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A Quantum-Hybrid Framework for Plant Disease Detection using Region-Oriented Lesion Detection Network

Mrs. Dhivya J[1], Dr.S. Srividhya[2]

[1]Research Scholar, KPR College of Arts, Science and Research, Coimbatore,
Email: dhivyajayakumar8@gmail.com, 0009-0007-0407-8891
[2]Associate Professor, KPR College of Arts, Science and Research, Coimbatore,
Email: srividhya.s@kprcas.ac.in, 0000-0003-3679-9654

Abstract
Detecting Plant Diseases (PD)is a delicate activity in precision agriculture where leaf diseases are accurately and early detected this can lead to a high yield and quality crop. However current Deep Learning (DL) models to have certain drawbacks, including the sensitivity to noise, inability to segment complex backgrounds, and the absence of lesion-level analysis. To overcome these issues, this researchproposes a new quantum-hybrid framework, which combines several steps to analyze plant diseases. This research aims to increase the accuracy of detection by integrating effective denoising, segmentation and lesion detection in a single pipeline. The methodology that has been proposed consists of Quantum-Adaptive Non-Local Mean Filtering (Q-ANLMF) to remove noise, Adaptive Spectral Segmentation Network (ASS-Net) to extract the areas accurately, and Region-Oriented Lesion Detection Network (RoLD-Net) to detect and identify the diseases with a high level of accuracy and precision. In Evaluation,the proposed model tested on Moringa, Spinach and Curry leaf datasets. Experimental performance is high with Q-ANLMF getting high PSNR (42.92 dB) and ASS-Net getting PSNR (42.33 dB) and RoLD-Net getting 94.44% accuracy. These findings validate that the proposed framework is able to greatly improve the quality of images, precision of segmentation and reliability of disease detection. The system, in general, offers an effective and powerful solution to the real-world plant disease diagnosis in smart agriculture.

*Keywords:*Adaptive Segmentation, Deep Learning, Image Denoising, Lesion Detection, Plant Disease Classification, Quantum Hybrid Model

1. Introduction

Early and precise diagnosis of leaf diseases is very important in contemporary agriculture since timely detection of PD directly influences crop production, quality and food security. Automated plant disease classification systems have been of great interest with the development of image processing and Deep Learning (DL). Nonetheless, in practice, agricultural images may have issues like noise, complicated background, different light, and overlapping objects, which complicates the detection and analysis of objects. The current methods mainly concentrate on classification processes without considering fundamental preprocessing processes such as denoising, accurate segmentation and lesion-level examination that constrains their applicability in the real-life setting of the field.

There are a few studies that investigated DL models like EfficientNet-based classification [1], end-to-end ML and DL systems, [2] and CNN-based systems to detect diseases more accurately [3]. Methods based on Vision Transformers [4] and massive datasets such as FieldPlant [5] have also advanced feature learning models, whereas attention-based RNN models [6] and hybrid CNN models [7] enhanced classification. Moreover, more interpretable and robust models are also achieved by optimized EfficientNet models [8], Bayesian CNN methods [9], and explainable AI-based predictors [10]. Even with these developments, the majority of the available methods do not have combined models of noise elimination, precise segmentation and lesion-specific detection. To overcome these shortcomings, this research propose an entire quantum-hybrid framework, incorporating Quantum-Adaptive Non-Local Mean Filtering (Q-ANLMF) to denoise, Adaptive Spectral Segmentation Network (ASS-Net) to segment and -Oriented Lesion Detection Network (RoLD-Net) to detect lesions, providing better accuracy, robustness, and practical use in the field of plant disease

They are main contribution and motivations are,

- To construct a strong framework that enhances accuracy in the detection of PD in real-world conditions of noisy and complex images.
- To present a new Q-ANLMF algorithm, which can be used to effectively denoise and retain important disease-related characteristics.
- To create ASS-Net to select leaf areas with high accuracy and filter a background.
- The aim of the study is to propose RoLD-Net as the appropriate tool to localize the lesion and classify the disease with high accuracy.
- To combine all steps into a single quantum-hybrid pipeline with increased performance and ability to apply in agriculture.

Organization: Section 2 is the background study in current methods of detecting PD. Section 3 will explain the proposed methodology, such as the algorithm design, workflow, architecture, equations, and pseudocode. Section 4 covers the results and performance of the experiment in terms of denoising, segmentation, and disease detection phases. Lastly, Section 5 summarizes the research with a conclusion of the important findings and future studies.

2. Background Study

Ali, A. H., et al. (2024) [11] developed an ensemble DL architecture that will improve the accuracy of the PD classification. A number of CNNs have been incorporated in the model to improve the feature extraction and classification. The results of experiment were more precise than the single models. However, the system mainly focused on the classification and did not have the lesion localization at the level that limited the analysis of disease areas.

Wang, H., et al. (2022) [12] created a better lightweight YOLOv5 that is used in real-time to detect and classify plant diseases. The algorithm worked well in identifying disease regions of leaf images at a faster rate of inference. Although the model was discovered to be efficient in detection tasks, it failed to take into account the disease estimation severity and multi-objective analysis and focused on detection and classification.

Sood, M., & Singh, P. K. (2020) [13] proposed a mixed approach of detecting the presence of the disease in plants through a texture feature analysis method. The system would then pick out the features texture based image of leaf image and then apply ML classifiers to determine the diseases. There was improved recognition performance. However, scalability was not as high and the strategy was not so relevant to the real world environment of complexities since it relied on manually developed features.

Upadhyay, S. K., & Kumar, A. (2022) [14] proposed the model of a DCNN to identify diseases in rice plant leaves. The model was able to automatically learn hierarchical features with leaf image and high classification accuracy. The technique was practical and was limited to classification and not supplemented with sophisticated information processing as attention, lesion localisation or disease prediction.

Rao, D. S., et al. (2022) [15] proposed a deep bilinear CNN architecture that was applied to classify plant diseases. The architecture used two convolutional networks to reflect the more complex relationship of features resulting in an improved classification performance. However, this model was unfeasible to compute and was not aimed at estimating the severity of the disease and providing decision-support information.

Shafik, W., et al. (2025) [16] proposed an inception-xception CNN-based model that detects and classifies plant diseases. The model has taken advantage of the strengths of two architectures in improving the precision of feature extraction and classification. Although the results showed a better performance, the system was predominantly founded on the classification and failed to analyze the lesion prediction and analysis.

Wang, H., et al. (2023) [17] proposed an attention-based MobileNetV2 to classify plant disease. The methodology also employed attention mechanisms so as to reduce on the important portions of leaf images, boosting classification accuracy and computing efficiency. Nevertheless, the strategy still was based on conventional DL models and failed to investigate complex optimization algorithms or a fine lesion analysis.

Tabbakh, A., &Barpanda, S. S. (2023) [18] a TLMViT model, which is grounded on Transfer Learning (TL) to detect plant diseases. It took pre trained models and transformer architecture to learn global relationship between features of images. The results revealed improved classification error on different diseases. However, the process was not only costly in terms of training data, but also failed to identify lesions, as well as forecast their severity at the lesion level.

Naveed, F., et al. (2025) [19] proposed a sustainable AI model that depends on the ResNet18 algorithms with the few-shot learning in identification of plant disease. The methodology was to minimize need to work with massive data through learning on small samples. The results in the experiments proposed acceptable results with fewer images in training. Nonetheless, it was a system that was limited by classification and omitted the detection of lesions, estimation of severity and recommendation of treatment.

Baek, E. T. (2025) [20] proposed a multi-vision transformer model based on a score of attention to classify PD. The model showed global feature relations to transformer architecture and was more precise compared to the traditional CNN model. The method was computationally intensive, irrespective of its efficiency, and lacked lesion localization ability.

Alsuhaibani, A., et al. (2026) [21] research postulated LeafDeSNet, a multi-class plant leaf disease classifier based on entropy-regulated GLEO to select features. The authors used DL with optimized feature selection that met the requirement to have precise multi-class classification but had constraints such as data heterogeneity and cost of computation, which had high classification accuracy and higher relevance of features.

You, H., et al. (2023) [22] proposed a model of classification of PD using SimAM-EfficientNet, adversarial training methods. The technique increased image noise and adversarial image perturbation resistance. Although the model showed better classification results, it was mainly concerned with the robustness and did not identify lesions or analyze the disease progression.

Adnan, F., et al. (2023) [23] presented a multi-class plant disease classification adaptive augmented DL model, which based on EfficientNetB3. The system added data to improve performance of the models and achieved high classification accuracy. Nonetheless, the algorithm was heavily based on built-up data and had no mechanisms of lesion localization and foretelling choice.

