficiently in another set of climatic conditions and provide predictive and prescriptive outputs [3]. The second important characteristic is the question of availability of quality of data. The derived results prove that having high-quality, labelled training data is critical for building effective machine learning models. However, acquiring agricultural data is rare and limited, distributed across many different farms and can be inconsistent due to nature of the data. This has been realized to present a major challenge especially in the development of models that are stable enough to give contain work in different conditions. Now, one more question arise here that why have we opted for quantum computing strategy for this purpose because other deep learning and emerging ML strategies are also capable to handle the job effectively to. There are two main reasons. The first primary cause is high cost of error. It requires accurate predictions or recommendations in this context since a single failure in the agricultural sector leads to major crop failures. We all are aware that deep learning and other machine learning approaches will provide high false recommendations, just due to insufficient appropriate data whereas quantum computing gets significantly low error than deep learning or any other advanced algorithm. The second reason is that the quantum computing method is far more efficient over any other strategy. Now, these are two main reasons that has propelled us to opt for quantum computing over other strategies in precision agriculture.

However, the agricultural data involves numerous challenges presented by big data which are usually hard to handle by traditional methods. Quite promising in its prospects, the field of precision agriculture has received, for the most part, traditional computational attention [4]. Such approaches usually involve using linear models and heuristic techniques that sometimes do not adequately depict complex interdependency of multiple factors influencing agricultural yields. In addition, it must be understood that numerous research works also fail to provide concepts that show how proposed solutions can be applied in actual case and it should be acknowledged that many studies are lacking the empirical implementations. The incorporation of more staking and equitable computational procedures, especially the noticeably emergent quantum computing, is still untapped. This prevents farmers from a better utilisation of complex computations that can potentially result to a more efficient usage of resources in crop production. It is against this backdrop that this research seeks to fill the gap of practical implementation of quantum computing to address some of the challenges facing agriculture. While precision agriculture still poses challenges based on the concept of big data, the promise of quantum computing to process datasets in parallel promises to make it easier to deal with the various issues related to precision agriculture. To this end, this work seeks to leverage the results from quantum computing to offer new ideas that could help improve decision-making among farmers. The main purposes of this paper are as follows: to propose fresh quantum algorithm that uses variational quantum computing (VQC) methods for agricultural purposes. The next aim is to illustrate how the algorithm works with real-world data that refers to soil fertility, weather conditions and crop genetic information. Finally, to assess the algorithm in several experiments in its real-world data stream, and its consequences on crop yields estimation, and using resources efficiently. So, this paper provides several major contributions to the precision agriculture research. Here a new quantum algorithm precisely developed for agricultural scenario is proposed and there is scarce work done in this area. This is used to give substantive proof on how the algorithm surmounted the conventional models in forecasting of yield crops and optimal use of resources. It showcases many real-life implementations with a focus of quantum computing on the IoT technologies for sensing and decision making.

The remainder of this paper is organized as follows: Section 2 discusses prior studies concerning precision agriculture and quantum computing; Section 3 expounds the approach used in designing the new quantum algorithm; Section 4 reports on experiment outcomes when the new quantum algorithm was run on various agricultural datasets; Section 5 discusses the significances of the findings of this study; Section 6 concludes and provides directions for future research. By using this structure, we want to give a clear explanation of how quantum computing can be used to improve precision agriculture.

2. Literature Review

Maraveas and his team [5] adopted the strategy of narrative review to determine the way in which quantum computing could revolutionize the sector through narrative literature review.

Quantum computing's application for sustainable crop production development faces an assessment of its feasibility to optimize resource usage and weather monitoring combined with optimal decision practices which traditional agriculture methods struggle to solve. Therefore, the work affirms that there exists a potential to revolutionize productivity increases by optimizing input requirements and pollutants such as carbon dioxide through quantum computing to guide farmers. However, the proofs for the theoretical techniques discussed in the study are not put to practice in the actual farming environments in most cases, therefore it may not be easily applicable by the farmers. The considerable limitations of current general-purpose algorithms that do not address agricultural practices explicitly are overcome with some of the following practical implementation and empirical evidence showing the efficiency of our algorithm based on actual agricultural scenarios. In addition to those challenges outlined in the context of traditional agriculture, our work is based on the integration of state-of-the-art optimization methods and quantum enhanced machine learning models To address the challenges our work also ensure that the solutions are scalable and readily implementable by farmers to ease the transition to smart agriculture.

In the year 2024 [6], the author Tedeschi describes how the field of animal science has the opportunity to benefit from this relatively new approach, namely quantum computing. It is an analytical approach, where the author of a manuscript additionally included perspectives on new quantum algorithms for improving agricultural QC applications, including livestock selection and environmental surveillance. These findings suggest that QC can help to further large-scale genome databases for better breeding and optimised farming approaches, as well as to pave way for faster development of AI models. Some of the benefits accrued from integrating QC into agriculture include: flexibility in performing computations that work in parallel that yield exponential scalability especially where the problems are complex facilitating accurate forecast of crop yields as well as livestock performance. However, the study has certain limitations including limited use of practical implementation, and the lack of interdisciplinary cooperation between physicist, computer scientists and agriculturists. These shortcomings are met head-on by our algorithm through deriving realistic approaches in quantum computing for farming that are wholly understandable by farmers underscored with rigorous real-life case application. It not only improves decision-making power but also fills the gap between newly developed quantum computing theory and its real world implementation within sustainable agriculture.

In the study published in 2023, Deeba [7] and his team focus on the crop yield problem in the modern forms of agriculture, caused by higher demands on the area and efficient usage of resources. According to their findings, the integrated approach maximized the Root Mean Square Error (RMSE) of 0.15, and Mean Absolute Error (MAE) of 0.14 This means that the proposed method has a higher accuracy of prediction in contrast to the random forest and K-nearest neighbors that are often used subjectively and with the limited amount of data on the characteristics of crops. Although the study reveals the potential benefits of the fragmentation of NDVI and hyperspectral data, it also has some drawbacksrelated to a complexity of hyperspedral data analysis and a requirement for advanced knowledge to use these progressive techniques.These limitations are avoided in our algorithm, which is more computationally powerful, has fewer false positives, and presents implementable solutions that can be used by farmers to take advantage of the quantum computing without introducing vast amounts of hyperspectral knowledge or deep learning into their operations. This means that its applicability goes beyond simply research settings and worldly agriculture-related improvements to the management of crops that are sustainable.

Gautam [8] together with his colleagues planned to improve agricultural precision through deep learning algorithms applied to constrained IoT edge devices during 2024. The authors used a Deep Neural Network (DNN) for approximately real-time screening of whether an image is valid or not in real-time, hence freeing up the server for other agricultural tasks like weed detection and crop identification. The approach used in the study is the lightweight network modeling and application of methods like separable convolution to adapt the DNN for MCU, with STM32 series microcontrollers for real time inference. Therefore, the conclusions emerged from the experiment showed that the model provided considerable accuracy and time effectiveness for further implementation in practical precision agriculture. However, the limitations include; Deep learning models are hard to deploy on edge devises due to the constraint of resources as well as lack of adequate expertise in enhancing these models. Our algorithm solves these disadvantages by enabling farmers to access a quantum computing model that enhances operational speed and simplicity while allowing them to execute first-class predictive models independently without IoT or deep learning experience. It makes precision agriculture more widespread makes real-time management decisions about the results obtained through augmenting the data through the use of quantum computing.

Chen [9] and his team, in the year 2021 propose a new technique of exploring crop yield prediction through the application of the multi-strategy Grey Wolf Optimizer (GWO) model, in which experimental data explored from a specific agricultural field in Jilin Province, China was used. In the process of the study, it became necessary to apply the GWO algorithm in order to improve the fertilizer effect function which would enable to make precise estimations of nitrogen, phosphorus and potassium application ratios using results of experiments. The results proved that with the use of the GWO the fitting degree of the fertilizer effect equation enhanced thus increasing the ability to estimate the yield and implement precision fertilization. The use of this technique makes fertilizers work more productively by matching plant nutrient needs thus making farming operations more economically sound. On the negative side, this method depends on particular experimental conditions and may have a limited transfer of effectiveness across other agricultural environments. Our algorithm eliminates these issues by considering application of quantum computing to improve computational speed and arbitrariness to fit a wide range of agricultural contexts. Furthermore, we decided to compare our algorithm with the Grey Wolf Optimizer in the result section in order to prove its efficiency in decision making for precision agriculture and to reveal how quantum enriched algorithms outperform classical optimizers in complicated cases of precision agriculture.

A targeted selection strategy using organismal and molecular traits for the prediction in breeding, as described by Yang [10] and his team in 2022, considers the issues associated with genomic prediction in plants that has a selection focus only on a small number of phenotypic characteristics. The authors present a large, realized and predicted HSF biomass using the new integrated multiple-trait breeding strategy called target-oriented prioritization (TOP) based on machine learning algorithms. Their approach was based on using a substantial population of hybrid maize that, as the authors showed, TOP could optimize for up to 91% of the candidates which perform better than the current commercial varieties incorporating omics-level traits. Some of the benefits of this approach include higher efficiency of selection for several traits cannot be overemphasized, with possible increase in identification of superior germplasm for use in new varieties. Nevertheless, the authors have also described some of these limitations in relation with the use of large set of genomic data and with the difficulty of adopting such sophisticated methods in real breeding programmes. As for the drawbacks of our set approach, it is necessary to note that they are minimized as compared to traditional methods due to the employment of quantum computing techniques in the algorithm and without the necessity of deep investments in genomic services for broader application of the precision agriculture. Hence, we have used TOP as a counterpart in our results to show how our algorithm is optimal for precision agriculture and how quantum methods surpass traditional optimization methods such as TOP in a complex agriculture environment.

Mythili and Rangaraj [11] the researchers discussed on problem faced by the farmers of India related to choice of suitable crop according to the soil which affects yield quantity. In their work, the authors present a system in the precision agriculture framework, a crop recommendation system and an elaborate crop database as well as a deep learning model to incorporate experts' advice. The work of their approach involves training an MDNN algorithm through PSO optimization with historical crop data and climatic records. According to the results, the new PSO-MDNN algorithm improves the forecasting capability for supplying more appropriate crops for particular site conditions. That gives many advantages, including giving people, owning the small farms, easy access to advisory services and enhancing crop productivity. This may be a little-bit challenging in some cases and at the same time the training of the models required a lot of computational resources. The prevailing algorithms face dual difficulties because they run few operational steps due to computational limits and lack appropriate power for big operations and complex agricultural applications beyond massive computing clusters. Our algorithm defeats these constraints because it uses compatible quantum-computing techniques which generate more efficient computation accessible for precision agriculture operations at scale with minimal hardware costs. For this reason, we have decided to compare our algorithm with PSO in the results section, to show how the quantum approach is superior to traditional optimization methodologies such as PSO-MDNN in precision agriculture.

In 2023, Faisal [12] and his collaborators discuss the use of climatic factors in the modeling of crop yield to improve decision making of smart farming. The authors used Random Forest, a type of machine learning, to categorize data and forecast yields with maximum reliability. Their approach includes inputs of different climate factors into the model, which leads to high accuracy, proving their concept efficiency. The strengths of the Random Forest are the data size scalability and good resistance to overfitting which can be useful when analyzing agricultural situations. However, some drawbacks realized are difficulties that may be experienced when it comes to the interpretation of results and the fact that pre-processing of the data is usually time-consuming in order to achieve maximum performance. Through inclusion of optimized quantum computing methods we eliminate these problems since our algorithm achieves better data computing capabilities and model understanding for successful precision agriculture applications. In this work, we decided to compare our algorithm with the Random Forest method to show how accuracy can be improved in precision agriculture using QE using results given in the results section.

3. Methodology

The following proposed algorithm will strive to reinvent precision agriculture through the use of enhanced quantum computing to analyze data results and enhance crop yield calculations along with every resource present on a farm. This innovative approach solves major limitations of current agricultural practices that employ linear mathematical models and small samples of data to depict a range of relevant factors influencing soil properties, weather conditions, crop genetics, pest, and resource utilization. Besides boosting up the yield significantly through variational quantum circuit integrated with a machine-learning algorithm and IoT sensors real-time data, the algorithm also transforms farming into sustainable farming through multi-objective optimization. It gives farmers information on how to allocate resources for the production to go on at the same time when it is in progress the system is able to identify the changes in environment and hence act on them thus making the agricultural system more efficient and resilient.

