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Quantum-enhanced Diagnosis: Revolutionizing Tomato Leaf Disease Detection

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Plants and plant-produced vegetables are crucial for every age group due to their rich nutrient content, and tomatoes, as one of the leading vegetables, make a significant impact on human well-being.Tomatoes can easily be affected by environmental conditions and fungal infections, causing significant losses for farmers. Experimentation of Quantum machine learning and image processing creates stunning results in early disease detection in medical field. This research takes this guidance and endeavors to apply various quantum machine learning classification techniques with optimization to classify diseased tomato leaves. Quantum Neural Network (QNN), Quantum Convolution Neural Network (QCNN), and Quantum-Classical Hybrid Convolution Neural Network (QCHCNN) with Quantum Approximate Optimization Algorithm (QAOA), COBOLYA (Constrained Optimization by Linear Approximation and Simultaneous Perturbation Stochastic Approximation (SPSA) were experimented for tomato leaf disease detection to identify a timely and low-cost model. These classifiers achieved accuracies of 87%, 90%, and 99% respectively. The results suggest Quantum-Classical Hybrid Convolution Neural Network (QCHCNN) as the preferred choice for tomato leaf disease detection.

Keywords: Quantum Machine Learning, Quantum Neural Network, Quantum Convolution Neural Network, Quantum-Classical Hybrid Convolution Neural Network, Tomato Leaf Disease Detection.

1. Introduction

Around the world, consumers find tomatoes unavoidable, and simultaneously, the productivity of tomatoes is quickly affected by global changes. Hence, farmers need an immediate solution to overcome the loss. Recent research experiments show that image processing techniques play a major role in disease identification. The concept of quantum and quantum machine learning is an evolving area that remains in the experimentation stage. It is challenging to definitively determine the benefits of quantum machine learning at this point.

Quantum computing is a branch of quantum physics and it works based on the concept of qubits. Qubits follows the concept of super position principle and these linear complex states represented as follows

$$|\psi> = \sum_{i}^{N} \propto_{i} \ . |\psi_{i}> \text{------}1$$

The researchers find that it efficiently works for image identification and pattern recognition. Typically, image processing handles optimization problems, while quantum machine learning utilizes the Quantum Approximate Optimization Algorithm (QAOA), COBOLYA (Constrained Optimization by Linear Approximation and Simultaneous Perturbation Stochastic Approximation (SPSA) to address optimization challenges in this research.

Quantum machine learning excels in feature extraction, demonstrating its ability to capture complex features from plant leaf images. The utilization of quantum algorithms enhances the precision and effectiveness of feature extraction processes, allowing for a more nuanced understanding of intricate patterns associated with plant diseases.

The inherent ability of quantum machine learning to perform efficient analyses has the potential to significantly impact the field of tomato leaf disease detection. Quantum machine learning techniques, harnessing the principles of quantum computing, offer the prospect of developing highly sensitive and precise detection models. These models can transcend the limitations of classical computing methods, These models surpass classical computing, enhancing the processing of complex datasets related to subtle patterns and variations in tomato leaf diseases.

The parallelism and superposition properties of quantum computing enable the simultaneous exploration of multiple possibilities, allowing for a more comprehensive assessment of the features associated with diseased tomato leaves.

Background :

By integrating quantum machine learning and image processing principles with the intricacies of plant pathology, this research aims to contribute to the creation of efficient tools for the timely and accurate detection of diseases impacting tomato crops. The ultimate goal is to empower farmers with advanced technologies, mitigating potential losses and ensuring the sustainable cultivation of tomatoes for the benefit of both agricultural communities and consumers.

Existing problem:

Many AI algorithms have been experimented for the classification of tomato leaf diseases, but quick analyses have not been adequately documented.

Proposed Solution:

The nature of quantum machine learning facilitates quicker results than existing algorithms, thereby enabling farmers to promptly control potential losses.

2. Related Work:

Sri Silpa (2023) et al. This paper suggests that finding the appropriate characteristics' weights in both forward and backward propagations is the model's primary goal. Additionally, it expands on the pictures found in the current dataset. By eliminating the final layer from the pre-trained GoogleNet model, the suggested method refines it and applies it as a "Feature Extraction" model. In order to expedite the process, it additionally adds normalization layers to the concealed layers and modified them.[1]

Sowmiya (2023) et al. Discovered the best course of action for preventing this severe agricultural calamity, suggested utilizing a machine learning (ML) model to assess a set of images with tomato disease, and resulting in an Improved Quantum Whale Optimization with Principle Component Analysis (IQWO-PCA). The study's dataset came from a readily accessible plant village dataset. Following the systematic review's optimization of the hyper-parameters, the network is created. The transmission learning-based DNN is developed using four trained prototypes: DenseNet121, VGG16, Alexnet, and ResNet50. Subsequently, the suggested model is assessed by conventional machine learning techniques to ascertain its superiority for loss rates and accuracy metrics.[2]

Shakti (2022) et al. This work uses CNN, InceptionV3, and Resnet 152 V2 deep learning models to classify cotton leaves or plants as fresh or sick. These models are used to identify unhealthy cotton leaves. The accuracy findings shows the importantce of these approaches can be in resolving this problem: 99.057, 97.170, and 98.113 regarding CNN, Resnet 152V2, and Inception V3.[4]

Haya (2023) et al.Presented a method in this research named ARVDC-QIMFODL(Deep Learning-Based Quantum Inspired Moth Flame Optimizer) for Automatic Rice Variety Identification and Classification. The automated recognition and classification of various types of provided rice varieties is the main goal of the ARVDC-QIMFODL technique. The modified Wiener filter with median (MMWF) approach is used by the ARVDC-QIMFODL technique for the noise removal procedure in order to achieve this. A refined ShuffleNet model then performs the feature extraction procedure. The long short-term memory (LSTM) method was used to detect and classify rice varieties. Lastly, to maximize the LSTM system's detection outcomes, the hyperparameter selection procedure is carried out using the QIMFO method. Using a dataset of rice images, the ARVDC-QIMFODL method's simulation results are examined.[6]

