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QUANTUM-ENHANCED DEEP LEARNING MODEL FOR CROP-WEED CLASSIFICATION IN SORGHUM IMAGERY USING THE SORGHUM CROP WEED DATASET CLASSIFICATION

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SUMMARY

Classification of crops and weeds is an important aspect in precision agriculture, as it aids in providing a means for efficient weed control and reduced herbicide applications to achieve high crop productivity. In this paper, a quantum-classical hybrid deep learning approach is presented for accurate identification of crops and weeds from sorghum images using the dataset Sorghum Crop Weed Dataset_Classification. In this hybrid framework, a convolutional neural network (CNN) for feature extraction in the spatial domain, along with a variational quantum circuit (VQC) to provide better feature representation and classification abilities in higher-dimensional quantum space, is used. This allows for effective differentiation of crop and weed instances that appear alike in different agricultural conditions. Data preprocessing methods like resizing, normalization, and data augmentation (rotation, flipping, and brightness adjustment) are performed to ensure uniformity in data and increase the generalizability of the trained model. According to experimental evaluations conducted using traditional metrics, the designed model attains an accuracy of 97.3%, precision of 96.9%, recall of 97.2%, F1-score of 97.1%, and a training loss of 0.09. The results show a significant increase from baseline approaches such as CNN (92.5% accuracy), ResNet (94.0% accuracy), and transfer learning (95.0% accuracy). In addition, the designed model performs well when tested under challenging situations encountered in the real-world agricultural environment, such as varying illuminations, partial occlusion, and background noises. In summary, the above results prove the success of combining classical deep learning and quantum feature learning to enhance classification performance.

Key words: *quantum computing, deep learning, weed detection, crop weed classification, sorghum weed detection, sorghum crop weed dataset_classification dataset.*

INTRODUCTION

Precision agriculture is a revolutionary paradigm in modern agriculture, which enables decisions based on data and optimal allocation of resources. One of the crucial factors to guarantee success in this regard is the automated identification of crop and weed species. This is necessary to ensure reduced use of herbicides and sustainable farming practices [3]. The current challenge of the agricultural industry involves the implementation of real-time and highly precise detection of crops and weeds. This challenge is particularly critical for the situation where a wide range of diverse field conditions requires reliable identification of crops and weeds to preserve their yield and reduce negative impact on the environment [1].

The traditional approach for weed management is associated with the application of chemical herbicides across the entire spectrum of crop fields. However, despite the development of classical deep learning that greatly increased the ability of image classification, the contemporary methods have several drawbacks, such as high computational costs and poor generalization due to the variability of the environment [5].

In order to overcome such shortcomings, this study will investigate the potential of the application of quantum-powered deep learning algorithms to images of sorghum plants. Utilizing the power of CNNs to extract spatial features together with the expressive capability of VQC-based computation offers a way of modeling such high-dimensional interactions between features that would otherwise not be possible using classical machine learning [8]. The quantum-classical approach represents an excellent area for investigation that can contribute to improved classification performance in next-generation smart farming.

Key Contributions

- Proposes an integrated approach that combines a CNN and a variational quantum enhanced circuit in order to enhance the class separability of crop-weed images
- Includes an effective data pre-processing stage, including resizing, normalization, and data augmentation to deal with illumination changes, occlusions, and background noise in realistic farming environments
- Shows improved classification efficiency compared with the existing CNN, ResNet, and transfer learning models in terms of accuracy and reliability on test sets.

This research paper is structured as follows: Section I gives the introduction, Section II is a review of the literature, Section III contains the methodology, including architecture, dataset, preprocessing, CNN, VQC, classification, complexity, and algorithm. Section IV is the experimental analysis part, Section V is the results section, and finally, Section VI is the conclusion.

LITERATURE REVIEW

Current progress in precision agriculture indicates the rising application of deep learning methods and quantum-enhanced models in crop monitoring and disease detection. In studies, it was proved that quantum convolutional neural networks considerably enhance agricultural image classification tasks due to the representation of complicated features that cannot be captured by classical models [1]. Quantum kernels used in conjunction with deep learning approaches also prove efficient in improving the detection of crop diseases, especially wheat panicle classification [2]. More advanced agricultural models underline the importance of deep learning in optimizing the process of crop production according to climate change, which emphasizes the importance of intelligent models able to adapt to changing conditions [3]. Additionally, hybrid CNN-QNN models proved successful in diagnosing rice diseases in real-time decision-making applications on edge devices, which shows the possibility of implementation of quantum-enhanced models in agriculture [4]. Leaf disease detection in tomato and cotton crops proves

the efficiency of quantum-enhanced deep learning in fine-grained classification tasks, while survey studies provide additional insights on the relevance of quantum learning methods in agriculture [5][6]. Hybrid quantum frameworks used in yield prediction models show promising results in combining remote sensing and environmental information [7].