Table 1: Background Researchof Recent DL-based Plant Disease Classification

Author (Year)	**Concept**	**Methods Used**	**Limitations**	**Research Gap**	**Results**
Bi, L., & Hu, G. (2020) [24]	Improve disease detection with small dataset	GAN (Generative Adversarial Network) to generate extra images	Complex, needs training, may generate unrealistic images	No lesion localization, only classification	Improved accuracy with limited data
AbdAlgani, Y. M., et al. (2023) [25]	Optimized DL for disease classification	CNN + optimization techniques (hyperparameter tuning)	Needs large dataset, high computation	No explainability, no region detection	High classification accuracy
Macdonald, W., et al. (2024) [26]	Smart plant monitoring system	Lightweight CNN model	Less accurate than deep models	No detailed lesion detection	Fast and efficient system
Ullah, N., et al. (2023) [27]	DeepPlantNet for disease classification	Deep CNN architecture	Black-box model, needs training data	No localization of disease regions	Very high classification accuracy
Falaschetti, L., et al. (2022) [28]	CNN-based disease detection	Convolutional Neural Network (CNN)	Requires labeled data, training heavy	No adaptive detection, no explainability	Good classification performance
Kabya, N. D., et al. (2026) [29]	Self-supervised attention-based detection	Attention mechanism + self-supervised learning	Still needs training, complex design	Limited interpretability, not fully training-free	Improved detection accuracy
Khan, K., et al. (2022) [30]	Semantic segmentation of diseased areas	End-to-end CNN segmentation	Needs pixel-level labeled data	Not suitable for small datasets	Accurate segmentation

Table 1, recent articles devoted to the detection of PD primarily with the help of DL techniques. Despite the high accuracy of classification of these methods, they had difficulty in efficient denoising, accurate segmentation, and accurate localization of lesions. The majority of the methods needed big training sets and were not

interpretable. Such restrictions led to the necessity of a more flexible and the proposed process was created to improve the quality of denoising, segmentation, and lesion detection.

Research Gap

- Current techniques primarily concentrate on classification and do not incorporate denoising, segmentation, and lesion-level lesion analysis to be accurate in the real world.
- The majority of methods demand huge amounts of data and are ineffective in the presence of noise, complicated backgrounds and varying illumination.
- The existing models are not interpretable, and they do not give a detailed localization of the disease and a severity based analysis.

3. Proposed Methodology

In this section the proposed methodology is presented, including the description of the design and implementation of the developed algorithm and its entire workflow as well as its system architecture. Each stage of processing such as denoising, segmentation and lesion detection is systematically described with mathematical formulations to facilitate clarity and reproducibility. The section also shows the pseudocode and operation flow to have a complete picture of the proposed framework and its practical implementation.

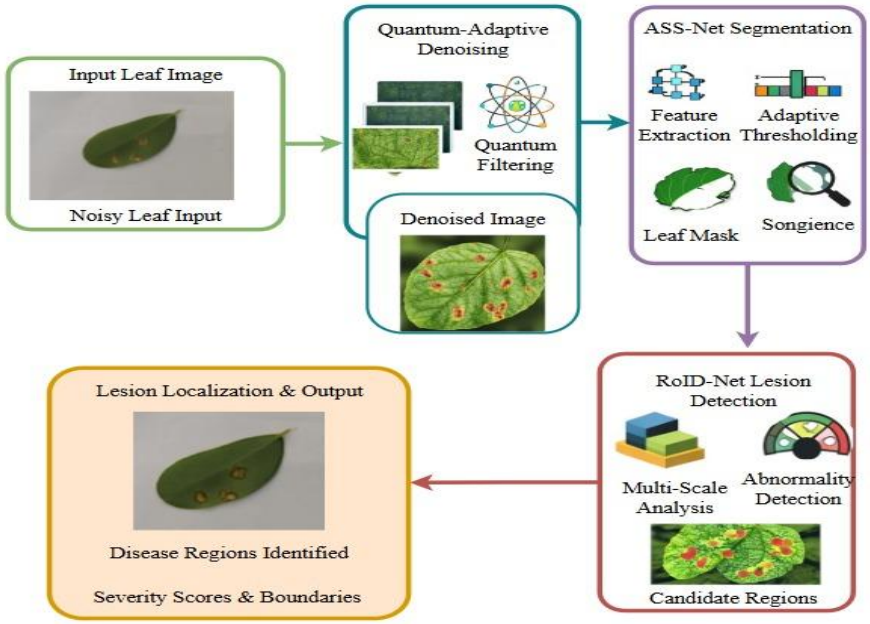


Figure 1: Quantum Adaptive Plant Disease Detection and Lesion Localization Workflow Architecture.

This proposed framework, seen in the above figure 1, begins with Quantum-Adaptive Denoising to cull noisy leaf inputs, before using quantum filtering to clear the image to a higher level of precision to proceed with downstream analysis. The ASS-Net Segmentation step then obtains features and uses adaptive thresholding to create leaf masks, which are then sent to the RoID-Net Lesion Detection module to identify multi-scale abnormalities. Lastly, the system carries out Lesion Localization, which detects particular disease areas and produces severity scores and accurate bounding boundaries to agricultural diagnostics.

3.1 Dataset Description

Dataset 1 (Moringa Leaves):https://www.kaggle.com/datasets/sadmanskhan/moringa-leaf
Dataset 2 (Spinach Leaves):https://data.mendeley.com/datasets/skf6w2s2h2/3
Dataset 3 (Curry Leaves):https://data.mendeley.com/datasets/rryf548b6p/1

The proposed structure presents a quantum-hybrid disease detection and analysis framework in Moringa, Spinach and Curry leaves in this paper. The former is the Q-ANLMF used in the first stage to remove the noises without distributing the major disease related textures and structural content of the original leaf images. The refined photos are further sliced with the help of the ASS-Net that separates the part of the photo that is vulnerable of being leaf and the part that is not. The RoLD-Net detects abnormal regions, and generates lesion

masks to study those regions. After preprocessing, the lesion regions are then passed through LeAF-FE to extract discriminative lesion features in terms of spatial and texture. These features are called the QHA-Net and are a combination of CNN feature learning and quantum-inspired attention mechanisms to learn both local and global disease patterns. Lastly, QPR-Net predicts the severity of diseases, their affected region, and the risk of the disease progression to offer the treatment of the crop in its adaptive way.

3.1Quantum-Adaptive Non-Local Mean Filter Using Image Enhancement

Quantum-Adaptive Non-Local Mean filter is recommended as image enhancing algorithm that possesses efficient ability of removing the noises in environment and acquisition and preserving disease-specific structures. Noise in leaf images in a real field agricultural environment can occur as a result of variations in illumination, camera sensor distortions and background distortions that can degrade the effectiveness of segmentation and classification. The algorithm presented first is a transformation of raw RGB leaf images to multi-scale intensity representation to achieve structural information of the images at different levels of resolution. This is then succeeded by classical NLM technique that is used to locate similar pixel neighborhoods in the image. In order to improve the dynamic nature, quantum inspired weighting mechanism dynamically scales similarity measures according to contextual relations between pixels. This adaptive weighting eliminates noise without the loss of important edge or disease pattern. Compared to the conventional techniques of e.g. Gaussian or median filtering used to denoise images, Q-ANLMF does not suffer over-smoothing, which may remove lesion patterns of interest of critical importance. Improving lesion detection tasks and downstream segmentation accuracy, the algorithm improves the structural integrity, yet eliminates noise. This approach has proven particularly effective in realistic agricultural imagery when the images have varying light conditions, complex background, and sensor artifacts.

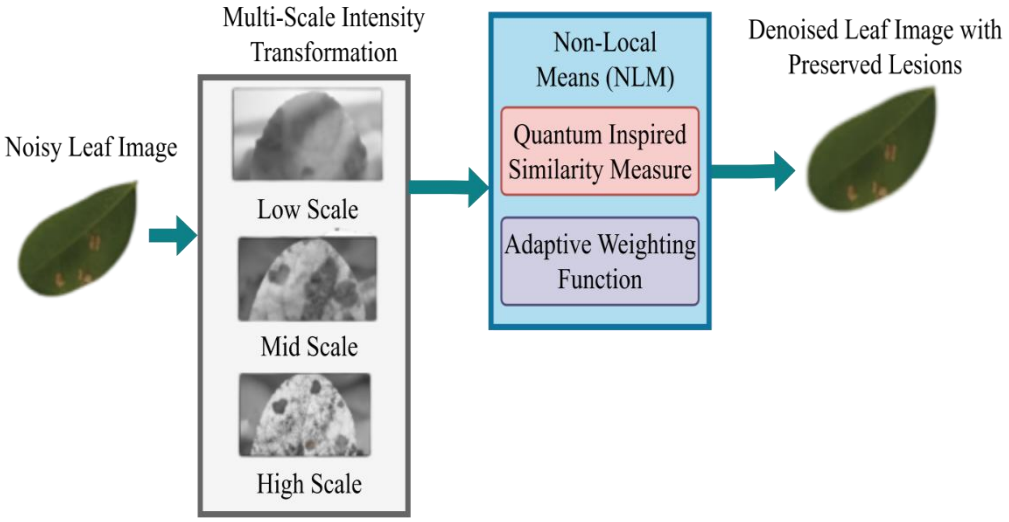


Figure 2: Multi-Scale Quantum-Inspired Non-Local Means Denoising Framework of Leaf images.