Towfek (2023) et al. Researched a deep convolutional neural network, or Deep CNN, to suggest a unique method for the identification of plant diseases in their leaves. Photographs of the leaves of 39 different plant species are included in this dataset. Image inversion, gamma correction, noise injection, principal component analysis (PCA), color enhancement, rotation, and scaling were the six data augmentation techniques that were applied. Deduced model's accuracy can be increased by including more data. Throughout its development, the suggested model was trained with a variety of epochs, batch sizes, and dropout rates. Numerous simulations show that the suggested model can classify data with an amazing 83.12% accuracy.[7]

Vikram (2023) et al. Examined the three primary categories of plant illnesses that impact rice. Aside from brown spot, bacterial leaf blight, and leaf smut are the other three diseases that can infect rice plants. The suggested method uses a Faster R-CNN deep architecture in conjunction with VGG-16 transfer learning to extract features. The random forest method is used to categorize the collected attributes after the transfer learning step is finished. The radish field was split into three different sections by the random forest classifier. The UCI Machine Learning Repository is where the pictures of rice plant leaves were obtained. With regard to rice disease imaging class prediction, the suggested method achieves an average prediction accuracy of 97.3%.[8]

Sundas (2023) et al. Aimed to provide an image processing and performance testing-based diagnostic system for paddy disease detection. The system has employed and it was created in C++ and tested with a dataset of photos of infected leaves. The dataset includes the several types of spotted leaves brought on by paddy disease. The four main functions of the system are image acquisition, pre-processing, feature extraction, and performance measurement. Each of these phases carries out a certain assignment. Furthermore, the study offers a conclusive account of the paddy disease.[9]

Beulah (2022) et al. Presented an adaptable extreme learning machine (AELT) for disease classification. To increase the accuracy of disease detection, segmentation and feature extraction are done prior to classification. For segmentation, a probability-induced butterfly optimization technique combined with multilevel thresholding-based K-means clustering is described. Plant photos are used to extract the entropy-based properties. The AELT classifier receives the characteristics. The outcomes are assessed using the industry standard dataset and contrasted using cutting edge methods.[10]

Sergey (2023) et al. Reviewed the techniques based on Raman scattering, LiDAR technology, and the scattering and absorption of light in the UV, Vis, IR, and terahertz ranges. The use of optical techniques to several pathogen categories, all plant sections, and different data collection scenarios is taken into consideration. The review highlights the variety, successes, development trends, and future promise of contemporary optical approaches for the identification of contagious plant illnesses.[11]

Mbulelo (2023) et al. This study's objective was to evaluate plant disease detection models, namely those developed during the last 20 years, in order to determine the current state of the field's research and to pinpoint areas that could use more investigation. The study found that the real-time monitoring of disease start signals before they spread throughout the entire plant has not received much attention in the literature. Once a disease was diagnosed, there was also a marked decrease in the attention given to real-time mitigation strategies such actuation operations, fertilizer and pesticide spraying, etc. The integration of monitoring and phenotyping functions into a single model that can perform several tasks has received very little attention in research. As a result, the study identified a few areas that warrant additional attention.[12]

Matanel (2023) et al. Presented the paper on machine learning-based image analysis made it possible to classify infected and uninfected leaves in inoculated plants objectively and to systematically identify and quantify spots. By comparing redox and chlorophyll fluorescence imaging, it was possible to observe that infected leaf areas with mislocalized chl-roGFP2 also exhibited higher quantum PSII yield (ΦPSII) and reduced non-photochemical quenching when compared to the surrounding leaf areas. The results indicate that mislocalization of proteins targeted to chloroplasts is a useful indicator of late blight infection and show how whole-plant redox imaging may be used to monitor the disease's biotrophic stage in a non-destructive manner.[13]

Gurunathan (2023) et al. Proposed image processing for the identification of leaf disease based on the KNN Classifier. Preprocessing images, contrast enhancement, RGB conversion, feature extraction, segmentation, and K-nearest neighbor classification are steps in the process of diagnosing an illness. Histogram Equalization is first applied to the leaf samples after they have been image-preprocessed and resized to 256x256 pixels in order to enhance the quality of the splint samples. The splint samples' instructional features are rated using a matrix known as the Grey Level Co-occurrence Matrix. The features are grouped using machine learning methods similar to K-Nearest Neighbor (K-NN). The quality of the suggested model is assessed using K-NN.[14]

Mridul (2023) et al. Described a straightforward technique for identifying biotic and abiotic stress in plants. The degree of stress that plants experience is determined by how much more nutrients they take in as a form of self-defense. Since agarose is the growing medium for Cicer arietinum (chickpea) seeds, the rate of change of nutrients in the media was estimated using a continuous electrical resistance measurement. Drude's model was applied to ascertain the charge carrier concentration in the growth medium. In two tests, outliers in electrical resistance and relative variations in carrier concentration were discovered, which helped identify abnormalities and predict plant stress.[15]

Jiao (2023) et al. The study used a number of characterisation approaches. The resulting carbon quantum dots featured high-resolution lattice stripes with lattice spacings ranging from 0.20 to 0.23 nm, together with a quasi-spherical shape. Additionally, they had elemental O, C, and N on the surface as well as functional groups like amino and hydroxyl groups that had strong hydrophilic qualities. The fluorescence quantum yield of carbon quantum dots is a critical factor in determining their photoluminescence capabilities. Therefore, six machine learning analytical models based on 480 samples were used to study the link between the fluorescence quantum yield and biochar preparation parameters.[16]

