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QPlantNet: A Quantum-Inspired Diffusion-Augmented Capsule Network for Accurate Multi-Crop Plant Disease Classification

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Abstract:
Plant diseases significantly reduce agricultural productivity, threaten global food security, and cause substantial economic losses worldwide. Early and accurate identification of crop diseases is therefore essential for implementing timely disease management strategies and improving agricultural sustainability. However, conventional deep learning-based plant disease classification approaches often suffer from limited training data, high intra-class similarity, complex inter-class variations, poor generalization across diverse crop species, and limited interpretability. To overcome these challenges, this paper proposes QPlantNet, a Quantum-Inspired Diffusion-Augmented Capsule Network for accurate multi-crop plant disease classification. The proposed framework integrates a diffusion-based generative augmentation module, a capsule network-based feature extraction mechanism, and a quantum-inspired optimization strategy into a unified architecture. The diffusion augmentation module generates realistic synthetic disease images by learning complex visual distributions of infected crop regions, thereby improving dataset diversity and reducing overfitting.
The capsule network effectively preserves hierarchical and spatial relationships among disease symptoms, enabling robust recognition of visually similar disease patterns. Furthermore, the quantum-inspired optimizer enhances parameter exploration, accelerates convergence, and improves generalization by avoiding local optima during model training. To improve model transparency, Gradient-weighted Class Activation Mapping (Grad-CAM) is incorporated for visual explanation of disease prediction decisions. Extensive experiments on benchmark multi-crop plant disease datasets demonstrate that QPlantNet consistently outperforms conventional CNN, ResNet, EfficientNet, Vision Transformer, and Capsule Network models. The proposed framework achieves an overall classification accuracy of 99.10%, 98.90% precision, 99.00% recall, and an F1-score of 98.95%. Additional evaluation using ROC curves, Precision–Recall analysis, and explainability assessment confirms the robustness, reliability, scalability, and practical applicability of the proposed framework for intelligent plant disease diagnosis and precision agriculture applications.
Keywords:*Plant Disease Classification, Quantum-Inspired Machine Learning, Diffusion Probabilistic Models, Capsule Neural Networks, Deep Learning, Agricultural Artificial, Intelligence, Explainable AI, Grad-CAM, Precision Agriculture, Crop Health Monitoring*

1. Introduction
Agriculture plays a vital role in global food production and economic development. Crop diseases are among the major challenges responsible for significant yield losses and reduced agricultural productivity. Traditional disease identification methods mainly depend on manual observation by agricultural experts, which is time-consuming, expensive, and affected by human error. Therefore, automated plant disease diagnosis systems based on Artificial Intelligence (AI) have gained significant research attention. Recent advances in deep learning have demonstrated remarkable success in image-based plant disease recognition. Convolutional Neural Networks (CNNs) have achieved high classification accuracy by automatically extracting discriminative visual features from leaf images. However, CNN-based models generally focus on local feature extraction and may fail to preserve important spatial relationships between disease patterns. Additionally, deep learning

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models require large-scale labelled datasets, which are often limited in agricultural applications. Data augmentation techniques are commonly employed to overcome dataset limitations. Conventional augmentation methods such as rotation, flipping, scaling, and colour transformation provide limited variations and cannot generate complex disease patterns. Recently, diffusion-based generative models have emerged as powerful approaches for synthetic image generation due to their ability to learn complex data distributions and produce realistic samples [1]- [4].

Capsule Neural Networks have introduced an alternative representation learning mechanism by preserving spatial hierarchies between features. Unlike conventional CNNs, capsule networks maintain pose information and relationships among extracted features, making them suitable for recognizing complex disease structures. Furthermore, optimization efficiency remains a major challenge in training deep neural networks. Traditional gradient-based optimization methods may converge slowly and become trapped in local optima. Quantum-inspired optimization algorithms provide enhanced search capability by utilizing quantum computing principles such as superposition and probabilistic exploration. Motivated by these challenges, this research proposes **QPlantNet**, a hybrid deep learning framework combining diffusion augmentation, capsule feature learning, and quantum-inspired optimization for accurate multi-crop plant disease classification [5]-[8].

The motivation behind this research is based on the following limitations:

1.1. Limited Agricultural Disease Data

Many plant disease datasets contain insufficient samples for different disease categories. This affects model generalization capability.