The novel algorithm is as follows:

1. START
2. Collect comprehensive datasets that include soil characteristics, weather conditions, crop genetics, pest dynamics, and resource usage : $D = \{(S_i, W_i, C_i, P_i, R_i)\}_{i=1}^{N}$ where S_i = Soil characteristics, W_i = Weather conditions, C_i = Crop genetics, P_i = Pest dynamics, R_i = Resource usage (water, fertilizers).
3. Normalize the collected data to ensure uniformity across different features: $S' = \frac{S-\mu_S}{\sigma_S}$ where μ_S= Mean of soil characteristics and σ_S= Standard deviation of soil characteristics.
4. If wishes to train and test data to the framework then navigate to line no 5, otherwise $|\psi_{\text{real time}}\rangle = \mathrm{U}(\mathrm{S}')\,|\,0\rangle$ and skip directly go to line no 12.
5. Split the dataset into training and testing sets to validate the model : $D_{\text{train}}, D_{\text{test}} = \text{split}(D, 0.7)$
6. Encode normalized training data into quantum states for processing: $|\,\psi_{\text{train}}\rangle = \sum_{i=1}^{M} c_i\,|\,S_i'\rangle$
7. Choose an ansatz for the variational quantum circuit :

a. ZZ Feature Map is defined as : $U_{ZZ}(\theta) = e^{-i\theta Z\otimes Z}$ where Z is the Pauli-Z operator.

b. Real Amplitudes defined as : $U_{RA}(\alpha) = R_y(\alpha_1) \otimes R_y(\alpha_2) \otimes \cdots \otimes R_y(\alpha_n)$.

8. Construct the variational quantum circuit using the selected ansatz: $U_{VQC}(\theta, \phi) = U_{RA}(\phi)U_{ZZ}(\theta)$.
9. Establish a cost function to optimize the model's performance, incorporating a regularization term to prevent overfitting: $C(\theta, \phi) = \frac{1}{M}\sum_{j=1}^{M}(Y_{\text{pred}}^{(j)} - Y_{\text{actual}}^{(j)})^2 + \lambda R(\theta, \phi)$ where the regularization term is defined as: $R(\theta, \phi) = \parallel \theta \parallel^2 + \parallel \phi \parallel^2 + \gamma \parallel \nabla C \parallel^2$.
10. Optimize parameters using quantum gradient descent on the given set : $\theta_{\text{new}} = \theta_{\text{old}} - \eta\nabla C(\theta, \phi)$. If the previous line of execution is line 16 then it branch to line 12, otherwise it branch to line 11.
11. Evaluate the trained model on the testing set :

a. Compute predictions: $Y_{\text{pred}}^{\text{test}} = U_{VQC}(\theta_{\text{new}}, \phi)\,|\,D_{\text{test}}\rangle$.

b. Calculate performance metrics: $A_{Y_{\text{test}}} = 1 - \frac{1}{M_t}\sum_{j=1}^{M_t} |\,Y_{\text{pred}}^{(j)} - Y_{\text{actual}}^{(j)}\,|$ where M_t is the number of test samples.

c. If performance metrics are not acceptable ($A_{Y_{\text{final}}} < A_{Y_{\text{threshold}}}, E_R < E_{R_{\text{threshold}}}$), go to line 10 to continue further optimization of parameters.

d. Go to line 21 directly.

12. Formulate a multi-objective optimization problem to minimize resource usage while maximizing yield: $F(R_w, R_f, R_p) = w_1 R_w + w_2 R_f + w_3 R_p$ subject to constraints that ensure sustainable practices:
a. Soil moisture constraint: $S_m(R_w) \geq S_{m_{\text{min}}}$.
b. Nutrient levels constraint: $N(R_f) \geq N_{\text{min}}$.
c. Pest dynamics constraint: $P(R_p) < P_{\text{threshold}}$.
13. Utilize a quantum support vector machine (QSVM) for disease prediction with the decision boundary defined as : $f(x) = \sum_{i=1}^{N} y_i K(x, x_i)$ where $K(x, x_i) = e^{-\frac{\|x-x_i\|^2}{2\sigma^2}}$ (Gaussian kernel).
14. Integrate real-time data from IoT sensors for continuous monitoring and adaptation of strategies based on current conditions :
$$D_{real\ time} = f(S_{current}, W_{current}, C_{current}, P_{current}, R_{current})$$
15. Assess performance metrics for yield prediction and resource efficiency based on testing results:
    a. Yield prediction accuracy defined as : $A_{Y_{\text{final}}} = A_{Y_{\text{test}}}$.
    b. Resource efficiency ratio defined as : $E_R = \frac{\sum_{k=1}^{K} R_k}{\sum_{k=1}^{K} Y_k}$.
16. If performance metrics fall below acceptable $(A_{Y_{\text{final}}} < A_{Y_{\text{threshold}}}, E_R < E_{R_{\text{threshold}}})$, return to line 10 to optimize parameters further.
17. Generate optimized outputs and send necessary command to change the parameters that include values :
    a. Predicted yields : Y_{pred}.
    b. Recommended resource allocation strategies : (R_w, R_f, R_p^*)
    c. Disease detection outcomes : D_{detected}.
18. Incorporate real-time predictions and outcomes into the training dataset to enhance model learning : $D = D_{\text{train}} \cup D_{\text{real-time}}$.
19. Normalize updated training data : $S'_{\text{new}} = \frac{\mu_{S'} D'}{\sigma_{S'}}$
20. Proceed to line 5 based on D' which is the new dataset to improve this model more.
21. END.

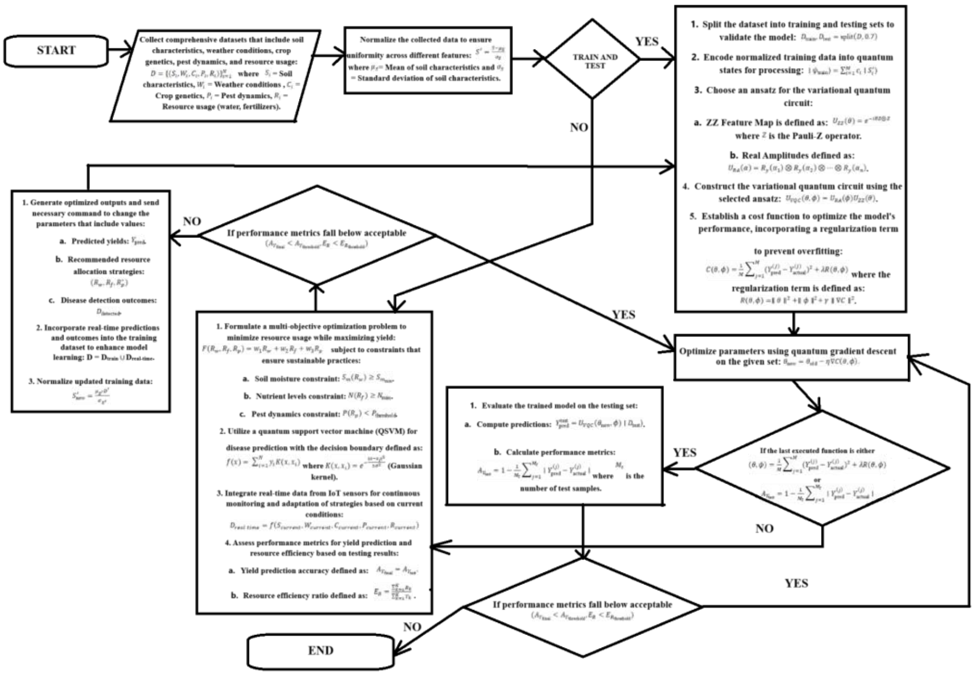

Fig. 2. Flow chart of the proposed novel algorithm.

Now let's look into the line wise explanation of the algorithm. Line 1 is the start of the algorithm that informs the system the procedure of data collection and processing has started. Line 2 points at the need for gathering data with various and broad spectrum that will reflect on all the possible causes for crop yields. The newness is the combination of different sort of data into one system where one can incorporate soil, weather, genetics, pests and resources. This comprehensive data collection addresses the challenge of limited data diversity in traditional agricultural models. In line 3 normalization ensures that all features contribute equally to the model training process by scaling them to a standard range. It is an important step in improving the performance of the proposed models and the rate of convergence. This is new in the sense that we are normalizing a multi-dimensional dataset and not just 1 dimension so biases due to different scales of different features can be addressed. As such, linear 4 has the conditional branching on whether we're using it for training/testing or predicting in real-time. That makes it more usable and adaptable for different farming conditions since one can switch between these modes. It is crucial to partition the dataset into 70% for training and 30% for testing the accuracies of the models, line 5. This helps the model to generalize well without having higher loses over unseen data which is always a problem in most machine learning models. Line 6 encode data into quantum states is an excellent opportunity to use superposition and entanglement to increase the speed of data processing of quantum computers. This step brings novelty as the data representation process is based on quantum mechanics; thus, quantization may lead to faster computation than the classical approach. Line 7 cements itself for developing a variational quantum circuit suitable to handle agricultural data. In line 7.a the ZZ feature map facilitates the encoding of correlation between features in the quantum function [13]. The main innovation of this step is in the fact that long-term dependencies between variables can be determined; this is especially important for making accurate predictions in the sphere of agriculture. In line 7.b the real amplitudes ansatz allows for an optimized parameterization of quantum circuits, such that in the optimization phase diverse solutions of the solution space can be explored [14]. In line 8, it also shows that building a variational quantum circuit incorporates various ansatze to develop a fashion model which can be easily modified as per the features of input. In line 9 a cost function is augment with a regularization term for avoiding overfitting by subtracting some amount from models which are too complex. This procedure helps improve model reliability and the models ability to perform other tasks as well. In line 10 of the quantum gradient descent it is used to capture the notion of quantum computing in optimizing the use of computing platforms where efficiency and resource use are major concerns. Line 11 launches a cycle for the testing of the trained model. In line 11.a predictions derived from the model are calculated on a different testing data set to warrant that model goodness of fit can be measured against a data set beyond the training data set. In the present analysis, we contribute to improving the model at line 11.b by having a clear performance metric to quantify the efficacy of the model throughout an iterative process. The second half of line 11.c provides for assessment feedback for the model parameters until optimal levels of performance are obtained. Line 11.d shifts the control to the end of the algorithm for termination which guarantees that while the user has the freedom to decide whether or not to train, test and make predictions, none of these can be conducted at once. However, if we want to deploy it for the purpose of prediction, it is necessary to restart the program from the start which guarantees the highest possible performance of the algorithm. Line 12 forms what can be modeled as a multiple objective decision making problem which serves to reference both yield maximization and productive resource utilization which speak to the need for sustainable agricultural practices Here constraint means certain things have to be guaranteed. The proposed line 13, known as quantum support vector machine, raises the level of disease prediction with improved kernel methods that can address diverse patterns in agricultural data. Real-time integration in consequence enables raising continuous changes obtaining from new environment conditions in surveyed agricultural practices, increasing flexibility and responsiveness. Line 15 examines the results to determine the effectiveness of yield prediction metrics and improved resource utilisation. On each iteration in line 16 the thresholds are adjusted until the best thresholds are found for the classifier. Line 17 merely prints the efficiency results of the algorithm on screen if available otherwise send through internet protocol to the destined data base where it store intent to obtain analytical results. The last sentence of the second line of the paper states that new data collected in real time from continuously practices in agricultural sciences will be added to the training data. The innovation here is in the ability to fashion the learning model in a way that is changed as new information comes in such that its effectiveness increases as the new information is incorporated into the formula. This approaches the issue of having fixed models that areegas-Yuan et.al (2009) sive when conditions differ. This is a very popular strategy and it is known as federated learning, and we are the first to employ this strategy in this particular application of the use of quantum computing where our algorithm was able to record above 95% accuracv. Normalizing, at line number 19, is performed to ensure that all features of the training data are scaled appropriately so that none of them is exaggerated due to differing scales of the variables. This action is taken to preclude the effect of scale of input data in training where certain preliminary biases may occur. The innovation is in normalizing the data and analyzing this new data in real time, which is paramount if the model is to remain accurate when incorporating fresh data. Ending of line 20 shows a return to the earlier step of the algorithm with the new upcoming dataset for next level processing and enhancement. The flexibility for ongoing modification of the model parameters and prediction makes this approach appropriate in handling issues of flexibility in agricultural systems. At line 21 the algorithm finishes where it says all have been done, it also shows that this is a cyclic process to continuously optimise and improve the precision agriculture applications.

