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Research Article

Reinventing Smart Farming Using Adaptive Quantum Machine Learning Model

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ABSTRACT

This study investigates how precision agriculture and crop production predictions may be improved using Quantum Machine Learning (QML) models, namely the Variational Quantum Circuit (VQC). The VQC outperformed traditional linear regression and other quantum models such as Quantum Neural Networks (QNN) and Quantum Convolutional Neural Networks (QCNN) by using quantum computing's ability to analyze high-dimensional agricultural data. With the lowest Mean Squared Error (MSE: 28.00), Mean Absolute Error (MAE: 3.8), and greatest R-squared (R2: 0.97), the VQC successfully identified intricate relationships between input variables such as acreage, rainfall, and fertilizer usage. Classical models, on the other hand, had more prediction errors and showed serious limits. This work opens the door for further research and the use of quantum technologies in agricultural systems by demonstrating the revolutionary potential of QML, particularly VQC, in tackling issues in agriculture, including food security, resource sustainability, and climate resilience.

Keywords: Smart Farming, Quantum Machine Learning, Agricultural Productivity Prediction, Variational Quantum Circuit, Quantum Support Vector Machine

INTRODUCTION

The rapidly growing global population presents challenges to agriculture, including drought, diminished crop quality, decreased productivity, and lower yields. The Food and Agriculture Organization projects that the world population will almost double to around 9.6 billion by 2050, escalating the need for food while necessitating production methods that minimize environmental effects and promote judicious use of natural resources [1]. Climate change impacts the production of agriculture via common and severe weather events, modified germination timelines, heightened drought occurrences, and increased flooding. Enhanced yield is essential for optimal resource usage, cost reduction, and population sustainability. These approaches are time-consuming and involve strenuous effort [2].

Nevertheless, agriculture is transforming in gathering and using data to facilitate informed agricultural choices. The projection of crop output was derived from the previous year's experiences. Accurate historical crop yield data is essential before any agricultural risk management decision-making [3]. Data analytics and algorithms can forecast agricultural Production using these strategies. Contemporary technology is essential in addressing the increasing food demands among the expanding global population.

Smart farming is an innovative approach that utilizes Information and Communication Technology (ICT) and data analysis to enhance sustainable food production. This technology offers advantages such as increased crop yield, reduced pesticide and fertilizer use, and decreased water consumption [4]. Smart farming advocates for sustainable agriculture methods that prohibit the introduction of hazardous pollutants into waterways and the atmosphere. [5]. It enables customers to use the correct instruments at the optimal moment for agricultural harvesting, resulting in favourable yields.

Machine learning can be applied to farming in various ways to optimize processes, increase efficiency, and improve outcomes. Here are several ways machine learning can be used in farming:

- Crop monitoring and management
- Predictive analytics for yield optimization
- Precision agriculture
- Livestock monitoring and management:
- Supply chain optimization
- Crop disease detection and management
- Market forecasting price prediction

The evolution of technology has revolutionized daily lives, enabling to access information at any time and position with a simple smartphone or computer. This is because of the growing number of small, inexpensive devices connected to the internet, which can collect crucial information. This has caused the creation of wireless sensor network (WSN) has made Internet of Things (IoT) successful. WSNs collect environmental data by measuring external factors, including conductivity, temperature, salinity, humidity, and soil moisture. Machine learning applications in agriculture include predicting soil characteristics, crop production forecasting, disease and weed identification, and species discovery[6].