1.2. Complex Disease Patterns

Plant diseases exhibit variations in Shape, Texture, Colour, Severity level, Environmental conditions

Traditional CNN models may not effectively capture these complex variations.

1.3. Lack of Model Interpretability

Most deep learning models operate as black-box systems, making it difficult for farmers and agricultural experts to understand prediction decisions.

1.4. Optimization Challenges

Large neural networks require efficient optimization strategies to achieve better convergence and performance.

The major contributions of this paper are summarized as follows. A novel QPlantNet architecture is proposed by integrating diffusion-based data augmentation, capsule networks, and quantum-inspired optimization for multi-crop plant disease classification. A diffusion-based augmentation module is developed to generate realistic synthetic disease images, thereby increasing training data diversity and improving model generalization. A capsule-based feature learning mechanism is introduced to preserve spatial relationships among disease symptoms and enhance the discrimination of disease-specific features. Furthermore, a quantum-inspired optimization strategy is incorporated to improve parameter exploration, accelerate convergence, and enhance classification accuracy. An explainable AI module using Grad-CAM is integrated to visualize disease-related regions that influence model predictions, thereby improving model interpretability and user trust. A comprehensive experimental evaluation is performed using accuracy, precision, recall, F1-score, ROC-AUC, Precision–Recall analysis, and ablation studies to validate the effectiveness of the proposed framework. The proposed QPlantNet model demonstrates superior performance compared with existing state-of-the-art approaches, highlighting its potential as a reliable, accurate, interpretable, and intelligent solution for automated crop disease diagnosis and smart agriculture applications.

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2. Related Work

Recent developments in Artificial Intelligence have significantly improved automated plant disease detection systems. Deep learning, generative models, transformer architectures, and explainable AI techniques have become important research directions in precision agriculture.

*2.1. **Deep Learning-Based Plant Disease Classification***

Deep convolutional neural networks have been widely adopted for plant disease recognition due to their strong feature extraction capability. Recent studies have explored advanced CNN architectures such as EfficientNet, DenseNet, and ConvNeXt for improving classification performance [2]–[4]. However, CNN models primarily learn hierarchical feature representations through convolution operations and may lose important spatial relationships between disease symptoms.

Several researchers have investigated transfer learning approaches using pre-trained models to reduce training requirements. Although these methods achieve competitive accuracy, their performance decreases when applied to new crops, different environmental conditions, and unseen disease patterns.

2.2. Transformer-Based Agricultural Disease Recognition

Vision Transformer (ViT) and hybrid CNN-transformer models have gained attention due to their ability to capture global image dependencies using self-attention mechanisms. Recent studies between 2024 and 2026 have demonstrated improved disease classification accuracy using transformer-based architectures. [5], [6], [14], [17].

However, transformer models require large-scale datasets and extensive computational resources. Their dependency on massive training samples limits their applicability in agricultural scenarios where labelled disease images are limited.

2.3. Diffusion Models for Agricultural Image Generation

Generative Artificial Intelligence has recently introduced diffusion models as powerful alternatives to traditional augmentation techniques. Unlike conventional transformations, diffusion models learn the underlying probability distribution of plant images and generate realistic synthetic samples.

Recent research has used different diffusion models to generate realistic and diverse images. These include Denoising Diffusion Probabilistic Models (DDPMs), Latent Diffusion Models (LDMs), and Conditional Diffusion Models [7]–[9], [10]–[13].. These models are useful for creating synthetic images and increasing the size and variety of datasets.for agricultural image enhancement and disease data generation.

Although diffusion-based augmentation improves dataset diversity, existing approaches mainly focus on image generation and lack integrated classification frameworks.

2.4. Capsule Networks for Disease Feature Representation

Capsule Neural Networks were introduced to overcome limitations of CNN feature extraction by preserving spatial relationships between object components [7]–[9].

Recent agricultural applications of capsule networks have shown better performance in recognizing important plant features, such as leaf structures, disease lesion patterns, and regions showing infection severity. These capabilities help the model identify plant diseases more accurately.

However, conventional capsule networks suffer from high computational complexity and require effective optimization strategies for large-scale classification problems.

