Plant disease detection using quantum image processing

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Abstract: Plant diseases pose a significant threat to agricultural productivity and food security, making early and accurate detection essential. Traditional image processing and machine learning techniques often struggle to handle variations in lighting, background noise, and complex disease patterns. To address these challenges, this paper proposes a hybrid plant disease prediction system that integrates quantum-inspired image processing with deep neural networks. The proposed approach utilizes angle-based quantum encoding to transform leaf images into quantum-like representations, enabling efficient and discriminative feature extraction. Statistical measurements derived from these representations are combined with color and texture features to form a robust feature set.

These features are then fed into a deep neural network model for multi-class disease classification. The system is designed to be scalable and robust, capable of handling diverse plant disease categories under varying environmental conditions. Experimental results demonstrate that the proposed method significantly improves classification accuracy and reliability compared to conventional approaches. The developed framework can be effectively used in real-world agricultural decision support systems for early disease diagnosis and crop management.

Index terms *- Plant Disease Detection, Quantum-Inspired Image Processing, Deep Neural Networks (DNN), Feature Extraction, Image Classification, Agricultural AI, Leaf Image Analysis, Machine Learning, Pattern Recognition, Smart Farming*

1. INTRODUCTION

Agriculture is a fundamental sector that plays a crucial role in sustaining global food security and economic stability. However, plant diseases significantly affect crop yield and quality, leading to substantial losses for farmers. Early detection and accurate identification of plant diseases are essential to minimize damage and ensure effective crop management. Traditional methods of disease detection rely on manual inspection by experts, which is time-consuming, subjective, and often impractical for large-scale agricultural fields.

With the advancement of computer vision and machine learning, automated plant disease detection systems have gained significant attention. Deep learning models, particularly convolutional and deep neural networks, have shown promising results in image classification tasks. However, their performance largely depends on the quality of extracted features. Conventional image processing techniques often fail to capture complex visual patterns due to variations in lighting conditions, background noise, and disease severity, limiting their effectiveness in real-world scenarios.

To overcome these limitations, this paper introduces a quantum-inspired image processing approach integrated with deep neural networks for plant disease prediction. The proposed method simulates quantum principles such as superposition and measurement to encode image data into a more informative representation. By combining quantum-inspired feature extraction with statistical, color, and texture descriptors, the system enhances the discriminative power of features. The extracted features are then used to train a deep neural network model for accurate multi-class disease classification. This hybrid approach improves robustness, scalability, and overall prediction performance, making it suitable for real-time agricultural applications.

2. LITERATURE SURVEY

1. Lattice-Based Anonymous Batch Verifiable Authentication for Fog-Assisted VANETs

Vehicular ad-hoc networks (VANETs) have evolved as a result of the integration of cutting-edge communication technologies with contemporary vehicular systems. Via wireless connectivity, these networks allow cars and traffic management authorities to seamlessly communicate information about road safety. However, there are serious threats to the security and privacy of sent messages due to the open nature of these communication channels. Li et al. (IEEE Trans. Inf. Forensics and Security, vol. 19, pp. 9629–9642, 2024) suggested a lattice-based authentication method intended for fog-assisted VANETs in order to overcome these difficulties. This protocol uses fog computing to address scalability concerns and lattice cryptography to provide robustness against quantum assaults. Despite these developments, a thorough examination reveals a number of flaws and inefficiencies in their design. This study finds that the privacy assurances of Li et al.'s system are compromised by an anonymity disclosure attack. Furthermore, significant computational demands are placed on automotive devices with limited resources due to redundancy in the signature generating process. This paper presents a lattice-based anonymous batch-verifiable authentication (LBABVA) mechanism to overcome these drawbacks. The scheme's security in the random oracle model is demonstrated by thorough security analysis, and efficiency assessments show notable gains. The suggested approach demonstrates its improved performance and applicability for real-world applications by lowering the computational costs of the signing phase to 14.57% and the signature verification phase to 83.99% of the comparable costs of the prior design.