Other than disease detection, more literature has focused on the development of advanced precision agriculture methods, such as smart farming technologies and AI-based agricultural automation [8]. Hybrid quantum neural networks have been employed for weed and crop detection problems, showing enhanced classification performance with efficient quantum circuit design [9]. Quantum CNN models have been successfully used for plant stress detection and nutrient detection applications [10]. On the other hand, machine learning approaches in soil nutrient analysis support the application of data-driven methods in optimizing agriculture. Additionally, surveys in quantum deep learning have provided theoretical backgrounds and potential applications [11][12]. Federated learning has also been studied to increase data privacy and collaboration in agricultural scenarios [13]. In addition to that, explainable AI methodologies have been used to enhance classification interpretability, and hybrid machine learning techniques have been implemented in various applications, including horticultural applications and materials analysis [14][15][16]. Bibliometrics and scient metrics also prove the increasing presence of AI in agriculture [17][18]; in addition, multimodal AIoT and federated solutions contribute to the development of smart agriculture [19]. Security-oriented studies guarantee the stability of the agricultural cyber-physical systems, and optimal ensemble-based approaches continue to increase the weed classification accuracy [20][21]. All the aforementioned studies provide an excellent base for the implementation of quantum-classical learning in weed and crop classification systems.

Previous studies show impressive results in relation to quantum and deep learning in agricultural systems; nevertheless, most of the techniques have some issues with generalization, efficiency, and fine-grained weed classification. That is why a quantum-classical learning model would be beneficial.

PROPOSED METHODOLOGY

Overall Architecture of the Proposed Hybrid Framework

The proposed method utilizes classical deep learning techniques combined with quantum computing for the enhancement of the classification of crops and weeds in the imagery of sorghum. First, the image is preprocessed via resizing, normalization, and data augmentation. Subsequently, the preprocessed image is provided to the CNN model, which automatically detects discriminative spatial features, including textures, shapes, and structures of leaves. These detected features are used as inputs for the Variational Quantum Circuit (VQC), where the complex relations of features are learned in a high dimensional quantum feature space. Finally, the quantum-assisted features are provided to a dense layer with a SoftMax classifier to classify crop and weeds. This proposed architecture makes the process of collaboration of classical feature extraction and quantum feature learning more efficient.

The workflow of the proposed hybrid Quantum–Classical Deep Learning model is presented in figure 1 below. The sorghum images are initially preprocessed using operations such as image resizing, normalization, and data augmentation prior to being used to extract features by means of the classical CNN architecture. The obtained features are then optimized by a Variational Quantum Circuit (VQC), and finally, the classification is performed by use of dense and SoftMax layers.