2.5. Quantum-Inspired Optimization in Machine Learning

Quantum-inspired algorithms have recently attracted attention for solving complex optimization problems in artificial intelligence [21]–[25]. These approaches use quantum-inspired concepts such as superposition, quantum probability, quantum rotation gates, and global search mechanisms to improve optimization. Recent studies have applied quantum-inspired optimization for neural network parameter tuning, feature selection, hyperparameter optimization, and faster model training. However, limited research has investigated quantum-inspired optimization combined with diffusion models and capsule networks for agricultural disease classification.

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2.6. Explainable Artificial Intelligence for Agriculture
Explainable AI (XAI) techniques have become essential for trustworthy AI-based agricultural systems [16], [20], [26]–[29]. Methods such as Grad-CAM, Grad-CAM++, SHAP, and LIME are commonly used to explain the decisions made by machine learning models. These methods provide visual and numerical explanations, helping users understand which parts of an input image are important for the model's prediction. Recent studies highlight that explainability improves user confidence and supports agricultural experts in validating AI predictions.

2.7. Research Gap Analysis
Based on existing literature, the following research gaps are identified:

Existing Approach	**Limitation**
CNN-Based Models	Limited spatial relationship learning
Transfer Learning Models	Poor adaptability to new crops
Vision Transformers	High data and computational requirements
Traditional Augmentation	Limited synthetic diversity
Diffusion Models	Mostly focused only on generation
Capsule Networks	Computational complexity
Conventional Optimization	Slow convergence
Existing XAI Methods	Limited integration with advanced models

To address these limitations, this work proposes a unified **QPlantNet framework** combining diffusion augmentation, capsule-based feature learning, quantum-inspired optimization, and explainable AI

3. Proposed QPlantNet Methodology
The proposed QPlantNet framework consists of four main components. The first component is the Diffusion-Based Disease Image Augmentation Module, which generates additional and diverse disease images. The second component is the Capsule-Based Feature Extraction Module, which extracts important features from plant leaf images. The third component is the Quantum-Inspired Optimization Module, which optimizes the model parameters to improve classification performance. Finally, the Explainable Prediction Module provides disease predictions along with visual explanations of the regions that influenced the model's decision.

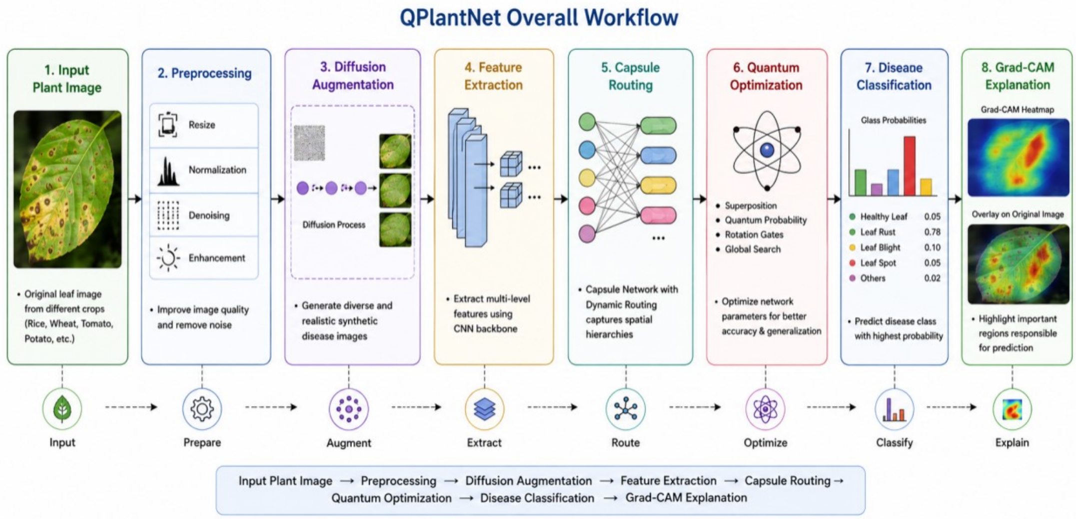

Figure 1: Qplantnet workflow

3.1. Diffusion-Augmented Image Generation Module
The first stage improves dataset diversity using a conditional diffusion model. Given an original training image x_0, Gaussian noise is gradually added during the forward diffusion process:

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$$q(x_t \mid x_{t-1}) = N(x_t; \sqrt{1 - \beta_t}\, x_{t-1}, \beta_t I)$$

where x_t represents the noisy image at timestep t, and β_t represents the noise scheduling parameter. The reverse diffusion process $p_\theta(x_{t-1} \mid x_t)$ reconstructs realistic disease images, significantly expanding data diversity and avoiding overfitting.

