Hybrid Quantum Classical AI System to Detect High-accuracy Leaf Disease Recognition and Oesophageal Cancer Diagnosis

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Abstract. Medical and agricultural sector needs to make timely and accurate diagnosis of the disease in order to sustain crops and keep patients alive. Although conventional deep learning models can be also applicable to provide good performance, they are also typified with high-computational and scaling along with high-dimensionality agricultural and medical images. In a bid to overcome these challenges, the current paper proposes a Hybrid Quantum -Classical Artificial Intelligence (HQCAI) system that should be used in dual-domain image classification, namely, plant leaf disease classification and oesophageal cancer classification. The proposed architecture implements a conventional Convolutional Neural Network (CNN) to obtain spatial features of high quality and quantum-enhanced classifiers to optimize the decision boundaries relying on quantum superposition and parallelism with Variational Quantum Circuits (VQCs) and Quantum Support Vector Machines (QSVMs). It presents a common knowledge representation layer in order to help in the effective storage of characteristics, cross-domain learning and intelligent inference between heterogeneous data sets. Experiments are carried out with the help of the data collection. The proposed hybrid model gives a better classification rate of 98.42, with precision of 98.11, recall of 97.94 and F1-score of 98.02 compared to CNN and CNN-SVM models in the state of the art. Convergence and performance of the system is also better when noises are present. The results support the practical role of quantum-enhanced visual classification and describe the prospects of hybrid quantum classical intelligence of the agricultural diagnostics and medical diagnostics systems in the future.

Keywords. Hybrid Quantum -Classical AI, Convolutional Neural Network, Variational Quantum Circuit, Quantum Support Vector Machine, Leaf Disease Detection, Oesophageal Cancer Diagnosis, Medical Image Classification, Quantum Machine Learning.

1.Introduction

Prompt and precise identification of the diseases of the plant leaves are critical in enhancing crop productivity and in making sure that agricultural activities are sustainable. Conventional visual inspection systems are time consuming and subject to human error and they are usually not able to detect infections at early stages. The latest developments in the field of deep learning have made it possible to classify diseases with automated and accurate methods using leaf images, which is much better than traditional methods. The application of Convolutional Neural Networks (CNNs) has gained significant popularity due to the capability of learning spatial and hierarchical features and producing strong results in various crop datasets . Nevertheless, classical deep learning models can have difficulty handling high-dimensional images and thus involve high resource consumption, including a longer training period. In order to address these challenges, hybrid quantum-classical models have been developed, which capitalize on features of quantum computing, including superposition and entanglement, to provide a better representation of features and increases classification accuracy . These quantum-enhanced approaches have the potential to enhance boundaries in decision-making and generalization of models especially in complex or noisy data . Also, it has been suggested to use multi-prediction strategies that will be able to locate the crop type and to detect the disease at the same time, making it even more accurate and applicable in practice . Inspired by these developments, the current research suggests Hybrid Quantum -Classical AI system to detect leaf disease with high accuracy, which will involve classical CNNs and quantum-enhanced classifiers to attain quicker convergence and target better results.

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1.1 Objective

- To develop and design a Hybrid Quantum -Classical Artificial Intelligence (HQCAI) architecture to classify diseases accurately in agricultural and medical imaging fields.
- To classify high- quality and discriminative spatial features of plant leaf and oesophageal images with the help of a classical Convolutional Neural Network (CNN).
- To implement quantum-enhanced classifiers to variational quantum circuits (VQCs) and quantum support machine (QSVMs) to maximize the boundary of decisions using quantum superposition and parallelism.
- To assess the performance of the proposed HQCAI system based on conventional performance rates of accuracy, precision, recall and F1-score as well as to compare the performance of the proposed system with that of the current CNN and CNN-SVM models.
- To examine the strength of the proposed system and convergence behaviour of the proposed system with noisy data conditions to prove that it is suitable to be used in the future agricultural and medical diagnostic processes.

1.2 Working contribution

- It's improved image-based disease classification in agricultural and medical applications, a hybrid quantum-classical artificial intelligence model is proposed, that is, classical convolutional neural networks implementation is coupled with quantum machine learning models to implement improved and enhanced disease classification through a hybrid framework.
- A CNN is used to extract high-quality spatial features on plant leaf and oesophageal images and encode them into quantum states, which are used in quantum-enhanced learning.
- Variational Quantum Circuits and Quantum Support Vector machines are used to maximise the decision boundaries by using quantum superposition and quantum parallelism resulting in more accurate classification.
- A common knowledge representation system is proposed to facilitate effective storage of features, cross domain learning as well as intelligent inferences between heterogeneous agricultural and medical data.
- Experimental analysis shows that the suggested hybrid system is more accurate, converges faster and is more robust to noisy environments than the current CNN and CNN-SVM models.