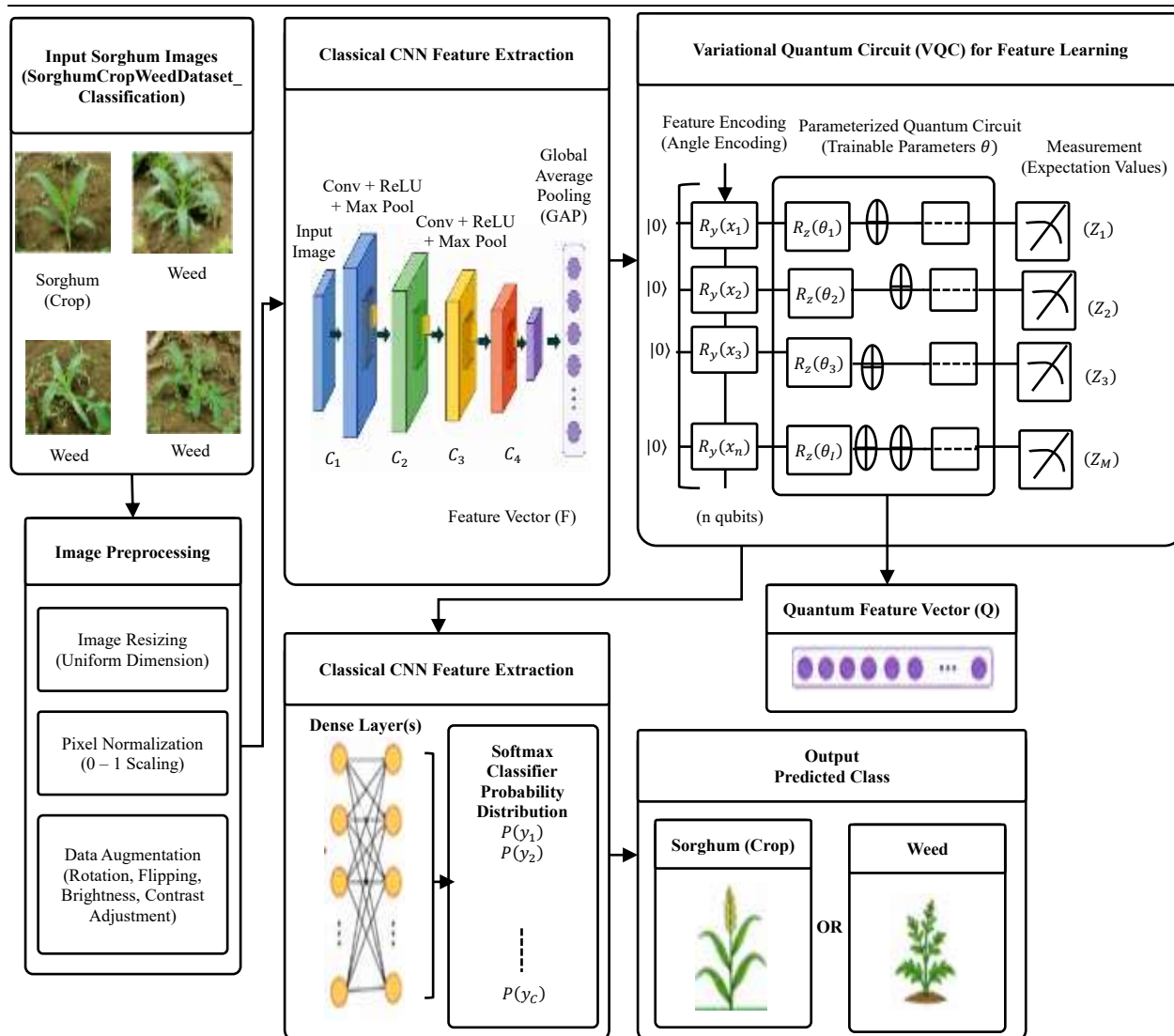


Figure 1. Proposed hybrid quantum–classical framework

SorghumCropWeedDataset Classification Dataset

The proposed model is based on the use of the Sorghum Crop Weed Dataset Classification dataset accessible at Mendeley Data [22]. The dataset is made up of RGB images of the sorghum crops and weeds acquired within realistic agricultural conditions. In addition, the images vary in terms of illumination, plant appearances, background complexity, and partial occlusion. As such, this dataset can be considered appropriate for testing the robust crop–weed classification models.

Dataset usage: “Sorghum Crop Weed Dataset Classification”

<https://data.mendeley.com/datasets/4gkcyxjyss/1>

Image Preprocessing

Data preprocessing is done prior to feature extraction in order to improve data consistency and increase the robustness of the model. First, all images are scaled to the same spatial resolution in order to ensure the same input size in the learning process. The next step is normalizing pixel intensities to improve numerical stability and facilitate fast convergence of the optimization algorithm. In order to improve generalization under various agricultural settings, data augmentation through image rotation, horizontal/vertical flipping, and illumination changes is used. This allows the proposed framework to

deal effectively with illumination changes, partial occlusion, and background interference, usually present in an agricultural environment.

Classical CNN Feature Extraction

Classical CNN layer automatically extracts discriminative spatial features from the preprocessed sorghum images. Convolution layers are trained to build the hierarchy of representation of leaf contours, texture changes, shapes, and structure features without the need for any handcrafted feature engineering. This results in very informative feature vectors that can be used for further quantum learning. Compared to other feature extraction algorithms, CNN is capable of automatically adjusting its filter during the training phase to discriminate better between crop and weed classes in diverse environments.

Variational Quantum Circuit (VQC) for Feature Learning

This extracted feature vector of the CNN is used as an input to a Variational Quantum Circuit (VQC), which provides enhanced feature learning. The VQC helps learn the complex and non-linear relationship among the extracted features in a high dimensional quantum feature space with the help of quantum parameters that can be trained. Both the classical CNN and quantum circuit parameters get optimized during optimization. This quantum-enhanced feature representation allows better discrimination among the crop and weed species, which look similar visually.

The quantum feature transformation is represented as (Equation 1):

$$Q = f_{VQC}(F, \theta) \quad (1)$$

where;

- Q denotes the quantum-enhanced feature representation,
- θ represents the trainable quantum parameters.

Hybrid Quantum–Classical Classification Model

The enhanced quantum feature representation obtained from the VQC is fed into the fully connected dense layer to make decisions. The dense layer aggregates the obtained quantum features before feeding them into the SoftMax classifier that determines the likelihood of each image belonging to either a crop or a weed. The combination of both classical and quantum learning allows the use of complementary feature representations and thus increases classification accuracy in different agricultural field environments (Equations 2 to 4).

The dense layer output is

$$Z = WQ + b \quad (2)$$

The SoftMax classifier is

$$P(y_i) = \frac{\exp(Z_i)}{\sum_{j=1}^C \exp(Z_j)} \quad (3)$$

The predicted class is

$$\hat{Y} = \arg \max(P(y_i)) \quad (4)$$

Where;

- C denotes the total number of classes.