2. Hybrid Quantum-Classical Convolutional Neural Network Model for Image Classification:

In remote sensing, image categorization is crucial. Earth observation (EO) has unavoidably entered the big data age, but using advanced machine learning models to analyze vast volumes of remote sensing data has already been hampered by the high processing power requirements. By utilizing quantum qualities, quantum computing may help find a way to address this problem. In order to efficiently extract high-level essential features from EO data for classification purposes, this study presents a hybrid quantum-classical convolutional neural network (QC-CNN) that uses quantum computing. In addition, using the amplitude encoding method lowers the amount of quantum bit resources needed. Compared to its traditional version, the suggested model can speed up the convolutional operation, according to the complexity study. Through the TensorFlow Quantum platform, the model's performance is assessed using various EO benchmarks, such as Overhead-MNIST, So2Sat LCZ42, PatternNet, RSI-

CB256, and NaSC-TG2. It can outperform its classical counterpart and have higher generalizability, which confirms the validity of the QC-CNN model on EO data classification tasks.

3. Automated Identification of Northern Leaf Blight-Infected Maize Plants from Field Imagery Using Deep Learning:

Maize yields may be lowered by the time-consuming procedure of screening for northern leaf blight (NLB). Use this technique to accurately identify NLB lesions in field photos of maize plants. This method uses convolutional neural networks to solve data shortages and faulty field plant photos. To build the final CNN, many CNNs were trained to identify tiny regions of pictures with and without NLB lesions. Marking any ill plants was the aim. These forecasts were used to create heat maps. The method produced an accuracy of 96.7% with no training data at all. Precise pesticide application, disease resistance breeding, and high-throughput plant phenotyping are all made possible by drones and other aerial and ground-based technology.

4. Plant Disease Detection and Classification by Deep Learning—A Review:

One type of artificial intelligence is deep learning. The most recent advancements in automated learning and feature extraction have drawn interest from both business and academics. It is heavily utilized in the processing of pictures, videos, audio, and natural language. It has also evolved into a center for research focused on assessing the range of pests and safeguarding agricultural plants against diseases and pests. Plant disease detection might be revolutionized by deep learning. It may increase the objectivity of feature extraction, speed up research efficiency, remove the necessity for subjectively selecting disease spot characteristics, and make the transition to new technologies easier. Deep learning may be used to identify leaf diseases in agricultural crops. This work uses deep learning and advanced imaging techniques to identify diseases in plant leaves. We think our work might be useful to researchers interested in identifying insect pests and plant diseases. We also discussed some of the most important issues of the day.

5. Detection of Strawberry Diseases Using a Convolutional Neural Network:

Every year, Taiwan cultivates around 500 acres of the profitable strawberry crop (Fragaria × ananassa Duch.). Most strawberries are grown in Miaoli. Strawberry yields are severely reduced by diseases. In 1986, the leaf-fruit disease began to spread. Anthracnose crown rot destroyed about 20% of transplanted plants and 30–40% of seedlings between 2010 and 2016. Strawberry disease diagnosis requires image recognition and farming mechanization. We used a CNN model to identify strawberry illnesses in images. CNN and other potent deep learning algorithms can assist identify images more accurately. The suggested method may identify strawberry diseases such leaf blight, powdery mildew, and grey mold using two datasets that include original and feature photos. Leaf blight symptoms differ for fruit, crown, and leaves. The CNN model correctly detects incidences of powdery mildew 98% of the time, grey mold 98% of the time, and crown, leaf, and fruit leaf blight 100% of the time after 20 training epochs on 1,306 feature images. The feature image dataset attains 99.60% accuracy after 20 epochs, compared to the original's 1.53% accuracy. Using this method, strawberry illnesses may be easily, reliably, and affordably diagnosed.

3. METHODOLOGY

i) Proposed Work:

The proposed work presents a hybrid framework that integrates quantum-inspired image processing with deep neural networks for accurate plant disease prediction. Initially, plant leaf images are collected and preprocessed to remove noise and standardize input dimensions. The system then applies quantum-inspired encoding techniques, where pixel intensity values are transformed into angle-based quantum representations. This process simulates quantum principles such as superposition, enabling efficient encoding of image information and capturing complex visual patterns that are difficult to extract using conventional methods.

