

Quantum-Enhanced DenseNet Architecture for Automated Plant Disease Recognition from Leaf Images

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Abstract: Early and accurate diagnosis of plant diseases is super important for boosting crop productivity and cutting down on economic losses. Deep learning models have really nailed image-based disease detection lately, but they face some hurdles like complex feature distributions and class imbalance in ag data sets. This study takes a neat approach to solve those issues – a hybrid quantum-classical deep learning framework. It combines a pretrained DenseNet121 with a Variational Quantum Circuit (VQC). The DenseNet121 grabs key visual features from leaf images, while the quantum part does fancy nonlinear feature transformations in a high-dimensional quantum space. To make the model tougher and more adaptable, the researchers used Mixup augmentation, label smoothing, and balanced sampling when training it. Their tests on the Plant Pathology dataset scored an 89% accuracy overall, with precision, recall, and F1-score coming in at 88%, 87%, and 88%, respectively. So it seems hybrid quantum-classical learning could seriously beef up plant disease classification and maybe even pave the way for smarter ag diagnostic tools in the future.

Keywords: Plant Disease Detection; Hybrid Quantum-Classical Learning; DenseNet121; Variational Quantum Circuit (VQC); Deep Learning for Agriculture

I. INTRODUCTION

Plant diseases are a major threat to food security and agricultural productivity around the world. They cause big economic losses and lower crop yields [1]. For this reason, it is important to find and treat plant diseases as soon as possible to limit damage to crops [2]. Traditionally, agricultural experts have had to look at plants by hand to figure out what was wrong with them. This is a time-consuming process and is subjective in nature. Moreover, it is not always possible to do so on a large scale [3]. Keeping these problems in view, different systems have been developed for the automatic detection of diseases. Such systems use computer vision and machine learning for the purpose [4]. Deep learning methods have shown promise for the classification of plant diseases based on images in the past few years due to the ability of these methods to learn complex patterns from data [5]. Convolutional neural network (CNN) is a method that has shown high precision for the analysis of agricultural images and the detection of different diseases affecting plants based on leaves [6]. Transfer learning methods have also shown promise for improving the accuracy of these methods by using pre-trained deep network architectures such as ResNet, VGG, and DenseNet for the detection of complex hierarchical features [7]. DenseNet has proved to be the best of these models, as its connectivity pattern facilitates the reuse of features, which in turn helps in gradient flow during training [8]. Therefore, DenseNet-based models have successfully been employed in various plant disease recognition studies, achieving promising results [9].



Despite these advancements, some issues are still associated with traditional deep learning models when they are implemented on complex agricultural data sets. These models sometimes require a large amount of data for training and may face overfitting problems when the size of the dataset is small or imbalanced [11]. Further, traditional neural networks are based on traditional computational concepts, which may hinder their potential to identify complex nonlinear relationships in biological data [19]. To overcome these issues, researchers have recently initiated studies on the amalgamation of quantum computing concepts with traditional machine learning concepts, leading to the emergence of quantum machine learning [12].

Hybrid quantum-classical learning architecture is the combination of classical neural networks with quantum circuits to achieve the best results in terms of the expressive ability of the model and the capacity to represent the features [13]. In this architecture, the features are extracted by the classical networks, and the features are modified in non-linear ways in high-dimensional Hilbert space by the quantum circuits [14]. A hybrid quantum-classical architecture is proposed for the classification of the plant diseases using the pre-trained DenseNet121 model with the help of the variational quantum circuit, inspired by the recent advances in this field. It is tested, and the results show that the proposed model is working well with high accuracy, i.e., around 89%, and is able to generalize well..