Adarsh (2023) et al. Reviewed the latest developments in quantum UAV-based networks and quantum satellites. In this article, the significance of cutting-edge technologies is examined from a network viewpoint, including quantum artificial intelligence, blockchain, quantum machine learning, quantum satellites, and quantum unmanned aerial vehicles. This work also covered the function of artificial intelligence and satellite-based imagery. The most successful quantum networks produced to date have been based on fiber communication lines and satellite-to-ground links. Free-space quantum communication is more efficient when it uses a UAV, satellite, or both since it eliminates the lower loss limit of space and the requirement for continuous ground connections.[17]

Priynka (2023) et al. In this experiment, they used images taken camera bias in situ utilizing a deep literacy frame to classify wheat conditions with colorful assessments. In our sample, there are four orders of wheat complaints: normal, heroic, powderly, and stem rust.There were 207 pictures in every order. Convolutional neural network training was used to develop our classifier (CNN). One of CNN's biggest advantages is its ability to recycle the raw photos directly and automatically reward features. Farmers can utilize the model, which reached a delicacy of 94.54, to protect wheat crops from conditions in which they are covered by forests.[18]

Zhiyong (2023) et al. Suggested SE-VRNet integrated a module for squeeze and excitation

(SE) with an attention mechanism together with a deep variation residual network (VRNet) to address the challenge of feature extraction provided by the leaf disease's dispersed location. 99.73% and 99.98%, respectively, are the accuracy of the top-1 and top-3 achieved by the SE-VRNet model on NewData, while 95.71% and 99.89%, respectively, are the accuracy of the top-1 and top-3 acquired by the model on SelfData. In comparison to other cutting-edge techniques, the experimental findings on the PlantVillage, OriData, NewData, and SelfData datasets showed the efficacy and viability of the suggested SE-VRNet in identifying leaf diseases using mobile gadgets.[19]

Dennis (2023) et al. Solved a number of industrial use-cases involving different machine learning issue categories by benchmarking their most crucial characteristics; and incorporate Quantum Machine Learning (QML) algorithms into this automated solving approach of the AutoML framing, this work describes the selection approach and analysis of existing AutoML frameworks. In order to do that, a market overview using the open-source technologies that are currently accessible is created, and appropriate frameworks are methodically chosen using a multi-phase, multi-criteria approach. This is accomplished by taking into account methods for software selection as well as AutoML's technological viewpoint. Regarding their software and machine learning attributes, the requirements for the framework selection are separated into hard and soft criteria.[20]

Lauren (2023) et al. Presented a decadal of suggestions from a symposium on artificial intelligence, machine learning, and modeling applications that address these space biology concerns and were arranged by the National Aeronautics and Space Administration. In the end, artificial intelligence will help life to flourish in deep space by advancing our biological understanding of the effects of spaceflight, facilitating predictive modeling and analytics, supporting fully automated and repeatable experiments, and effectively managing spaceborne data and metadata.[21]

Ankita (2023) et al. This research's workflow is predicated on a number of predictions regarding the application of pre-processing techniques, wheat canopy segmentation techniques, and the potential adaptability of current models from previous studies to categorize water stress in wheat crops. Therefore, it was shown that the most beneficial pre-processing procedures were min-max contrast stretching and total variation with L1 data fidelity term (TV-L1) denoising using a Primal-Dual algorithm in order to build an automation model for water stress detection. The random forest approach is best suited for building water stress detection models and has the highest global diagnostic accuracy (91.164%).[22]

Rhea (2023) et al. Focussed on the developments in detection approaches, particularly the smaller systems that have emerged in the past ten years. There are two categories of analytical approaches for detecting plant pathogens: direct detection and indirect detection. It has been addressed how direct methods, which use laboratory techniques like polymerase chain reaction, enzyme-linked immune-sorbent assays, and immunofluorescence, have advanced recently. Likewise, a classification and assessment process has been applied to indirect approaches of plant disease detection that depend on the detection of plant stress indicators. For on-field plant disease detection, a number of high sensitivity and selectivity detection systems have been developed and commercialized in the last ten years into handheld devices and solutions.[23]

Shankey (2023) et al. Presented a lightweight transfer learning model with limited sample sizes to classify plant diseases. By using sparse labeled data for training, few-shot classification seeks to discover previously undiscovered classes. In order to effectively classify plant diseases using minimal data, the suggested study uses an aggregated loss function that is created by combining triplet loss and cross-entropy loss with MobileNetV2 as the basic model. The suggested work was evaluated using two freely available datasets: PlantVillage, which contains 54,303 leaf samples, and Plantdoc, which has 2598 leaf samples. For the plantdoc dataset, two domain splits were taken into consideration; using 30 samples, the accuracy was approximately 81%.[24]

Jayapriya (2023) et al. Proposed a maize illnesses based on optimization, this paper uses Improved Gaussian Conducted Particle Swarm Optimization [IGCPSO] to optimize convolution neural networks. Initially, a deep learning architecture called Contrast Limited Adaptive Histogram Equalization [CLAHE] is used to divide a given image into specific, non-overlapping segments of comparable sizes. Graph cut segmentation is used to divide a preprocessed image into many segments. In order to obtain the discriminative features for the remaining processes, segmented disease areas are useful. The performance of the suggested model is enhanced in terms of dice coefficient, sensitivity, and specificity for disease identification through research using experiments utilizing the plant village dataset.[25]

Sidrah (2023) et al. Suggested a deep model built on CNN. There are thirty-three layers in the suggested model. For the purpose of early leaf blight detection, employed a guava dataset that has two classes. At first, leaf blight detection involved preprocessing using the YCbCr color scheme. Due to the modest size of the initial dataset, data augmentation was done. For feature acquisition, DarkNet-53, AlexNet, and the suggested SidNet were employed. To achieve the ideal outcomes, the attributes were combined. For feature selection, Binary Gray Wolf Optimization (BGWO) was used to the fused features. The KNN and SVM classifier variations were trained with the optimum features for classification. The studies were run using cross validation on five and ten folds. The maximum results that could be obtained were 98.9% with a 5-fold.[26]