In this figure 2, the proposed denoising pipeline is shown, a noisy leaf image is first broken down into different intensity scales (low, mid and high) to extract both coarse and fine features. These multi-scale representations are then handled with a NLM module which is improved with a quantum-inspired similarity measure and an adaptive weighting function to ideally remove noise. The end result will be a denoised image of a leaf, with the lesion details maintained, so that significant disease-related details are not lost to further processing.

$$\hat{I}(p) = \sum_{q\in\Omega} \omega(p,q) I(q) \qquad (1)$$

In Equation (1) $I(q)$is the intensity of the adjacent pixel q, $\omega(p,q)$ is the similarity weight between pixel p and q, $q \in \Omega$ is the search neighborhood window, and$\hat{I}(p)$ is the denoised pixel intensity. The equation computes the denoised value by taking the weighted average of pixels that have similar intensity patterns

$$w(p,q) = \frac{1}{Z(p)} \exp\left(-\frac{|I(p)-I(q)|^2}{h^2}\right) \qquad (2)$$

Equation (2) is used to describe the similarity weight $w(p,q)$, pixel intensity, $I(p)$ and $I(q)$, filtering parameter$h$, and normalization factor, $Z(p)$. In this equation, pixels with similar intensities have greater weights.

$$Z(p) = \sum_{q\in\Omega} \exp\left(-\frac{|I(p)-I(q)|^2}{h^2}\right) \quad (3)$$

Equation (3) $Z(p)$represents the normalization constant that makes all the weights add up to one, $I(p)$ and $I(q)$ are pixel intensities, and h is a smoothing strength. This equation normalizes weights of similarity in the neighborhood.

$$Q(p,q) = \alpha w(p,q) + (1-\alpha)e^{-\gamma d(p,q)} \quad (4)$$

In Equation (4), $O(p,q)$ is the quantum-adaptive weight, $w(p,q)$ is the classical similarity weight,$d(p,q)$ is the spatial distance between pixels, α is a balance between similarity and spatial influence and γ is a decay parameter.

$$I_{enh}(p) = \sum_{q\in\Omega} Q(p,q)I(q) \quad (5)$$

In Equation (5)$I_{enh}(p)$ represents the pixel intensity that has been enhanced by quantum-adaptive filtering, $Q(p,q)$is the adaptive weight, $I(q)$ is the pixel intensity of the neighbors, and Omega represents the search area.

$$E = |I - I_{enh}|^2 \quad (6)$$

In Equation (6) indicates that E represents the reconstruction error, I is original image, and I_{enh}denotes that denoised image. This equation is used to quantify difference between original and filtered image.

Algorithm 1: QNALMF for Image Denoising

```
Input: Noisy leaf images (healthy, diseased dataset)
Begin
Define Q-ANLMF:
- load_image(path):
   Read image → normalize
- cap(image):
Resize if required → work_image
- adaptive_noise_estimation(image):
   Estimate noise using local variance → sigma
- scale_decomposition(image):
 Multi-scale decomposition → l1
- nlm_similarity(image):
   Compute patch similarity → l2, sim_map
- quantum_weighted(image, sim_map):
   Fuse classical + quantum similarity → l3
- edge_preserved(original, image):
   Apply edge + texture preservation → l4 (final)
- Q_ANLMF_all_layers(image):
   sigma = adaptive_noise_estimation(image)
   l1 = scale_decomposition(image)
   l2, sim = nlm_similarity(l1)
   l3 = quantum_weighted(l2, sim)
   l4 = edge_preserved(image, l3)
   Return l1, l2, l3, l4
- compute_metrics(original, output):
   Compute MSE, PSNR, SSIM
Main Pipeline:
   For each image in dataset:
      image = load_image(path)
work_image = cap(image)
      layers = Q_ANLMF_all_layers(work_image)
      final = layers[l4]
      metrics = compute_metrics(work_image, final)
      Display results
End
Output: Denoised image, PSNR, SSIM, MSE
```

The Q-ANLMF pseudocode, Algorithm 1 outlines a quantum-adaptive noise removal algorithm that can be used to improve raw leaf images by reducing sensor and environmental noise and maintaining fine edge and texture information. This is done by multi-scale intensity analysis with adaptive non-local similarity weighting such that the disease relevant structures are not lost to further analysis. The output is an image that is clean with edges intact making the other segmentation and lesion detection processes more accurate.

3.2 Adaptive Spectral Segmentation Network Using Segmentation

Adaptive Spectral Segmentation Network is also a technique that can be used to classify many objects in a frame, based on the orientation of the edges in the frame. The ASS-Net is developed so that it is able to isolate useful leave areas and eliminate the background noise at the cost of the disease analysis phase. They have overlooked segmentation or have segmented using simple thresholding techniques in most of the existing systems of detecting plant diseases; these techniques in real field images are not effective as the leaves and their complex background such as soil, shadows etc. overlap. The proposed ASS-Net overcomes this shortcoming by integrating spectral and spatial feature extraction based on a low-weight convolutional neural network backbone. Adaptive thresholds are configured to the network to detect the leaf areas and the background pixel using the learnt spectral and structural features. Consistency of the regions modelled using attention is then used to refine the boundaries regions and improve the segmentation accuracy. This is to ensure that anything that has been extracted concerning areas of interest is only useful leaf information and rest of the background information is discarded. The ASS-Net can be used to simplify other detection and feature extraction tasks with the generation of the precise segmentation masks that are used to determine candidate abnormal regions. It brings about a reduced computational cost and makes the localization of the disease and consequently the framework more robust on heterogeneous real-world data with Moringa, Spinach, and Curry leaves.

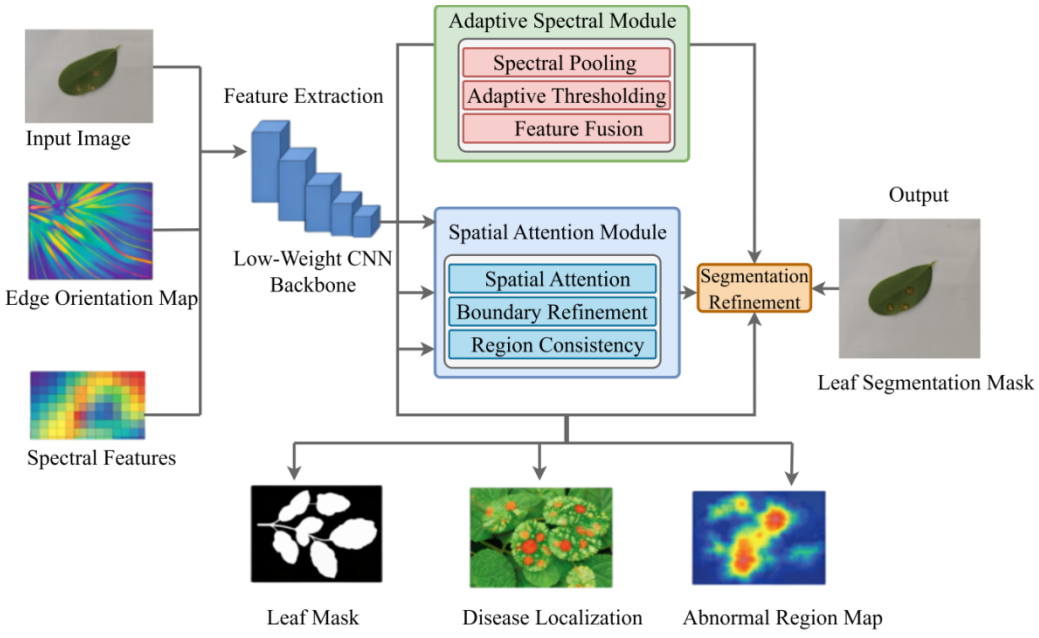


Figure 3: Architecture of the Proposed Adaptive Spectral–Spatial Leaf Segmentation Framework

This figure 3 illustrates overall pipeline of proposed model, where the input image, edge orientation map, and spectral features are processed through a lightweight CNN backbone for feature extraction. The extracted features are enhanced using an Adaptive Spectral Module (spectral pooling, adaptive thresholding, and feature fusion) along with a Spatial Attention Module (attention, boundary refinement, and region consistency). Finally, segmentation refinement produces an accurate leaf segmentation mask along with outputs such as leaf mask, disease localization, and abnormal region map.

$$F = \sigma(W * I + B) \qquad (7)$$

In Equation (7), F is the extracted feature map, Idenotes that input image, W is a weight of the convolution kernel, B is the bias term, $*$ is a convolution operation, and σ is the activation function like ReLU. This equation is deep feature extractor that uses convolution and activation function.