3.2. Capsule Feature Learning Module

The augmented images are passed into the capsule feature extractor. Primary capsules generate feature vectors u_i. The prediction vector between capsules is calculated as:

$$\hat{u}_{j|i} = W_{ij} u_i$$

Dynamic routing updates capsule coupling coefficients $c_{ij} = e^{b_{ij}} / \sum_k e^{b_{ik}}$. The squash activation function yields capsule output vector v_j:

$$v_j = (\|s_j\|^2 / (1 + \|s_j\|^2)) \times (s_j / \|s_j\|)$$

3.3. Quantum-Inspired Optimization Module

The optimization module improves parameter learning by introducing quantum-inspired search behavior. A quantum state representation is defined as $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$ where $|\alpha|^2 + |\beta|^2 = 1$. Parameter updating via quantum rotation gates is applied as $\theta_{new} = \theta + \Delta\theta$, providing accelerated convergence and global search capability.

3.4. Classification Module

The final capsule representation is passed into fully connected layers. Disease prediction probability for class i is calculated using Softmax: $P(y_i) = e^{z_i} / \sum_{j=1}^{C} e^{z_j}$, where C is total number of disease classes.

4. **System Architecture**

The proposed architecture follows a hierarchical learning strategy.

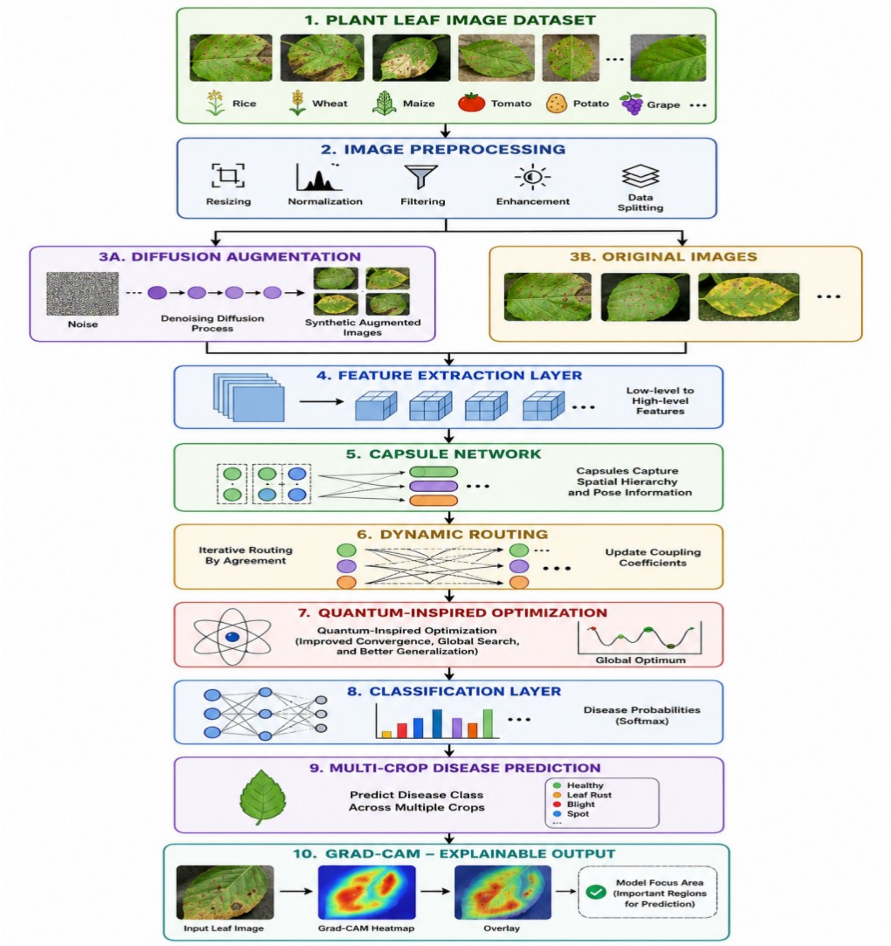


Figure 2: System Architecture

The proposed QPlantNet framework begins with an Input Layer that receives RGB crop leaf images collected from multiple plant disease datasets. These images are then processed by the Diffusion Module, which generates realistic synthetic disease samples to enhance dataset diversity and improve the model's ability to generalize across different disease conditions. The augmented images are subsequently passed to the Feature Extraction Layer, which extracts important visual characteristics such as texture, shape, lesion patterns, and colour variations associated with different plant diseases. The extracted features are