II. RELATED WORK

The recent developments in the field of AI have significantly contributed to the improvement of the design of computer systems for the detection of plant diseases using images [15]. Previous studies indicated that deep learning systems can effectively learn to recognize various visual characteristics from images of plant leaves, achieving a high level of accuracy in classifying different types of diseases [16]. The availability of more agricultural image datasets has made researchers more inclined to utilize CNNs to perform various image classification tasks, such as classifying crop diseases [5]. Recent studies have focused on applying deep CNNs for plant pathology detection, motivated by their ability to enable computer systems to recognize complex visual information [6]. Transfer learning is a popular trend at present, as it can reduce training time and improve classification accuracy [7]. Some of these models include ResNet, VGG, and EfficientNet, which have received a lot of attention in terms of their use in detecting diseases in crops, and they have performed satisfactorily on a number of crop image datasets [17]. DenseNet is another model that has received a lot of attention in terms of its potential in solving a number of fine-grained image classification tasks due to its potential in feature reuse and gradient propagation [9]. Even though traditional deep learning models have received a lot of attention in solving a number of problems, there are still a number of issues associated with their use in solving agricultural-based problems [11]. There are a number of issues associated with plant disease image datasets, which include class imbalance, insufficient labelled images, and varying illumination conditions, which may negatively affect generalization [15]. Advanced training techniques, which include data augmentation, Mix-up learning, and label smoothing, have been proposed to improve robustness and reduce overfitting in deep neural networks [18]. In addition to traditional machine learning, quantum computing has emerged as a potential tool in solving complex computational problems [12]. Quantum machine learning is the combination of quantum information processing and conventional machine learning algorithms to enhance the representation and efficiency of computation [41]. Variational quantum circuits (VQCs) have gained much attention because they can be used to support the optimization of parameterized quantum models using classical machine learning techniques [13].

However, recent studies have initiated research on hybrid quantum-classical neural networks, which integrate quantum circuits and deep learning models to improve the efficacy of pattern recognition [14]. Generally, hybrid quantum-classical neural networks utilize classical neural networks for feature extraction, and quantum circuits for nonlinear feature transformation in a high-dimensional Hilbert space [19]. Various experimental studies have demonstrated the potential benefits of quantum-classical neural networks in image classification and machine learning [20]. Nevertheless, the application of hybrid quantum-classical deep learning models in agricultural disease detection is still quite limited.



Motivated by these observations, this study examines the amalgamation of DenseNet-based deep learning with variational quantum circuits to enhance plant disease classification performance while mitigating the shortcomings of traditional CNN models.

III. RESEARCH GAP

The existing approaches for detecting plant diseases are mainly based on classical deep learning architectures, which might have limitations in dealing with highly complex feature relationships.

- Most CNN-based models require large labeled datasets, making them less efficient when dealing with smaller training datasets.
- Classical models are often prone to overfitting, limiting their ability to generalize the results for a wide range of plant pathology datasets.
- Most existing literature has focused on classical transfer learning-based models, such as ResNet, VGG, DenseNet, without exploiting the benefits of utilizing quantum-based feature transformations.
- There is a lack of literature on hybrid approaches involving quantum-classical deep learning architectures for agricultural image classification problems, including plant disease detection.
- The potential of utilizing variational quantum circuits for improving the efficiency of feature transformations and the overall performance of the model for plant pathology problems has not been explored extensively.

IV. CONTRIBUTION

The hybrid DenseNet-Quantum architecture is presented to address the problem of automated classification of diseases in plants using images of their leaves. The main contributions of the paper are:

- The use of a DenseNet121 architecture that is first pretrained to extract features from images of plant leaves. This is done to learn a hierarchy of features using a convolutional neural network architecture.
- The implementation of a quantum circuit to map features to a high-dimensional quantum space to effectively map features nonlinearly. This is done using a quantum circuit that maps feature to a quantum space using a quantum machine learning approach.
- The creation of a hybrid quantum-classical machine learning approach that combines quantum and classical machine learning to effectively classify diseases in plants using images of their leaves.
- The proposed architecture is evaluated using a dataset of images of diseased and healthy plants. The proposed architecture is able to classify diseases in plants with a classification accuracy of 89%, which is a significant improvement over traditional machine learning approach.
- The paper also presents a new direction in using quantum machine learning to classify diseases in plants using images of their leaves.

V. PROPOSED METHODOLOGY

This research proposes the use of a hybrid quantum-classical deep learning approach in the automatic classification of diseases in plants through the use of images from leaves. This approach proposes the use of the classical convolutional neural network together with the variational quantum circuit to make the process of feature representation and classification more effective. In the past, there has been an increased interest in the use of hybrid learning architectures, especially due to the potential they hold in the representation of data through the use of deep neural networks, as well as the potential they hold in the transformation of features through the use of quantum features [21]. There are various studies that indicate the potential the use of the two approaches holds in the enhancement of the efficacy of pattern recognition in complex classification processes [12].