$$S = \sum_{k=1}^{K} F_k \quad (8)$$

In Equation (8) is a spectral feature representation, F_k is ak^{th} feature channel and K is no. of channels. This equation is a multi-channel spectral aggregation.This equation combines multi-channel feature maps to a single representation. It increases the richness of features.

$$P(x) = \frac{e^x}{\sum_{i=1}^{n} e^{x_i}} \quad (9)$$

Equation (9)$P(x)$ is used to represent the probability output of softmax function, x is an input score, and n is a no. of classes. This equation converts to the raw scores into the probability values.

$$T = \mu + \beta\sigma \quad (10)$$

In Equation (10), T is the adaptive threshold, μ is the average intensity value, σ is the standard deviation, and β is the sensitivity of the threshold. This equation calculates threshold using image statistics. It divides the foreground and background areas.

$$M(x,y) = \ \llbracket \{cases\}1 \ \&I(x,y) > T \ \backslash\backslash \ 0 \ \&"\{otherwise\}\rrbracket \ \{cases\} \quad (11)$$

In Equation (11) $M(x,y)$ is a segmentation mask, $I(x,y)$ is a pixel intensity and T is the adaptive threshold that is used to distinguish between foreground and background.This equation generates binary mask using adaptive thresholding.

$$R = \lambda M + (1 - \lambda)A \quad (12)$$

In Equation (12)R is the refined segmentation output, M is the original segmentation mask, A is attention-guided refinement, and λ is a balance between the two. This equation optimizes segmentation with attention-weighted. It enhances accuracy of boundaries.

Algorithm 2: ASS-Net for Image Segmentation

```
Input:  Denoised leaf images
FUNCTION LoadImage(path)
   Read RGB image
   Convert to float [0,1]
   Return image
FUNCTION SpectralFeatures(image)
   Convert image → HSV (H, S, V)
   Compute Excess Green (ExG)
   For each channel in {H, S, V, ExG}:
      Apply depthwise directional convolution (0°,45°,90°,135°)
      Extract feature maps (f1, f2, f3)
   Concatenate all features → FeatureMaps
ReturnFeatureMaps, spectral channels
FUNCTION AdaptiveThreshold(FeatureMaps)
   For each feature channel k:
Tk = mean(Fk) + α * std(Fk)
      Mk = sigmoid(beta * (Fk - Tk))
   Return BinaryMaps, ThresholdVector
FUNCTION AttentionRefinement(BinaryMaps, Image)
   Compute channel weights from variance
  A = weighted sum(BinaryMaps)
   Compute local variance (window filter)
 A = A - λ * local_variance(A)
   Compute edges (Sobel)
   A = blend(A, original A using edges)
   Return RefinedAttention
FUNCTION CRF_Refine(Mask, Image)
   Convert image → LAB space
   Repeat iterations:
```

```
        For each pixel:
            Compare with 8 neighbors
            Compute color similarity
            Compute spatial similarity
            Update mask using weighted neighbor agreement
    Normalize mask
    Return refined mask
FUNCTION SoftROIMask(Image, Attention, ExG)
  Suppress background using ExG
    Mask = CRF_Refine(Mask)
    Normalize Mask
    Compute adaptive alpha using mask coverage
ROI_Image = Image + alpha * Mask * (Image - mean(Image))
    Return Mask, ROI_Image
FUNCTION ASS_Net(Image)
FeatureMaps, Spectral = SpectralFeatures(Image)
BinaryMaps, T =AdaptiveThreshold(FeatureMaps)
    Attention = AttentionRefinement(BinaryMaps, Image)
    Mask, ROI = SoftROIMask(Image, Attention, Spectral)
    Return Mask, ROI, FeatureMaps
MAIN PIPELINE
For each leaf in dataset:
    For each class in {healthy, diseased}:
        For each image:
            Image ← LoadImage
     Mask, ROI ← ASS_Net(Image)
            Compute:
                MSE = mean((Image - ROI)^2)
                PSNR
                SSIM
Visualize:
        Input → Spectral → Threshold → Attention → Mask → ROI
Compute  metrics
Print final results
END
Output: Segmented Region of interest images
```

In Algorithm 2, the ASS-Net pseudo code, the spectral-spatial segmentation process isolates useful leaf areas of the background clutter by extracting features and applying adaptive thresholding. The method also sharpens the boundaries of regions with attention-guided consistency modeling to generate region-of-interest masks. This guarantees that only informative leaf areas are forwarded, minimizing the computational complexity and enhances the performance of lesion localization in different image conditions.

3.3 Region-Oriented Lesion Detection Network using Detection

The Region-Oriented Lesion Detection Network is proposed to detect and locate diseased areas in the segmented leaf images. The entire leaf image is banked in the extraction of the features in most of the currently existing classification based systems and therefore the healthy areas or background artifacts can influence the classification. RoLD-Net addresses this inadequacy by making attempts to focus on the unusual visual patterns, which indicate the symptoms of a disease. Convolutional feature pyramids are taken to the network segmentation to extract the multi-scale texture variation and structural irregularities, in the regions analyzed by the network. It determines the abnormal regions based on the contrast deviations and spatial inconsistencies, which are likely to be the typical effects of lesions, spots or discoloration patterns. The regions are then graded in terms of each region considering a confidence score in terms of region-wise classification modules and areas of low confidence are filtered with adaptive thresholds. The output obtained is very accurate lesion masks and bounding regions that indicate disease-relevant information. RoLD-Net minimizes contamination of features by normal tissues by isolating abnormal features and this increases its reliability in classification. This local lesion-detecting algorithm is resistant to visual noise, light change, and background artifacts which would occur in realistic field agricultural scans.

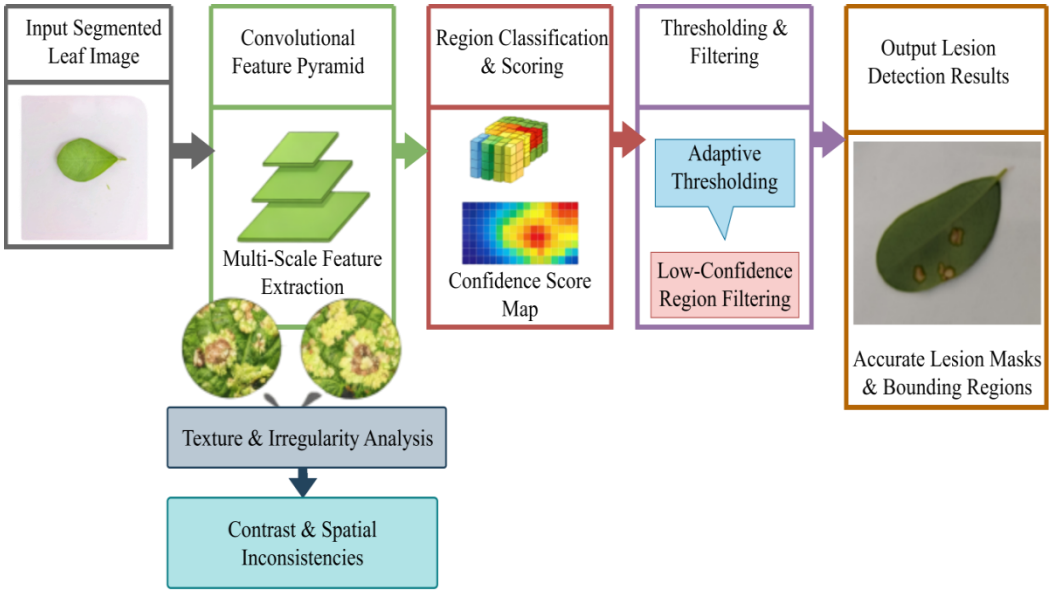


Figure 4: Region-Oriented Lesion Detection and Adaptive Filtering Framework.

This figure 4 shows the sequential lesion detection pipeline which begins with input leafless image and then multi-scale feature extraction and spectral-spatial analysis. Analysis of texture and irregularity detects contrast and spatial variations related to disease areas. Finally, adaptive thresholding and low-confidence area filtering is used to clean up the output and a disease-leaf image is presented with the right amount of accuracy.

$$F_p = \text{Conv}(I) \quad (13)$$

In Equation (13),$F_p$is the output of feature pyramid of the image I by convolutional operations to represent features at multiple scales. This equation derives multi-scale feature representations of image. It records patterns of lesions on varying scales.

$$D = |F_p - \mu| \quad (14)$$

In Equation (14), D is deviation of normal texture patterns, $F_p$is extracted feature values and μ is mean feature value of normal regions.This equation quantifies the abnormality of normal texture patterns.

$$C = \frac{1}{N}\sum_{i=1}^{N} d_i \quad (15)$$

In Equation (15) C is the regional contrast score, $d_i$is the deviation of each pixel in a region.This equation calculates mean change in intensity in an area.

$$P(r) = \sigma(W_r F_r + b_r) \quad (16)$$

In Equation (16), $P(r)$ is the probability of region r to be abnormal, $F_r$is region features, W_r is learned weights and$b_r$is bias.This equation classifies region as normal or abnormal. It approximates the probability of lesions.

$$B = \{r | P(r) > \theta\} \quad (17)$$

In Equation (17), B is the collection of identified lesion areas,$P(r)$ is the probability of abnormality, and θ is the confidence level.This equation picks out areas of high abnormal probability.

$$L = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (18)$$

In Equation (18), L is the loss function, y_i is a ground truth label and$\hat{y}_i$denotes that predicted output. This equation is used to measure prediction error in training.It enhances the accuracy of the model.