1.3 Organization of the paper

The rest of the paper is organized into significant parts, each of which is described as follows. Section ii lists the research projects Hybrid Quantum classical AI System to detect high-accuracy leaf disease recognition and oesophageal cancer diagnosis completed by various authors. The suggested method's workflow is defined in section iii, and the results and performance analysis of Hybrid Quantum classical AI System to detect high-accuracy leaf disease recognition and oesophageal cancer diagnosis are presented in section iv. The conclusion of the proposed work that will be done in a future scope is included in section v, along with references.

2. Related Works

QEFS is a quantum-inspired evolutionary features selection scheme that is suggested by **Anand et al., (2025)** to forecast diseases in plants. This method is much more effective in analyzing agricultural images in dimensionality reduction and accuracy, convergence speed and strength in terms of optimization of discriminative features prior to classification in comparison to the conventional method of feature selection.

VQ-Rice was proposed by **Verma et al., (2025)**, a variational quantum circuit-based rice disease, which is an improved version of VQ-Rice based on deep-learning. It has been illustrated that the hybrid architecture has adopted the advanced correlation of features and efficacy of quantum models on the accuracy of the agriculture systems has been clarified by the fact that hybrid architecture is feasible practically in terms of feature classification.

Al **Muntazhar et al., (2024)** have suggested a hybrid quantum neural network in the classification of rice leaf disease. The visual characteristics that classical CNNs generate are computed using quantum layers to improve the representational power and it improves classification with the benefits of hybrid quantum-classical learning.

The hybrid quantum-classical algorithms were studied by **Arquam et al., (2025)** so as to classify binary diseases according to neural networks. Their method substitutes the classical preprocessing and quantum variational circles that are more correct and stable as compared to the purely classical circles with the strength of scaling out hybrid quantum learning to medical and farming diagnostics.

In the study, **Das et al., (2025)** came up with a quantum convolutional neural network to detect crop disease. QCNN is effective in encoding the spatial patterns and less level of complexity of the computation and enhance the accuracy of the classification thus making a contribution in the execution of the intelligent and sustainable farming decision-support systems.

Gunisetti et al., (2024) were also able to develop some hybrid optimized deep quantum neural network that would be applied on an IoT system to detect the maize leaf disease. This system can also enhance the accuracy of detection, energy optimization and real-time monitoring of smart agriculture setting because it is a hybrid of routing optimization and quantum learning.

The parallel, hybrid quantum and classical neural network architecture created by **Xu et al., (2025)**, is a high-level neural network architecture that classifies images using the hybrid neural network architecture. The model allocates learning of features along quantum and classical paths, and has increased scalability, quicker training and augmented durability, and it displays scalability of quantum-aided models on medium-scale image recognition issues.

According to **Rahmani et al., (2025)**, a Quantum Vision Transformer may be applied to identify tomato leaf disease. The model is useful in the global contextual data capture compared to CNN-based, by quantum attention, which results to more diagnostic values and fortification in complex image conditions in the agricultural field.

What **Genemo et al., (2023)** suggested is the proposed quantum convolutional neural network that can be used to carry out agricultural mechanization and plant diseases detection. The QCNN has the ability to assess the pattern recognition potential, which encodes quantum characteristics and convolutes them, and the performance of this technology is higher than its classical Analog in the detection of early stages of plant diseases.

The suggested Q Trans Leaf Net Q Trans Leaf Net introduced by **Kumar et al., (2025)** was a quantum-enhanced and interpretable neural network applied to the disease prediction of the apple leaf disease segmentation and classification. This model combines quantum layers and explainability mechanism to offer high accuracy with explainable insights that are relevant in offering credible agricultural decision-making systems.

3. Proposed Methodologies

The suggested Hybrid Quantum Classical Artificial Intelligence (HQCAI) approach combines the classical deep learning with quantum machine learning to create highly accurate disease classification in the agricultural and medical imaging fields. To start with, the original input plant leaf images and the oesophageal endoscopic images are pre-processed by resizing, normalization and noise reduction in order to provide a uniform data quality. A standard Convolutional Neural Network (CNN) will then be used to get the robust and discriminative spatial features of the high-dimensional image data. These features which are extracted are then encoded into quantum states with the help of appropriate quantum feature mapping methods. Quantum Support Vector Machines and Variational Quantum Circuits are quantum enhanced classifiers and are trained to use quantum superposition and quantum parallelism to better define the classes and optimal decision boundaries. It is integrated with a knowledge representation layer in order to store acquired features and cross field sharing the knowledge between agricultural and medical data. Lastly, the system is classified and evaluated with standard performance measures, which is known to provide better accuracy, convergence quicker and is more robust to noisy condition than traditional classical learning models.