Süleyman (2023) et al. Researched a deep learning techniques were used to classify illnesses in sugarcane leaves. Five classes—healthy, mosaic disease, redrot disease, rust disease, and yellow leaf disease—across a total of 2521 photos make up the dataset we use. This dataset is first subjected to the convolutional neural network (CNN) model DenseNet121, then to the Vision Transformers (ViT) model, and lastly to the ViT + CNN combination. The outcomes are then compared. Following the observations, it is believed that the corresponding precisions of 92.87%, 93.34%, and 87.37% were attained.[27]

Nattanong (2023) et al. Aimed to create an integrated computational framework based on TYLCV sequences (isolated in Korea) for the precise detection of symptoms (mild or severe). In order to create the framework, 11 distinct feature encodings and hybrid features out of the training set. Next, investigated 8 different classifiers and used randomized 10-fold cross-validation to create the corresponding prediction models for each classifier. The top 90 models were then chosen after a thorough evaluation of these 96 created models, in which the projected class labels were pooled and treated as reduced features.[28]

Peng (2023) et al. Resulted the two machine learning algorithm models—the random forest

(RF) model and the light gradient boosting machine (LightGBM) model—performed better than the other in inverting the Pn of function-leaves in cotton and the FAPAR of the cotton canopy, respectively. These models were based on six different forms of hyperspectral transformations. on order to diagnosis nitrogen nutrition and cotton growth state on big farms, these studies offer sophisticated metrics for the non-destructive tracking of cotton nitrogen status.[29]

Shrikrishna (2021) et al. Overviewed a imaging methods and their uses in plant phenotyping is given in this work. An extensive overview of current machine vision techniques for classifying and estimating plant traits is provided in this work. Information regarding publicly accessible datasets is included in this research to enable consistent comparisons between the most advanced phenotyping techniques. Additionally, this study outlines future objectives for research on the application of deep learning-based machine vision algorithms for plant classification investigations, physiological and temporal trait assessment, and structural (2-D and 3-D) studies.[30]

Pappu (2023) et al. Investigated the convolution neural network (CNN)-based deep learning, in conjunction with classical machine learning (ML) based computer vision algorithms, can effectively classify "Furr" mandarin leaves with canker and four other conditions, and "Valencia" orange fruit surfaces with CBS infection along with four other conditions. Using a bespoke shallow CNN with SoftMax and RBF SVM, fruits with CBS and the other four criteria (marketable, greasy patch, melanose, and wind scar) were categorized with an overall accuracy of 89.8% and 92.1%, respectively. Similarly, canker leaves could be classified with an F1-score of 85% and an overall accuracy of 82%, incorporating four additional criteria, using a modified VGG16 network with SoftMax.[31]

Douaa (2023) et al. Researched a diagnoses of rice diseases are made using a hybrid model that combines a support vector machine (SVM) with a deep convolutional neural network (CNN) called Residual Network 50 (ResNet50). The deep learning model ResNet50, which excels in image classification tasks, was utilized to extract characteristics from rice plant photos. Based on these attributes, SVM was then used to classify the disorders. Complex patterns in the images could be detected by the ResNet50, and the SVM could then use these patterns to determine the categorization of the images with accuracy. With an accuracy of almost 99%, our hybrid model enabled for high precision in diagnosis of rice illness.[32]

Sofia (2023) et al. Focussed on agriculture 5.0 and the primary attributes and technological advancements will be used in the highly anticipated 6G-IoT communication systems are first covered in the article. After that, emphasized the significance and impact of these emerging technologies on the continued development of smart agriculture, and wrapped up with a look at the potential and difficulties that lie ahead. Based on the expanding 5G network infrastructure, agriculture 5.0 can take advantage of it. But as the pertinent scientific literature and study indicate, only 6G-IoT networks will be able to provide the technological advancements that would allow the complete implementation of Agriculture 5.0.[33]

Sreeraman (2023) et al. Explored the idea of DL structures and its uses in medication creation and diagnostics. The following sections of the article concentrate on current advancements of DL-based techniques in biology, particularly in structure prediction, cancer medication development, COVID infection diagnostics, and drug repurposing strategies, even if these approaches have applicability in many other domains. A number of state-of-the-art, recently developed DL-based approaches are summarized in each review area. Additionally, presented the methods used by them, which prediction accuracy is comparable to that of the most advanced computer models. Wrapped up the overview by talking about the advantages and disadvantages of DL approaches and laying out the future directions for gathering data and creating effective computational models.[34]

Musa (2023) et al. Proposed to identify the disease known as leaf blight by dividing leaves entering three categories: healthy, early, and late blight. There are two phases to this work: division and categorization. To segment, MobileNetV2 is employed, for classification, QCNN is used, a forthcoming quantum machine learning method.The primary goal is to supply and recommend a rapid, efficient, automated method for classifying additionally diagnosing blight illness, therefore facilitating growers ability to detect the illness. The suggested model had a 0.969 classification accuracy. The outcomes were further confirmed by comparison with more recent research in the sector. The results indicate that the model performs exceptionally well.[35]

3. Methodology

The research methodology, illustrated in Fig. 1, delineates the essential steps undertaken in the study's execution. The utilization of quantum machine learning for classification integrates optimization techniques, including the Quantum Approximate Optimization Algorithm (QAOA), Constrained Optimization by Linear Approximations (COBYLA), and Simultaneous Perturbation Stochastic Approximation (SPSA). These optimization strategies effectively diminish the dimensionality of the feature space while augmenting feature representation. The intricate patterns within the feature space are revealed through diverse feature maps such as the Z feature map and ZZ feature map with ansatz. The refined dataset undergoes additional processing with fine-tuned models, including the Quantum Neural Network (QNN), Quantum Convolutional Neural Network (QCNN), and Quantum-Classical Hybrid Convolutional Neural Network (QCHCNN). Comprehensive evaluations are conducted using metrics such as accuracy, precision, recall, F1 score, and AUC, with log loss serving as the chosen cost function. Ultimately, the selection of the proposed model is based on its superior performance in disease detection.