Algorithm 3: RoLD Net for Disease Detection
Input: Leaf image dataset

```
Step 1: Load Image
      Read RGB image
      Normalize and resize
Step 2: Foreground Mask
      Extract leaf region
      Remove background using colorthresholding + morphology
Step 3: Feature Extraction
      Compute multi-channel features:
         - Color (HSV / green index)
         - Texture (filters)
     Combine into feature map
Step 4: Deviation Map
      Compute local intensity deviation
    Normalize to form heatmap
Step 5: Region Detection
      Threshold heatmap
      Extract connected components as candidate regions
Step 6: Region Filtering
      Remove regions based on:
         - size constraint
         - foreground overlap
         - shape constraint
Step 7: Scoring
      Assign confidence score to each region
      Keep high-score regions
Step 8: Final Output
      Generate lesion mask
      If no region detected → Healthy
      Else → Diseased
Return:
   Lesion mask
END
Output: Bounding mask, Confidence Score
```

The pseudo code, Algorithm 3, of the RoLD-Net outlines a region-based lesion detection system that detects abnormal leaf areas through the use of texture inconsistencies and spatial variations. It gives scores of confidence to candidate regions, and removes non-informative areas with adaptive thresholds. This leads to accurate localization of lesions with delineating masks whereby disease areas only contribute to the final classification and the background is kept to a minimum.

4. Results and Discussions

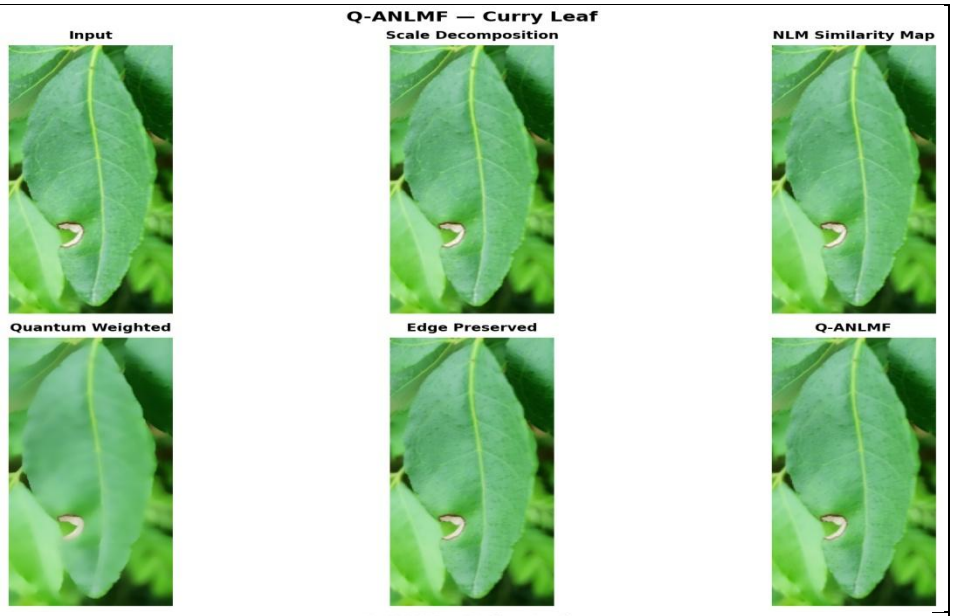
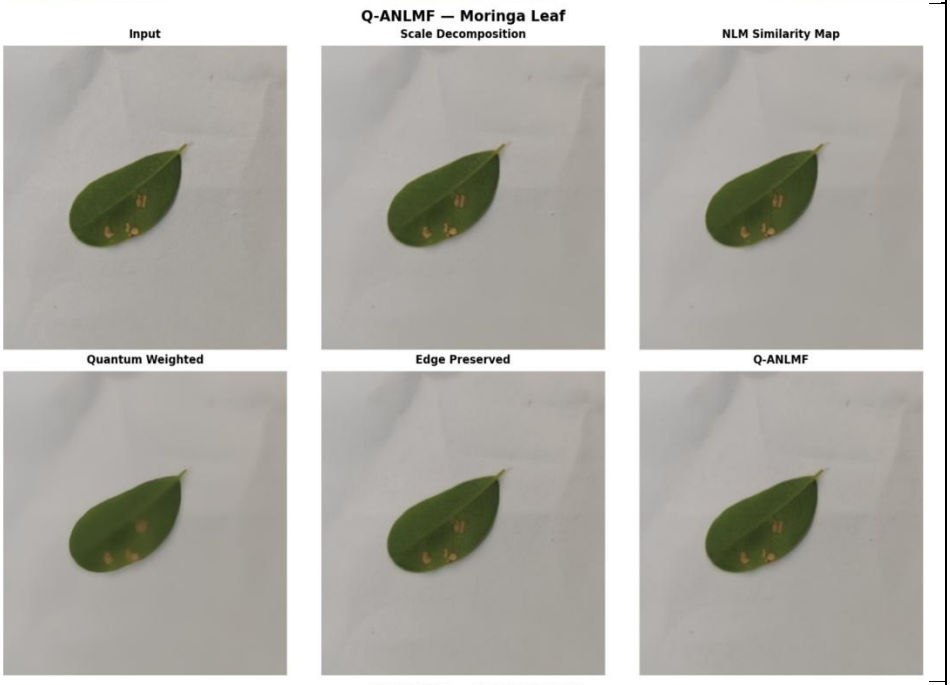
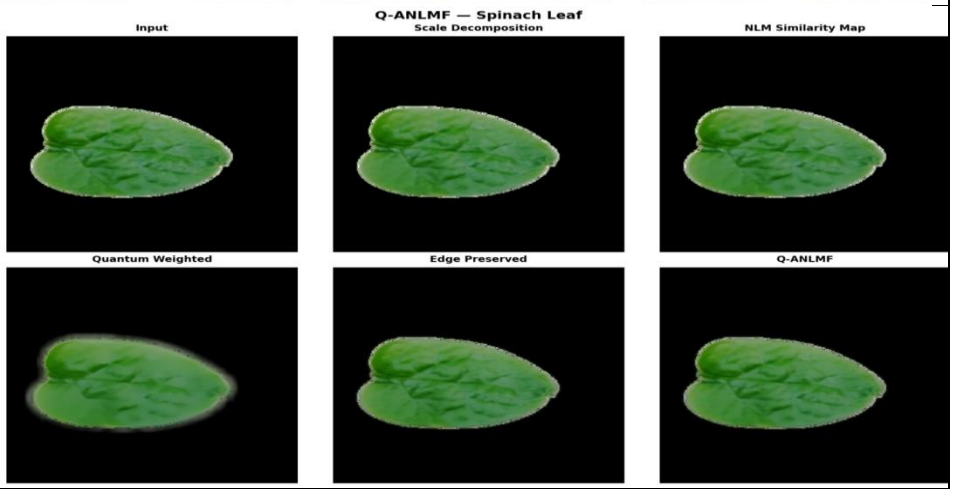
This section describes performance analysis of framework proposed in terms of denoising, segmentation and disease detection phases. The results of experiment are applied and processed with the help of Python programming environment, which guarantees the correct calculation of measures and visualizations. The results indicate that proposed method is efficient in enhancing quality of images, accurate delineation regions and accurate classification of diseases.

4.1 Denoising

The denoising section displays the denoising process with the proposed Q-ANLMF method that effectively reduces noise on leaf images preserving vital structural and disease-related details in them to be better analyzed.

Table 2: Comparative Visualization of Q-ANLMF Denoising Among Leaf Type.

Image	**Leaves**	

1	Curry	
2	Moringa	
3	Spinach	

The table 2 above shows the progressive steps of the Q-ANLMF denoising process of various types of leaves such as Curry, Moringa and Spinach. The rows depict the image to noise reduction process with the help of

similarity mapping, quantum weighting and edge-preserving filtering. The findings indicate that Q-ANLMF is effective in eliminating noise and preserving the structure and fine details of different leaf samples.

Table 3: Denoising Process Q-ANLMF Performance Metrics.