Computational Complexity Analysis

Computational complexity of the proposed hybrid model comprises two main parts; first is classical CNN based feature extraction and second is quantum feature learning using Variational Quantum

Circuit. CNN extracts hierarchical features from images, and VQC boosts feature representation power by applying quantum computation on extracted features. Despite quantum layer adding more computational steps to the architecture, it greatly improves feature representation ability while keeping the process of inference efficient for applications of precision agriculture. Thus, the total computational complexity can be expressed as (Equation 5)

$$O_{Total} = O_{CNN} + O_{VQC} \quad (5)$$

Where;

- O_{CNN} denotes the computational complexity of CNN feature extraction,
- O_{VQC} denotes the computational complexity of quantum feature learning.

Algorithm 1: Quantum–Classical Crop–Weed Classification

Input: Raw sorghum image I

Output: Predicted crop or weed class $\hat{Y}$

1. Read the input sorghum image I .
2. Resize the image to a fixed resolution.
3. Normalize pixel values.
4. Apply data augmentation techniques.
5. Generate the preprocessed image I_{pre} .
6. Extract spatial features using the CNN to obtain $F = f_{CNN}(I_{pre})$.
7. Forward the extracted features into the Variational Quantum Circuit.
8. Generate the quantum-enhanced feature representation $Q = f_{VQC}(F, \theta)$.
9. Pass Q through the dense layer.
10. Compute SoftMax probabilities for all classes.
11. Assign the class with the highest probability as the final prediction $\hat{Y}$.
12. Output the classified sorghum crop or weed species.

Algorithm 1 gives the total steps involved in the proposed Quantum-Classical Deep Learning model for the purpose of crop-weed classification in sorghum images. The first step involves obtaining the raw input image I that is preprocessed via image resizing, pixel normalization, and data augmentation for better consistency and robustness. The input image obtained after preprocessing is fed into the classical CNN model where the spatial features (F) are automatically identified. The features F are converted into a quantum-enabled feature representation Q utilizing a Variational Quantum Circuit (VQC) with trainable parameters (θ). The quantum features are fed into a fully connected dense layer and then to a Softmax classifier, which generates the probability distribution of the target classes. Finally, the algorithm predicts the class of the input image to be either the sorghum crop or weed.

EXPERIMENTAL SETUP

Experimental Environment

The suggested Quantum-Classical Deep Learning algorithm was coded with Python 3.10 in combination with TensorFlow/Keras for creating and training the classical CNN part of the architecture. Variational

Quantum Circuit (VQC) will be simulated via PennyLane with Qiskit quantum backend for performing quantum operations and training parameterized circuits. Preprocessing and augmentation will be done with the help of OpenCV and NumPy libraries, whereas evaluation will utilize Scikit-learn metrics. All experiments will be conducted on the Ubuntu 22.04 operating system with CUDA-enabled GPU for computations.

Hyperparameters Settings

The hyperparameters of the suggested model were tuned to achieve optimal performance in classification tasks. The learning rate was 0.001, and the Adam optimizer was used to train the model. The batch size was kept constant as 32 to obtain stable convergence. The epoch numbers were varied between 50 and 100 based on convergence properties. Categorical cross entropy was the chosen loss function. Parameters for data augmentation consisted of rotation, flipping, and brightness changes.

Baseline Models

The performance evaluation of the proposed model was conducted by employing several baseline models. The models to be compared with the proposed model include standard Convolutional Neural Network, ResNet, and Transfer Learning model. The Convolutional Neural Network model acts as a basic deep learning model baseline, while ResNet adds a deep representation of features through the addition of residuals. The Transfer Learning model will compare the performance improvement through the use of pre-trained weights. These baselines help demonstrate the superiority of the proposed quantum-enhanced model in terms of classification accuracy, as shown in figure 2.