4. Dataset

About a thousand examples of both healthy and unhealthy images can be found on Kaggle, where the image under test was found . The resolution of the images is 256 × 256.

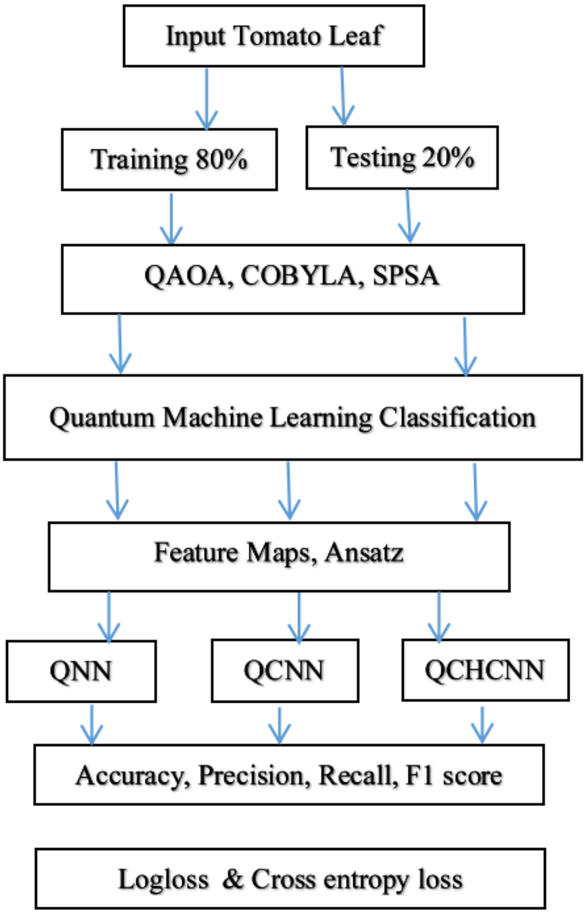

Fig 1: Proposed Methodology

Feature maps :

It acts as the fundamental structure for classification within the realm of quantum machine learning, facilitating the conversion of supplied data into a quantum feature space. The feature map plays a pivotal role in quantum circuits, crafted to encode classical data into quantum states, with the experiment utilizing the Z feature map and ZZ feature map. This process facilitates the recognition of intricate patterns in classification

. $\phi : R^d \rightarrow H$, where: $\vec{x} \xrightarrow{\phi(\vec{x})} |\phi(\vec{x})\rangle\langle\phi(\vec{x})|$ for quantum cases, it's a feature map transformation.

$\vec{x}$: Classical features

$|\phi(\vec{x})\rangle\langle\phi(\vec{x})|$: Quantum state vector

Optimization:

It helps to improve the accuracy of the model and the Optimizers COBOLYA (Constrained

Optimization by Linear Approximation, Simultaneous Perturbation Stochastic Approximation (SPSA) and Quantum Approximate Optimization Algorithm (QAOA) which works on noisy problems in dataset and log loss function is used for this experiment.

Quantum Neural Network (QNN)

Quantum circuits integrate classical neural network features to construct quantum neural networks, contributing to the field of quantum machine learning. The resulting output, either +1 or -1, mimics the functionality of classical neural networks in unveiling hidden patterns within data, facilitated by the Qiskit machine learning library. The training process commences with data loading through Feature Maps, followed by the employment of a quantum neural network with Ansatz. To optimize classification accuracy, parameters within the quantum neural network circuit are fine-tuned using optimization algorithms like COBYLA, SPSA, QAOA, while minimizing the specified log loss. The schematic representation of this process can be simplified as follows

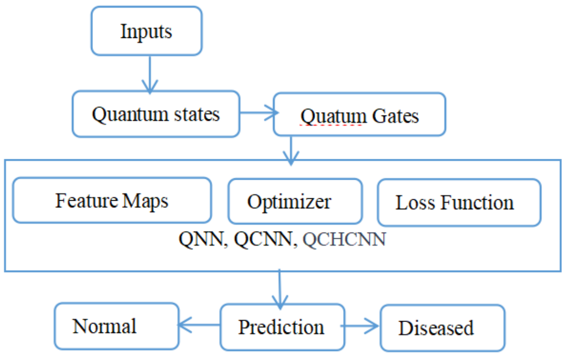

Fig 2. General methodology of QNN, QCNN, QCHCNN

Quantum Convolution Neural Network (QCNN)

QCNNs process image data by utilizing quantum circuits. Similar to classical CNNs, convolutions, pooling, and other operations are carried out using quantum gates and operations. The purpose of quantum circuits is to take advantage of entanglement and quantum parallelism, which may be advantageous for some computational tasks. Prior to processing, image data must be quantum-state encoded.

Quantum convolutional layers, which apply convolutional operations to the quantum-encoded image, are a feature of QCNNs. Quantum gates and operations unique to convolutional tasks make up these layers.

Similar to the classical pooling layers in CNNs, quantum pooling operations are used for downsampling. The spatial dimensions of the quantum feature maps are lowered in part by these operations. It could function alongside traditional neural networks. The advantages of quantum and classical computing are combined in hybrid quantum-classical models. While QCNNs handle particular quantum tasks, classical neural networks may be employed for specific processing stages. Model training is aided by optimization algorithms, and quantum backpropagation is used to modify the quantum circuit's parameters in order to minimize a specified cost function.