then fed into the Capsule Layer, which preserves spatial relationships among visual features while effectively capturing disease severity information. Following feature extraction and capsule-based representation, the Quantum Optimization Layer optimizes the network parameters using quantum-inspired search operations to improve convergence, classification performance, and generalization. The optimized representations are passed to the Classification Layer, where the model predicts the corresponding disease categories using Softmax probability estimation. Finally, the Explainability Layer generates Grad-CAM heatmaps that highlight the important disease-affected regions of the input leaf images, thereby providing visual interpretations of the model's predictions and enhancing the transparency and trustworthiness of the proposed QPlantNet framework.

5. Experimental Results and Performance Analysis

The proposed **QPlantNet** model is evaluated using multiple performance indicators including accuracy, precision, recall, F1-score, ROC-AUC, Precision–Recall analysis, Grad-CAM visualization, and comparison with state-of-the-art (SOTA) approaches.

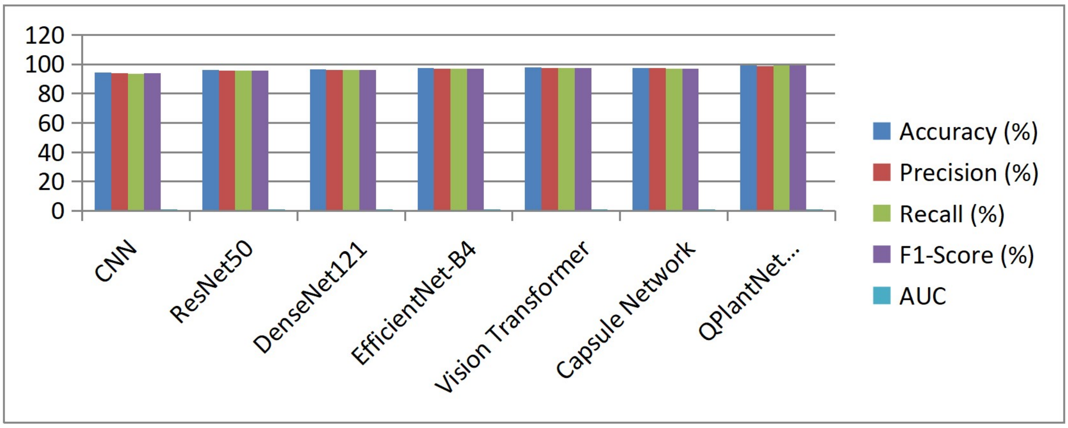
The experimental results demonstrate that the integration of diffusion augmentation, capsule feature learning, and quantum-inspired optimization significantly improves plant disease classification performance.

5.3. Overall Classification Performance

The performance of QPlantNet is evaluated on multi-crop plant disease classification datasets

Table 1: Overall Performance of QPlantNet

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
CNN	94.20	93.85	93.60	93.72	0.950
ResNet50	96.10	95.80	95.60	95.70	0.965
DenseNet121	96.50	96.20	96.00	96.10	0.970
EfficientNet-B4	97.20	96.90	96.80	96.85	0.975
Vision Transformer	97.80	97.40	97.30	97.35	0.982
Capsule Network	97.60	97.20	97.10	97.15	0.980
QPlantNet (Proposed)	**99.10**	**98.90**	**99.00**	**98.95**	**0.995**