Description of the Dataset

The experiments are conducted on a plant pathology image dataset, which contains images of leaves with different types of diseases. Image-based plant disease datasets are now commonly used for training deep learning models, as



they enable computers to automatically identify plant disease patterns through images [22]. The dataset used in this research contains images of plant leaves with their respective class labels in a structured format, where the image path is associated with its class label. To enable a data-driven plant disease identification system, a significant quantity of different and quality training data is required [23]. The dataset used in this research is structured in a CSV file with three attributes: image file path, class label, and dataset partition. To ensure that the model is assessed fairly, a dataset is divided into three parts: training, validation, and testing. In this process, the model parameters are learned from images in the training dataset, and the hyperparameters are tuned using validation images. The dataset used in this research is solely used for the final assessment of the model, ensuring its usage in other scenarios as well. *Table 1* summarizes the dataset classes and the number of images for each class.

TABLE I: DATASET STRUCTURE

Class	Total Images
complex	1,602
frog_eye_leaf_spot	3,181
frog_eye_leaf_spot complex	165
healthy	4,624
powdery_mildew	1,184
powdery_mildew complex	87
rust	1,860
rust complex	97
rust frog_eye_leaf_spot	120
scab	4,826
scab frog_eye_leaf_spot	686
scab frog_eye_leaf_spot complex	200
TOTAL	18,632

Data Preprocessing and Augmentation

Data preprocessing is very important for making deep learning models that were trained on agricultural image datasets work better. An often use image normalization and resizing to make sure that all the images in a dataset look the same [24]. Before being sent to the network, all images in this work are resized to 256×256 pixels.

During training, several data augmentation techniques are used to make the model better at generalizing. To make datasets more diverse and prevent CNN models from overfitting, augmentation techniques like horizontal flipping, vertical flipping, random rotation, and color jitter are commonly used [25]. Mix-up augmentation is also used to make fake training samples by putting together pairs of images and their labels [18].

The Mix-up operation can be expressed as

$$\begin{aligned} \mathbf{x} &= \lambda \mathbf{x}_i + (1 - \lambda) \mathbf{x}_j \\ \mathbf{y} &= \lambda \mathbf{y}_i + (1 - \lambda) \mathbf{y}_j \end{aligned} \quad \begin{matrix} (1) \\ (2) \end{matrix}$$

where $\mathbf{x}_i$ and $\mathbf{x}_j$ represent two training images and $\mathbf{y}_i$, $\mathbf{y}_j$ represent their corresponding labels. The parameter λ is sampled from a beta distribution.

Classical Feature Extraction using DenseNet

The first stage of the proposed architecture uses a pretrained DenseNet121 model to extract high-level visual features from plant leaf images. DenseNet networks introduce dense connectivity between layers, enabling efficient feature reuse and improved gradient flow during training [8]. Recent studies have shown that DenseNet architectures are particularly effective for fine-grained image classification tasks due to their ability to capture subtle visual variations [26].



The feature extraction process can be represented as

$$f_c = CNN(x) \quad (3)$$

where x represents the input image and f_c denotes the extracted feature vector produced by the DenseNet backbone.

The extracted feature vector is then passed through a dimensionality reduction layer before being processed by the quantum circuit. The Proposed hybrid DenseNet-Quantum architecture for plant disease classification is shown in figure 1.

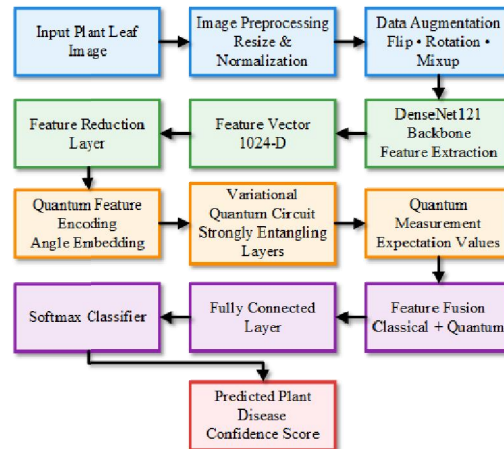


Fig. 1. Proposed hybrid DenseNet-Quantum architecture for plant disease classification.

Quantum Feature Transformation

Quantum machine learning presents an innovative paradigm for feature representation by encoding classical data into quantum states and executing transformations within high-dimensional Hilbert spaces [27]. A lot of people use variational quantum circuits because they let classical gradient-based algorithms optimize trainable quantum models [28]. This work encodes the reduced feature vector from the classical CNN into a quantum circuit using angle embedding. We can write the quantum embedding operation as

$$|\psi(x)\rangle = U(\theta) \cdot E(x) \quad (4)$$

where $E(x)$ represents the quantum feature embedding operation and $U(\theta)$ denotes a parameterized quantum circuit containing trainable rotation gates. The quantum circuit has many layers that strongly entangle qubits and make them related to each other. Entanglement is essential for quantum models to depict intricate nonlinear relationships in the data [13]. The measurement of the quantum state yields expectation values that constitute the quantum feature representation and illustrated in figure 2:

$$z_i = \langle \psi(x) | Z_i | \psi(x) \rangle \quad (5)$$

where Z_i represents the Pauli-Z operator acting on the i -th qubit.