Quantum-Classical Hybrid Convolution Neural Network (QCHCNN)

The input image data is preprocessed and encoded into a quantum state. Quantum convolutional layers perform convolution operations on the quantum-encoded image. These layers consist of quantum gates and operations specifically designed for image processing tasks. The convolutional operations aim to capture hierarchical features in the input image. Quantum pooling operations are employed for down-sampling the quantum feature maps. These operations reduce the spatial dimensions of the quantum data while preserving important features.

The quantum processed data is transformed back to classical data. This transformation can involve measurements on the quantum states to obtain classical information.

Classical neural network layers are integrated into the architecture. These layers process the classical data obtained from the quantum processing stages.

Classical layers include fully connected layers, activation functions, and other components commonly found in classical neural networks. Optimization algorithms involves adjusting the parameters of the quantum operations to minimize a defined cost function.

Evaluation Metrics:

Accuracy evaluates the overall equilibrium of the model, computed as the proportion of accurate predictions to the total number of predictions.

$$\text{Accuracy} = \frac{\text{TruePositive} + \text{TrueNegative}}{\text{TruePositive} + \text{TrueNegativ} + \text{FalsePositive} + \text{FalseNegative}}$$

Precision strives to minimize the occurrence of false positives, calculated as the division of true positives by the sum of true positives and false positives.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Recall seeks to mitigate false negatives and is computed as the proportion of true positives to the sum of true positives and false negatives.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} * 100$$

The F1 Score aims to achieve a balance between minimizing false positives and false negatives. It is determined as the harmonic mean of precision and recall, offering a holistic assessment.

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

5. Result and Discussion

In the domain of tomato leaf disease detection, Quantum Machine Learning (QML) techniques were employed, leveraging classifiers such as Quantum Neural Network (QNN), Quantum Convolutional Neural Network (QCNN), and Quantum Convolutional Hybrid Neural Network (QCHCNN). The implementation and testing of these algorithms were carried out using

Python in the Google Colab environment, with the support of Qiskit and Cirq.

The accuracy of the experimented algorithms was visualized for 15 epochs, employing various feature maps including ZZFeaturemap and ZFeaturemap, and Ansatz types such as EfficientSU2 and RealAmplitudes. The optimization process utilized COBYLA, QAQO, and SPSA optimizers. The parameter outcomes demonstrating effective performance are showcased in the subsequent table.

Table 1. Classifier Accuracy

FeatureMaps	Ansatz	Classifiers	QNN		QCNN		QCHCNN	
			Train	Test	Train	Test	Train	Test
ZZFeaturemap	EfficientSU2	COBYLA	0.87	0.87	0.90	0.89	0.97	0.97
		QAQO	0.87	0.87	0.91	0.90	0.99	0.99
		SPSA	0.87	0.86	0.89	0.88	0.97	0.96
	RealAmplitudes	COBYLA	0.86	0.85	0.89	0.88	0.96	0.95
		QAQO	0.87	0.85	0.90	0.89	0.97	0.96
		SPSA	0.86	0.84	0.88	0.87	0.96	0.94
ZFeaturemap	EfficientSU2	COBYLA	0.86	0.85	0.89	0.88	0.96	0.95
		QAQO	0.85	0.85	0.90	0.89	0.97	0.96
		SPSA	0.86	0.84	0.88	0.87	0.96	0.95
	RealAmplitudes	COBYLA	0.85	0.84	0.88	0.87	0.95	0.95
		QAQO	0.86	0.85	0.89	0.88	0.96	0.95
		SPSA	0.87	0.86	0.87	0.86	0.97	0.95