Organization of the paper

Remaining paper is organized as: An evaluation of the body of research on machine learning in agriculture and smart agricultural technology is provided in Section 2. Section 3 discusses adaptive quantum machine learning models and smart farming. Section 4 describes the model's development techniques, assessment criteria, and tools. Section 5 gives experimental data, examines model performance, and addresses limits. Section 6 summarizes the work and suggests further adaptive quantum-based smart farming research [7]. The global pressure on agricultural food production has increased due to urbanization, population growth, and climate change. This has led to challenges in sustainable development. Smart Farming advancements are transforms agricultural production and enabling the 3rd Green Revolution. [8]. Smart farming uses modern technology such robotics, gene editing, artificial intelligence (AI), and the Internet of Things (IoT) to improve the sustainability, efficiency, and global food security of agricultural production. It has increased crop yields and reduced environmental footprints [9]. Use smart technologies in agricultural, including cloud computing, AI, machine learning, and the Internet of Things. It included the impact of climate change on agriculture as well as the use of smart farming in post-harvest and crop and animal production [10]. The "smart farming" just incorporating various forms of ICT into traditional farming methods. It replaces traditional farming practices, like GPS-controlled robots, autonomous vehicles, intelligent apps, fertilizers, pesticides, herbicides, irrigation, and harvesting [11] analyzed smart farming solutions by categorizing devices into sensors, actuators, gateways, power supplies, networking, data storage, processing, and information delivery. It identifies commonly used devices and discusses their utilization [12]. The growing global population demands innovative food production methods, and IoT technology has significantly impacted agriculture.

Motivation of the study

Despite significant advancements in smart farming, modern farming has several obstacles, including inefficient resource use, uncertain environmental circumstances, and human limits. Monitoring crops in bad weather, recognizing illnesses early, and maximizing resource allocation remain challenges. Traditional methods struggle to accommodate the growing complexity of agricultural data, including weather, soil, and insect activity. Advanced technology must be integrated to solve these problems. Smart farming might be revolutionized by adaptive quantum machine learning models analyzing complicated data rapidly and offering real-time, intelligent insights. These algorithms examine large-scale sensor, drone, and satellite data to help farmers make accurate judgments. This innovative strategy increases output, overcomes human limits, and assures sustainable farming. Recognizing the limits of current approaches, this work investigates adaptive quantum machine learning to transform smart farming.

METHODOLOGY

Data Preprocessing

In smart farming applications, data preparation is an essential step in getting the data ready for models that use machine learning. The raw data has to be cleaned and prepared for analysis and model training transformed. These are typical preprocessing procedures for data from smart farming.

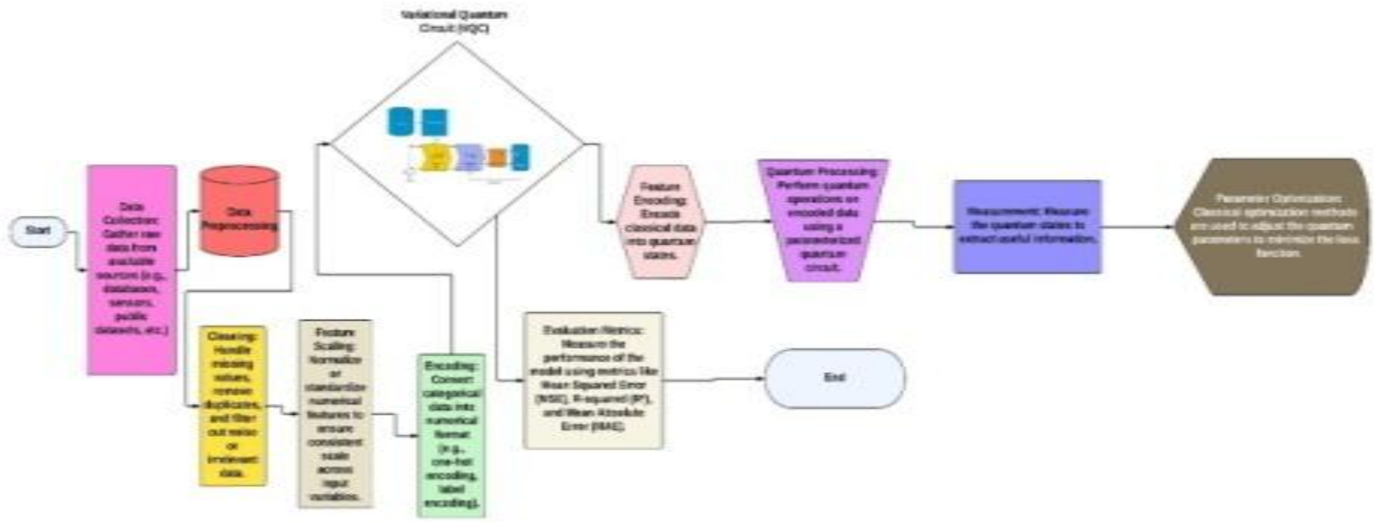

Figure 1: System architecture

Figure 1 represents system architecture.