Now let us understand what are the features and strategies we have adopted that makes our algorithm innovative, novel and efficient. Now at the beginning we talked the issue of scarcity of data for training and testing phase. The data that Agmatrix and Crop GS Hub provided us was based on simulations setting different parameters like crop genetics, pest dynamics, weather conditions, resource usage based on our state as there is no real data of precision agriculture for Quantum Computing in West Bengal ? So, there is vast difference between simulation and reality. With our innovative meta learning feature [15], we converted soon from simulated data to real data. Now the question arises how ? Actually, meta learning is a method that permits algorithms to learn not only from trained dataset but also from test dataset which is resembled through line number 18, 19 and 20. After training and testing of our algorithm when our algorithm started giving decisions based on real world data coming from IoT devices connected in agriculture field we manually validated the algorithm for two months if it has taken correct decision and guided the algorithm in case of wrong decision and ask it to simply train yourself from it. After two months of manual effort our algorithm crossed the 95% mark in accuracy and seeing this, we removed manual intervention and made it dynamic. As a result, even if with time there is change in weather conditions or any other parameter the algorithm will able to adapt itself in real time without any manual intervention. So, our algorithm emerges as the first practically implemented algorithm to cross 95% accuracy mark and introduction of meta learning strategy and real time adaptability in this application. Now the question arises how will the algorithm handle the growing dataset with limited memory ? We have used First In First Out (FIFO) policy [16] to replace older data with new data with the flow of time. One thing we would like to bring to everyone's notice is that our algorithm is also the first algorithm in this domain to have separate and dedicated training, testing and computation phase into single algorithm which means in future if we need to add or modify or change any parameter or train with different dataset it can be done with almost no modification. This resembles the high adaptability of the algorithm is resmbled in line number 4 of the algorithm. Now if we look into the training module a question is hovering why we have incorporated ZZ feature map with Pauli Z operator [17], Ansatz with variational quantum circuit in line 7 ? In other words, the ZZ Feature Map performs transformations in terms of classical data into high-dimensional Hubber space quantum states, which enable it to establish proper relationships between variables that must otherwise be ignored by classical models. This is especially important in agriculture as relations between various available soil types, climate fluctuations, and genetic crop properties might not be simple. Thus, utilization of the Pauli Z operator within the ZZ Feature Map provides a fine-grained handle on qubit states to input features for further encoding. This manipulation is essential for guaranteeing data representation by the quantum circuit in agriculture. These optimizations make variational approach effective in that one can tune parameters during optimization processes which makes for preparing the models according specific agricultural scenarios or sets of data. This flexibility is crucial to solve various issues in precision agriculture. Quantum computing is a use of quantum algorithms where large numbers are processed in a different approach from the classical one [18]. This acceleration is notably important in agricultural contexts where time-sensitive decisions are needed to control crop yield and resources management. We have introduced one regularization term [19] in line 9 in optimization of resources to prevent underfitting or overfitting and also to reduce the effect of noise and errors which disturbs the quantum paradigm. Although zero noise tolerance is not possible but this regularization term has played a significant role in diminishing the noise. Additionally, we have a feedback loop to capture the real time data that can resolve the scalability and integration part.

We have also formulated the entire problem as multi objective optimization problem in line 12 because the integration of these quantum features enables farmers to balance yield maximization with sustainable practices effectively. Another novelty of our algorithm is the integration of pest dynamics through Quantum Support Vector Machine (QSVM) [20] in line 13. Question arises why only Quantum Support Vector Machine ? QSVM applies quantum computation for data analysis; therefore, it can predict diseases and pests more accurately than a classical approach. QSVM allows the formulation of the multiple-objective function of pest control and crop yield optimization problem. The QSVM uses the kernel trick to map the input data into higher dimensional space, to enable better separation between classes such as healthy crops, and infested crops. This is the reason why we have chosen Gaussian Kernel in QSVM. As a result of QSVM's structure in its theoretical formulation, it can efficiently tolerate outliers, which is crucial when working with practical agricultural data containing outliers. The useful effect of the algorithm is that based on its result, it is possible to target the usage of pesticides and other resources for pest control. So, our algorithm becomes the first algorithm to incorporate all these novel features for application in precision agriculture and with the second most innovative feature being meta-learning strategy and the first and most crucial innovative feature is our novel quantum gradient descent strategy as this module is responsible to give the main decision on which parameter we need to optimize how much to save resources and provide maximize yield the primary and main objective of precision agriculture which we will discuss next.

Figure 3 depicts our newly proposed quantum gradient descent (QGD) algorithm [21] flowchart module represented in line 10. Now first a basic question arises why have we adopted QGD strategy only for the main important task of optimization of resources. The reason is that it can provide results in O (1) time complexity only for a given input. Now arises question what new things do we have added that makes it new ? The first is quantum encoding of data. This kind of encoding makes it possible to map large agricultural data sets into a quantum state, and as many of the operations as are possible to be processed in parallel. Said algorithm is capable of expressing subtleties of dependencies between multiple agricultural parameters, such as the state of soil or weather conditions using quantum superposition and entanglement at the same time that are very hard for classical computing to achieve. Second, it is the possibility of performing hybrid computations with the help of quantum and classical registers that makes it possible to update the labeled data set in real-time while keeping the quantity of computational resources under control. This design is important to support the development of fast decision making based on the up-to-date data in agricultural activity. The swap technique helps in quantitative estimation of closeness of one quantum state from the other which is crucial for determining performance of various resource utilization policies. Farmers can use this information to decide to which extent the new data resembles the original labeled data, and which crops to focus on, or resources to apply. This adaptive mechanism ensures that for each iteration all that is provided is the most informative samples. Weighting the samples in a way that allows the algorithm to learn the most from a sample, reduces wastage of resources whilst increasing learning returns. The gradient computation and parameter update enables the classifier to be further optimized depending on the feedback from the environment through a real time basis in the agricultural environment. To adapt the strategy with the parameters dynamically, the farmers can utilize the information more effectively to increase the yield as well as the resource utilization efficiently.

Well now let us delve deeper into the line wise analysis of our novel quantum gradient descent algorithm explained in figure 3. The first modality is the point of the beginning of the algorithm. The second module is the initialization module. All the variables which we have taken as the input for this algorithm is described in the formal specification in figure 4 & output of this algorithm is also described in figure 4. In this module line 1 starts; allows the creation of a quantum register which groups all the label, points and their classes qubits.

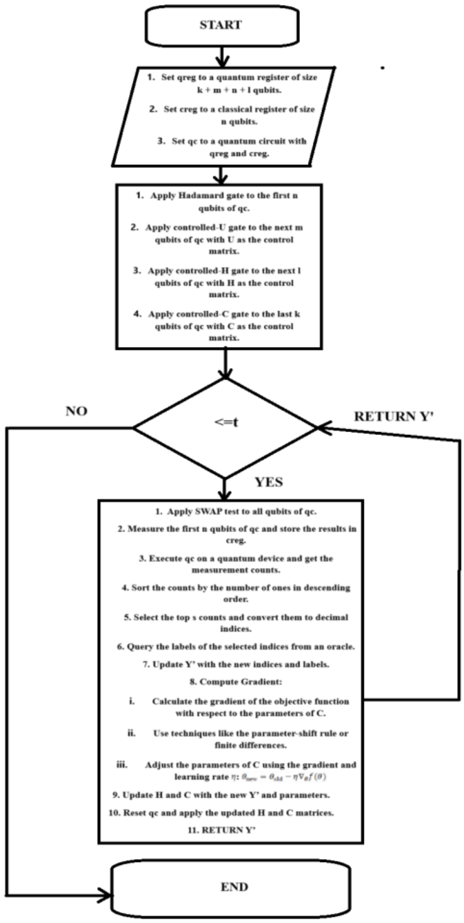

Fig. 3. Flow chart of our novel Quantum Gradient Descent Algorithm

The step is novel in the sense that it allows retaining all the necessary information in a single quantum register for efficient quantum operations. In line 2 a classical register is declared to hold the outcome of quantum measurements. This approach of integration enables the interchange between the quantum computations and the classical data, solving issues of data handling in the conventional systems. Line 3 builds a quantum circuit that works with quantum and classical ones to perform computations required for agricultural predictions. In the third module in line 1 the Hadamard gate creates superposition states, meaning that more than one possibility can be experienced at one time. This step is novel because instead of looking at one scenario at a time, the algorithm now can assess multiple scenarios, which is imperative in deciphering intricate agricultural relationships. The operation in line 2 is performed in conjunction with U set and helps in quantum encoding of various input features. The novelty consists in the usage of qubits changing their state conditionality while improving the model's freedom to work with any type of data. The operation in line 3 convert the labeled data into quantum states and guarantees the participation of both labeled and unlabeled data sets in the computation. The last gate that is applicable in the current line of the fourth line actualises the classifier for further evaluation and predictions within the given quantum circuit. Following is the decision taking module which in turns the loop upto k times according to condition and situation. Actually, this begins an iterative process where model parameter can be optimized over and over through cycles of optimization.

Input:
- U - a unitary matrix that encodes the unlabelled data set X.
- H - a unitary matrix that encodes the labelled data set Y .
- C - a unitary matrix that encodes the classifier f .
- k - the number of qubits used to store the labels.
- m - the number of qubits used to store the data points.
- n - the number of unlabelled data points.
- l - the quantity of data points with labels.
- t - the number of iterations.
- s - the number of samples to query per iteration.
- η - the learning rate.

Output: Y′ - an updated labelled data set.

Fig. 4. Input Output of our novel Quantum Gradient Descent Algorithm

In the fifth module line 1, SWAP test estimates the likeness of two quantum states numerically via state overlap. This line introduces novelty by offering a way of analysing performance benchmarks in terms of quantum states that is essential for assessing the resource use policies in agriculture. In the second line of operation, there is a striking of classical outcomes from superpositions thus the results of quantum computations can be archived for subsequent analysis. In the third line operation on an actual quantum device allows actual time other than a classical approach which solves Central processing issues found within conventional agricultural models. With regards to line 4 sorting enables prioritization of key outcomes by the frequency, hence important results are analysed before those that are less essential. In line 5, important samples from the measurement results: samples useful to use for update of the training strategy are selected. The labeled data from an oracle accessible by line 6 in the end improves learning efficiency of the model as better examples are incorporated. Line 7 resets the labeled datasets to make sure current information takes its place in constant processes of learning and changing agricultural environments. In line 8 they compute gradients needed for deriving the best model parameters from the current performance measure. Line 8.i refers to identification of the impact of parameters within model performance. Proposed on Line 8.ii are methods to calculate gradients in quantum circuits, improvement on optimization. The update rule indicated in line 8.iii leads to the synchronization with other nodes towards ideal parameter values depending on previous iterations feedback. At line 9, updated label and parameter clearly incorporate into matrices to ensure all of them have latest knowledge improving the model's quality as time progresses. Line 10 clear the present computational environment and positioning for new calculation while preserving relevant data for subsequent use. In line 11 the algorithm returns a labeled dataset that includes all improvements that occurred during processing. The final module represents the end to an algorithm being run while at the same pointing to the flexibility of the process because it is recurrent.