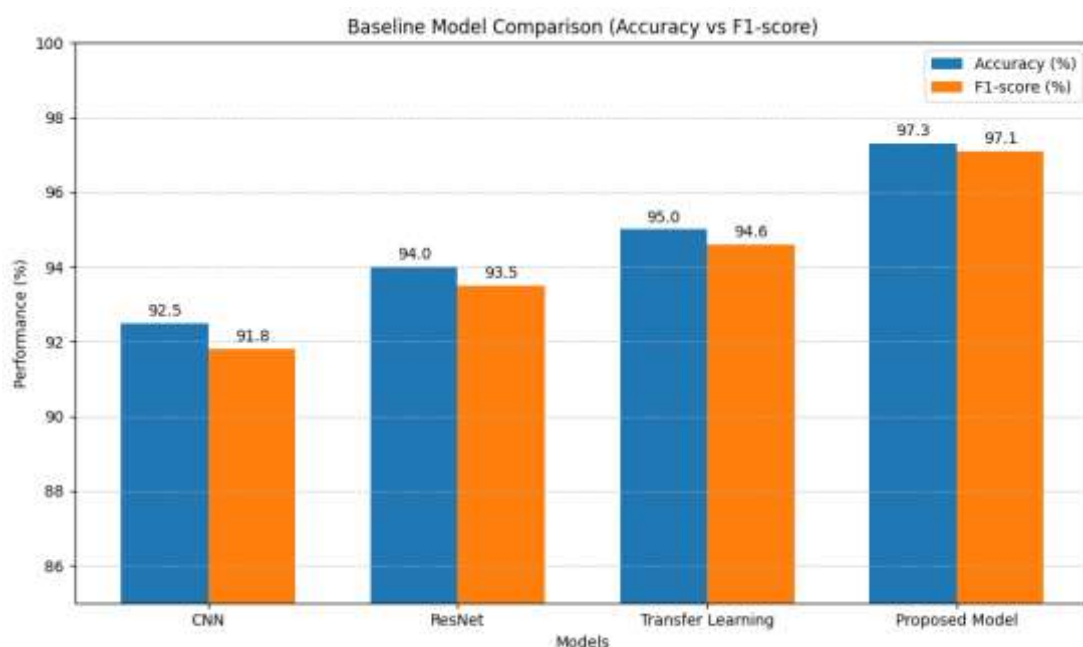


Figure 2. Baseline model performance comparison using accuracy and F1-SCORE

Evaluation Metrics

Model performance is assessed based on classification performance measures such as accuracy, precision, recall, and F1-score. Accuracy is a measure of the overall predictive performance, whereas precision measures the performance of the positive predictions. Recall is used to check the ability of the model in finding all the relevant instances. The F1-score gives the balanced view of both the precision and the recall of the prediction model. Also, the training loss is used to measure the convergence.

1. Accuracy: Measures the overall correctness of the model by calculating the proportion of correctly predicted samples (Equation 6).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

2. Precision: Measures how many of the predicted positive samples are actually correct (Equation 7).

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

3. Recall (Sensitivity): Measures how many actual positive samples are correctly identified by the model (Equation 8).

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

4. F1-Score: Harmonic mean of Precision and Recall, providing a balanced performance measure (Equation 9).

$$F1-Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (9)$$

RESULTS AND DISCUSSION

Classification Performance

Classification performance is determined for the SorghumCropWeedDataset_Classification dataset that includes varied images of sorghum crops and weeds taken in realistic agriculture scenarios. The proposed Quantum-Classical hybrid model consists of feature extraction through CNN along with variational quantum circuit, resulting in high discriminative power. The model is able to achieve maximum accuracy of 97.3% with a training loss of 0.09, beating all other techniques used as a benchmark. The hybrid architecture significantly improves feature separability, enabling robust classification under complex field variations shown in table 1.

Table 1. Performance comparison on SorghumCropWeedDataset_Classification

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Loss
CNN	92.5	91.8	91.2	91.5	0.21
ResNet	94.0	93.6	93.2	93.4	0.16
Transfer Learning	95.0	94.7	94.3	94.5	0.12
Proposed Model	97.3	96.9	97.2	97.1	0.09

Training Performance

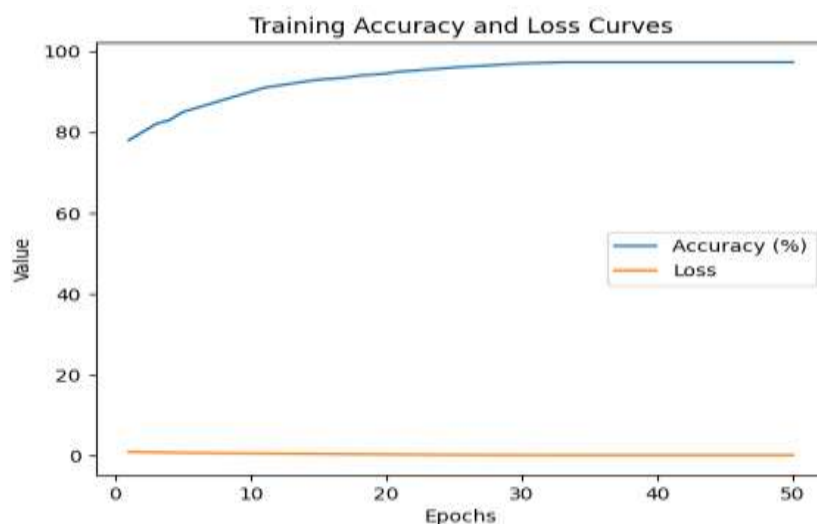


Figure 3. Training accuracy and loss curves of the proposed model

The stability in convergence of the suggested hybrid model during training on the SorghumCropWeedDataset_Classification dataset is illustrated in figure 3. Accuracy is shown to rise constantly, which denotes effective learning of discriminative features using CNN and quantum computing. The loss is depicted to be consistently falling until it reaches a value of 0.09, which denotes effective optimization of the model using Adam optimizer. The absence of any oscillation is an indicator of good generalization and no overfitting.