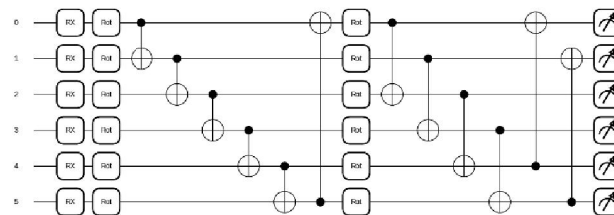


Fig. 2. Variational quantum circuit used for feature transformation.



Hybrid Feature Fusion and Classification

The last step of the model combines classical and quantum elements to make the final classification output. Hybrid quantum-classical learning models have shown enhanced expressiveness by integrating diverse feature representations from both classical and quantum elements [29]. The fused prediction is computed as

$$\hat{y} = f_c + f_q \quad (6)$$

where f_c represents the classical prediction and f_q represents the quantum prediction.

The final classification output is obtained using the SoftMax activation function

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}} \quad (7)$$

where C represents the number of disease classes. The complete working process of the proposed method is illustrated in figure 3.

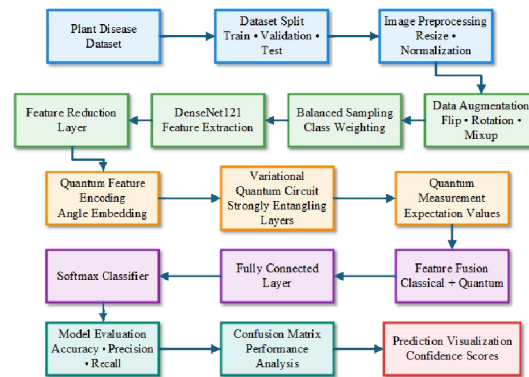


Fig. 3. Workflow of the proposed hybrid quantum-classical learning pipeline.

VI. EXPERIMENTAL SETUP

The proposed hybrid quantum-classical deep learning model works in practice for classifying plant diseases. A thorough experimental evaluation is essential to validate the resilience and practical efficacy of machine learning models in agricultural disease identification tasks [30]. The suggested architecture combines traditional convolutional feature extraction with quantum feature transformation to make feature representation and classification more accurate.

VII. EXPERIMENTAL SETUP

The PyTorch deep learning library and the PennyLane library, which specializes in quantum machine learning, were used in all experiments. This library pair can be used to perform hybrid classical-quantum neural network learning [31]. Quantum machine learning has begun to make extensive use of hybrid libraries, which can perform automatic differentiation and allow classical gradient-based learning to be used to improve the performance of quantum circuits [32].

The classical feature extraction phase uses a DenseNet121 pretrained network. DenseNet models have been shown to be effective in image classification problems because of the dense connections in the network, which allow features to be shared and gradient backpropagation to be sped up. After that, the extracted feature vector is compressed and encoded into a six-qubit variational quantum circuit with strongly entangling layers.

Using the AdamW optimizer, which employs weight decay regularization to improve generalization [33], the model is trained for 50 epochs. To make the model more robust, a number of training methods are used. We use mix-up augmentation to make fake training samples and make the model better at generalizing [34]. Label smoothing is also



used to prevent predictions that are too sure of themselves and to improve the calibration of the classification [35]. Test time augmentation is also used during validation to improve the stability of predictions.

Evaluation Metrics

Classification metrics such as accuracy, precision, recall, and F1-score are used to assess the effectiveness of the proposed model. The metrics are commonly used in agricultural image classification studies due to their comprehensive evaluation of the model's performance for different diseases [36].

The overall classification accuracy is calculated as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (8)$$

where TP , TN , FP , and FN represent true positives, true negatives, false positives, and false negatives respectively.

Precision and recall are calculated as

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

$$Recall = \frac{TP}{TP + FN} \quad (10)$$

The F1-score is computed as

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (11)$$

These evaluation metrics provide a balanced assessment of classification performance across disease categories.