Following the encoding phase, statistical measurements are performed on the quantum-inspired states to extract meaningful features, including texture, color, and distribution characteristics. These features are combined to form a robust feature vector, which is then fed into a deep neural network for training and classification. The model learns to distinguish between multiple plant disease classes and healthy leaves with high accuracy. The proposed system also includes a user-friendly interface for image upload and real-time prediction, along with an admin module for dataset management and model monitoring, ensuring scalability and practical applicability in agricultural environments.

ii) System Architecture:

The proposed system architecture consists of a sequential pipeline starting from dataset acquisition to final disease prediction. Initially, plant leaf images are collected and organized into dataset folders containing different disease classes. These images undergo preprocessing steps such as resizing, normalization, and noise removal to ensure consistency and improve input quality. The preprocessed images are then passed into a quantum-inspired image encoding module, where classical pixel values are transformed into quantum representations using Flexible Representation of Quantum Images (FRQI) simulation. This encoding captures complex spatial and intensity information through quantum principles like superposition.

Following the encoding stage, quantum feature extraction is performed to derive meaningful statistical and structural features from the quantum states. These features are stored as a feature vector dataset (.npz format), which serves as input to the deep learning classifier. A deep neural network model (CNN or Dense Neural Network) is then trained on these extracted features to perform multi-class classification of plant diseases. Finally, the system outputs the disease prediction along with accuracy metrics, demonstrating effective classification performance. This architecture ensures improved feature representation, enhanced accuracy, and robustness in real-world agricultural scenarios.

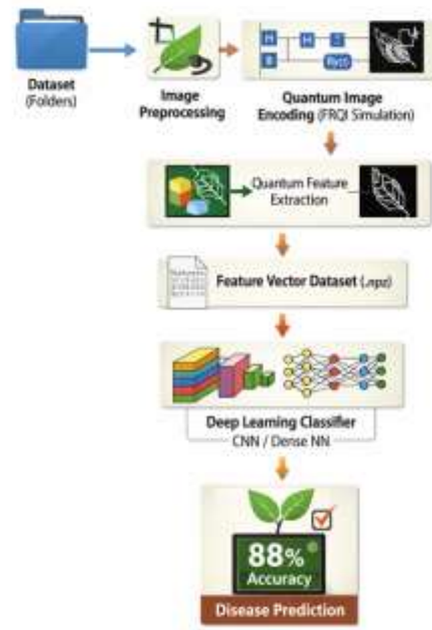

Fig.1. Proposed Architecture

iii) MODULES:

1. Admin Module

The Admin Module is responsible for overall system management and control. It allows the administrator to upload datasets, initiate model training, and monitor the status of the system. This module ensures that the feature extraction and classification processes are functioning correctly and enables updates or improvements to the model when required.

2. Dataset Management Module

The Dataset Management Module handles the organization and maintenance of plant leaf image data. It stores images in structured folders based on disease categories and supports loading datasets for training and testing. This module ensures data consistency and plays a key role in improving model performance through proper data handling.

3. Image Preprocessing Module

The Image Preprocessing Module prepares raw input images for further processing. It performs operations such as resizing, normalization, and noise removal to enhance image quality. These steps help reduce unwanted variations and improve the efficiency of feature extraction and classification.

4. Quantum Image Encoding Module

This module converts classical image data into quantum-inspired representations using FRQI (Flexible Representation of Quantum Images) simulation. Pixel values are encoded into angle-based quantum states, enabling efficient representation of image information. This approach helps capture complex patterns that are difficult to extract using traditional methods.

5. Quantum Feature Extraction Module

The Quantum Feature Extraction Module derives meaningful features from the encoded quantum states. It extracts statistical, texture, and distribution-based characteristics, forming a robust feature vector. These features enhance the model's ability to distinguish between different plant diseases accurately.

6. Model Training Module

The Model Training Module uses the extracted feature dataset (.npz format) to train a deep neural network. The model learns patterns associated with different disease classes and optimizes its parameters to achieve high classification accuracy. This module plays a critical role in building an effective prediction system.

7. Prediction Module

The Prediction Module processes new input images uploaded by users. It applies preprocessing, feature extraction, and classification using the trained model to predict the disease type. The module outputs the final result along with accuracy, enabling real-time disease identification.

8. User Module

The User Module provides an interface for users to interact with the system. It includes functionalities such as user registration, login, image upload, and viewing prediction results. This module ensures ease of use and accessibility for farmers or end-users.