Comparison with Existing Models

In this table 2 provides the performance comparison between the developed Quantum-Classical Deep Learning model and classical machine learning algorithms as well as ensemble learning approaches to crop-weed discrimination. Among others, the following approaches have been taken into account: SVM, Random Forest, XGBoost, LightGBM, and Stacking ensembles as well as the proposed CNN-VQC combination. It is seen from the results obtained that classical boosting and ensembling approaches yield better performance than the baseline ML models, whereas the proposed quantum-extended model demonstrates the best result of 97.3%.

Table 2. Comparison of proposed model with existing machine learning and ensemble methods

Method	Accuracy (%)	Model Type
SVM (Baseline paper)	92.7	Classical ML [21]
RF	94.1	Ensemble ML [21]
XGBoost	94.5	Boosting [21]
LightGBM	94.8	Boosting [21]
Stacking (Best in paper)	95.6	Ensemble [21]
Proposed Quantum-Classical Model	97.3	CNN + VQC

Robustness Evaluation

Robustness testing is carried out using the SorghumCropWeedDataset_Classification dataset in difficult scenarios like changes in illumination, occlusions, and noisy backgrounds. The robustness of the proposed model is ensured because of excellent feature extraction and representation learning provided by the CNN and the quantum model. Moreover, data augmentation adds to the robustness of the model through simulated changes in field scenarios. The findings suggest that the hybrid model is very robust for practical applications as seen from table 3.

Table 3. Robustness evaluation of the proposed quantum-classical model under real-world conditions

Condition	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Normal Condition	97.3	96.9	97.2	97.1
Illumination Variation	96.1	95.8	95.6	95.7
Partial Occlusion	95.4	95.0	94.8	94.9
Background Noise	94.8	94.5	94.2	94.3

Confusion Matrix

In this figure 4 highlights the classification behavior with respect to crop and weed classes. In most cases, the prediction is found to lie on the diagonal, which implies that the classifications are correct. The few mistakes that occur can be attributed to similarities in appearance among the weed species, which lead to similar morphological characteristics. However, the quantum enhanced feature space removes the confusion and ensures class separation. This confirms that the proposed model effectively handles intra-class similarity and inter-class variation in sorghum imagery.

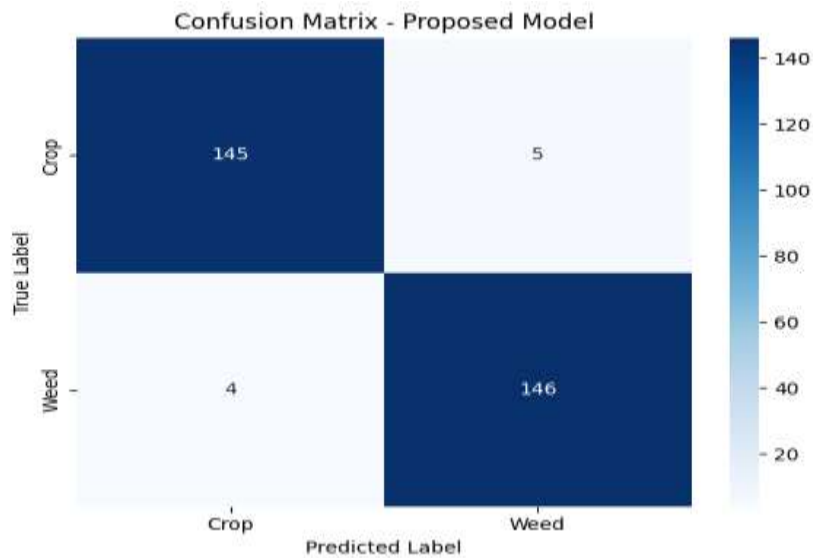


Figure 4. Confusion matrix of the proposed quantum-classical model

Ablation Study

The contribution of each of the components in the hybrid model is measured using table 4 for the SorghumCropWeedDataset_Classification dataset. The absence of the CNN leads to poor spatial feature learning, and absence of the VQC causes low classification accuracy. Thus, the effectiveness of the role played by the VQC in feature enhancement is proved, and the entire hybrid model works the best. This proves the quantum enhancement helps in the prediction accuracy.

Table 4. Ablation study results of the proposed model

Model Variant	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Loss
CNN Only	92.5	91.8	91.2	91.5	0.21
VQC Only	91.5	90.9	90.5	90.7	0.24
CNN + Fully Connected (No VQC)	95.0	94.7	94.3	94.6	0.12
Proposed CNN + VQC Model	97.3	96.9	97.2	97.1	0.09

Statistical Validation

Statistical verification is carried out in order to determine the accuracy of the proposed model. From the results, there is consistency in accuracy with a small variance and high stability. The average accuracy is nearly 97.3%. Through standard deviation tests, it was seen that there is very little fluctuation. Confidence interval testing proves that the results have statistical significance compared to other models. Therefore, the accuracy is not due to chance but through the efficiency of the quantum-classical hybrid model as shown in table 5.