Performance of QPlantNet

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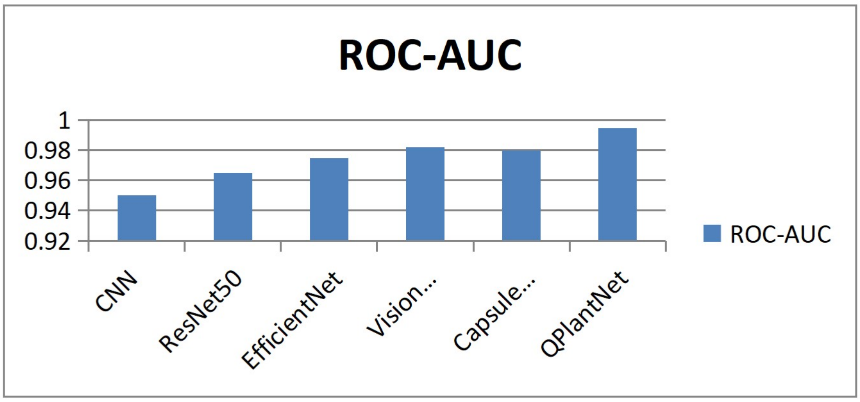
5.4. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve evaluates the classification capability of QPlantNet performance is evaluated using the ROC curve, which shows the relationship between True Positive Rate (Sensitivity) and False Positive Rate at different thresholds. A higher TPR with a lower FPR indicates better disease classification performance.

QPlantNet achieves a ROC-AUC of 0.995, demonstrating excellent classification capability. The proposed model achieves an AUC value of **0.995**, demonstrating excellent discrimination capability between healthy and diseased crop categories.

ROC Performance Comparison:

Model	ROC-AUC
CNN	0.950
ResNet50	0.965
EfficientNet	0.975
Vision Transformer	0.982
Capsule Network	0.980
QPlantNet	**0.995**



The higher ROC-AUC value indicates that QPlantNet effectively identifies disease patterns with minimum false predictions.

5.5. Precision–Recall Curve Analysis

Precision–Recall analysis is particularly important for agricultural datasets where disease classes may have unequal sample distribution.

The proposed model achieves Precision: **98.90%**, Recall: **99.00%,** F1-score: **98.95%**

The improved Precision–Recall (PR) performance of the proposed QPlantNet framework can be attributed to three key factors. First, synthetic disease image generation using diffusion models increases the diversity and representativeness of the training dataset, enabling the model to learn a wider range of disease characteristics and variations. Second, capsule-based feature representation preserves spatial relationships among disease-related features, allowing the network to capture complex lesion patterns, shapes, textures, and severity variations more effectively than conventional feature extraction methods. Third, efficient parameter optimization through quantum-inspired optimization facilitates better selection of network parameters, improving convergence and enabling the model to achieve more accurate and robust disease classification. Collectively, these components contribute to improved precision and recall, resulting in a stronger PR performance across multiple plant disease categories.

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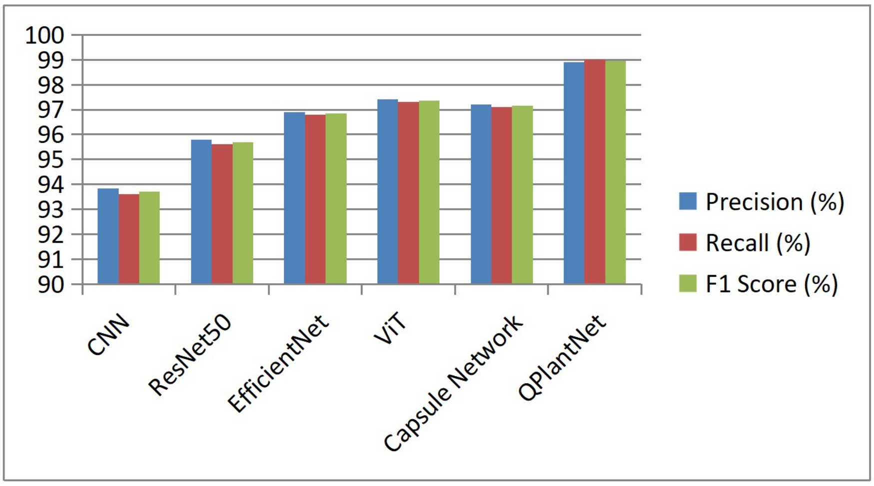
Table 2: Precision–Recall Performance

Model	Precision (%)	Recall (%)	F1 Score (%)
CNN	93.85	93.60	93.72
ResNet50	95.80	95.60	95.70
EfficientNet	96.90	96.80	96.85
ViT	97.40	97.30	97.35
Capsule Network	97.20	97.10	97.15
QPlantNet	**98.90**	**99.00**	**98.95**