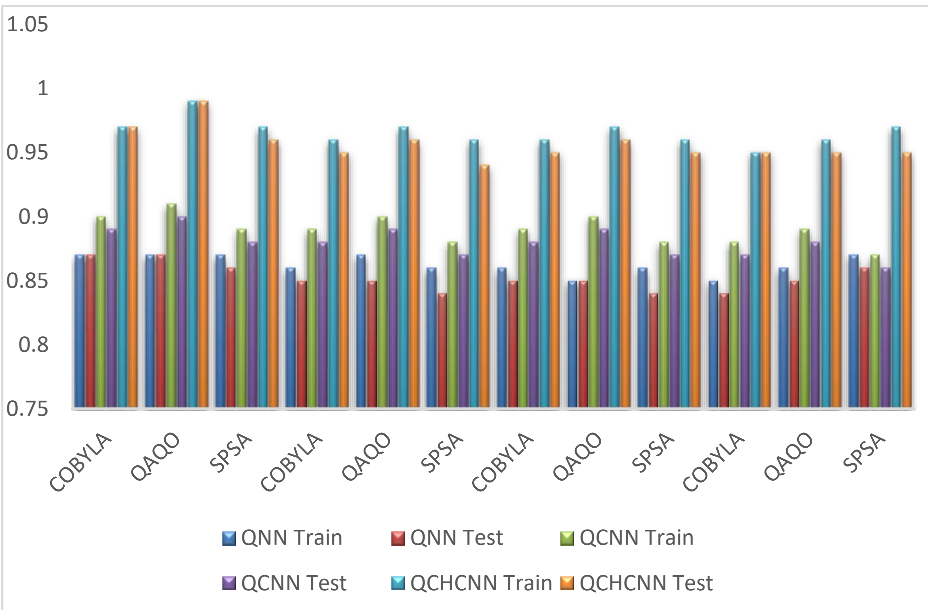

Fig.3. classifiers accuracy

Following figures shows the train and test performance of each algorithm

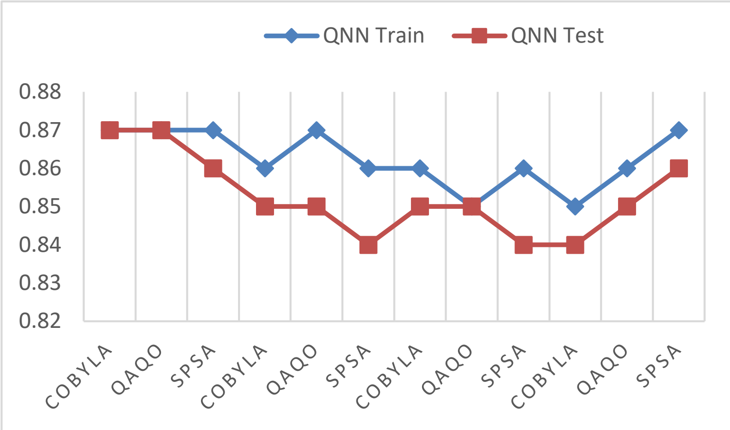

Fig.4 (a). Train & test performance of QNN

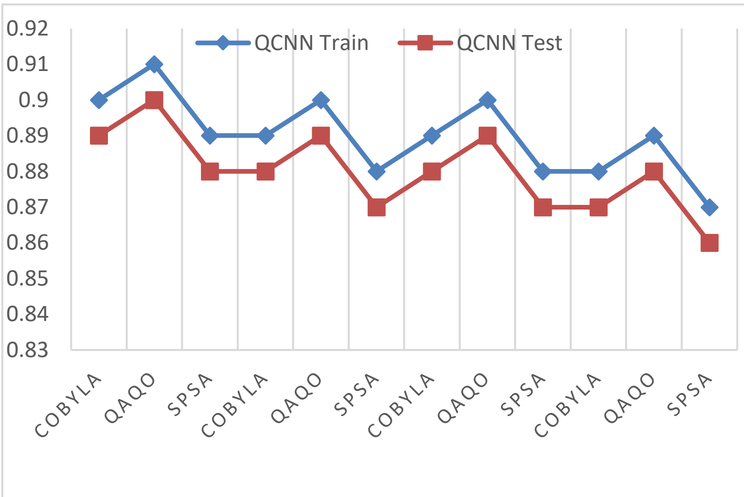

Fig.4 (b). Train & test performance of QCNN

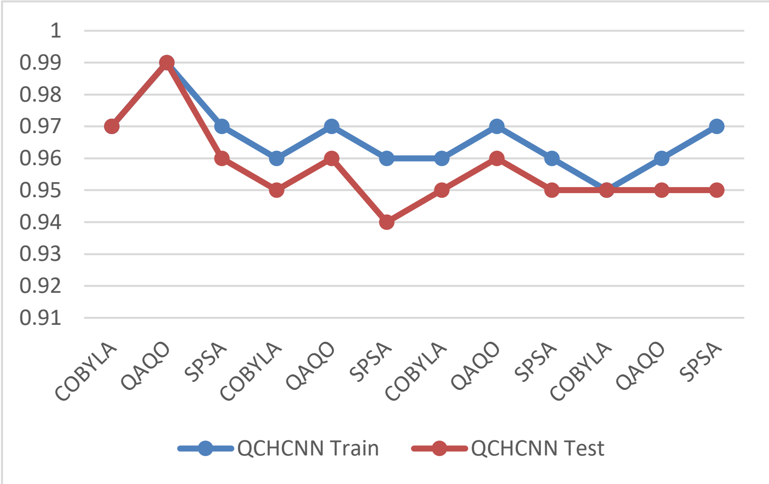

Fig.4 (C). Train & test performance of QCHCNN

The chart utilizes the y-axis to represent performance metrics and the x-axis to depict various algorithms.

The table provided below presents detailed results obtained for epochs 5, 10, and 15. In this analysis, ZZFeaturemap is employed as the designated feature map, while EfficientSU2 is selected as the Ansatz. Furthermore, the optimization process involves the use of three distinct optimizers: COBYLA, QAQO, and SPSA. These outcomes and setups provide valuable insights into the performance and behavior of the quantum algorithm under examination across diverse epochs and with various combinations of feature maps and optimizers.

Table 2. Classifier performance at epoch 5, 10, 15 for COBYLA

Feature map : ZZFeaturemap Ansatz : EfficientSU2 and Optimizer COBYLA								
Algorithms	Accuracy		Precision		Recall		F1Score	
	Train	Test	Train	Test	Train	Test	Train	Test
Epoch 5								
QNN	0.83	0.82	0.19	0.54	0.21	0.59	0.26	0.44
QCNN	0.86	0.84	0.22	0.63	0.23	0.54	0.20	0.56
QCHCNN	0.90	0.89	0.17	0.49	0.33	0.38	0.70	0.60
Epoch 10								
QNN	0.85	0.84	0.23	0.61	0.37	0.49	0.45	0.54
QCNN	0.88	0.87	0.34	0.70	0.54	0.67	0.32	0.65
QCHCNN	0.94	0.93	0.41	0.65	0.62	0.78	0.77	0.80
Epoch 15								
QNN	0.87	0.87	0.21	0.34	0.31	0.29	0.26	0.44
QCNN	0.90	0.89	0.26	0.53	0.27	0.34	0.20	0.56
QCHCNN	0.97	0.97	0.10	0.39	0.56	0.77	0.78	0.84

Table 3. Classifier performance at epoch 5, 10, 15 for QAQO

Feature map : ZZFeaturemap Ansatz : EfficientSU2 and Optimizer QAQO								
Algorithms	Accuracy		Precision		Recall		F1Score	
	Train	Test	Train	Test	Train	Test	Train	Test
Epoch 5								
QNN	0.84	0.85	0.10	0.24	0.32	0.49	0.35	0.34
QCNN	0.88	0.87	0.21	0.33	0.24	0.44	0.24	0.36
QCHCNN	0.91	0.90	0.25	0.29	0.30	0.29	0.50	0.70
Epoch 10								
QNN	0.87	0.86	0.23	0.21	0.17	0.39	0.25	0.31
QCNN	0.89	0.88	0.27	0.50	0.44	0.57	0.30	0.45
QCHCNN	0.96	0.95	0.31	0.45	0.52	0.68	0.66	0.70
Epoch 15								
QNN	0.87	0.87	0.22	0.45	0.19	0.30	0.26	0.44
QCNN	0.91	0.90	0.24	0.36	0.27	0.45	0.66	0.56
QCHCNN	0.99	0.99	0.30	0.41	0.37	0.70	0.77	0.84