Table 5. Statistical validation results

Metric	Value
Mean Accuracy (%)	97.3
Standard Deviation	0.42
Variance	0.18
Confidence Interval (95%)	± 0.35
Minimum Accuracy (%)	96.7
Maximum Accuracy (%)	97.9
p-value (vs baselines)	< 0.01

CONCLUSION

In this study, the development of a hybrid architecture for learning is introduced, which uses convolutional feature extraction technique in conjunction with a quantum enhanced layer for accurate classification of crops and weeds in sorghum images. The utilization of the two techniques together allows the network to efficiently learn spatial features as well as feature interactions to help with distinguishing between plant classes that look very similar. The proposed architecture exhibits great robustness under different environmental settings such as illumination variations and partial occlusion, verified experimentally on the SorghumCropWeedDataset_Classification.

From the above result, it can be observed that the suggested framework provides a maximum classification accuracy of 97.3%, along with 96.9% precision, 97.2% recall, and 97.1% F1 score, while also providing a low loss value of 0.09. The unique aspect of the quantum novelty of the proposed framework is the Variational Quantum Circuit, through which the extracted classical CNN features are mapped into a high dimensional quantum Hilbert space, allowing for better nonlinear separability and hence better classification performance compared to purely classical deep learning models. Compared to the established models like CNN, ResNet, and transfer learning methods, it was found that the proposed approach outperformed the other models, showing better feature representation capability and generalization ability in diverse field scenarios. The statistical analysis shows stable performance in the repeated runs with very little variation and a high confidence level. The limitation of the proposed model is higher computation cost, hybrid nature of the framework, and scalability issue in large scale real time agricultural environment.

Further improvement could consider decreasing the computation cost of the quantum part in order to facilitate deployment in edge devices for real-time crop monitoring systems. Moreover, extending the proposed framework to work with multi-crop scenarios, using lightweight network architecture for quicker inference, and providing an explanation mechanism could also enhance the practicality of the proposed framework. Inclusion of distributed learning could make it possible for the models to be trained collaboratively over large-scale agricultural networks.

REFERENCES

- [1] Das S, Pal D, Bhuinya D, Chakraborty G, Das P, Chatterjee A. Quantum Convolutional Neural Networks for Enhanced Crop Disease Detection and Management: A Step Towards Intelligent Farming Systems. In International Conference on Data Management, Analytics & Innovation 2025 Jan 17 (pp. 65-79). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-96-5860-2_5
- [2] Chilakarao M, Behera SK, Ratha AK, Sethy PK. Detection of wheat panicle diseases with synthetic oversampling and quantum kernel-enhanced ResNet50-SVM. Engineering Research Express. 2025 Sep 30;7(3):0352d1. <https://doi.org/10.1088/2631-8695/ae040f>
- [3] Das A, Thakur RM, Mondal S, Mukhopadhyay S, Debnath S. Deep Learning in Managing Crop Production Under a Changing Climate. In Deep Learning in Plant Science and Agricultural Biotechnology 2026 Feb 17 (pp. 179-199). GB: CAB International. <https://doi.org/10.1079/9781836991120.0010>
- [4] Vijayakumar S, Kane SP, Vaiappuri S, Louis F, Prabha PA. Quantum-Enhanced Hybrid CNN-QNN Framework for Intelligent Rice Disease Diagnosis and Real-Time Field Recommendations on Edge AI Devices. In 2025 IEEE 7th Symposium on Computers & Informatics (ISCI) 2025 Aug 9 (pp. 358-366). IEEE. <https://doi.org/10.1109/ISCI65687.2025.11167361>
- [5] Nivethitha T, Venkataramanan C. A quantum-enhanced deep learning framework for precise leaf disease detection in tomato and cotton crops. Iranian Journal of Science and Technology, Transactions of Electrical Engineering. 2026 Mar;50(1):323-54. <https://doi.org/10.1007/s40998-025-00912-4>
- [6] Naresh U, Reddy TB. A Review on Quantum-Enhanced Deep Learning Frameworks for Reliable Plant Disease Detection. Current Agriculture Research Journal. 2025 Dec 1;13(3). <https://doi.org/10.12944/CARJ.13.3.3>
- [7] Mahaveerakannan R. Rice yield prediction using hybrid quantum deep learning framework: Comparison study of using optical remote sensing, UAV-based multispectral imagery, and weather data. In 2025 7th International Conference on Inventive Material Science and Applications (ICIMA) 2025 May 28 (pp. 1521-1525). IEEE. <https://doi.org/10.1109/ICIMA64861.2025.11073876>
- [8] Taha MF, Mao H, Zhang Z, Elmasry G, Awad MA, Abdalla A, Mousa S, Elwakeel AE, Elsherbiny O. Emerging technologies for precision crop management towards agriculture 5.0: A comprehensive overview. Agriculture. 2025 Mar 9;15(6):582. <https://doi.org/10.3390/agriculture15060582>