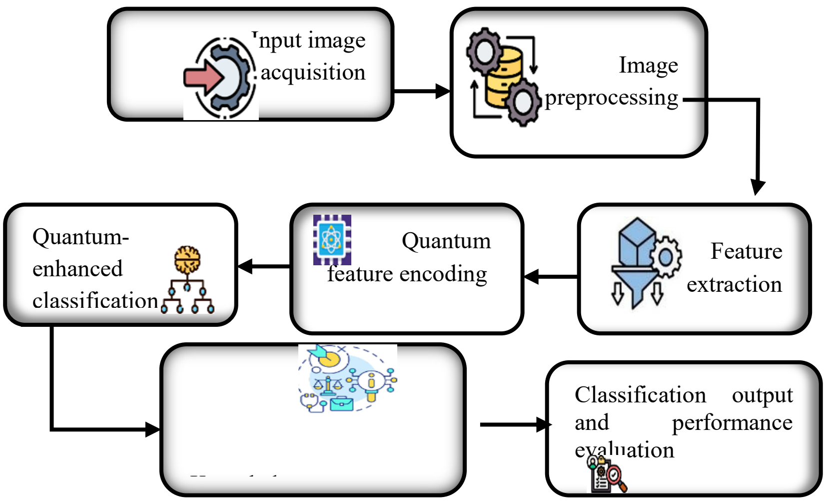


Fig. 1. Block diagram for proposed system

The proposed Hybrid Quantum-Classical AI model presented in figure 1 illustrates depicts the process starting with image gathering and processing and then moving on to CNN based feature extraction and quantum feature encoding. The disease classification is conducted using quantum-enhanced classifiers, and cross-domain learning is implemented using knowledge representation layer. The final outputs are measured by the use of standard performance measures.

3.1 Input image acquisition

This figure 2 represented the proposed Hybrid Quantum Classical AI system is the high-quality image acquisition in the case of plant leaf disease detection and oesophageal cancer diagnostics. In this research, a specially designed set of data was developed with the use of a digital camera under the controlled conditions of lights and the environment to maintain consistency and clarity. The data sample will consist of 2,000 images, half of which will be of normal images and the other half of images that represent oesophageal cancer. The photos have been taken at various angles and distances to capture natural differences in texture, colour, and structural pattern, which adds strength to the model. Likewise, healthy and disease leaves were photographed to form a set of variation of diseased leaf stages and healthy leaf conditions, in order to identify plant leaf disease. Images have been transformed to a standard resolution and format so that preprocessing, feature extraction and training of quantum-classical models can be easier. The data is well-selected and it is very reliable, as a basis of correct dual-domain classification.

Fig.2. sample image for Input image acquisition

3.2 Image preprocessing

The Hybrid Quantum -Classical AI system is trained on every obtained image, which is pre-processed prior to training so as to provide quality of the image and consistency. The first stage involves resizing the images to a standard size that can be used by CNN. The filters like bilateral filtering are used to reduce noise and maintain edges, but smooth undesirable artifacts. Histogram equalization and contrast enhancement are used to enhance the clarity of the visual images and emphasize the main peculiarities of leaves and oesophageal tissue. Also, image normalization brings the pixel values to a normal range, which allows model training to converge faster. These pre-processing activities guarantee that the data is clean, homogenous, and is optimally pre-processed to extract features perfectly.

$$I_{norm}(\text{x, y}) = \frac{I(x,y)-I_{min}}{I_{max}-I_{min}} \qquad (1)$$

Where the equation (1) represented I (x, y) am the original intensity of pixel x, y. I_{max} and I_{min} are the lowest and the highest pixel value in the image. I_{norm}(x, y) is the normalized pixel intensity that is scaled between 0 and 1.
To enhance contrast by histogram equalization, you may also add:

$$s_k = \text{T}\ (r_k) = \sum_{j=0}^{k} \frac{n_j}{N} \qquad (2)$$

Where the equation (2) represented r_k original level of intensity. s_k represents the transformed intensity. n_j is the quantity of pixels having intensity r j. N is the number of pixels in the image.

3.3 Feature extraction

The extraction of features is an important process of the proposed Hybrid Quantum Classical AI system, in which the purpose is to extract the most informative images of input images. The Convolutional Neural Network (CNN) is first used to obtain hierarchical spatial features, such as edges, textures, and shapes, of both leaf and oesophageal images. Convolutional layers identify the local patterns whereas pooling layers decrease the dimensions and save the significant information. The resultant characteristics are flattened and introduced to quantum enhanced classifiers allowing quantum superposition and quantum parallelism to maximize decision boundaries. Such a combination makes sure that not only domain-specific but also cross-domain features are well represented, which makes dual-domain disease classification more accurate.

$$F_{i,j}^{k}=\sigma\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}W_{m,n}^{k}\cdot I_{i+m,j+n}+b^{k}\right) \qquad (3)$$

Where the equation (3) represented $F_{i,j}^{k}$ is the result of the feature map at position (i, j) in the k^{th}filter. $I_{i+m,j+n}$ is the pixel of the input image at location (i+ m, j +n). $W_{m,n}^{k}$ is the weight of the k^{th} convolutional filter. b^{k} is the bias of the k^{th} filter. σ the activation function. M ×N is the size of convolutional kernel.