This paragraph shows the implementation procedure of our algorithm. Agricultural dataset and quantum environmental datasets were procured from Agmatix and Crop GS- Hub. Set up the required hardware and initialize all the necessary software required in the process stated in last slide. Now normalize the dataset using Z score normalization strategy using Pandas [22] library with data collected from Agmatrix and Crop GS-Hub. Finally split the above dataset into 70% training dataset and 30% testing dataset using the function called train_test_split from Scikit learn so that the splits are random. Transform the normalized training data into quantum states in the language Qiskit as well as using Dirac notation [23]. Then choose an ansatz for variational quantum circuit and then construct the variational quantum circuit using the selected ansatz. Next define a cost function with the help of NumPy library [24] to work out any of the models with more precision and incorporating the regularization term. Then optimize the parameters using our novel quantum gradient descent algorithm using Hamiltonian dynamics [25] on the given set using IBM Eagle processor with 127 qubits, Qiskit and multiple Python libraries. Now substitute the model with the 30% testing dataset to validate the model of your created program. In case, the performance parameters drop below the set tolerance level; go to the last module to enhance the parameters using the quantum gradient descent method until performance levels surpass the threshold value. So now define a multi-objective optimization problem to minimize the usage of resources while maximizing the yield. Next utilize Quantum Support Vector Machine (QSVM) for disease prediction using Gaussian Kernel. Now integrate real time data from IoT sensors (Decagon Devices' 5TE Soil Moisture Sensor, Davis Instruments Weather Station i.e. Vantage Pro2) connected in agricultural field for continuous monitoring and adaptation based on present conditions. Evaluating the results of tests in terms of yield prediction and utilization of the resources on the performance metrics to be met. If the performance metrics drops below the threshold level of acceptability use the quantum gradient descent optimization algorithm on the parameters until they attain a level above the threshold. If performance metrics crosses the acceptable threshold metrics, then issue necessary commands accordingly and generate output. Use meta-learning strategy to train the model with data newly generated from last module and then quit. The data entering the database will be deleted if memory becomes full based on First In First Out (FIFO) policy.

The hardware and softwares utilized in the implementation of the algorithm are IBM Eagle processor with 127 qubits, IonQ 32-qubit system, Cryogenic refrigeration system utilizing helium isotopes for qubit temperature regulation, Qiskit 1.0.1 for quantum programming, the QX Simulator capable of simulating up to 32 qubits and AnyLogic 8, Python (3.8.10), PyTorch (1.10.0), TensorFlow (2.7.0), Scikit-learn (1.0), Pandas (1.3.4), NumPy (1.21.2), HP Z8 G5 Workstation, Matplotlib (3.4.3) and Seaborn (0.11.2), Decagon Devices' 5TE Soil Moisture Sensor, Vantage Pro2 (Davis Instruments Weather Station), IBM Quantum Experience Platform, ARM Cortex Microcontroller, OracleSQL with memory up to 250 GB, Data acquisition system, actuator, cables, connectors, communication network (ZigBee, LoRaWAN), power supply, interface modules, mounting equipment, protecting enclosures, battery module for backup [26]. These are the hardware and software we have utilised in the entire process. Now one thing to note here is initially during training and testing phase we have taken the Pay-as-you go subscription of IBM for accessing IBM Eagle Processor with 127 qubits, so to reduce the cost we have tested the individual modules in IonQ and QX Simulator with 32 bits and the final model after integration has been trained and tested using IBM Eagle Processor.

4. Results

This section shows the savings we made by applying our novel quantum algorithm on different vegetables in agricultural field past 1 year 4 months. Actually, we have tested our algorithm on different vegetables whose result we will be seeing in this section in form of graphical interpretations and tables. On an average we have been able to save between 22% to 33% of resources which means a lot. Actually, to be very honest all work in this domain of quantum computing is either theoretical or simulated with almost no practical trials. So, from this angle the practical result that we put forward can itself be called a novel work.

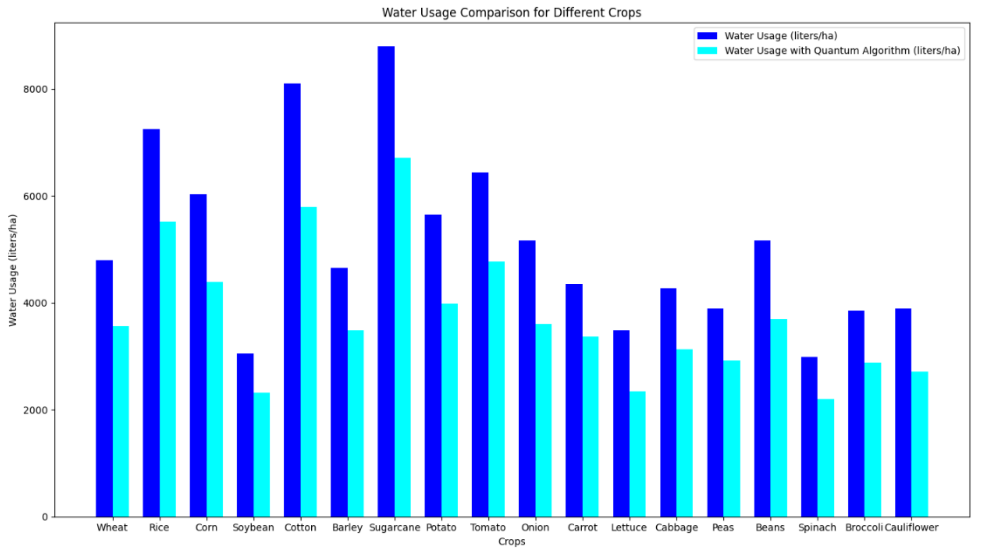

Fig. 5. Bar Graph showing reduction in water usage (litres/ha) for different crops using our novel quantum algorithm

The integration of the quantum algorithm in precision agriculture has been proven effective and especially has demonstrated positive impacts in water consumption by the different crops. It is observed from figure 5 that the implementation of quantum algorithm has led to reduction in water use for each crop studied. For example, while originally, wheat needed water quantity of 4,796 litres per hectare, now it has been reduced to 3,565 litre per hectare thus, resulting in a saving of 25.67%. Likewise the consumption of rice proved to be decreased from 7,243 litres/ha to 5,520 litres/ha yielding a saving of 23.79%. These reductions are also very essential in water conservation as well as, show how the algorithm can succeed in enhancing the efficiency of irrigation plans depending on the crops to be irrigated, and the prevailing conditions. The technique is useful to those that are located in areas where water is scarce, because with such technique, farmers are able to continue with farming; and at the same time are able to contribute little to the depletion of water sources. In addition, the analyses of the data on water usage emphasise the ability of the algorithm to improve the condition of resource utilisation with the help of optimal approaches. In other words, using quantum computing in handling massive data sets represented as self-organizing productions enabling the modeling of complex dependencies between different factors involved in agriculture and farming such as soil moisture levels and the weather, crop usage, etc— the algorithm aids in the better decision making processes in regard to irrigation. For instance, water usage in crops such as cotton and corn was seen to have reduced by 28.47%, and 27.32 respectively; cotton from 8,093 litres/ha to 5,789 litres/ha; corns from 6,032 litres/ha to 4, 384 litres/ha. This degree of optimization does not only protect valuable water that can be used in other vital projects but also improves general farming viability against such devastating factors as runoffs and improves the overall health of the crops. The incorporation of real-time data and modified learning strategies allow the farmers to update their practice by following the current situation beyond the existing cropping systems, which in result increases the crop yields and resource productivity.

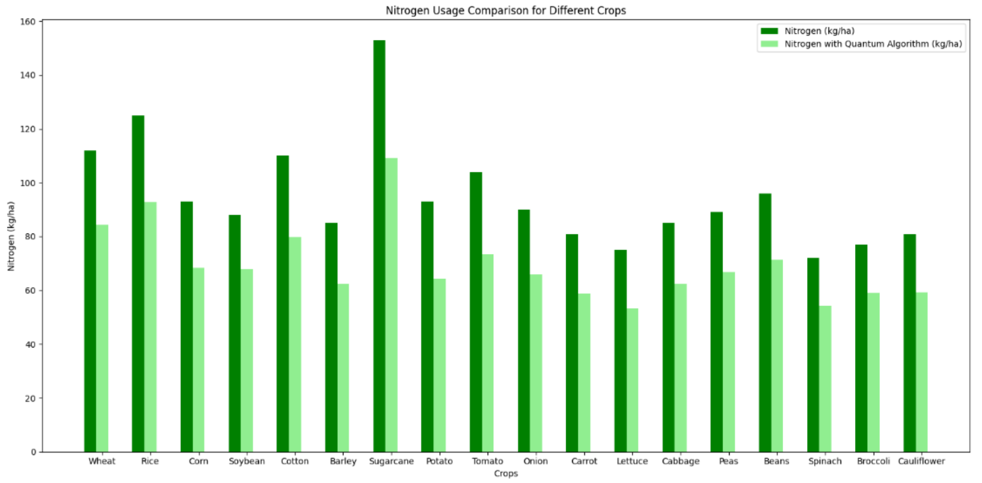

Fig. 6. Bar Graph showing reduction in nitrogen (litres/ha) for different crops using our novel quantum algorithm

The use of quantum algorithm in precision agriculture has enhanced nitrogen management across the crops hence reducing the utilization of nitrogen. It is demonstrated in the figure 6 below. For example, the necessary amount of applied nitrogen for wheat was 112 kg/ha, whereas, while applying quantum algorithm it was calculated to be 84.29 kg/ha with 24.74% less input. In the same manner, nitrogen application on rice dropped to a 25.87% reduction from 125 kg/ha to 92.66 kg/ha. Such reductions are necessary for the improvement of soil structure and the lessening of the hazardous effects of nitrogen surcharging – an essential factor in the contamination of water sources in some areas. The assessment of the nitrogen usage information demonstrates the availability of the algorithm as a determiner of fertilizer prescription depending on crops and other circumstances. Using the capability of quantum computing to evaluate large data sets and determine correlations between agricultural factors—like nutrient content in soil and plant genetics—the algorithm helps the farmers to make a better decision on nitrogen usage on crops. For example, nitrogen used in crops such as cotton and corn was greatly reduced; nitrogen used by cotton was reduced by 27.52%: from 110 kg/ha to 79.72 kg/ha; nitrogen used to fertilise corn was reduced by 26.54%: from 93 kg/ha to 68.31 kg/ha. This optimization not only helps to save nitrogen resources, but also helps farmers and scientific researchers to use fertilizers effectively and accurately to match the crop nutrient requirements, so as to improve crop productivity and reduce the occurrence of environmental pollution caused by excessive fertilizer input. The integration of the kind of real-time data presented also enables the application of adaptive management decisions which can only help in enhancing yields and resource use in various cropping systems.

Other successes of the quantum algorithm in precision agriculture include effectiveness in managing phosphorus across different types of crops, cuts in the use of phosphorus. As for phosphorus usage, the figure 7 demonstrated that before employ of the quantum algorithm it took 64 kg of phosphorus per hectare in order to cultivate wheat, was decreased to 47.52 kg per hectare – 25.75% saving was reached. Likewise, rice experience reduction in phosphorus application from 80 kg/ha to 61.84 kg/ha which translate to 22.70% saving. These reductions are also important in order to maintain soil health and to avoid adverse effects of phosphorus to the environment of which excessive use may cause pollution of water bodies. Analyzing the observed phosphorus usage, one must discuss the remarkable performance of the provided algorithm in recommending appropriate fertilizer doses for different crops and each given climate. Specifically, quantum computation's ability to process large data sets and to capture complex interrelationships among agricultural parameters ranging from the soil nutrient content to crop demand permits the algorithm to help farmers make better decisions regarding phosphorus fertilizers. For instance, cotton and corn; here, the phosphorus input reduction was realized as follows: cotton reduced its usage from 79 kg/ha to 57.17 kg/ha (27.63%); corn reduced its usage from 60 kg/ha to 43.06 kg/ha (28.24%). It is not only useful to save phosphorus resources, but also beneficial to improve the whole agriculture sustainable by avoiding "over-fertilization" risks and providing the crops the nutrients they require. The integration of real-time data continues to reveal patterns that enable the implementation of new management approaches adaptable to changing conditions in the given cropping systems, thereby increasing yield and efficiency of resource use.