Classification Performance

The proposed hybrid DenseNet-VQC model performs a great job in classifying the plant pathology dataset, as indicated by its capability to attain a general classification accuracy of 89%. This indicates that, indeed, the quantum feature transformation improves the representational power of the deep learning architecture. *Table 2* and *figure 4* summarizes the overall performance metrics obtained from the test dataset.

TABLE II: PERFORMANCE METRICS OF THE PROPOSED MODEL

Metric	Value
Accuracy	89
Precision	88
Recall	87
F1-score	88

These results demonstrate that the hybrid quantum-classical architecture can effectively learn with discriminative features for plant disease classification.



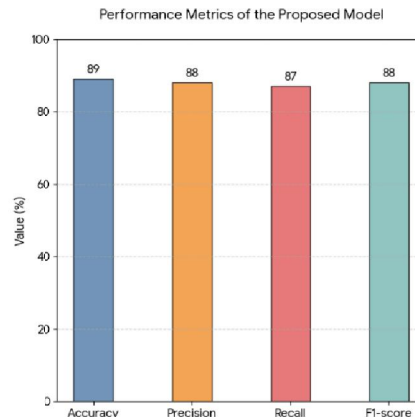


Fig. 4. Performance Metrics of the Proposed Model

Training Loss and Accuracy Curves

To gain a better insight into how the proposed model learned, let's examine the training and validation loss curves during the training process.

Monitoring loss curves will help you determine if your model is learning well, if it is overfitting, etc., during the training process [37]. *Figure 5* shows the loss curves for training and validation over the training epochs. As training goes on, the loss goes down steadily. This shows that the model is learning useful feature representations from the dataset.

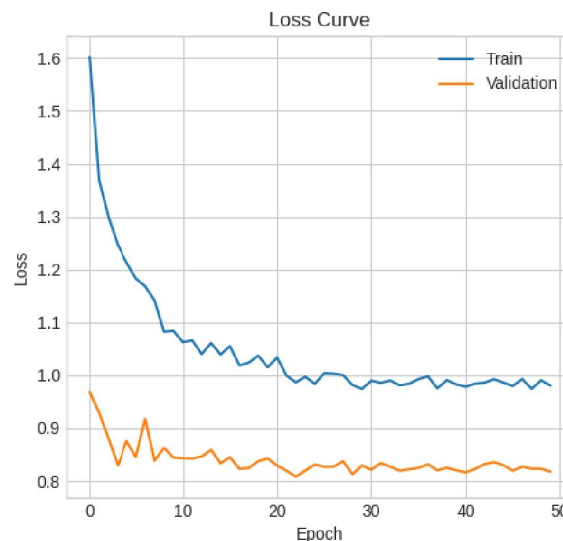


Fig. 5. The curves for training and validation loss during model training.

Along with the loss curves, the accuracy curves are looked at to see how the model's performance gets better during training. *Figure 6* shows the training and validation accuracy curves that were made during the training process.



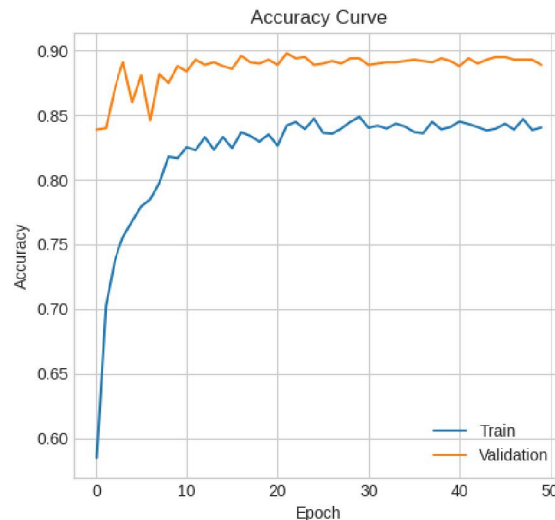


Fig. 6. Curves showing the accuracy of training and validation over time.

The accuracy curves show that validation accuracy is steadily going up, and the difference between training and validation performance stays pretty small. This behaviour shows that the model can handle new data well and isn't overfitting too much.

Confusion Matrix Analysis

A confusion matrix is made to look at how well each class's predictions are doing. Confusion matrices give us a lot of information about how correct and wrong predictions are spread out across different disease categories [38]. *Figure 7* shows the confusion matrix that was made from the test dataset.