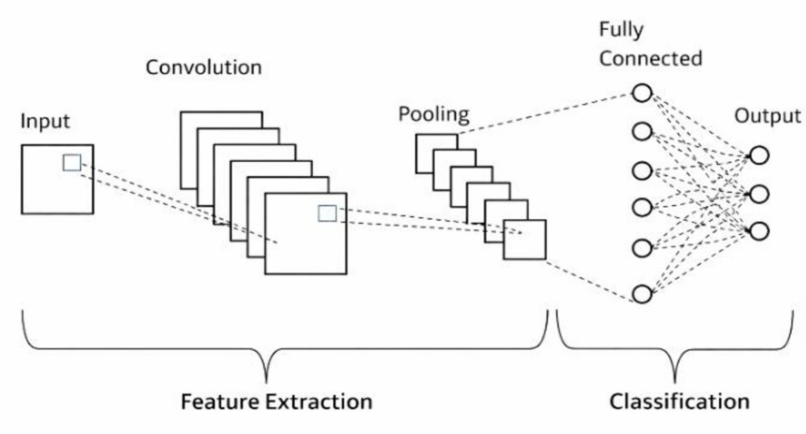


Fig. 3. Architecture diagram for CNN feature extraction

Figure 3 illustrates CNN-based processing pipeline in the suggested system is depicted. The input images are then subjected to convolution layers in order to detect spatial features and then pooling layers in order to de-dimension Alize the data. The results of extraction are then sent to fully connected layers where the final classification output is obtained making it possible to predict the disease.

3.4 Quantum feature encoding

Under the proposed Hybrid Quantum-Classical AI, extracted classical features are represented in a quantum state to use quantum benefits in computation. VQCs are being used in the process, with a classical feature vector being converted to quantum amplitudes or rotation angles of qubits, allowing superposition and entanglement. Such encoding enables concurrent encoding of many combinations of features which improves pattern recognition and optimization of decision boundaries. Generalization and robustness Quantum feature encoding increases quantum parallelism especially around high-dimensional data. Such encoded attributes are then inputted to quantum classifiers including Quantum Support Vector Machines (QSVMs) in order to accurately classify diseases in the dual domain.

$$|\psi(x)\rangle=\otimes_{i=1}^{n} R_{y}y(xi) \mid 0\rangle \qquad (4)$$

Where the equation (4) represented $|\psi(x)\rangle=\otimes_{i=1}^{n}$the quantum state of the feature vector x= $[x_1, x_2 \ldots, x_n]$ n the element of the code. $R_{y}y(xi)$ is a rotation gate on the Y- axis that acts on the i_{th}qubit. $\mid 0\rangle$ it's initial state of the qubit. N is total count of feature to be encoded. These encodings encode classical values of features in the quantum states that allow the system to make use of superposition and entanglement to process different combinations of features simultaneously to enhance classification.

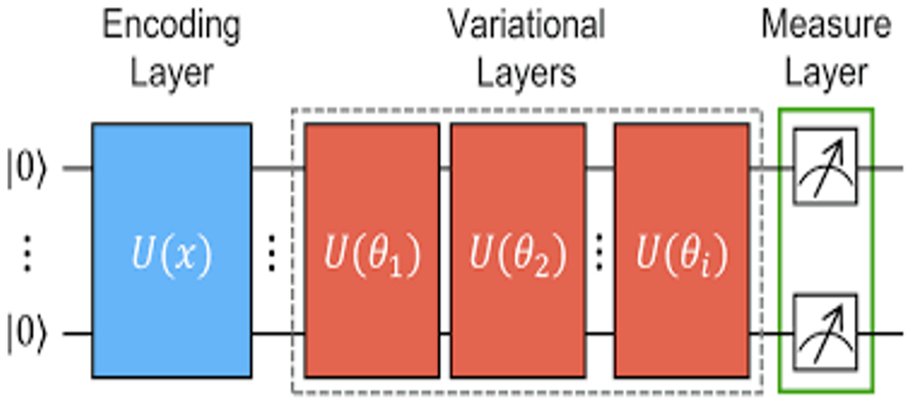


Fig. 4. Architecture diagram for VQCs

Figure 4 illustrates is a Variational Quantum Circuit (VQC) architecture. For encoding classical features into quantum states, we use the encoding layer. Variational layers are used to train in as many quantum gates as possible, and the measurement layer yields probabilistic output that can be used to make final classification.