Dataset	MSE	PSNR (dB)	SSIM
Spinach	0.0002	37.61	0.9720
Curry	0.0001	43.54	0.9892
Moringa	0.0000	47.60	0.9945

The table 3 above provides the denoising performance of the Q-ANLMF algorithm to various plant leaf datasets. Reduced MSE and increased PSNR and SSIM values are good indicators of efficient noise removals without compromising the quality of the image.

Table 4: Performance Metrics Compared to Existing Methods and Proposed Q-ANLMF

Algorithm / Method	MSE	PSNR (dB)	SSIM
EfficientNet [1]	0.0003	37.85	0.9710
InceptionNet [2]	0.0004	36.92	0.9685
AlexNet [3]	0.0005	35.60	0.9620
Vision Transformer (ViT) [4]	0.0002	40.15	0.9801
DenseNet [5]	0.0003	38.40	0.9735
Proposed Q-ANLMF	0.0001	42.92	0.9852

Table 4 above is a comparison between the denoising of performance of the standard DL models in proposed Q-ANLMF approach. The method proposed has lowest MSE and the best PSNR and SSIM, that is, it has the best noise reduction and maintenance of image quality.

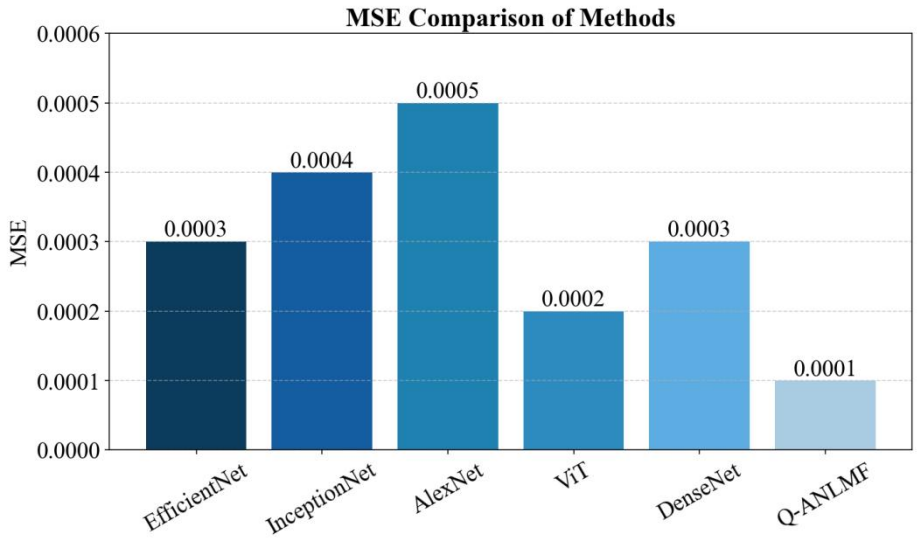


Figure 5: Comparison of MSE of Denoising methods through Q-ANLMF Framework.

The analysis above figure 5 compares accuracy of various denoising techniques on a pixel level. The proposed Q-ANLMF method has the lowest MSE value and this implies that there is only a small error between an original and denoised images. This emphasizes its ability to eliminate noise and at same time retain in necessary details of the image.

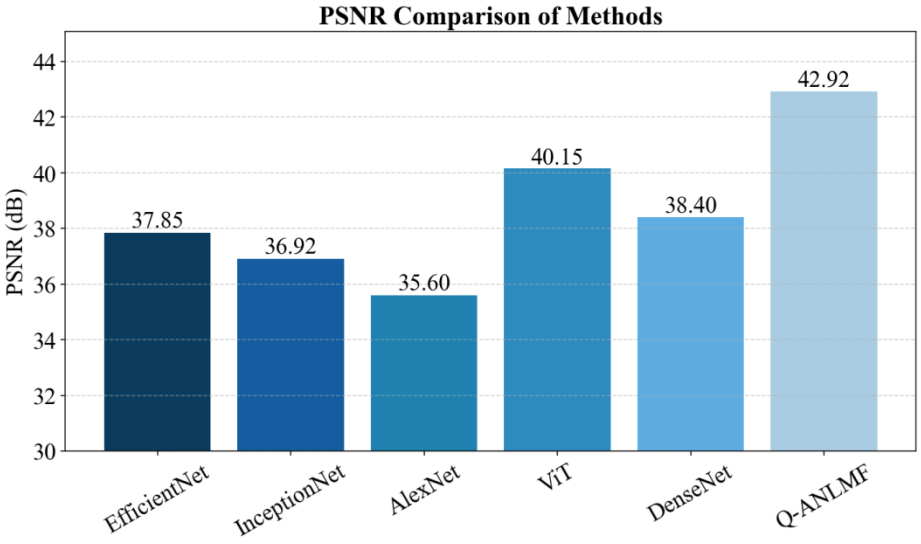


Figure 6: PSNR Analysis of Image Denoising Performance of Q-ANLMF.

This above figure 6 comparison is used to measure the quality improvement in the post denoising. Maximum PSNR is attained in Q-ANLMF that demonstrates improved noise reduction and image quality. This proves the quality of the denoised results of the model.