Table 4. Classifier performance at epoch 5, 10, 15 for SPSA

Feature map : ZZFeaturemap Ansatz : EfficientSU2 and Optimizer SPSA								
Algorithms	Accuracy		Precision		Recall		F1Score	
	Train	Test	Train	Test	Train	Test	Train	Test
Epoch 5								
QNN	0.85	0.84	0.15	0.26	0.34	0.52	0.35	0.34
QCNN	0.87	0.86	0.23	0.35	0.24	0.47	0.23	0.34
QCHCNN	0.90	0.89	0.27	0.31	0.32	0.31	0.50	0.70
Epoch 10								
QNN	0.86	0.85	0.23	0.21	0.23	0.36	0.25	0.31
QCNN	0.88	0.88	0.27	0.36	0.41	0.55	0.29	0.35
QCHCNN	0.95	0.94	0.32	0.43	0.43	0.54	0.56	0.60
Epoch 15								
QNN	0.87	0.86	0.23	0.41	0.17	0.28	0.24	0.32
QCNN	0.89	0.88	0.21	0.34	0.27	0.41	0.47	0.56
QCHCNN	0.97	0.96	0.28	0.39	0.35	0.50	0.68	0.76

Analyzing the table above reveals that the highest accuracy was attained under specific conditions. Specifically, at epoch 15, utilizing the QAQO optimizer, and employing the QCHCNN configuration yielded the most favorable outcome. This observation provides valuable insights into the optimal settings for achieving superior accuracy in the context of the presented experiment.

The following figure illustrates the accuracy and loss of QCHCNN over a few epochs

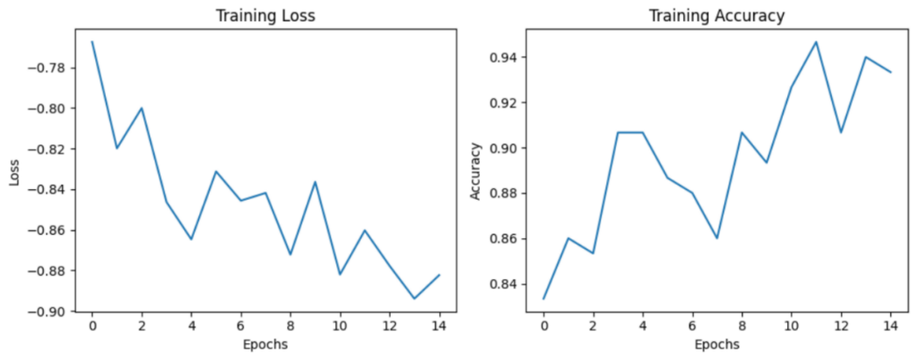

Fig.5.(a).Accuracy& Loss

The following figure shows the accuracy and loss values for QCHCNN and QAQO over epochs

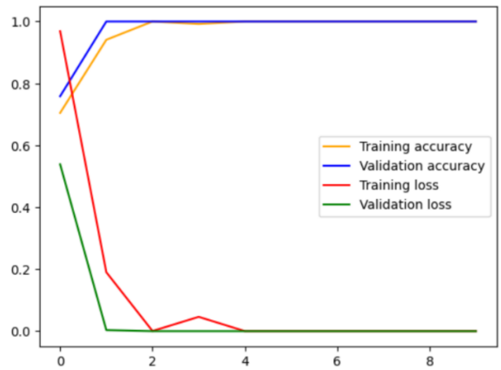

Fig.6.Accuracy & Loss value for QAQO optimization with QCHCNN

From the presented results, it is evident that QAQO optimization with QCHCNN achieves high accuracy and minimal loss.

6. Conclusion

The quantum nature of these algorithms can potentially address optimization challenges in parameter tuning, leading to improved adaptability and performance. Quantum machine learning's ability to handle large datasets and optimize complex models positions it as a promising tool for advancing the efficiency and effectiveness of tomato leaf disease detection.

While practical implementations of quantum machine learning in agriculture, specifically in tomato leaf disease detection, are still in the early stages of exploration, the ongoing advancements in quantum computing technologies hold the promise of transforming the landscape of crop health monitoring.As scientists persist in exploring and crafting quantum algorithms specifically designed for agricultural contexts, the incorporation of quantum machine learning into disease detection systems could prove instrumental in alleviating losses and safeguarding the overall well-being and productivity of tomato crops.

Quantum computing's inherent ability to process large datasets in parallel may facilitate the efficient analysis of extensive datasets of plant leaf images. This can lead to more robust and scalable disease detection models. pattern recognition could contribute to the development of highly sensitive and precise detection models. This model attains an accuracy of 87% for Quantum Neural Network (QNN), 90% for Quantum Convolutional Neural Network (QCNN), and an impressive 99% for Quantum Convolution Hybrid Convolution Neural Network (QCHCNN). The observations suggest that the QCHCNN demonstrates superior performance, making it a suitable classification model for the detection of Tomato leaf diseases.

Future Enhancement

Quantum machine learning, as a dynamic and evolving field, represents a frontier of exploration in this research. The current investigation, while employing a select set of techniques, paves the way for a broader spectrum of experimentation in disease detection through quantum methodologies. This research thus acts as a catalyst, encouraging scholars to embark on a scholarly journey to unravel the untapped capabilities inherent in the realm of quantum machine learning.

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