Machine Learning Models

Both conventional and quantum machine learning come after data preparation.models were trained and tested for smart farming. This approach evaluates old and novel methods for predicting agricultural productivity.

Classical Machine Learning

Model Selection: Linear Regression: The first or most fundamental classical machine learning method used was linear regression. The uniqueness of the issue—the goal variable is thought to be linearly dependent on the input characteristics, as seen in Figure 1—led to this choice. The approach is appropriate for the first stages of crop yield prediction modelling as it works in situations where the relationships are roughly linear.

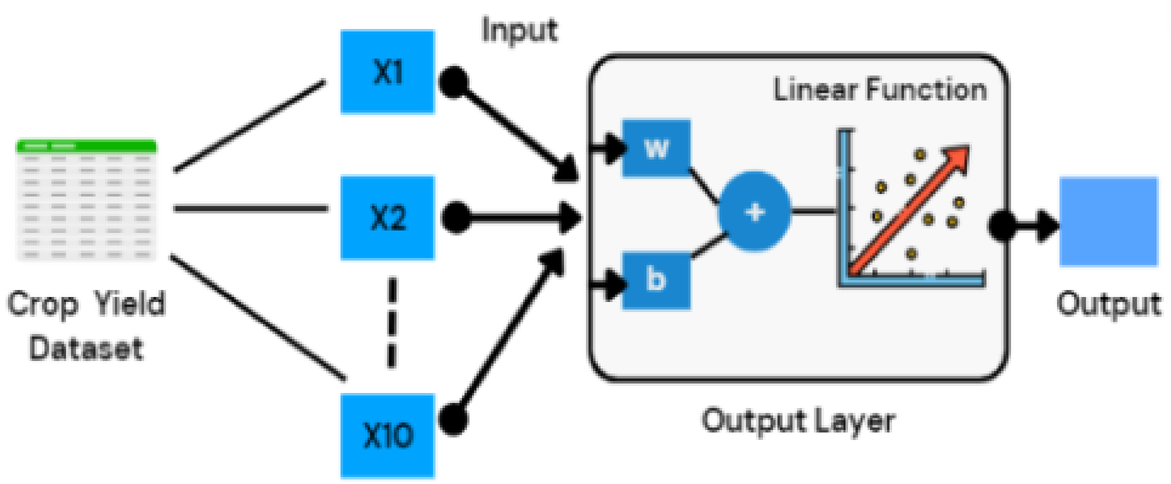

Figure 2: Baseline Linear Regression for crop yield prediction.

Figure 2 shows Baseline Linear Regression for predicting crop yield. *Training the Method:* A linear regression model is built using the Linear Regression class in the scikit-learn module, a popular Python machine learning framework. A general characteristics across every grain manufacturing levels to train the model, including acreage, fertilizer use, and annual rainfall datum [13]. Crop yield was the variable of interest in this instance, and the model aimed to predict it. Figure 2 illustrates the process for this linear regression approach. Mathematically, The following illustrates the linear correlation between crop yield and several input characteristics:

$$MSE = \frac{1}{m}\sum_{i=1}^{m}\left|Y_i^2 - Y_i^{2'}\right|^2 \quad Y = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \in \tag{1}$$