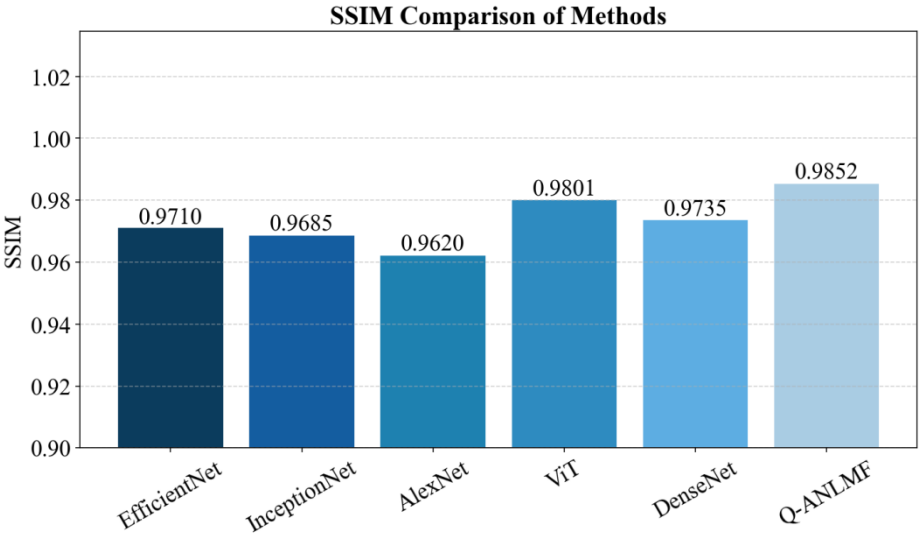


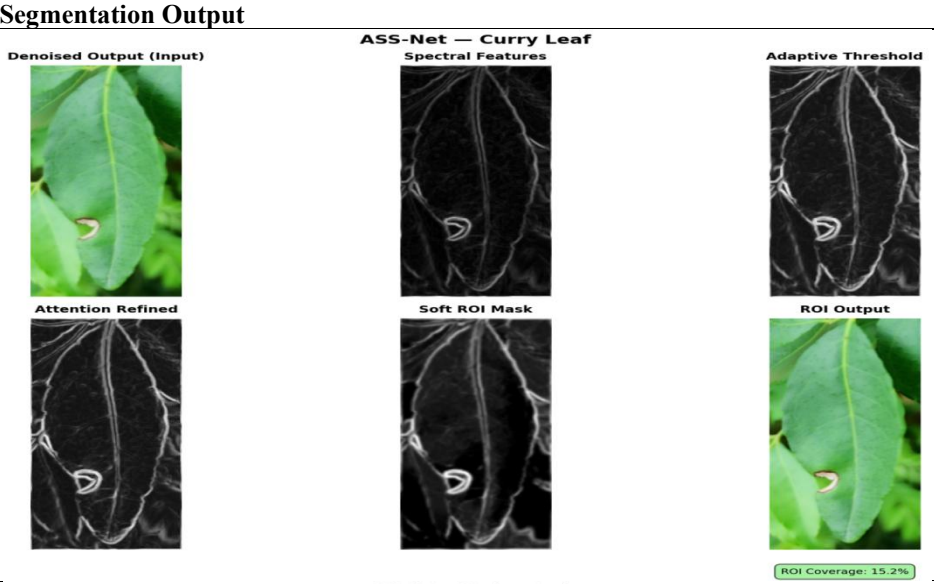
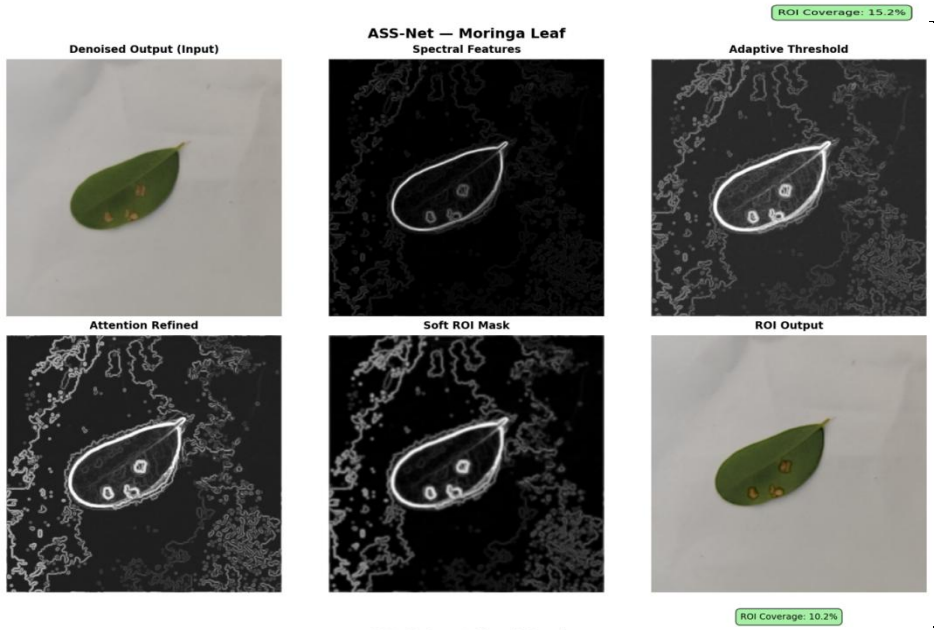
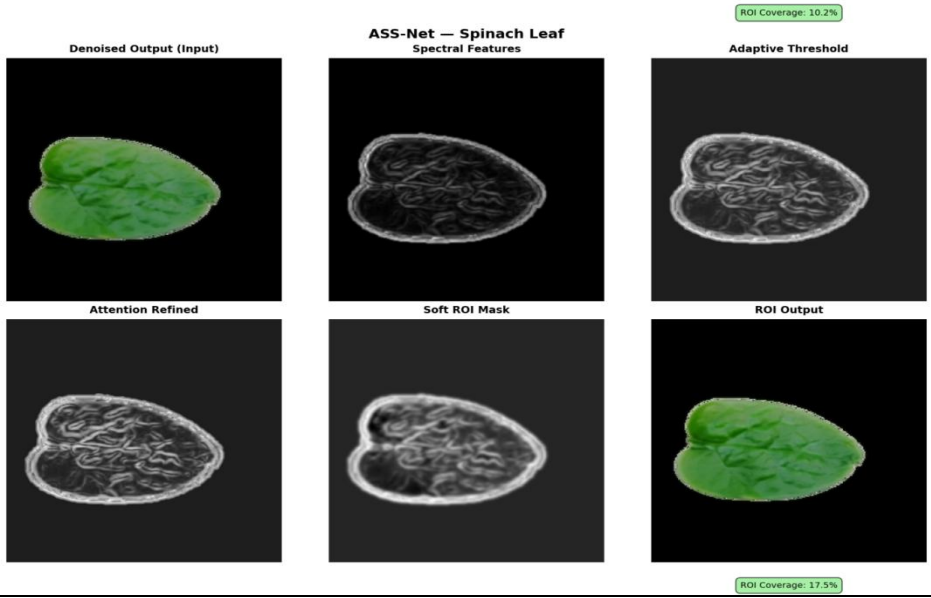
Figure 7: SSIM Evaluation of Structural Preservation in Q-ANLMF Denoising.

In above figure 7evaluation of the preservation of structural information in the denoising process. The Q-ANLMF method proposed provides the best SSIM score which indicates the preservation of textures and spatial features. This confirms its strength in preserving visual stability in the process of denoising.

4.2 Segmentation

This section shows the segmentation procedure with the proposed ASS-Net model that precisely identifies leaf areas and eliminates background noise to increase disease localization and examination.

Table 5: Visualization of ASS-Net Segments of Leaf Image Stages

Image	Leaves	Segmentation Output
1	Curry	
2	Moringa	
3	Spinach	

This above table 5 shows the sequential steps in the process of ASS-Net segmentation of various leaf samples like Curry, Moringa and Spinach. Every step shows how the input that is denoised is transformed to feature extraction, attention refining, and end region-of-interest segmentation. The findings affirm the effectiveness of ASS-Net in isolating diseased areas leaving structural boundaries and significant leaf features intact.

Table 6: Metrics of the Segmentation Process (ASS-Net) Performance.

Dataset	MSE	PSNR (dB)	SSIM
Curry	0.0001	42.99	0.9970
Moringa	0.0001	43.39	0.9985
Spinach	0.0001	40.62	0.9985

This above table 6 shows the segmentation performance of the ASS-Net model across different plant leaf datasets. Consistently low MSE and high PSNR and SSIM values indicate precise segmentation with minimal distortion and high structural similarity.

Table 7: Comparative Performance Indicators of the current approaches and proposed ASS-Net

Algorithm / Method	MSE	PSNR (dB)	SSIM
LSTM [7]	0.0003	39.80	0.9812
CNN [8]	0.0002	40.50	0.9850
Naive Bayes [9]	0.0004	38.90	0.9785
Random Forest [10]	0.0003	39.60	0.9820
YOLOv5 [12]	0.0002	41.10	0.9875
VGGNet [15]	0.0002	41.00	0.9868
Proposed ASS-Net	0.0001	42.33	0.9980

This table 7 above compare a segmentation performance of existing ML and DL models with proposed ASS-Net. The proposed approach has the least MSE and maximum PSNR and SSIM and proves to be more accurate in segmentation of plant leaf images and structural conservation.

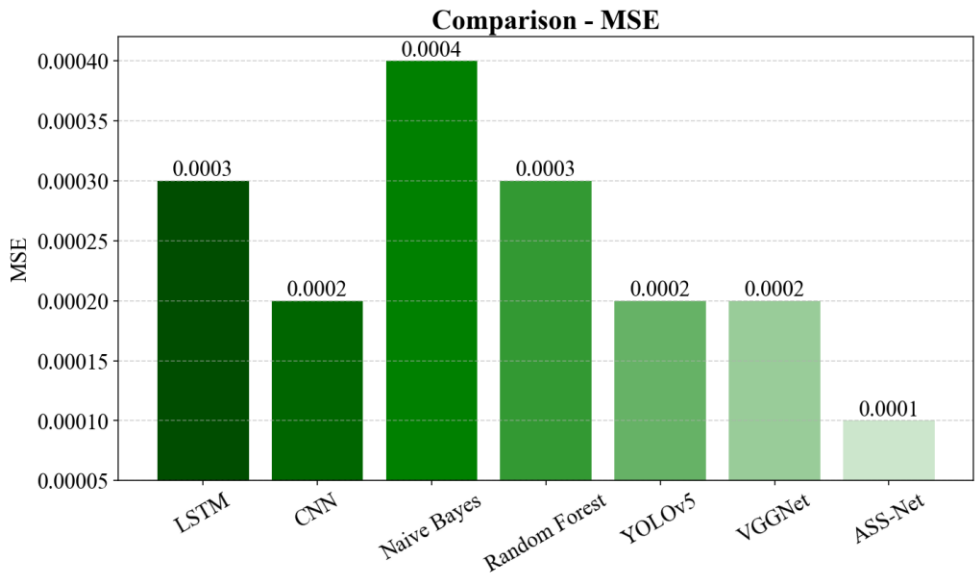


Figure 8: MSE Performance Comparison of the Segmentation Techniques in ASS-Net

This above figure 8 MSE comparison shows the accuracy of reconstruction of various algorithms in the segmentation process. The proposed ASS-Net attains the best value of MSE meaning that it has a low percentage of pixel errors in the process of segmentation. This shows its higher quality in maintaining fine-grained structural information of leaf areas of plants.

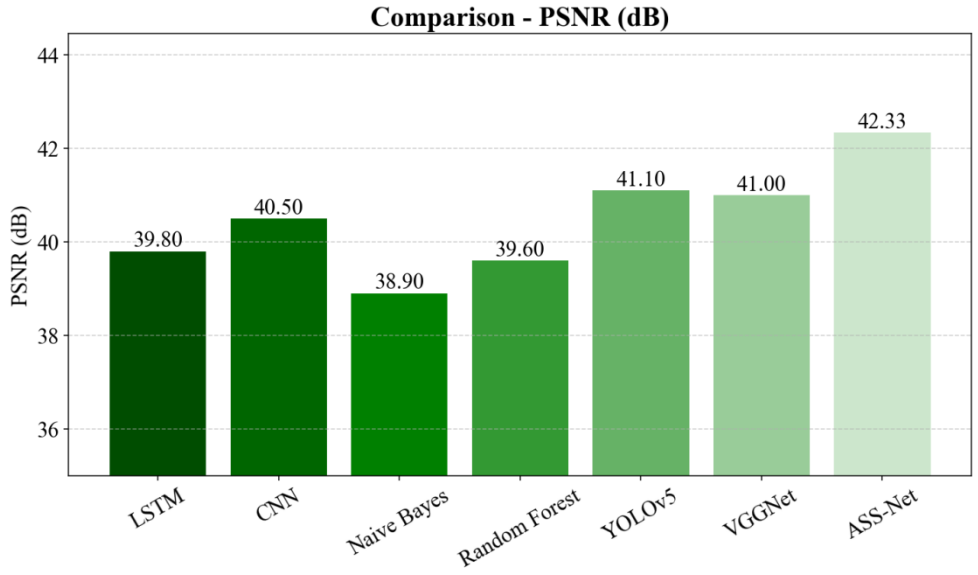


Figure 9: PSNR Results of Image segmentation with ASS-Net.