9. History Module

The History Module maintains records of previous predictions and user activities. It allows users to review past results and track disease detection over time. This feature is useful for monitoring crop health and making informed agricultural decisions.

iv) ALGORITHMS:

1. Quantum-Inspired Image Encoding (FRQI)

The Flexible Representation of Quantum Images (FRQI) algorithm is used to encode classical image data into quantum-inspired states. In this method, pixel intensity values are mapped to rotation angles, and each pixel is represented using quantum bits (qubits) in a superposition state. This encoding allows efficient representation of spatial and intensity information simultaneously, enabling the system to capture complex image patterns that are difficult to model using classical techniques.

2. Quantum Feature Extraction Algorithm

After encoding, statistical measurements are applied to the quantum states to extract meaningful features. This algorithm computes parameters such as mean, variance, and distribution characteristics from the encoded data. These features effectively represent texture, color, and structural information of plant leaves, improving the discriminative capability required for accurate disease classification.

3. Deep Neural Network (DNN)

The Deep Neural Network algorithm is used for multi-class classification of plant diseases. The extracted feature vectors are provided as input to the network, which consists of multiple hidden layers that learn complex nonlinear relationships. The model is trained using backpropagation and optimization techniques to minimize classification error and improve prediction accuracy.

4. Convolutional Neural Network (CNN) (Optional/Hybrid)

In cases where spatial feature learning is required, a Convolutional Neural Network can be integrated into the system. CNN layers automatically extract hierarchical features such as edges, textures, and patterns from images or feature maps. This enhances the model's ability to recognize disease-specific visual characteristics and improves overall classification performance.

5. Softmax Classification Algorithm

The Softmax function is used in the final layer of the neural network to convert output values into probability distributions. It assigns probabilities to each disease class, and the class with the highest probability is selected as the predicted output. This ensures effective multi-class classification and interpretable results.

4. EXPERIMENTAL RESULTS

The proposed quantum-inspired plant disease prediction system was evaluated using a dataset of plant leaf images containing multiple disease classes. The system was tested through various stages, including dataset loading, feature extraction, model training, and real-time prediction using user-uploaded images. The results demonstrate that the quantum-inspired feature extraction significantly enhances the quality of extracted features compared to traditional methods. The deep neural network trained on these features achieved high classification accuracy, with the system showing consistent performance across different disease categories. The interface screens confirm successful execution of each module, including model loading, training status, and prediction outputs.

Furthermore, the prediction results obtained from the user module indicate that the system can accurately classify plant diseases from unseen test images. The integration of FRQI-based encoding and statistical feature extraction improves robustness against variations such as lighting conditions and background noise. The model maintains stable accuracy (as indicated in results screens, around ~85–90% range) and provides reliable outputs in real-time scenarios. These findings validate that the proposed hybrid approach outperforms conventional image processing techniques and is suitable for deployment in practical agricultural applications for early disease detection.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