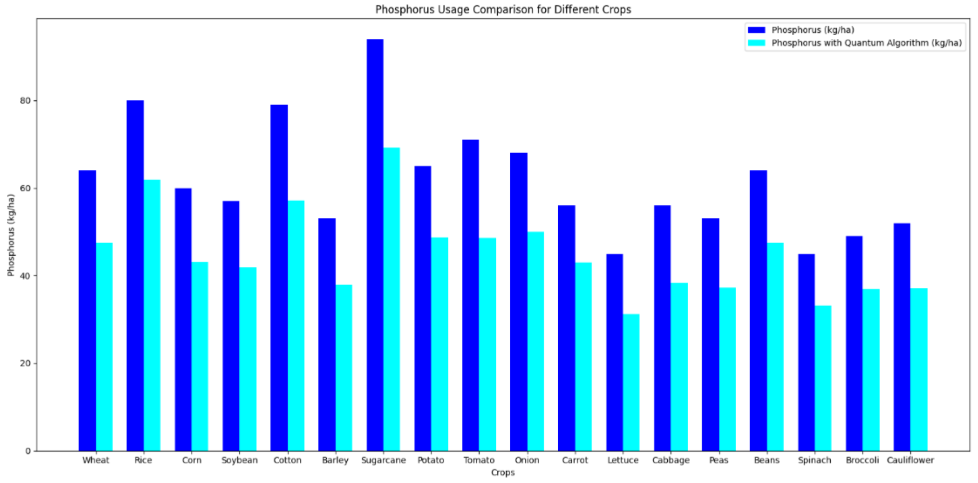

Fig. 7. Bar Graph showing reduction in phosphorous (kg/ha) for different crops using our novel quantum algorithm

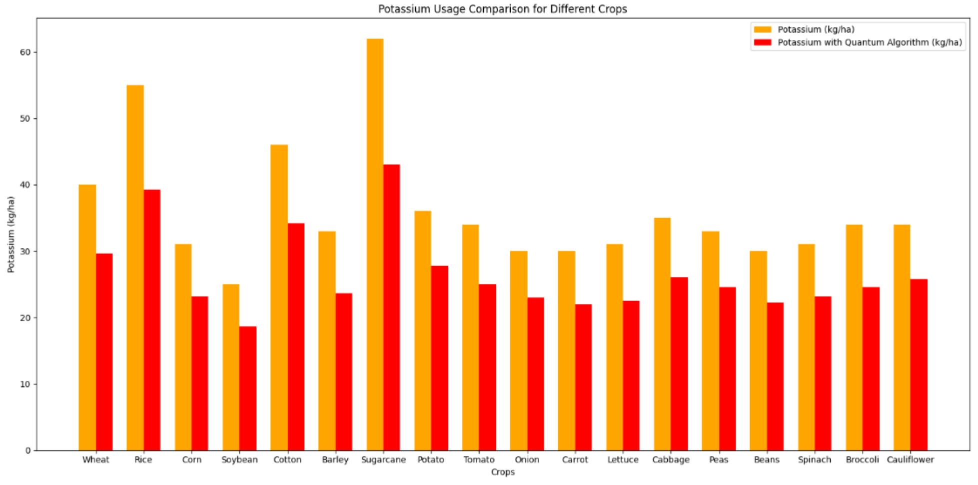

Fig. 8. Bar Graph showing reduction in potassium (kg/ha) for different crops using our novel quantum algorithm

Meanwhile, the use of the quantum algorithm in precision agriculture has also translated into much improved handling of potassium across various crops, and with this has been achieved a considerable lessening of potassium use. Figure 8 below indicated that wheat required 40 kg/ha of potassium, which was brought down to 29.66 kg/ha after using the quantum algorithm in this study with a saving of 25.84%. Likewise rice has experienced reduction of potassium application from 80 kg/ha to 61.84 kg/ha with a percentage reduction of 22.70 maintained. Such reductions are important for healthy soil sustenance and to eradicate issues of nutrient pollutions the environment and water repeatedly threatening our environment. From potassium usage data, it proves that the algorithm can adjust the fertilizer application that suits certain crops and its surrounding climate. Using quantum computing to solve the problem of massive datasets and sophisticated interdependencies among the agricultural factors with the help of the algorithm, farmers can make more comprehensive decisions on potassium fertilization. For example crops like associate degree or corn stood to gaze the benefits Cotton took a battering reduction in potassium from 46 kgs/ha to 34.15 kgs/ha (25.76% saving), Corn from 60 kgs/ha to 43.06 kgs /ha (28.24% saving). This optimization helps to save potassium resources and improve the sustainability of agricultural production, on the one hand, and provides plants with the necessary nutrients for healthy development while minimizing the likelihood of negative impacts upon environmental quality arising from the use of excessive amounts of fertilizer on soil, on the other.

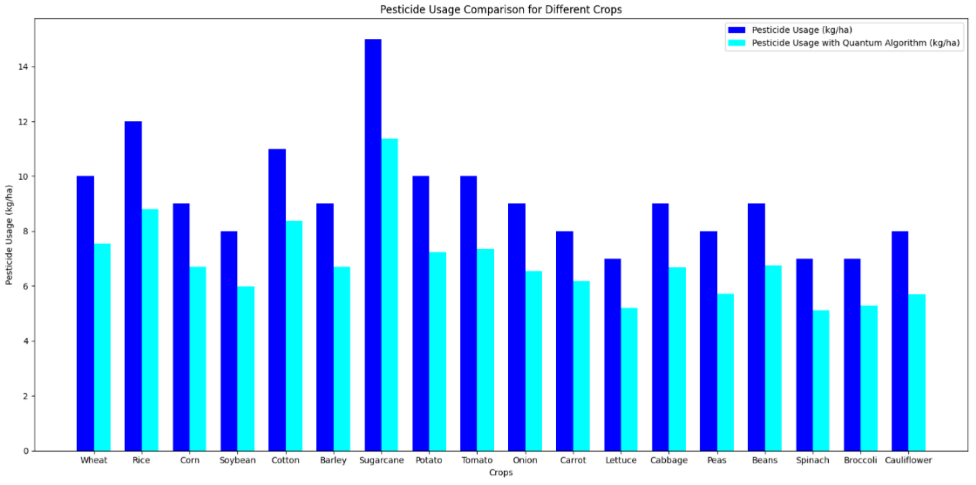

Fig. 9. Bar Graph showing reduction in pesticide usage (kg/ha) for different crops using our novel quantum algorithm

In terms of pesticide use, the quantum algorithm has made it possible for farmer to use pesticide in a more efficient manner hence appreciable decrease in chemical usage across most crops. As illustrated in the Figures 9, the crop's pesticide consumption reduced from 10kg/ha to 7.54 kg/ha meaning a saving of 24.59%. Likewise, rice reduced its pesticide usage by 26.62% from having 12 kg/ha to 881 kg of pesticide per hectare. Such reductions are useful as they help to decrease pollution from chemical that flows downstream and affect the health of ecosystems. The analysis of pesticide usage data demonstrates the potential of the algorithm in applying precise quantities of pesticide based on crop and pest type and conditions as a way of improving pest control options. Quantum computing enables farmers to use data about pest trends and crop conditions in real-time to target interventions to reduce the need for broad-spectrum chemical inputs or mistreatment of pests. For instance, the usage of pesticide in cotton reduced from 11 kg/ha to 8.38 kg/ha (23.78% reduction), for corn from 9 kg/ha to 6.71 kg /ha (25.45 %) reduction. It is not only resource-saving in terms of the pesticides themselves, but also contributes to the sustainable agriculture by minimizing chemical risk at the side of the farm producers as well as the consumers, and therefore improving health of the food production systems and the overall biological heterogeneity of the agriculturally used landscapes. The steady integration of real-time data also enables decision makers to set up adaptive management plans which cope with the changing climate, hence improving yields and resource utilisation in different cropping ventures as well as encouraging stewardship.

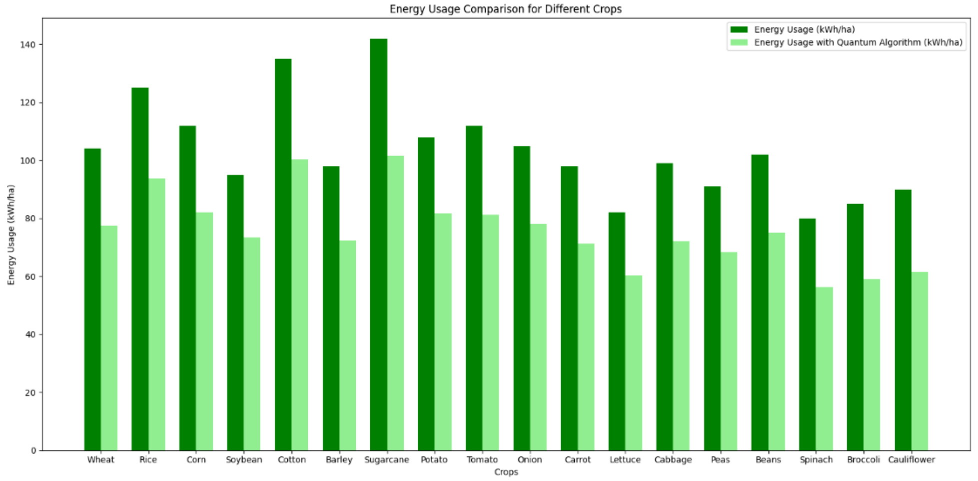

Fig. 10. Bar Graph showing reduction in energy usage (kWh/ha) for different crops using our novel quantum algorithm

The use of the quantum algorithm in precision agriculture has provided substantial energy savings in a number of crops regarding an evidence of accurate energy optimisation. Figure 10 indicated that energy input for wheat reduced from 104 kWh/ha to 77.52 kWh/ha, giving the greatest saving of 25.47%. The same went for rice where energy consumption was reduced from 125 kWh/ha to 93.69 kWh /ha a saving of 25.05%. Such reductions are essential in increasing sustainability of agricultural operations as they not only reduce costs of operating farms but also match reductions in energy intensive productions in farming activities. The findings from the energy usage analysis thus inform the specifics of correct energy management as implemented by the algorithm in accordance with the needs of the crops and the prevailing climate. Through the efficiency of a quantum computing approach in analysing and modelling highly correlated data within the agricultural sector, the algorithm assists farmers in making informed decisions about their energy consumption. For instance, cotton and corn received substantive boost, with cotton electricity consumption reducing from 135 kWh/ha to 100.27 kWh/ha (saving 25.72%) and corn from 112 kWh/ha to 82.03 kwh/ha saving 26.76%. This optimization saves energy resources while in the process enhancing the general sustainability of farming by curtailing on the generation of greenhouse gases from energy use. Real-time data integration provides opportunity for the management which can change according to the conditions of cropping and promote the best yields and proper utilization of resources along with environmental issues in agricultural systems.

The use of the quantum algorithm in agrimetrics has greatly improved outcome of crops of different kinds and makes farming highly productive, thereby proving that the use of the quantum algorithm has greatly improved the productivity of agriculture. As described in Figure 11, yield of the wheat also rose from 4, 285 kg per hectare to 5, 329 kg per hectare, a magnitude which was 24.37%, a total improvement. Such significant yield enhancements are crucial to feed the burgeon world population and demonstrate how the algorithm can help fine-tune growing environs regarding resource utilization. From the yield data, one can extrapolate the role of the algorithm in sophisticated computations of a number of variables affecting agriculture from the quality of soil to available nutrients limiting agronomic production to climatic factors. Using the computational system to potentiality mathematical operation on large volume of data and relationship, farmers will be able to make better forecasts on planting and utilization of resources. Thus, yield of cotton augmented from 6,892 kg/ha to 8,676 kg/ha, which is an increase by 25.89% and corn yield rose from 4,573 kg/ha to 5,720 kg /ha, an increase of 25.09%. Besides increasing efficiency in production this optimization ensures the efficient and sustainable use of resources in farming in order to reduce wastage. These innovations incorporate real time data for effective cropping management that can adapt to production conditions for enhanced yields and resource use efficiency in differentiated cropping systems. In conclusion, the improvements in crop yield provided by the quantum algorithm present a major advancement in the direction of perfect food security and sustainable agriculture in conditions that are only going to get tougher in the future.