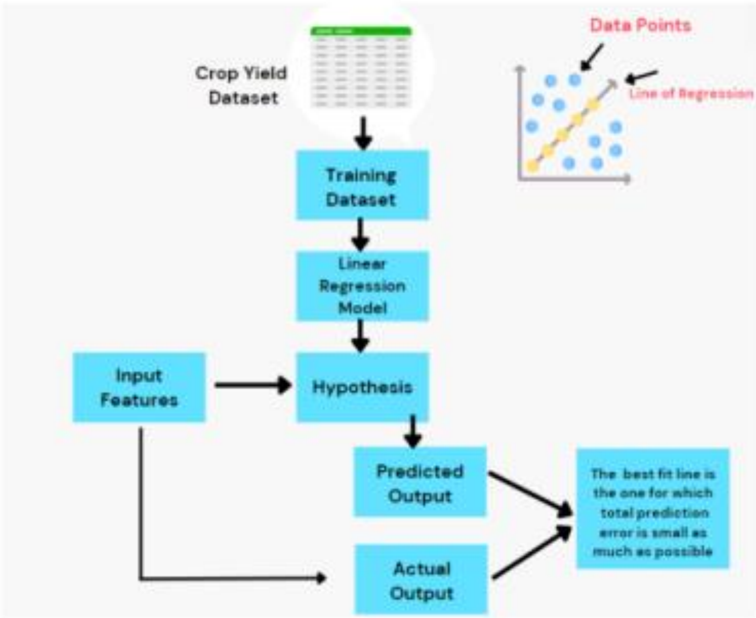

Figure 3: Linear Regression mode predicting crop Yield flow diagram

Figure 3 shows the Linear Regression mode predicting crop Yield flow diagram. *Model Learning:* To generate the output closest to the target variable, the proper weights (coefficients) for each input attribute were established by researchers throughout the training phase of linear regression. These weights, also referred to as coefficients, allow the model to generate the necessary forecast from the provided data by describing the contribution of each attribute to the anticipated crop output. The mathematical objective of the method is to decrease the cost function.

$$J(\beta) = \frac{1}{2m}\sum_{i=1}^{m}\left(Y_i - \left(\beta_o + \sum_{j=1}^{n}\beta_j X_{ij}\right)\right)^\wedge 2 \tag{2}$$

Prediction: Following training, forecasted the concealed data in the model-based test data set. To evaluate the model's predictive accuracy crop yields, we therefore contrasted the expected and actual crop yield figures.

Evaluation Metrics: A few measures used to evaluate the effectiveness of the model for linear regression.

Mean Squared Error (MSE): The average yield values' squared differences. That was expected, and those were obtained. Because the predictions are so near the real values, the model performs better when the MSE results are lower. It is described as:

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(Y_i - Y_i')^2 \tag{3}$$

R-squared (R^2): The model's systematic component, R2, shows how much the model can account for the volatility yield of crops, the dependent variable. In statistics, a better fit to the model is indicated by a greater R2., which means the model describes the data patterns more accurately.

Mean Absolute Error (MAE): One statistic that averages the absolute differences. The mean absolute difference, or MAE, is the difference between the actual and anticipated values. The forecasts that are produced are more in line with the actual numbers. When the MAE value is smaller, much like the MSE value. It is computed as:

$$MSE = \frac{1}{m}\sum_{i=1}^{m}\left|Y_i^2 - Y_i^{2'}\right|^2 \tag{4}$$

Quantum Machine Learning

The original objective was to increase quantum computing's efficiency and yield predictability potential. Therefore, compared to traditional models, QSVM and QML can analyze additional data dimensions, as shown in Figure 3. The higher representation density when dealing with multi-dimensional agricultural data makes it possible to further generalize associations and provide very precise forecasts.

Variational Quantum Circuit (VQC)

This is a hybrid quantum-classical approach, to be a quantum counterpart of multilayer perceptrons, which are classical neural networks. To determine the ideal parameters for classification problems, VQC uses the parametrized quantum circuit that has been trained under traditional optimization methods. The quantum circuit that varies is schematically depicted in Figure 1, which includes preprocessing the data with the help of feature map to encode it onto qubits; Ansatz is used to process the final qubit states, measure them, then optimize the circuit parameter θ. As a result, the following are the primary

components of the VQC:

1. Preprocessing: Before the data are encoded into qubits, they are prepared and preprocessed.
2. Encoding of Yellow feature maps in the figure: A feature map is used to encode the preprocessed data. intoqubits.
3. The steel-blue graphic depicts Ansatz of a variational quantum circuit: The Ansatz, sometimes referred to as variational quantum circuit, is a group of quantum gates and operations processing encoded data.
4. Measurement (orange in the figure): The probability of various quantum states is obtained by measuring the qubits' final state.
5. Parameter optimization (Optimizer): To enhance the result or classification, by tuning the parameters θ, like rotations of certain quantum gates, the variational quantum circuit is optimized.