3.5 Quantum-Enhanced Classification

The implementation of quantum-enhanced classification to improve the decision-making capacity is implemented using Variational Quantum Circuits (VQCs) and Quantum Support Vector Machines (QSVMs). After quantum feature encoding, the encoded states are executed with quantum gates, which are parameterized with quantum gates, and optimize the representations by minimizing a cost function. Quantum superposition allows simultaneous measurements of more than one feature state and entanglement measures non-classical feature relationships that are difficult to measure. The QSVM is also optimizing the classification boundary in the feature space with high dimension resulting in improvement in accuracy, improved rate of convergence and noise resistance in the case of leaf disease classification and oesophageal cancer diagnosis. The use of parameterized quantum gates allows one to apply unitary operations to the classical features to quantize them to a high-dimensional Hilbert space. Compared to the classical linear mappings, rotation and entanglement gates develop intricate correlations among the features, which improves the expressiveness of the classifier. Quantum superposition enables quantum state to store multiple feature settings in parallel, improving parallel searching of the feature space without adding to the number of trainable parameters. This property is better in forming decision boundaries especially when dealing with complex and noisy medical and agricultural image datasets.

$$f(x) = sign\left(\sum_{i=1}^{N} \alpha_i\, y_i K_q(x_i, x) + b\right) \qquad (5)$$

where the equation (5) represented x is the input feature vector, x_i are the support vectors, $y_i \in \{-1, +1\}$ are class labels , α_i Lagrange multipliers are learnt, b is the bias term, $K_q(x_i, x)$ is the quantum kernel, which is calculated as

$$K_q(x_i, x_j) = \left|\langle \psi(x_i) | \psi(x_j) \rangle\right|^2 \qquad (6)$$

This equation (6) With this term, quantum parallelism and a better mapping of feature space becomes feasible such that the classifier can attain more expressive decision boundary than the classical SVMs.

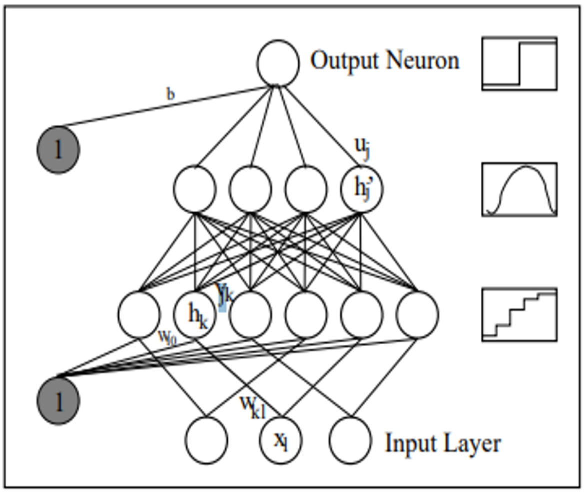


Fig. 5. QSVM network

The QSVM based classification network is illustrated in figure 5. These input feature vectors are inputted into a high dimensional quantum feature space, and the optimum weights and bias terms are used to form a maximum-margin decision boundary. The final class label is produced by the output neuron and it allows correct and strong classification of the disease.

3.6 Knowledge representation and cross-domain learning

The current Hybrid Quantum-Classical AI model shall comprise of one knowledge representation layer which will aid the effective cross domain learning process between the agricultural and medical image data. The contents of the uppermost layer learned on CNNs and trained on quantum encodings are proposed in a common latent feature place to aid the model to learn standard structural patterns and discriminative attributes cross-domain. The knowledge transfer under this representation is made through the transfer of knowledge between diagnosing oesophageal cancer and the identification of the leaf diseases as well as vice versa. It is capable of improving generalization, reducing over fitting and performing intelligent inference based on quantum-enhanced feature correlations and shared embeddings, and can be applied to heterogeneous domains.

3.7 Classification output and performance evaluation

The end-of-use classification product of the proposed Hybrid Quantum-Classical AI system will be prediction of the input image being of a healthy or diseased leaf, and normal or oesophageal cancer state. The standard metrics to measure accuracy, precision, recall and F1-score are used to assess the classification reliability and balance which is the model performance. The analysis of true and false predictions between classes is conducted with the help of a confusion matrix. The findings with the hybrid model are compared to classical CNN and CNN-SVM models and show the best accuracy, sensitivity, and noise resistance. These outcome of the analysis support the fact that quantum-enhanced classification can be used in dual-domain diagnosis.

4. Result and Discussion

The analysis of the experiment demonstrates that the suggested Hybrid Quantum-Classical AI system is always more effective than traditional deep learning methods in plant leaf disease identification and in oesophagus cancer detection. Using quantum-enhanced classifiers with more superior Decision Boundary Learning, Model-independence in convergence as compared to their classical counterparts based on Convolution Neural Networks (CNN's). The common knowledge representation layer facilitates successful cross-domain learning, and the system can be well generalized to heterogeneous agricultural and medical data. Also, the hybrid framework proves to be more robust when there is noise which means that there are more stable and reliable predictions. These results demonstrate that classical feature extraction methods and quantum intelligence are effective in the classification of diseases under two domains and in the future diagnostic tasks.