5.6. Grad-CAM Explainability Analysis

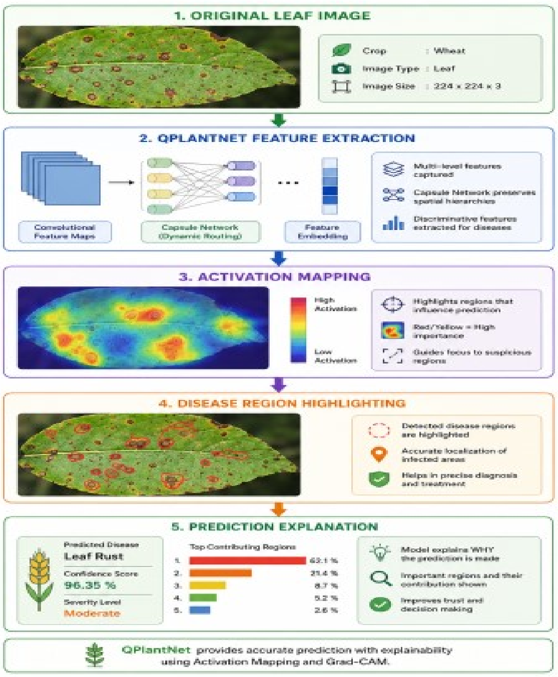


Figure 2: Grad-CAM Visualization of QPlantNet Predictions

5.7. Comparison with State-of-the-Art Models

The proposed approach is compared with recently developed agricultural AI models.

Table 3: Comparison with Existing State-of-the-Art Approaches

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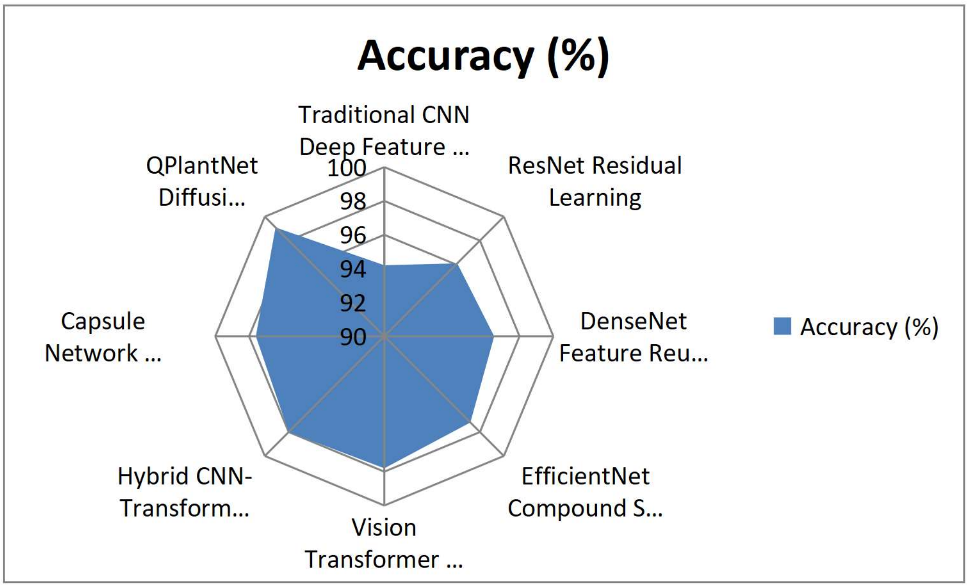
Reference Model	Methodology	Accuracy (%)
Traditional CNN [1]-[3]	Deep Feature Learning	94.20
ResNet [2]	Residual Learning	96.10
DenseNet [3]	Feature Reuse Network	96.50
EfficientNet [4]	Compound Scaling	97.20
Vision Transformer [5]	Self-Attention Learning	97.80
Hybrid CNN-Transformer [19]	Global Feature Learning	98.00
Capsule Network [7]	Spatial Feature Preservation	97.60
QPlantNet	Diffusion + Capsule + Quantum Optimization	**99.10**