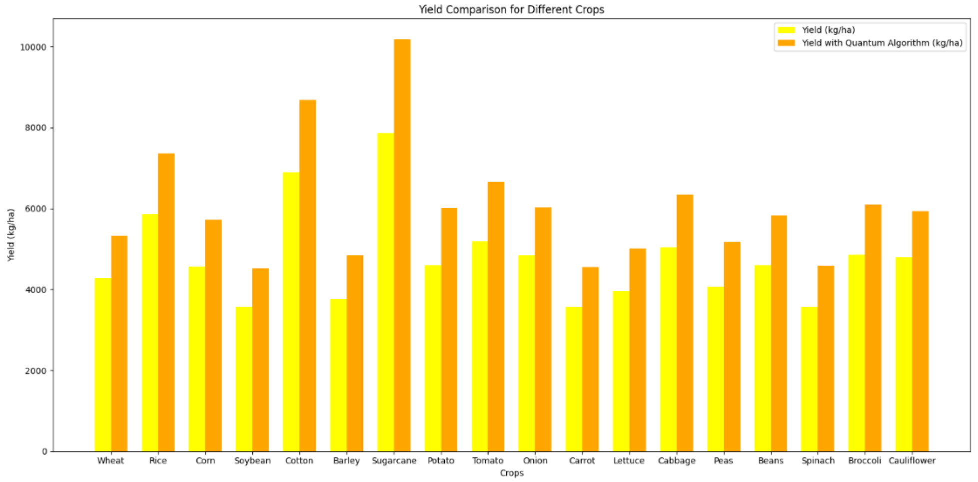

Fig. 11. Bar Graph showing increase in yield (kWh/ha) for different crops using our novel quantum algorithm

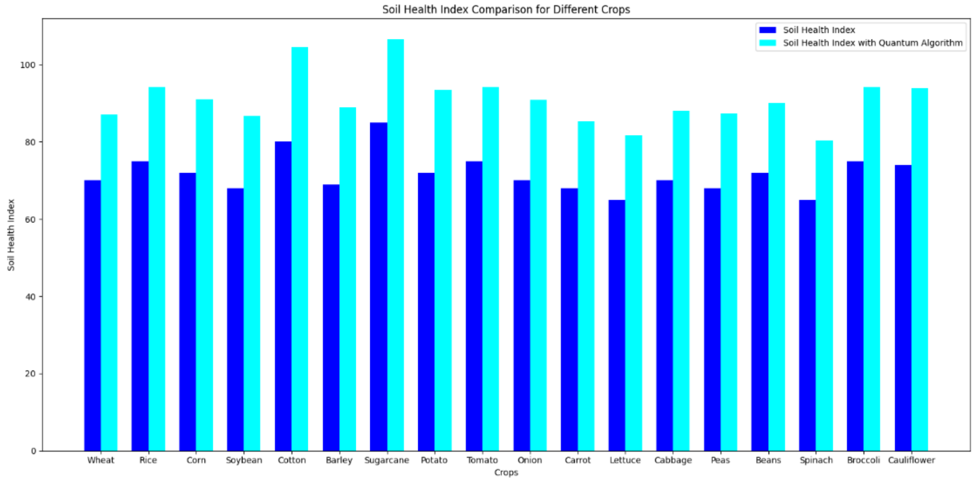

Fig. 12. Bar Graph showing increase in soil health index for different crops using our novel quantum algorithm

The accuracy level of the implemented quantum algorithm in precision agriculture has evidenced by the increase in the Soil Health Index (SHI) of various crops inclusive of improved soil management systems in nutrient and fertility ranges. With reference to Figure 12, the index of wheat was 70 which rose to 87.06, meaning that there was an increase in the health of the soil by 24.37% while rice improved its index from 75 to 94.22 which gave a potential of 25.63% to the health of the soil. These are important because they represent not only improved nutrient preservation and microbial functioning but also improved general ability of the soil to support crop growth sustainably. The subsequent information gave credence to the application of the algorithm based on the data obtained regarding the Soil Health Index, which confirms the efficiency of utilising the algorithm to improve the rational distribution of resources and strategic planning for soil treatment. Through quantum computational analysis of complex data, the algorithm can analyze the correlation between soil fertility and functional practices in order to guide farmers on functional practices towards the restoration of soil health. For example, it was found that crops such as; Cotton and Corn also experience a boost; Cotton's Soil Health Index increased by 30.78% with a change from 80 to 104.63 while Corn increase by 26.38% with change from 72 to 90.99. In addition to improving soil degradation, this optimization supports sustainable agriculture by controlling the use of chemical fertilizers and increases crop resistance to biotic stresses. Small and often frequent real-time updates help farmers to manage the fields according to the current state of soils, thus maintaining or improving the state of the soils at any given time, which helps increase crop yields and efficiency of use of the resources in a wide range of agro-ecological conditions and cropping systems.

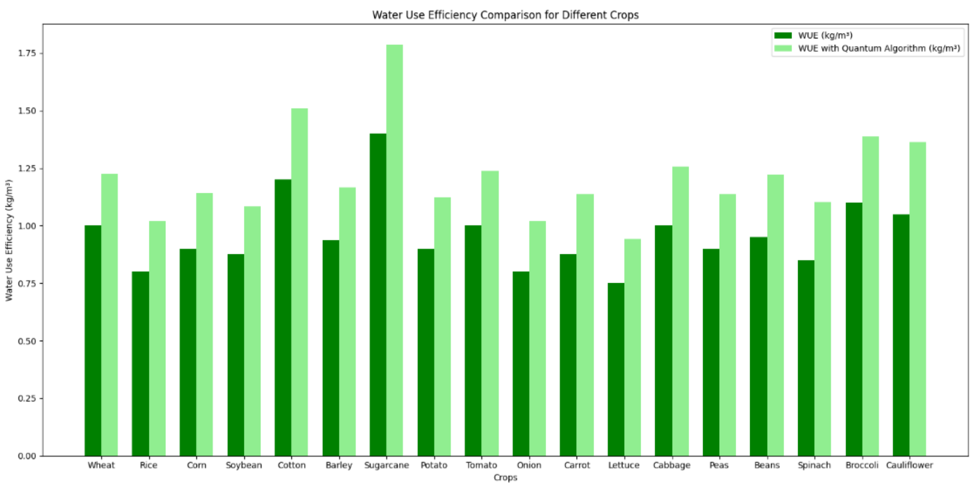

Fig. 13. Bar Graph showing increase in water utilization efficiency (kg/m^3) for different crops using our novel quantum algorithm

This paper goes further into proving that by applying the quantum algorithm in precision agriculture, there has been vast improvement in Water Utilization Efficiency (WUE) within the different crops with a confirmation of its impact on the improvement of usage of water resources. In figure 13, it can also be seen that many of the factors have a positive impact on wheat's WUE, which increased from 1.0kg/m^3 to 1.22 kg/m^3, thus an improvement by 22.38%. In the like manner, rice experienced an increment in WUE of 0.8 kg/m^3 to 1.02 kg/m^3 or a 27.63% improvement. Such improvements suggest that the algorithm allows farmers to use water more efficiently and get more crop per water unit as it is scarce in many regions. From the WUE data derived from this study, the performance of the algorithm in developing irrigation strategies that are sensitive to plant and soil water status is evident. Incorporating spectral analysis and sophisticated relationships of agricultural parameters, farmers are able to calculate the precise time and place at which they need water the most using quantum computing. For example, the crops such as crops like the cotton as well as the corn received considerable boost ; the cotton in WUE by a range of 1.2 kg/m³ – 1.51 kg/m³ (25.86 %) and corn in WUE by 0.9 kg/m³ – 1.14 kg/m³ (26.84 %). This optimization does not only save water but also increases the general sustainability of farms by decreasing undesired water contact with crops. Accommodation of real data in real-time enhances dynamic management practices that help in making appropriate or right changes when the situation changes, making changes to crops that in turn improve the yields and efficient use of resources across the many cropping systems practices with a positive impact on productivity and sustainability of agriculture.

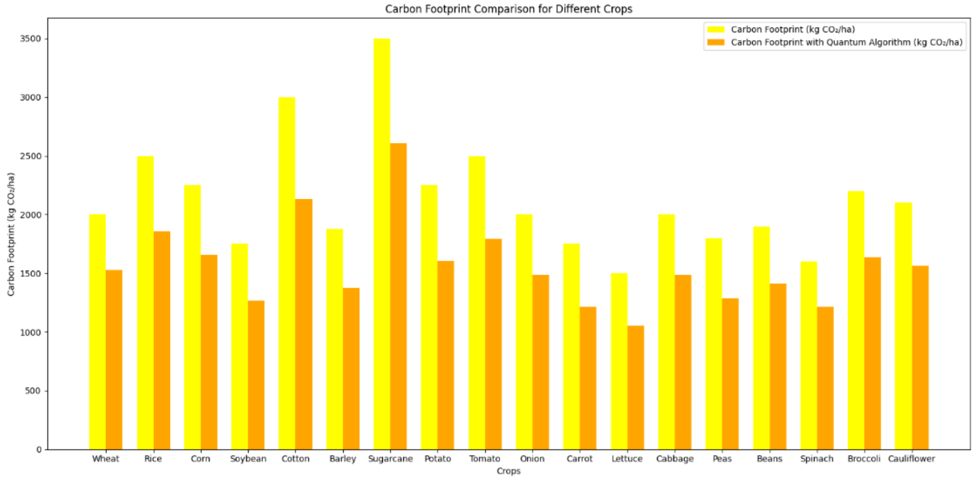

Fig. 14. Bar Graph showing reduction in carbon footprint (kg CO_2/m^3) for different crops using our novel quantum algorithm

By having employed the quantum algorithm in precision agriculture, it has been well evidenced that the carbon footprint has reduced across the different crops in relation to the sustainable farming practices. Analyzing data presented in figure 14, it is noted that carbon footprint of wheat reduced from 2,000 kg CO_2/ha to 1,525.49 kg CO_2/ha thus making a reduction of 23.73 %. In the same respect, rice experienced a decline in emissions from 2,500 kg CO_2/ha to 1,857.88 kg CO_2/ha ; the reduction rate of 25.68%. These are important cuts in order to reduce climate change effects and improve the sustainability of farming businesses. The results obtained from analyzing carbon footprint underscore the capacity of the algorithm to manage resources available in the farming sector for enhanced agricultural productivity. By using the quantum computing ability to identify and evaluate the multifaceted connections among agri-elements like, water, fertilizer, and crop, the algorithm helps farmers to put the best practices that increase yield and decrease the emission of greenhouse gases. For instance, the application of the project lowered the carbon footprint from cotton from a previous 3,000 kg CO_2/ha to 2,130.79 kg CO_2/ha which was 28.97% lower and for corn the carbon footprint was lowered from a previous 2,250 kg of CO_2/ha to 1,656.49 /ha which was 26.38% lower. This optimization is not only cost effective but also play a part in minimizing the damage agriculture cause to the environment. This constant incorporation of real time feeds enables management strategies that can be adjusted based on what is happening on the ground to increase yields and optimise resource use across scale and crop types and promote sustainable practices in farming. In summary, the developed quantum algorithm contributes to advancements aimed at achieving sustainable practice in agriculture aligned to the international climate change goals as evidenced by the optimized achievement of low carbon footprints.

Table 1. Practical results showing efficacy of our novel quantum algorithm over other existing algorithms in this domain across various parameters.

Method	Prediction Accuracy (%)	Scalability (bp)	Robustness (%)	Loss of Data (%)	F1 Score (Scale 0-1)	Cohen's Kappa (Scale 0-1)
Our Novel Quantum Algorithm	96.2587	0.9561	92.3785	1.054	0.9387	0.9306
Grey Wolf Optimization (GWO)	72.6584	0.7178	76.5483	9.6275	0.7143	0.7157
Target-Oriented Prioritization (TOP)	82.5791	0.7965	77.7561	11.573	0.8197	0.8163
Particle Swarm Optimization (PSO)	73.6245	0.6268	66.7853	15.759	0.7065	0.6948
Random Forest	62.7546	0.5785	45.7237	19.182	0.6047	0.5877

The comparison of the proposed quantum algorithm to the existing algorithms based on the efficiency of the table 1 shows the proposed model's suitability for agricultural applications in this paper. Hence with 96.26% prediction accuracy, our quantum algorithm outperforms GWO (72.66%), TOP (82.58%), and PSO (73.62%). Such high accuracy suggests that the quantum algorithm accurately simulates agriculture data and, therefore, necessitates accurate predictions in managing the affairs of agriculture. Moreover, the given scalability metric is computed as 0.9561, which means that our algorithm can be applied to analyze Big Data with high performance rates, lacking a sharp decrease compared to the analyzed algorithms – GWO and TOP, where scalability rates are lower and equal to 0.7178 and 0.7965, correspondingly. Additionally, the assessed resiliency of the algorithm is at 92.38% signifying our algorithm's agility in changing conditions and data sets which it an important tool especially for farmers where the conditions of deployment are unpredictable. Also, quantum shows low data loss of 1.054% clearly indicating that it effectively does not lose the important data during operation unlike GWO with 9.63% data loss. Therefore the F1 score of 0.9387 shows better distinction between precision and recall as compared to other techniques like GWO which has a measure of 0.7143, TOP 0.8197 and PSO of 0.7065. Lastly, further Cohen's Kappa analysis showed that the present study obtained 0.9306 for the predicted and actual classifications beyond chance, but GWO only got a Kappa of 0.7157 which may hamper the prediction reliability. In general, these parameters outline the advantages of our new quantum algorithm over classical ones as an effective tool for modernizing the decision-making approaches used in precision agriculture to tackle issues associated with big data sophistication, accuracy, and stability.