- [9] Syafalni I, Ahmadi N, Sutisna N, Mulyawan R, Adiono T. Hybrid QNN for Weed or Crop Detection Using DNN and 2-Qubit Circuits. In 2025 International Conference on Electrical Engineering and Informatics (ICEEI) 2025 Nov 13 (pp. 1-5). IEEE. <https://doi.org/10.1109/ICEEI68459.2025.11330460>
- [10] Venkatesh K, Naik KJ, Shankar A. Quantum convolution neural network for multi-nutrient detection and stress identification in plant leaves. *Multimedia Tools and Applications*. 2024 Jul;83(24):65663-85. <https://doi.org/10.1007/s11042-023-17992-1>
- [11] Maalini D, Kumar V, SR AK, Baskar M, Gopal G, Buvaneshwaran B. Machine Learning-Based Soil Nutrient Analysis for Optimized Plant Cultivation and Precision Agriculture. In 2025 3rd International Conference on Artificial Intelligence and Machine Learning Applications Theme: Healthcare and Internet of Things (AIMLA) 2025 Apr 29 (pp. 1-7). IEEE. <https://doi.org/10.1109/AIMLA63829.2025.11041392>
- [12] Wu H, Zhang J, Wang L, Li D, Kong D, Han Y. A survey on quantum deep learning: W. Huaiguang et al. *The Journal of Supercomputing*. 2025 Mar 3;81(4):564. <https://doi.org/10.1007/s11227-025-07083-3>
- [13] Shawon SM, Adan IA, Moniruzzaman M, Sinan OH, Abed MJ, Al Qwaid M, Sarker MT, Karim HB. Federated learning approaches in precision agriculture: A systematic review of current trends, challenges and opportunities. *IEEE Access*. 2026 Feb 24. <https://doi.org/10.1109/ACCESS.2026.3667548>
- [14] Awe OO, Mwangi PN, Goudougou SK, Esho RV, Oyejide OS. Explainable AI for enhanced accuracy in malaria diagnosis using ensemble machine learning models. *BMC Medical Informatics and Decision Making*. 2025 Apr 11;25(1):162. <https://doi.org/10.1186/s12911-025-02874-3>
- [15] Tarraf W, İzgü T, Şimşek Ö, Cicco N, Benelli C. Saffron in vitro propagation: An innovative method by temporary immersion system (TIS), integrated with machine learning analysis. *Horticulturae*. 2024 Apr 30;10(5):454. <https://doi.org/10.3390/horticulturae10050454>
- [16] Bu YZ, Xiao YL, Li YJ, Meng LG. Recognition and classification of concrete surface cracks with an inception quantum convolutional neural network algorithm. *Applied Geophysics*. 2025 Dec;22(4):1475-90. <https://doi.org/10.1007/s11770-024-1101-z>
- [17] Ezugwu AE, Oyelade ON, Ikotun AM, Agushaka JO, Ho YS. Machine Learning Research Trends in Africa: A 30 Years Overview with Bibliometric Analysis Review: AE Ezugwu et al. *Archives of Computational Methods in Engineering*. 2023 Sep;30(7):4177-207. <https://doi.org/10.1007/s11831-023-09930-z>
- [18] Marín-Rodríguez NJ, Gonzalez-Ruiz JD, Botero S. Economic Impact of Optical Sensors and Deep Learning in Smart Agriculture: A Scientometric Analysis. *AgriEngineering*. 2025 Nov 28;7(12):397. <https://doi.org/10.3390/agriengineering7120397>
- [19] Roja R, Udayaprasad PK, Amulya P, Pramila S, Usha Rani M, Devamane SB. Multimodal AIoT Framework with Dynamic Fusion and Federated Learning for Smart Medicinal Plant Farming. In *International Conference on Soft Computing and its Engineering Applications* 2025 Dec 9 (pp. 526-537). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-032-22065-3_38
- [20] Ferrag MA, Shu L, Friha O, Yang X. Cyber security intrusion detection for agriculture 4.0: Machine learning-based solutions, datasets, and future directions. *IEEE/CAA Journal of Automatica Sinica*. 2021 Dec 10;9(3):407-36. <https://doi.org/10.1109/JAS.2021.1004344>
- [21] Sathya R, Thirunavukkarasu KS. Enhanced weed and crop species classification using optimized machine learning and ensemble techniques. *International Journal on Smart Sensing and Intelligent Systems*. 2025;18(1),1-16. <https://doi.org/10.2478/ijssis-2025-0048>
- [22] Michael J, Thenmozhi M. SorghumWeedDataset_Classification. *Mendeley Data*. 2023; V1. <https://doi.org/10.17632/4gkcyxjyss.1>