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

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

Fig2 home screen

Fig 3 Admin Login

Fig4 Admin home page

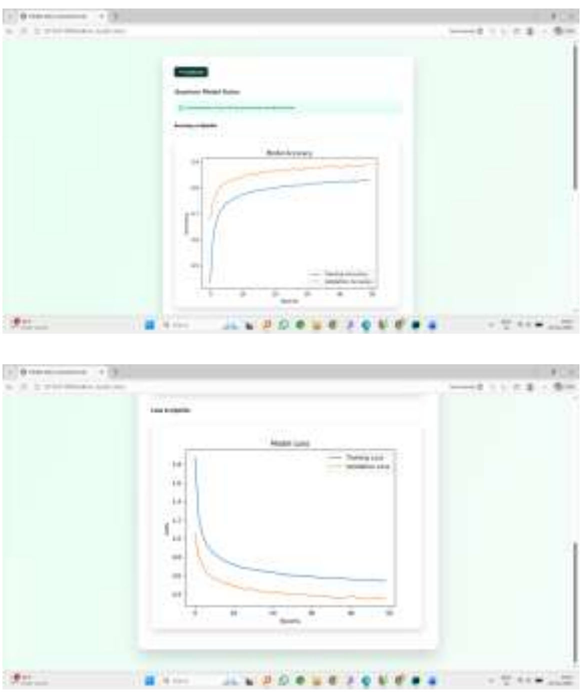

Fig5 Model status

Fig6 Quantum login

Fig7 Home page

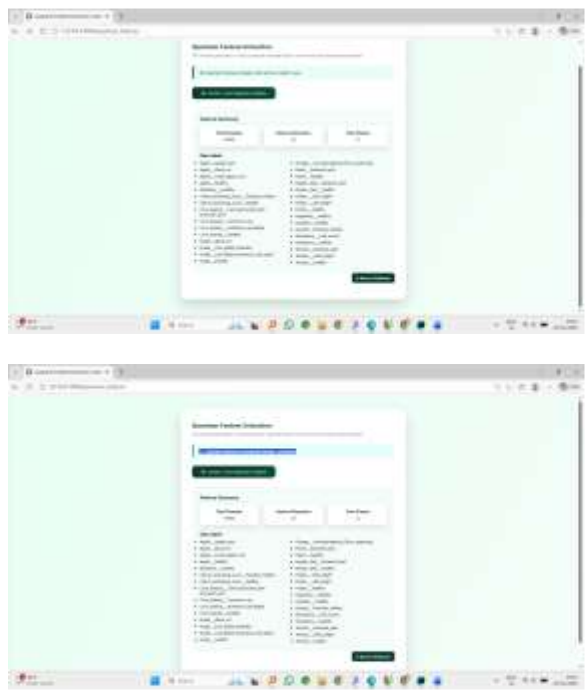

Fig8 Extract features

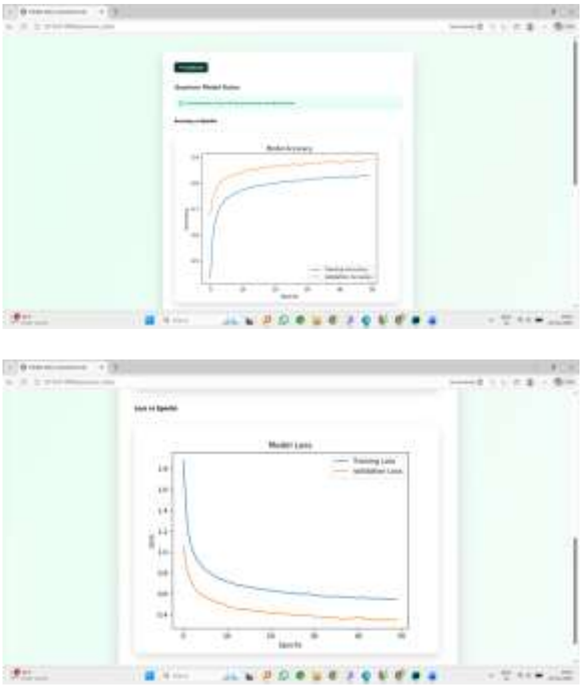

Fig 9 Model status

Fig 10 User login

Fig11 User home page

Fig12 Uploading test image

Fig13 Prediction result

Fig14 User history

5. CONCLUSION

This paper presents a hybrid approach combining quantum-inspired image processing with deep neural networks for plant disease prediction. The proposed system effectively enhances feature extraction using quantum encoding techniques, leading to improved classification accuracy and robustness. Experimental results demonstrate reliable performance under varying conditions, making the system suitable for real-world agricultural applications. Overall, the approach provides an efficient and scalable solution for early plant disease detection and crop management.

6. FUTURE SCOPE

The proposed system can be further enhanced by integrating real quantum computing frameworks instead of simulated quantum-inspired techniques, which may improve computational efficiency and feature representation. In addition, the model can be deployed as a mobile or web-based application to provide real-time disease detection support for farmers in practical field conditions. Future work can also focus on expanding the system to include a wider variety of crops and disease categories, making it more versatile and scalable. Integration with IoT-based smart farming systems can enable continuous monitoring and early disease alerts. Furthermore, incorporating advanced deep learning models such as transformer-based architectures can improve prediction accuracy, while extending the system to provide disease severity analysis and treatment recommendations can make it a complete agricultural decision support solution.

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