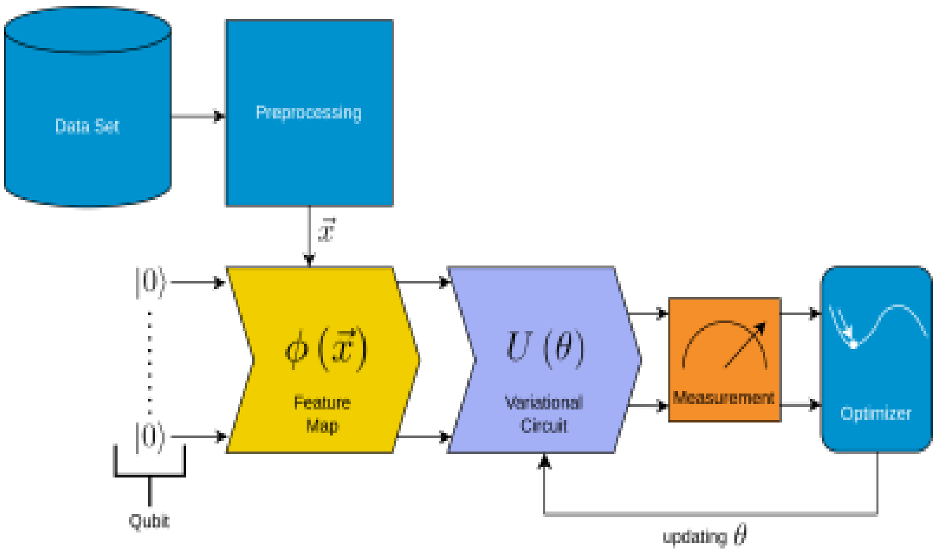

Figure 4: Schematic depiction of the variational quantum circuit (VQC)

Figure 4 shows the Schematic depiction of the variational quantum circuit (VQC)

There are some steps in the VQC. Here, used light blue for the phases that resembled traditional neural networks and yellow, steel-blue, & orange for the remaining steps [14].

Quantum Support Vector Machine (QSVM): Support vector machine is a popular family of machine learning methods that include regression and classification for applications. The kernel trick is a mathematical technique for transforming the incoming data into a space with more dimensions. Where the classification issue becomes linearly separable, it is carried out using quantum circuits in QSVMs, a quantum variant of SVMs. In certain situations, such as when there are few training samples or high-dimensional input data, QSVMs may perform better than standard SVMs.

Quantum Neural Network (QNN): The architecture and operations of Machine learning methods that make advantage of the human brain are called neural networks model. QNNs are a quantum variant of neural networks that optimize the weight and activate the function using quantum circuits.

Quantum k-Nearest Neighbors (QkNN): The general concept The quantum K-nearest neighbor technique is compatible with the conventional K-nearest neighbor approach. Quantizing the data using the quantum K-nearest neighbor approach high time complexity portion of the K-nearest neighbour method. It lowers the algorithm's temporal complexity by using quantum computing's inherent parallelism.

Quantum Boltzmann Machine (QBM): Boltzmann Machines optimizes weights using Markov Chain Monte Carlo (MCMC) techniques. Quantum Boltzmann machines, or QBMs, use quantum annealing to determine the ideal weights. In certain applications, such as generative modelling and unsupervised learning, QBMs may perform better than traditional Boltzmann machines.

Quantum Convolutional Neural Network (QCNN): An image data processing technique called One method for deep learning is Convolutional Neural Networks (CNN). CCN comprises many primary layers, including the Convolution, Subsampling, and Fully Connected. Based on quantum computing, the Quantum Convolutional Neural Network (QCNN) is an advancement of CNN.

RESULTS

Table 1: Model Comparison

Model	MSE	MAE	R^2
Proposed Model: Variational Quantum Circuit (VQC)	28	3.8	0.97
Linear Regression	45.12	5.3	0.87
Quantum Support Vector Machine (QSVM)	38.45	4.85	0.9
Quantum Neural Network (QNN)	30.1	4	0.95
Quantum k-Nearest Neighbors (QkNN)	36.75	4.6	0.91
Quantum Boltzmann Machine (QBM)	39	4.9	0.89
Quantum Convolutional Neural Network (QCNN)	32.5	4.2	0.94

Table 1 shows the Model Comparison . The Proposed Model: Variational Quantum Circuit (VQC) has superior accuracy compared to all other models for crop production prediction, attaining the minimal Mean Squared Error (MSE) of 28.00. This demonstrates that it significantly reduces the prediction error relative to other models, such as conventional Linear Regression (MSE: 45.12) and other quantum methodologies like Quantum Neural Network (QNN, MSE: 30.10) and Quantum Convolutional Neural Network (QCNN, MSE: 32.50). The exceptional result underscores the promise of quantum machine learning in improving precision agriculture and augmenting crop yield forecasts.