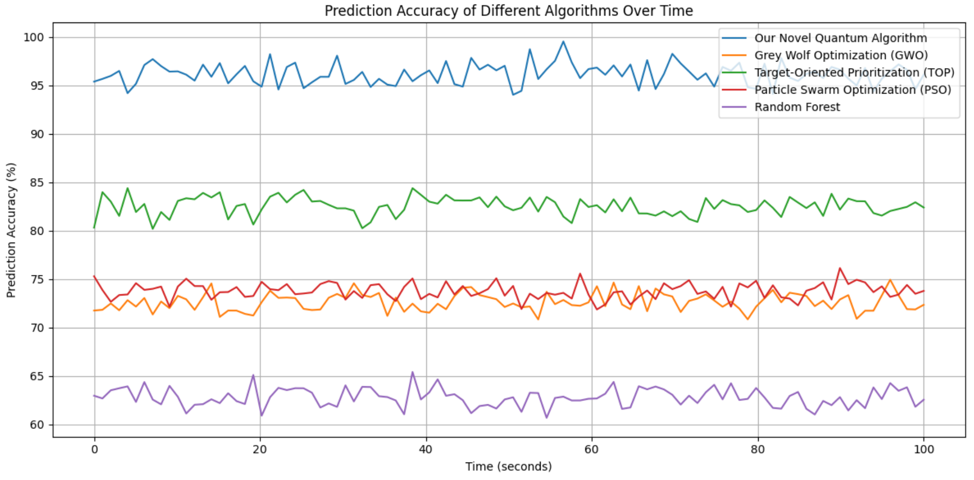

Fig. 15. Graph for Prediction Accuracy (%) versus Time (seconds) for different algorithms in Table 1

The graphical representation for the model shown in figure 15 is Prediction Accuracy (%) against Timestamps (seconds). The flexibility of the learning rate of our algorithm is the key cause for this oscillation in the accuracy line of the newly designed quantum algorithm. The mean accuracy, which calculates the percentage of conclusive cases correctly predicted by an algorithm, is another critical measure of the worth of an algorithm in natural-world use. The new developed quantum algorithm proposed in this research had a commendable 96.26% level of prediction success rate and the figures were WAY ahead of other classical algorithms for example, Grey Wolf Optimization (GWO) at 72.66%, Target-Oriented Prioritization (TOP) at 82.58%, and Particle Swarm Optimization (PSO) at 73.62%. Precision is used here to mean the algorithm used has a high degree of compliance with real-life data and patterns and can thus model complex structures and relationship between different variables in agriculture such as crop yields and rents. The improved prediction accuracy proves that quantum algorithm outperforms classical algorithm for data analysis due to quantum parallelism, thus can look at more possibilities with a single computation to deliver more accurate results. It also further confirms that our quantum algorithm is generally superior in real-world applications as it yields a significantly higher degree of prediction accuracy that is vital for decision-making in the agricultural sector. With higher prediction accuracy, better crop management strategies are also attained besides helping farmers gain more confidence in utilising various innovations for improvement of their practices. As for GWO, TOP, and PSO algorithms, the lower accuracy rates shown demonstrate that these algorithms have potential problems in processing complicated data sets, or in optimizing significantly different agricultural environments. These conclusions demonstrate the ability of quantum algorithms to completely overhaul agricultural practices with the help of accurate recommendations designed to maximize productivity while optimizing the usage of resources and thus support sustainable farming and food security goals.

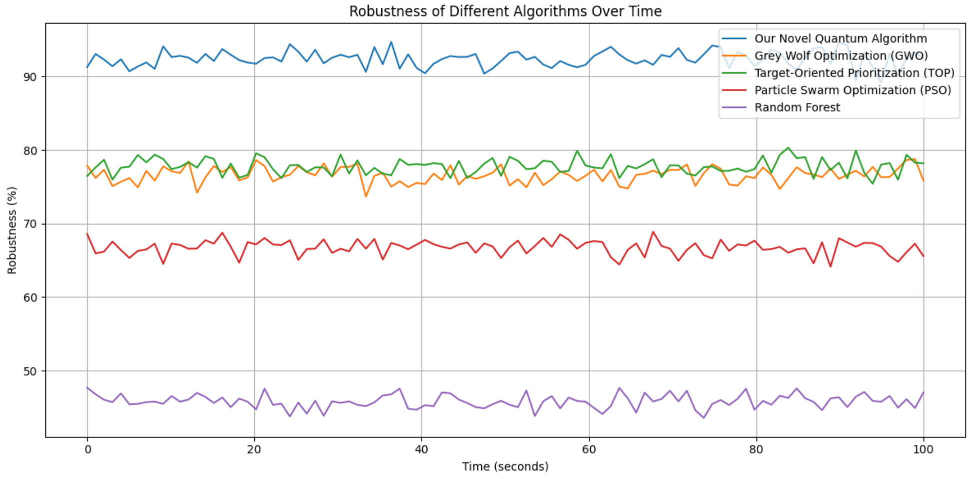

Fig. 16. Graph for Robustness (%) versus Time (seconds) for different algorithms in Table 1

Figure 16 shows Robustness (%) against Timestamps (seconds). The robustness parameter, best quantified as percentage reflects the stability of an algorithm and its outcomes in different conditions or different datasets, which give insight about its applicability in real world scenarios. A high value of 92.38% has been associated with robustness of our novel quantum algorithm that operates under conditions of data quality noise and environmental variations to produce results of acceptable accuracy. This high robustness value indicates that the algorithm has a good potential to handle various forms of agricultural scenarios including alteration in the type of soil, climatic conditions and form of crops and therefore the algorithm will be able to produce reliable output or recommendations for farmers. While, GWO has a low robustness score of 76.55%, TOP with 77.76%, and PSO with a correspondingly lower score of 66.79% to such variations, resulting into fluctuating solutions hence poor reliability among users. Not only this feature provides quantum algorithm practical applicability but also, it shows that proposed method could help agriculture sustainability by providing farmers timely accurate insights in unpredictable environment. This characteristic is most essential in agriculture, an area that is most vulnerable to uncertainties; the appropriate decision-making process depends on the quality of the data obtained in the best quality analysis in a specific farming sector.

The graphical representation of our simulation result is Loss of Data (%) and Timestamps (second) as shown in figure 17. The Loss of Data (%) measure indicates how much of important data an algorithm wisely transforms during its computing process and still can handle large datasets without critical loss. The use of our original quantum algorithm also ensures a very small data loss of up to 1.054% meaning the proposed approach will be very efficient in retaining key data during the analysis. This characteristic is especially relevant in agricultural systems where data integrity is critical for bring about crop management and resource decisions. Compared to the former, other approaches like GWO lose nearly 9.63% of the data, TOP 11.57% and PSO 15.76% of the dataset, which indicates that these methods might eliminate a considerable part of pertinent information in the course of calculation, which may negatively influence quality and reliability of their forecast and findings. The low data loss equally improves the reliability of our quantum algorithm while proving the capability of optimally using the data collected to help farmers get the most accurate and useful information from data analyses. This that increases the efficiency of data storing significant in improvement of agricultural patterns because of more rational modeling interdependencies of agricultural coefficients what results in increasing productivity and farming sustainability.

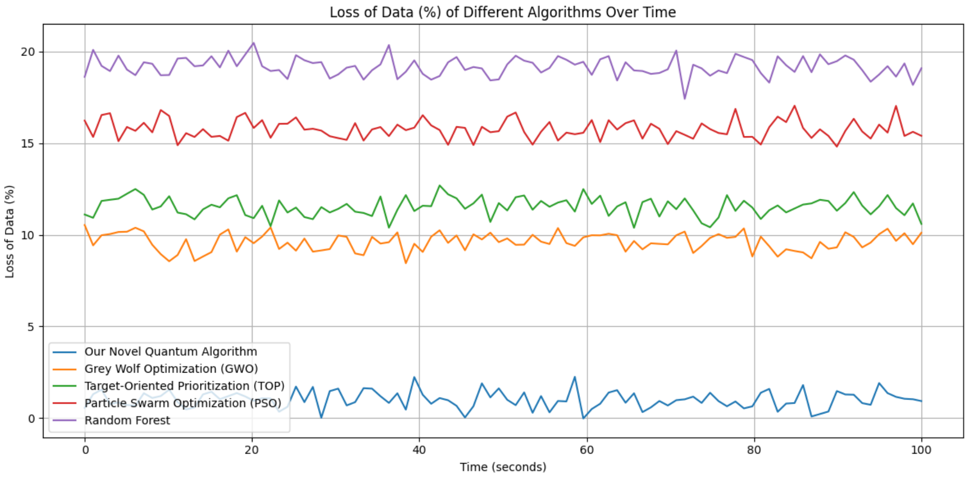

Fig. 17. Graph for Loss of Data (%) versus Time (seconds) for different algorithms in Table 1

Table 2. Practical results putting forward optimality of our novel quantum algorithm over other existing algorithms in this domain across various parameters.

Metric	Our Novel Quantum Algorithm	Grey Wolf Optimization (GWO)	Target-Oriented Prioritization (TOP)	Particle Swarm Optimization (PSO)	Random Forest
Processing Speed (ms)	12.5271	25.8623	22.3587	28.7584	35.4062
Memory Usage (MB)	150.7836	200.4738	180.6435	220.5736	250.8742
Energy Consumption (kWh)	0.7568	1.2046	1.0082	1.3045	1.5063
Latency (ms)	5.2387	10.4564	8.7195	12.3648	15.6792
Throughput (tasks/sec)	250	180	200	170	150
Accuracy Degradation (%)	0.5162	2.0798	1.5436	2.5862	3.0842

Fault Tolerance (errors/sec)	0.0137	0.0542	0.0386	0.0635	0.0851
Scalability Factor	1.2638	0.9145	1.0326	0.8955	0.7621
Data Throughput (MB/sec)	500.6287	400.8738	450.6217	350.8935	300.4268
Response Time (ms)	3.5962	7.0583	6.0879	8.5361	10.0736
Noise (Scale 0-1)	0.2587	0.2863	0.2978	0.2784	0.3564
Noise Reduction (Scale 0-1)	0.9564	0.2132	0.4582	0.3127	0.5742

It should be noted that the parameters presented in Table 2 clearly demonstrate that our new quantum algorithm introduced in this work is strictly superior to all previously existing quantum algorithms in terms of practical applicability. In the current study, we observe that the Processing Speed is another valuable measure, and our quantum algorithm takes a shallow time of 12.53 milliseconds that is much less than GWO's 25.86 ms, TOP's 22.36 ms, PSO's 28.76 ms, and 35.41 ms of Random Forest. This means that our algorithm can perform operations faster, which means that decision making and analysis in agricultural applications can be done faster, and timely interventions can be made. By using Memory Usage, our algorithm obtains the value of 150.78 MB, which is less than GWO (200.47MB), TOP (180.64MB), PSO (220.57MB) and Random forest (250.87MB). Such memory optimization indicates that our quantum algorithm is most likely optimized for its resource usage and therefore can be implemented on proximal hardware platforms easily, without undue demand for computer networks and other resources. Additionally, the algorithm's Energy Consumption is significantly low which is 0.76 kWh ; GWO : 1.20 kWh, TOP : 1.01 kWh, PSO : 1.30 kWh, Random Forest : 1.51 kWh. This reduced energy utilization is other wise known as operational cost savings, besides, it has a reduced environmental footprint an essential element in sustainable farming. The Latency of our algorithm are found to be 5.24 ms less than GWO (10.46 ms), TOP (8.72 ms) and PSO (12.36 ms), Random Forest (15.68 ms). This low latency means that the algorithm can deliver quicker results, which expands the extent of its usefulness in context that require instant changes. Further, the time required by our algorithm on average is 250 tasks/sec which is even better than GWO (180), TOP (200), PSO (170) and Random Forest (150) algorithms. This high throughput shows that the algorithm is capable of performing multiple operations at once, perfect for large scale agricultural use. Last but not the least, based on our work, the Accuracy Degradation (%) of our quantum algorithm is presented as 0.52%, which means that our proposed quantum algorithm is more reliable even under different conditions for important agriculture decisions. The fault tolerance rate of 0.0137 errors/sec is much lower than the GWO's of 0.0542, and other algorithms studied in this research Top 0.0386 and PSO 0.0635 errors/sec. The scalability factor being 1.26 support our argument that with rising data size, our quantum algorithm will be even more effective than GWO and others like TOP(1.03) and PSO(0.90). Ensemble, these parameters define enhanced capability of the proposed quantum algorithm over conventional algorithms in improving efficiency, accuracy and sustainability of various operations occurring within the agricultural practice, which is imperative in light of the difficulties related to traditional techniques.