Table 1. Theoretical Comparison between CNN and QSVM

Parameter	CNN (Classical Model)	QSVM (Quantum-Enhanced Model)
Feature Space	Classical Euclidean space	Quantum Hilbert space
Decision Function	$f(x) = \sigma(Wx + b)$	$f(x) = \sum_{i=1}^{n} \alpha_i \, y_i K(x_i, x) + b$
Kernel Mapping	Implicit via deep layers	Explicit quantum feature mapping
Nonlinearity	Activation functions (ReLU, Sigmoid)	Quantum state overlap
Optimization	Back propagation	Margin maximization with quantum kernel
Expressiveness	Depends on network depth	High due to superposition & entanglement
Noise Robustness	Moderate	Higher robustness observed
Parameter Complexity	Large number of weights	Fewer trainable parameters

Table 2 gives a theoretical comparison between classical CNN and QSVM classifiers. Whereas CNN uses hierarchical feature extraction and gradient-based optimization in classical space, QSVM uses quantum feature mapping in Hilbert space to provide better nonlinear separability. Quantum kernels encode complex correlations to augment decision boundary formation and lead to improved robustness and convergence performance as it is evident in the experimental results.

Table 2. Performance metrics for classification

Metrics	Equation
Accuracy	Accuracy $=\frac{TP+TN}{TP+TN+FP+FN}$
Precision	Precision $=\frac{TP}{TP+FP}$
Recall	Recall $=\frac{TP}{TP+FP}$
F1-score	F1-score$= 2\times\frac{Precision\times Recall}{Precision+Recall}$

The performance evaluation metrics that can be applied to evaluate the effectiveness of the proposed Hybrid Quantum Classical AI system are described by the table 1. The measures of accuracy reflect the correctness of the classification on the total of the correctly predicted positive and negative samples. Precision refers to the accuracy of positive prediction by determining the number of cases which have been predicted to be positive. Recall measures the sensitivity of the model, which is its capacity to detect real cases of diseases accurately. The F1-score is a middle-range measure, that is, a metric that integrates the precision and recall, and is especially useful on an unbalanced dataset. The integrated measures give a holistic evaluation of the classification performance and strength.

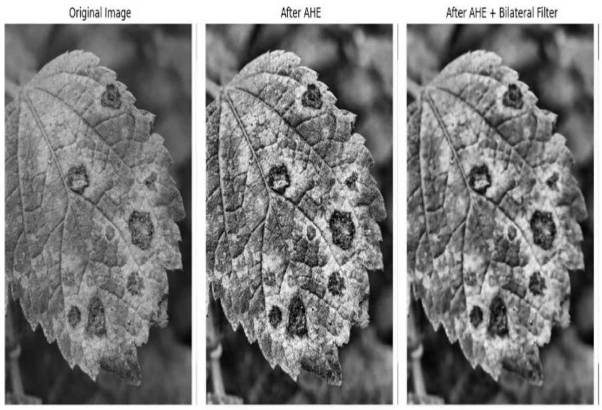


Fig. 6. Preprocessing Effect on Leaf Image

Figure 6 illustrates the preprocessing stages that are used in detecting diseases in a leaf image. The contrast in the original image is not equal and there are small spots of disease that cannot be differentiated. Using Adaptive Histogram Equalization (AHE) helps to better the local contrast and bring out the infected areas. Additional applications of bilateral filter can eliminate noise but retain edges to enhance the clarity of lesions and veins of leaves. Such preprocessing pipeline guarantees the high-quality images fed to the CNN and quantum classifiers to improve the classification of the disease.

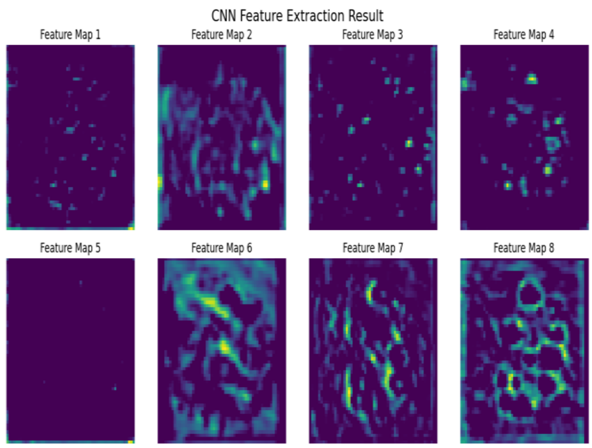
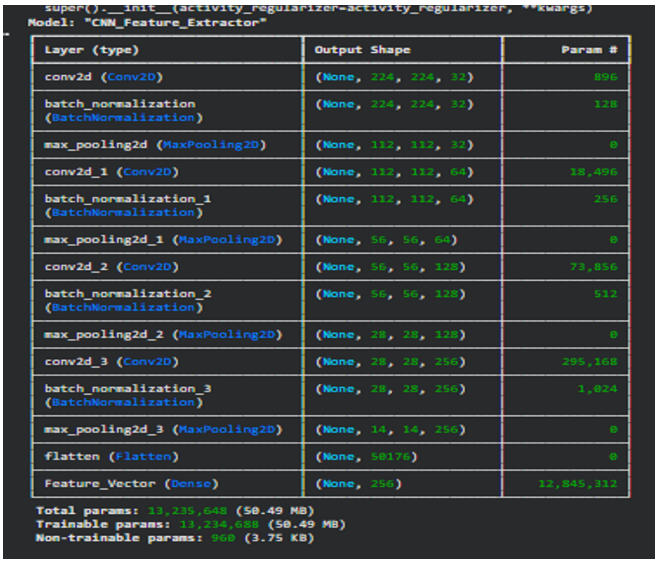