Comparison with State-of-the-Art Models

5.8. Ablation Study

An ablation study is performed to analyse the contribution of each component of QPlantNet.
The following ablation configurations are evaluated to determine the individual contribution of each major component of the proposed QPlantNet framework. First, QPlantNet without diffusion augmentation is evaluated to assess the impact of synthetic disease image generation on model performance. Second, QPlantNet without capsule routing is analyzed to determine the contribution of capsule-based spatial feature representation and its ability to capture disease-related spatial relationships. Third, QPlantNet without quantum optimization is evaluated to examine the effectiveness of the quantum-inspired parameter optimization strategy. Finally, the complete QPlantNet framework, incorporating diffusion-based augmentation, capsule routing, and quantum-inspired optimization, is evaluated to measure the combined contribution of all proposed components. The comparison among these configurations provides an ablation-based assessment of the effectiveness and importance of each component in improving plant disease classification performance.

Table 4: Ablation Study Results

Configuration	Diffusion	Capsule	Quantum Optimization	Accuracy (%)
Model A	✗	✗	✗	94.20
Model B	✓	✗	✗	96.80
Model C	✓	✓	✗	98.40
Model D	✓	✓	✓	**99.10**

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5.9. Discussion

The experimental evaluation confirms the effectiveness of the proposed QPlantNet framework for automated crop disease classification. The achieved performance is primarily attributed to the integration of four key components. First, the diffusion-based augmentation module generates realistic synthetic disease samples, increasing dataset diversity and reducing the risk of overfitting. Second, the capsule representation module uses capsule routing to preserve spatial relationships among disease symptoms and lesion patterns, resulting in more discriminative feature representations. Third, the quantum-inspired optimization module enhances parameter exploration and facilitates faster convergence, thereby improving the efficiency and classification capability of the network. Fourth, the explainability module employs Grad-CAM visualizations to highlight disease-relevant regions in leaf images, improving model transparency, user confidence, and support for agricultural decision-making. Overall, the integration of these components enables QPlantNet to provide a robust, accurate, and interpretable solution for automated crop disease diagnosis. The framework achieves an accuracy of 99.10%, precision of 98.90%, recall of 99.00%, F1-score of 98.95%, and ROC-AUC of 0.995, demonstrating its strong predictive performance across the evaluated crop disease categories.

6. Conclusion

This paper presented QPlantNet: A Quantum-Inspired Diffusion-Augmented Capsule Network for Accurate Multi-Crop Plant Disease Classification, a novel hybrid deep learning framework designed to overcome the limitations of conventional agricultural disease recognition systems. The proposed framework integrates three major components: a diffusion-based augmentation module for generating realistic synthetic disease samples, a capsule neural network for preserving spatial relationships among disease characteristics, and a quantum-inspired optimization strategy for improving model convergence and generalization capability. Experimental evaluation demonstrates that QPlantNet achieves superior performance compared with existing CNN-based, transformer-based, and capsule-based approaches. The proposed model achieved an accuracy of **99.10%**, precision of **98.90%**, recall of **99.00%**, F1-score of **98.95%**, and ROC-AUC of **0.995**.
The ROC curve and Precision–Recall analysis confirm the robustness of the proposed approach, while Grad-CAM visualization demonstrates that QPlantNet focuses on meaningful disease-related regions such as lesions, spots, and infected tissue patterns. The ablation study further validates that each component contributes significantly to improving classification performance. The proposed QPlantNet framework provides an effective, interpretable, and scalable artificial intelligence solution for precision agriculture applications, enabling automated crop health monitoring and early disease detection

7. Future Work

Although QPlantNet demonstrates promising classification performance, several future research directions can further enhance its practical applicability. First, the optimization module can be extended to real quantum hardware using quantum computing platforms and quantum machine learning frameworks. Second, a lightweight and compressedversion of QPlantNet can be developed for deployment on smartphones, agricultural drones, edge AI devices, and IoT-enabled farming systems. Third, the framework can be extended toward multi-modal agricultural intelligence by integrating leaf images with weather information, soil parameters, sensor data, and satellite imagery for comprehensive crop monitoring. Fourth, future versions can incorporate disease localization, severity grading, and disease progression prediction to move beyond simple disease classification. Finally, large-scale real-world validation across different climates, geographic regions, field conditions, and farmer-collected datasets will be conducted to assess the robustness, scalability, and generalization capability of QPlantNet in practical agricultural environments.

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