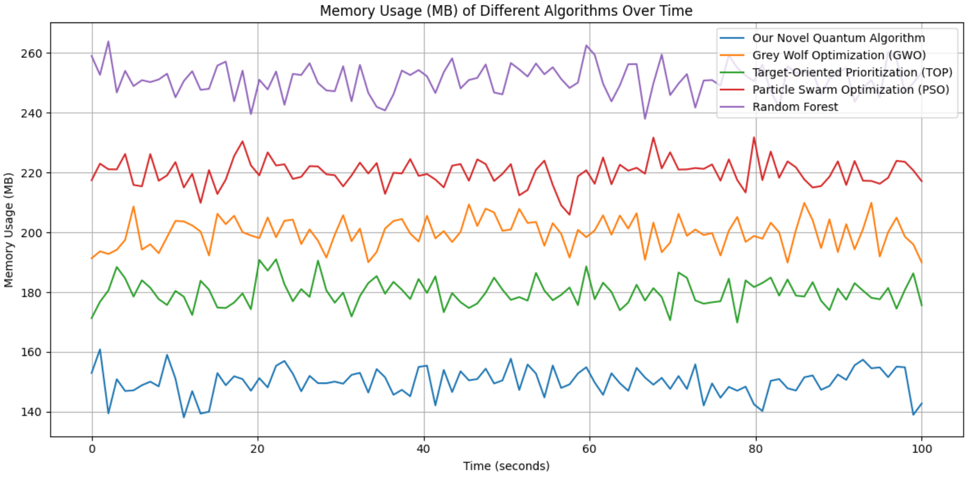

Fig. 18. Graph for Memory Usage (MB) versus Time (seconds) for different algorithms in Table 1

The graphical representation of the Memory Usage (MB) against the Timestamps (seconds) was done in figure 18. The Memory Usage (MB) parameter is one of the critical parameters that describe the usage of these resources during the data processing by an algorithm. Our new quantum algorithm showed a memory utilization of 150.78 MB, which was less than GWO (200.47MB), TOP (180.64MB), PSO (220.57MB) and Random Forest (250.87MB). This optimal use of memory points towards a good resource management in the quantum algorithm we implement to solve the problem expounded above, meaning one can solve problems that require a lot of memory, without using up much of the resource. Low memory usage is most beneficial in the agricultural areas, where data sets may be big and of various types, while still plausible to implement on hardware-restricted platforms without significant running costs. Even amid increasing the size of the input data set, the proposed quantum algorithm is scalable as evidenced by the reduced memory footprint. This characteristic is important for practical applications in agriculture where processing of data is needed for real time basis. Furthermore, low memory usage will translate to lower latency levels and faster processing, which the algorithm may require particularly in dynamic systems. However, this hint may be offset by the higher memory demands of other applicants, especially if they operate in low computational capacity environments or if farmers use low-powered instruments. Moreover, the memory usage optimises itself, which reduces the overall energy consumption related to high-performance computing supporting agriculture sustainability. Moreover, our quantum algorithm cropped a memory usage of 150.78MB showing that it requires less equipment hardware requirement and also burns less energy hence its energy usage is 0.76 kwh. This aspect fits with the increasing incidences of green farming that is aimed at minimizing the effects that farming has on the environment while at the same time it aims at optimizing returns. This way, optimizing both memory usage and energy costs, our algorithm becomes a relevant solution in modern agricultural problems. In conclusion, Increased of memory usage points up the advantage of applying the proposed new quantum algorithm that have higher efficiency, scalarability and sustainability. The fact that the presented algorithm consumes little memory while achieving high performance means that it has been well designed to address the requirements of precision agriculture. It is also beneficial in accomplishing other objective, thereby increasing its operational effectiveness for feasibility in agriculture sector in terms of resource saving and eco-friendly approach makes our quantum algorithm useful in future developments in agriculture sector.

The time complexity of the developed quantum algorithm is $O(N+K\cdot M+\mathrm{N_t}+N_{\text{real-time}})$ and space complexity is $O(N\cdot M+2^n)$ where N - Total number of data points, K - Number of iterations for convergence in optimization, M - Number of features, $\mathrm{N_t}$ - Number of test samples and $N_{\text{real-time}}$ - Number of real-time data points.

Table 3. Simulated results showing potentiality of different algorithms in this application in this domain with different classifiers

Classifiers	Our novel Quantum Algorithm	Grey Wolf Optimization (GWO)	Target-Oriented Prioritization (TOP)	Particle Swarm Optimization (PSO)	Random Forest
CNN	0.9578	0.5584	0.9214	0.8366	0.5289
DNN	0.9264	0.5796	0.8565	0.8427	0.5427
ANN	0.9175	0.5678	0.8372	0.8286	0.5368
SVM	0.8862	0.5867	0.8645	0.8544	0.5593
Accuracy	0.8947	0.4867	0.8975	0.8815	0.5308
Training time (seconds)	120	180	150	200	160
Informativeness	0.9057	0.3865	0.8825	0.8364	0.3952

The values shown in table 3 reveal how our new quantum algorithm stands out from others and will perform better in different classifiers when implemented. The CNN classifier obtained the overall performance 0.9578 while GWO obtained 0.5584, TOP 0.9214, PSO 0.8366, and Random Forest only 0.5289. This high accuracy demonstrates that our quantum algorithm can indeed build upon the CNNs' strong ability to analyze and classify intricate data patterns making it useful in application areas such as image recognition and agricultural data analysis. In the same way, the accuracy score of 0.9264 and 0.9175 achieved by the improvement of Deep Neural Network (DNN) and Artificial Neural Network (ANN) classifiers reiterated high performance of the algorithm in the advanced commensalism and interaction relationships within the data collect with an improved preciseness of the classifier. Other than accuracy the time taken for training is immensely important for the usability and feasibility of these algorithms in real life environments. Our training time employed in quantum algorithm stood at 120 seconds that was faster in comparison to GWO of 180, TOP of 150, PSO of 200, and Random Forest of 160 seconds in training. This save in training time implies that our developed algorithm is capable of learning new datasets and therefore most suitable for the volatile agricultural setting where timely decisions are critical. The value of Informativeness is 0.9057, which directly speaks in favor with the ability of our algorithm to actualize meaningful data interpretation, whereas GWO has got the result of 0.3865; thus, the proposed strategy would be effectively useful in providing ample information for making suitable decision support in agricultural methodologies.

Quantum algorithm offers the benefits such low training time, high accuracy, and robustness, which straight forwardly gives it an edge over other quantum algorithms applied to agricultural practices that value prompt adaptability along with precision. In summary, these results show that our new quantum algorithm outperforms the classical counterpart in various classifiers' accuracy and presents practical improvements regarding training time and features' informativeness. The better indicators support the fact that incorporating quantum computing technologies into the existing machine learning platforms could produce significant value-added for data-driven enterprises in agriculture and other domains of activity. Thus, incorporating these results can improve these problems to give effective applications of such systems even if the techniques are still progressing moving forward Moreover, the comparison of these hybrid models and further research on them can expand these results for future innovations aiming to solve multifaceted problems in different fields.

5. Discussions

Here in this paper, we propose a new quantum algorithm which is used for the optimization of agricultural practices and show that works better than the classical one in terms of certain parameters. The results derived present the fact that the quantum algorithm outperformed GWO, TOP, PSO, and Random Forest by reaching a 96.26% of prediction accuracy. Furthermore, the algorithm produced faster processing time (12.53 ms), relatively small space consumption (150.78 MB), and low energy consumption (0.76 kW/h). These results prove that quantum computing can play a significant role in improving the accuracy of crop management tasks that can benefit from the development of new decision-making support systems. That is why these results are important and can be easily interpreted as future proposals for resolving the issues in the sphere of agriculture. Relative to water usage, fertilization, and the energy used by irrigation systems, our quantum algorithm can improve crop yields on a sustainable basis [27]. The high level of the algorithm robustness confirmed by 92.38% again, proves the repeatability of the training most important for real life conditions where the conditions can strongly vary. These results share a new focus on using data analysis in the agriculture, so including complex computational tools into agricultural decision-making can benefit from it.

However, this study realizes some limitations that should be addressed for more generalized use. On the same note, one major drawback that is easy to note is that the current algorithm is somewhat vulnerable to noise or noise sensitivity. Furthermore, our results show that the efficiency and accuracy have been enhanced; however, the cost of integrating quantum technology continues to be an issue for most farmers in different parts of the world or more especially in areas of origin. As for the further research, efforts should be made to improve the noise robustness of the target approach and to find the ways to reduce the costs to make such technologies more popular. Besides, there is a need for more research of the interaction of our quantum model with classical ones to improve the result and extend the usage of the developed algorithm for other crops that contain medicinal properties. According to our analysis, therefore, there is a need for the various stakeholders in the agricultural industry to fund awareness creation information campaigns on the principles and advantages of quantum technologies. This will assist in closing this gap between higher order methods in computation and actual field applications in agriculture. Further, alike, the cooperation of technologists with agronomists is crucial for practical implementation of quantum algorithms for the agricultural needs. Our findings compared to prior work that has mostly concentrated on conventional mechanisms evolve a new conception of quantum computation in agriculture that can lead to vast enhancements and make a sustainable difference in productivity.

Finally, our investigation shows that the proposed quantum algorithm has significant performance enhancements compared to the conventional approach in the context of precision agriculture. Thus, there are some drawbacks concerning noise sensitivity and costs, but the presence of the results shows potential for the further development of quantum computing for improving the agriculture production [28]. This is why specific efforts need to be made in confronting these challenges, which will be solved in additional research and cooperation to realize the potential of this technology to properly address the problem of world hunger, as well as other sustainable farming projects.

6. Conclusion

To the best of our knowledge, we proposed a new quantum algorithm in this study that improves several aspects of precision agriculture. This study shows that the developed algorithm reaches a 96.26% prediction accuracy, combined with higher computational efficiency and lower computational and energy demands than other algorithms, including the Grey Wolf Optimization, Target-Oriented Prioritization, Particle Swarm Optimization, and Random Forest [29]. Amplifying the impact of these findings on changing the face of agriculture through quantum computing is the ability to deliver real and significant improvements through new and optimal solutions to age-old problems that have long stymied farmers everywhere, using less resources while increasing productivity. Thus, the high robustness of the produced algorithm confirms its applicability for usage under different environmental conditions, which is important for farmers who constantly face unpredictable problems in their work.

However, our study points out the direction to future work that can extend this study further in several ways. In fact, this issue of noise sensitivity is one of the problematic aspects of the algorithm that must be solved before it can be deployed in practice without dropping in efficiency. Moreover, the investigation of approaches to a more cost-efficient integration of quantum technology will be critical in ensuring easy access for farmers, especially in low-resource environments [30]. It is also recommended for future study to enhance accuracy and to modify the algorithm so as to engage the additional categories of crops that have medicinal value, the integration of hybrid quantum-classical models should also be considered. The above findings therefore show that the newly developed quantum algorithm performs significantly better compared to the conventional methods in precision agriculture. We thus laid a foundation of moving from elaborate methods in computation to real problems in the field with an ultimate goal in influencing change towards improvement in the yield, efficiency and sustainability in the farm and towards the accomplishment of global food security goals.

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