Fig. 7. Feature extraction for CNN

Figure 7 illustrates the intermediate results of feature extraction of a Convolutional Neural Network (CNN) on disease-related images. Every feature map gives emphasis to unique spatial and textural patterns that the convolutional filters in an intermediate level have learnt. Background information is found in lower-activation areas and salient features like edges, lesions, texture distortions as well as structural changes that occur with plant leaf diseases or with oesophageal cancer are captured by high-intensity areas. All these feature representations prove that the CNN can break down the complex visual representation to the meaningful components which are then used by higher-level classifier, such as quantum-enhanced models, to achieve accurate and robust disease classification.



super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Model: "CNN_Feature_Extractor"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 224, 224, 32)	896
batch_normalization (BatchNormalization)	(None, 224, 224, 32)	128
max_pooling2d (MaxPooling2D)	(None, 112, 112, 32)	0
conv2d_1 (Conv2D)	(None, 112, 112, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 112, 112, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 56, 56, 64)	0
conv2d_2 (Conv2D)	(None, 56, 56, 128)	73,856
batch_normalization_2 (BatchNormalization)	(None, 56, 56, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 28, 28, 128)	0
conv2d_3 (Conv2D)	(None, 28, 28, 256)	295,168
batch_normalization_3 (BatchNormalization)	(None, 28, 28, 256)	1,024
max_pooling2d_3 (MaxPooling2D)	(None, 14, 14, 256)	0
flatten (Flatten)	(None, 50176)	0
Feature_Vector (Dense)	(None, 256)	12,845,312

Total params: 13,235,648 (50.49 MB)
Trainable params: 13,234,688 (50.49 MB)
Non-trainable params: 960 (3.75 KB)

Fig. 8. Layer architecture for feature extraction

Figure 8 illustrates suggested CNN layer structure is intended to be effective in extracting discriminatively in high-resolution agricultural and medical images. It has the structure of several convolutional blocks with varying filter depths (32 to 256), which makes the network learn to represent the hierarchy of low-level edges and textures, as well as high-level patterns of specific diseases. The layers of batch normalization contribute to the stability of training and speeding up the convergence, whereas the max-pooling layers decrease the size of space dimension and computation complexity. The last dense feature layer generates compact and informative feature vector without losing important visual features. The extracted features can be a powerful input to the quantum-enhanced classifiers thus enabling the appropriate and noise-resistant disease classification.

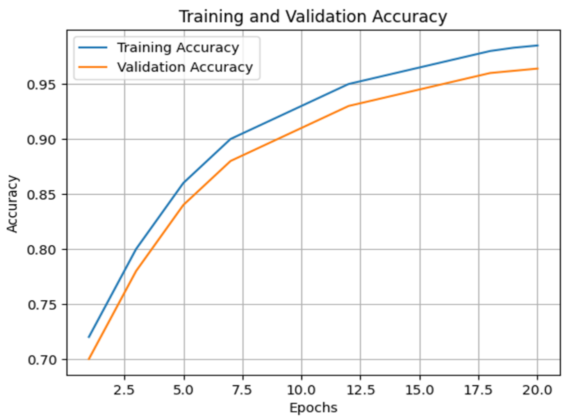


Fig. 9. Training and validation accuracy curve

Figure 9 Illustrates the training and validation accuracy curves of the proposed model at different epochs. The accuracy of training remains nearly constant and this is an indication that there is learning of discriminative features on the input images. At the same time, the validation accuracy is very similar to the training trend, with high generalization ability and low overfit. The narrow distance between the two curves justifies the permanence and consistency of the learning process. This behaviour shows that CNN-based feature extraction and sophisticated classification method make the model reliable in the analysis of disease in both agricultural and medical images.