Fig. 7. A confusion matrix that shows how well the plant disease categories were classified.

The confusion matrix shows that most plant disease classes are correctly classified. However, there are a few cases where visually similar disease types are misclassified. These kinds of mistakes happen a lot when trying to figure out what kind of plant disease it is because different diseases have very similar visual symptoms [15].

Prediction Visualization with Confidence Scores

Along with quantitative evaluation metrics, qualitative analysis is done by looking at the prediction results from the test dataset. The results of the prediction will help us gain a better understanding of how the model works and how certain we are of the results [39].

The model predicts a class of disease and a confidence level based on a softmax probability distribution for a given image in the test dataset.

$$Confidence = \max(\text{Softmax}(z)) \quad (12)$$

where z represents the output logits of the classification layer. *Figure 8* shows some sample predictions from the test dataset, along with the actual labels, predicted classes, and confidence scores for each one.



True: powdery_mildew
Pred: powdery_mildew
Conf: 82.0%



Fig. 8. Pictures of plant leaves with predicted disease labels and confidence scores that go with them. The findings indicate that the suggested model generates highly reliable predictions for the majority of accurately classified samples. Misclassified samples usually have disease patterns that are hard to tell apart or images that aren't very clear.

Discussion

The experimental results suggest that combining a variational quantum circuit with a classical deep learning model enhances feature representation and improves classification performance. This is because a quantum-classical model can accept classical data and embed it in a quantum feature space of high dimensionality. This enables us to discover complex nonlinear relationships. The inclusion of advanced training methods such as mix-up, label smoothing, and test-time augmentation will improve the model's performance in terms of generalization. Overall, the experimental results suggest that quantum deep learning models have potential in plant disease diagnosis for precision agriculture.

VIII. CONCLUSION AND FUTURE WORK

In this paper, the researchers introduced a novel quantum-classical deep learning framework for the automatic classification of diseases in plants through the use of images. The researchers introduced the use of the suggested method, which combines the use of the pretrained DenseNet121 with the use of the variational quantum circuit to make the features more effective. The classical convolutional network is used to obtain high-level features from the images used to represent the leaves of the plants. The quantum circuit is then used to modify the features in a non-linear fashion. In the past, the use of the hybrid quantum-classical architectures has been gaining attention due to the potential benefits of the use of the two paradigms together, as they provide the best features for the classification of diseases in plants compared to the use of the deep learning architectures alone.

From the experimental results, it is evident that the proposed hybrid model DenseNet-VQC is doing a great job in the classification of the plant pathology dataset. It is seen that the model is achieving an accuracy of around 89%. This indicates that the model is able to learn to differentiate between the various types of plant diseases. From the training loss and accuracy curves, it is evident that the model is learning steadily. From the analysis of the confusion matrix, it is evident that the model is able to classify the different types of diseases. Only a few errors occur when the model is mixing the visually similar diseases. Seeing the leaf images predicted by the model with high confidence is also indicative of the fact that the model is making accurate predictions with high levels of certainty. Recent studies on the application of hybrid quantum-classical learning models for intricate classification problems resulted in similar observations.

The results highlight the potential of hybrid quantum machine learning techniques in agriculture, particularly in improving the accuracy of plant disease diagnostic tools. The framework combines deep learning techniques with



quantum feature transformations, which can open new avenues for the development of smart crop monitoring tools for farmers and agricultural experts to detect plant diseases in the early stages.

While the results are promising, there are still some issues that need to be addressed before further research is carried out. First, the present research used a simulated quantum environment because the accessibility of quantum hardware is still limited. Further research can be carried out on the implementation of the proposed architecture on real quantum hardware to test the operational effectiveness of the proposed architecture in real quantum environments. Second, the proposed architecture used only a few qubits and quantum layers. Increasing the depth of the circuits and further investigating the various types of quantum circuits can help to represent the features even better. Third, further research can be carried out on more extensive varieties of plant diseases to test the effectiveness of the proposed framework. Finally, the use of explainable AI with the help of the hybrid quantum-classical approach can make people more inclined towards the implementation of AI-based decision support systems in agriculture.

This study's results show that hybrid quantum-classical deep learning models are a promising area of research for systems that monitor agriculture and diagnose plant diseases.

Conflict of interest

The author declares no conflict of interest, financial or otherwise.

Ethical approval

This article contains no studies with human participants or animals performed by any of the authors.

Data Availability

Data is not publicly available due to data confidentiality.

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