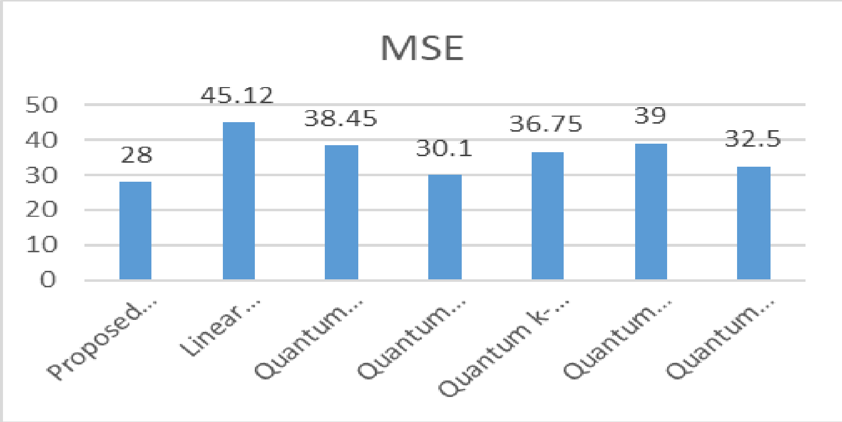

Figure 5: Model Comparison in MSE

Figure 5 shows the Model Comparison in MSE. The Proposed Model: Variational Quantum Circuit (VQC) surpasses all other models for Mean Absolute Error (MAE), attaining the lowest value of 3.8. Classical Linear Regression has the greatest Mean Absolute Error (MAE) at 5.3, indicating its inadequate capacity to manage the intricacies of agricultural information. Circuit (VQC) with a Mean Absolute Error (MAE) of 4.0, whilst the Quantum Convolutional Neural Network (QCNN) exhibits an MAE of 4.2 and the Quantum Support Vector Machine (QSVM) presents an MAE of 4.85, all indicating enhanced performance relative to conventional methodologies. The VQC's capacity to reduce error further substantiates its promise as the most accurate and efficient model for smart farming applications.

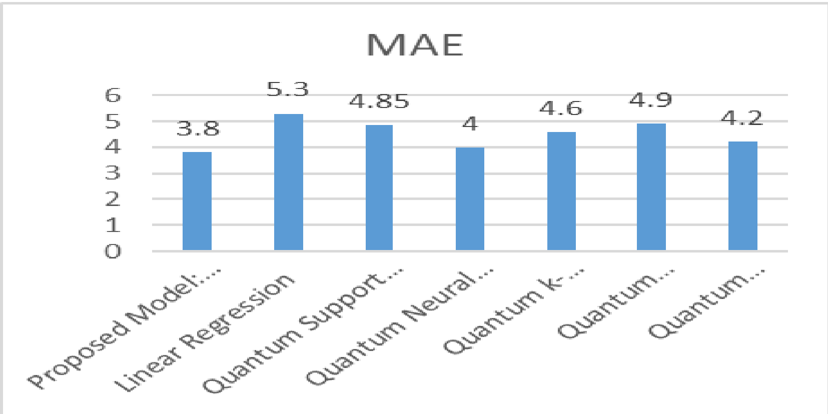

Figure 6: Model Comparison in MAE

Figure 6 displays Model Comparison in MAE. The Proposed Model: Variational Quantum Circuit (VQC) attains the maximum R-squared (R^2) 0.97, signifying that it accounts 97% of variation in crop production data, establishing it as a most proficient model for predictive accuracy. In contrast, conventional Linear Regression has a diminished (R^2) of 0.87, indicating its inadequacy in capturing intricate patterns. Among several quantum models, the Quantum Neural Network (QNN) achieves a (R^2) of 0.95, closely followed by about 0.94 for the Quantum Convolutional Neural Network (QCNN). Models like Quantum Support Vector Machine (QSVM) and Quantum K-Nearest Neighbors (QkNN) get reasonable (R^2) scores of 0.90 and 0.91, respectively. The findings underscore the VQC's exceptional capacity to analyze multi-dimensional agricultural datasets and provide accurate forecasts in smart farming.