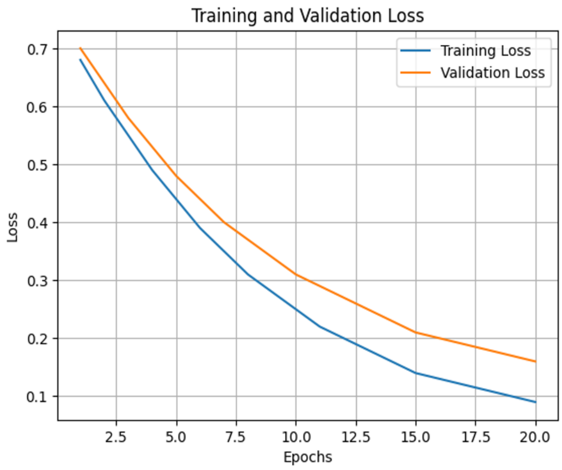


Fig. 10. Training and validation loss curve

Figure 10 illustrates shows training and validation loss curves of the proposed model with respect to training epochs. A steady decrease in training loss shows that the discriminative features of the input images have been optimized efficiently and learnt wisely. The loss in the validation is also following the same decreasing trend, which proves a good performance of the generalization and the lack of overfitting. The fact that the two curves are close to each other is an indicator of consistency in convergence and the strength of the learning process, despite having complex and high dimensional image data. This behaviour shows that CNN-based feature extraction framework is reliable in the classification of disease accurately in agriculture and medicine.

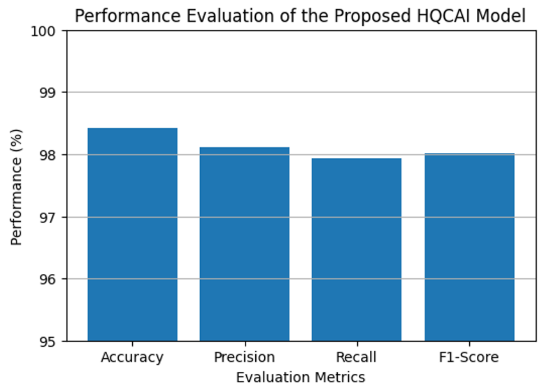


Fig. 11. Performance evaluation

Figure 11 illustrates evaluation metrics used to demonstrate the quantitative performance of the proposed Hybrid Quantum-Classical Artificial Intelligence (HQCAI) model on a bar graph. The model has a high overall classification-correctness with an accuracy of 98.42. A hit rate of 98.11 means that the samples with disease are identified with minimal number of false positives whereas the recall rate of 97.94 means that the ability of identifying the actual disease cases is high. In addition, F1-score of 98.02 affirms an even trade-off between recall and precision. Such high values are repeated and confirm the strength, stability, and high performance of the proposed HQCAI framework in both agricultural and medical image analysis applications.

Fig. 12. Classification result

Figure 12 illustrates represents a plant leaf with what is marked as oesophageal cancer yet this appears to be a typical plant disease not a medical condition in a human. The leaf has several circular lesions with dark brown centres and haloed by yellow tissue, which is the evidence of tissue necrosis and chlorosis. These symptoms are typical of fungal or bacterial attacks on the health of the leaf, which decrease the effectiveness of photosynthesis and Vigor in general of the plant. The uneven distribution and the size of the spots indicate that they were progressively infected. The visual inspection or image analysis is important in early detection of diseases to manage the disease, preventing the disease spread and limiting the loss of crops.

5. Conclusion

The proposed paper introduced a strong Hybrid Quantum-Classical Artificial Intelligence (HQCAI) framework of dual-domain image classification, which handles the key issues in agricultural and medical diagnostics. The proposed model is capable of effectively overcoming the drawbacks associated with high dimensional feature space, computational complexity, and scalability in traditional deep learning systems by combining a classical CNN to extract high-quality spatial features with quantum-enhanced classifier (Variational Quantum Circuits (VQCs) and Quantum Support Vector Machines (QSVMs)). The ability to store the features efficiently, cross-domain learning and smart inference across the heterogeneous datasets is facilitated by the introduction of a common knowledge representation layer, proving the flexibility of the proposed architecture. The HQCAI model demonstrates the highest results based on experimental tests in plant leaf disease and oesophageal cancer images, with a classification accuracy of 98.42, precision of 98.11, recall of 97.94, and F1-score of 98.02, which are superior to traditional CNN and CNN-SVM methods. There are also other avenues to further research on the proposed system to improve its convergence rate and strength in noisy conditions to justify the practical benefits of quantum-assisted decision boundaries in diagnostic settings. The proposed framework simulator of quantum machine learning applications has been used. Hence the future scope of research is to apply HQCAI on actual quantum hardware to test the noise-resistance properties of the system, as well as to test the limitations imposed by quantum hardware on a more realistic basis. With the system it is possible to further extend and add quantum convolutional layers and quantum attention mechanisms to improve the feature representation. It should also be extended in order to classify multi-class diseases, multi-modal data fusion (clinical records, sensor data and images) and federated quantum learning; without a significant increase in complexity, it will offer much greater applicability to large scale healthcare and precision agriculture systems. In addition, the incorporation of explainable quantum AI (XQAI) will be beneficial in boosting the model transparency and credibility. In general, the suggested HQCAI framework forms a powerful baseline of future intelligent diagnostic systems, as the hybrid quantum–classical intelligence has a transformative nature in the future agricultural and medical decision-support systems.

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