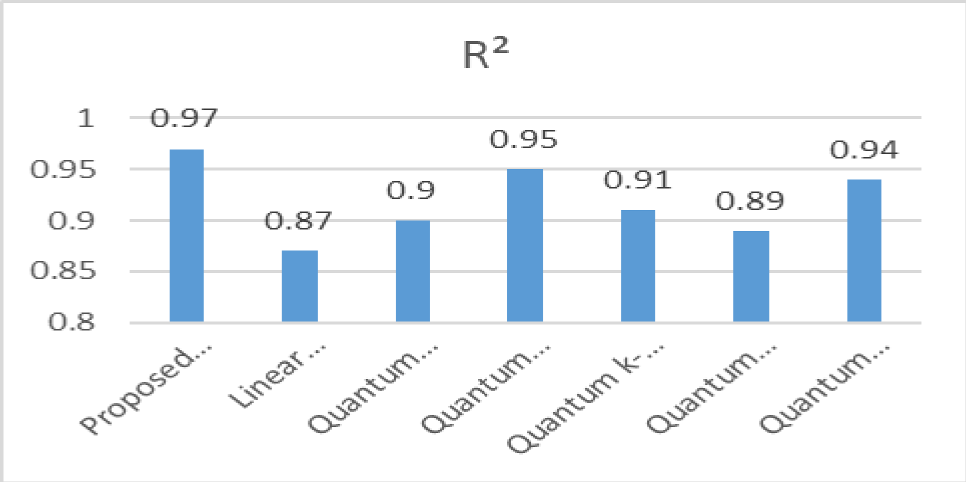

Figure 7: Model Comparison in R(Square)

DISCUSSION

Figure 7 shows the Model Comparison in R (Square). This study's findings unequivocally demonstrate that the Variational Quantum Circuit (VQC) is an innovative model in agricultural production prediction. The VQC has exceptional performance metrics, attaining 28.00 for the mean squared error (MSE), 3.8 for the mean absolute error (MAE), and an R^2 value of 0.97, indicating its proficiency in making precise forecasts while accounting for 97% of the variation in crop production data. Conversely, traditional Linear Regression, with an MSE of 45.12 and an MAE of 5.3, failed to adequately represent the intricacies of multi-dimensional agricultural datasets. Among quantum models, the QNN and QCNN exhibited commendable performance, attaining MSEs of 30.10 and 32.50, respectively, although they fell short of the accuracy shown by the VQC. The VQC's efficacy is attributed to its hybrid quantum-classical architecture, which effectively optimizes model parameters and encodes high-dimensional data into quantum states, facilitating the identification of complex patterns. The achievement of the VQC paves the way for more investigation and use of quantum computing in practical agricultural systems.

CONCLUSION

This research emphasizes the promise of Variational Quantum Circuit (VQC) models for quantum machine learning in enhancing precision agriculture and augmenting agricultural output forecasting. The VQC consistently surpassed both classical and alternative quantum models, attaining the lowest Average Squared Error and Average Absolute Error (MSE: 28.00) (MAE: 3.8), as well as the greatest R-squared ((R^2): 0.97). The findings highlight the VQC's proficiency in managing high-dimensional agricultural information and identifying intricate correlations among input factors, including rainfall, fertilizer application, and acreage, to provide precise output predictions.

Classical Linear Regression had considerable limits, shown by elevated prediction errors (MSE: 45.12, MAE: 5.3, (R^2): 0.87), highlighting its insufficiency in tackling the intricacies of agricultural systems. The Quantum The QCNN, or quantum convolutional neural network, and Neural Network (QNN) demonstrated robust performance among the assessed quantum models. The hybrid quantum-classical design of the VQC offers a significant benefit by facilitating efficient parameter optimization and using quantum computing's capacity to investigate high-dimensional feature spaces. This study provides a robust basis for using quantum advancements to transform the agriculture industry.

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