This above figure 9 PSNR comparison determines the quality of segmented outputs of different methods. The value of PSNR is the largest in ASS-Net which indicates the improved image clarity and the minimization of noise in the segmented areas. This shows that the model is effective in producing quality segmentation results.

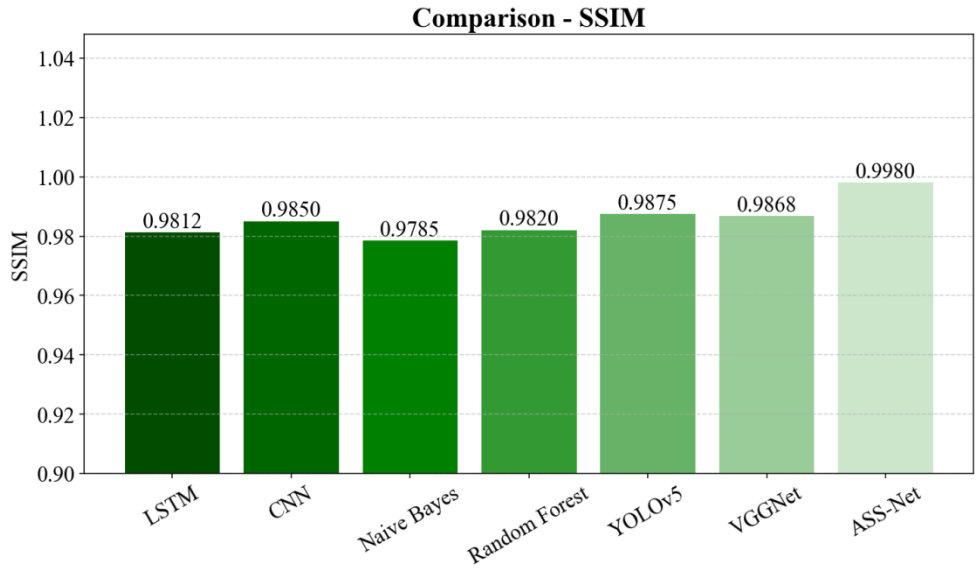


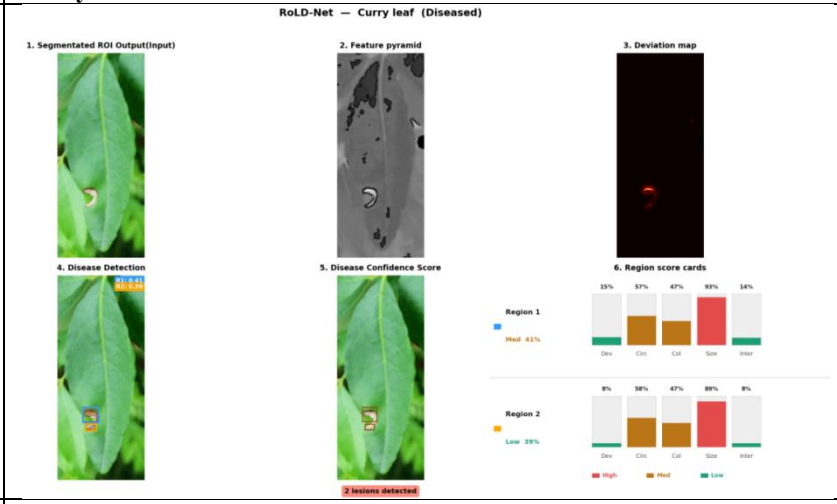
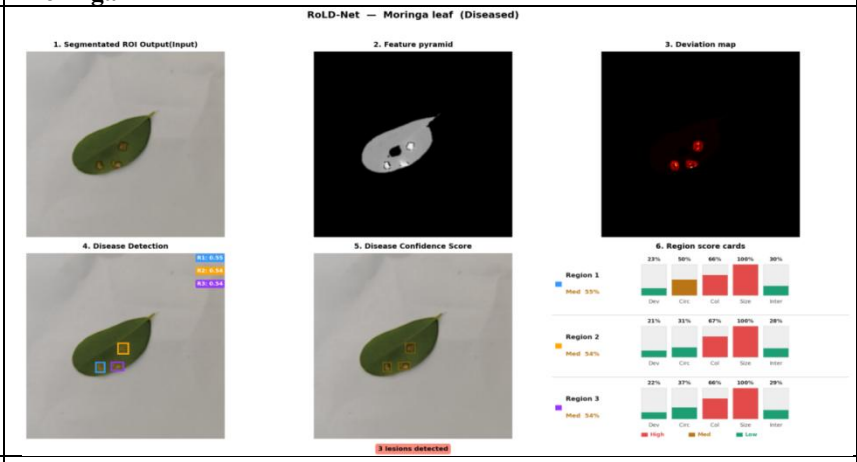
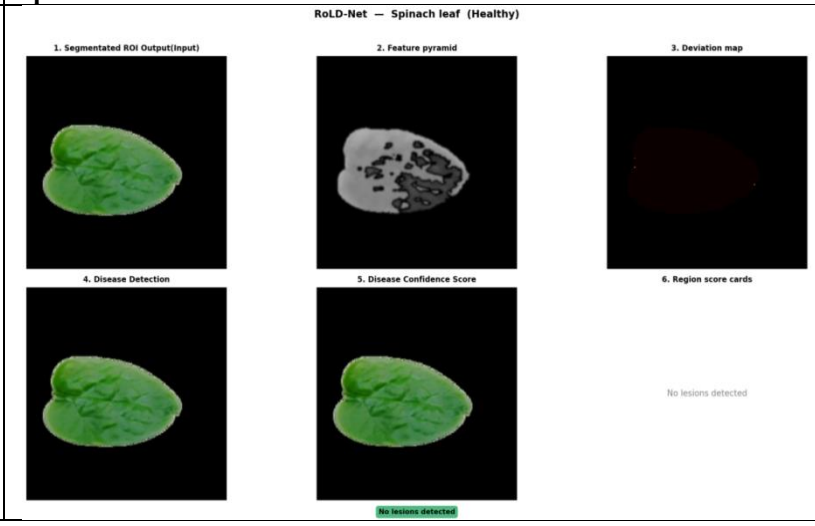
Figure 10: SSIM Performance of Segmentation in ASS-Net.

This above figure 10 SSIM comparison is a measure of the ability of the segmentation to retain structural information. In ASS-Net, the highest SSIM score is obtained, which means that the texture and spatial details were retained in the segmented images at the highest level. This justifies its strength in ensuring the visual consistency in the segmentation process.

4.3 Disease Detection

This section provides the disease detection procedure based on the designed RoLD-Net that precisely detects and localizes infected areas in leaf pictures ensuring consistent classification and analysis of plant diseases.

Table 8: Graphical Data of RoLD-Net Disease Detection.

Image	Curry	Status
1		Curry Leaf (Diseased)
Image	**Moringa**	**Status**
2		Moringa Leaf (Diseased)
Image	**Spinach**	**Status**
3		Spinach Leaf (Healthy)

This table 8 above shows the last phase of the proposed structure, whereby RoLD-Net identifies and classifies diseased leaves by using segmented leaf images. It shows how processed inputs are converted to feature analysis, where regions and classification outputs of various types of leaves are detected. The findings indicate that RoLD-Net is able to detect the presence of diseases and the health condition with high accuracy and reliability, which guarantees the quality and accurate assessment of the leaf condition.

Table 9: Comparative Performance Measures of Existing methods and Proposed RoLD-Net

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
ResNet18 [19]	91.20	92.00	89.50	90.70
Multi-Vision Transformer [20]	92.50	94.00	90.00	92.00
LeafDeSNet CNN [21]	93.00	95.00	91.00	93.00
EfficientNetB3 [23]	92.80	94.50	90.50	92.40
U-Net [30]	91.80	93.00	89.80	91.40
Proposed RoLD-Net	94.44	100.00	88.89	94.12

This above table 9 is comparison of the existing DL models and proposed RoLD-Net. RoLD-Net has best precision and competitive accuracy and F1-score, indicating its usefulness in a detection of plant leaf diseases.

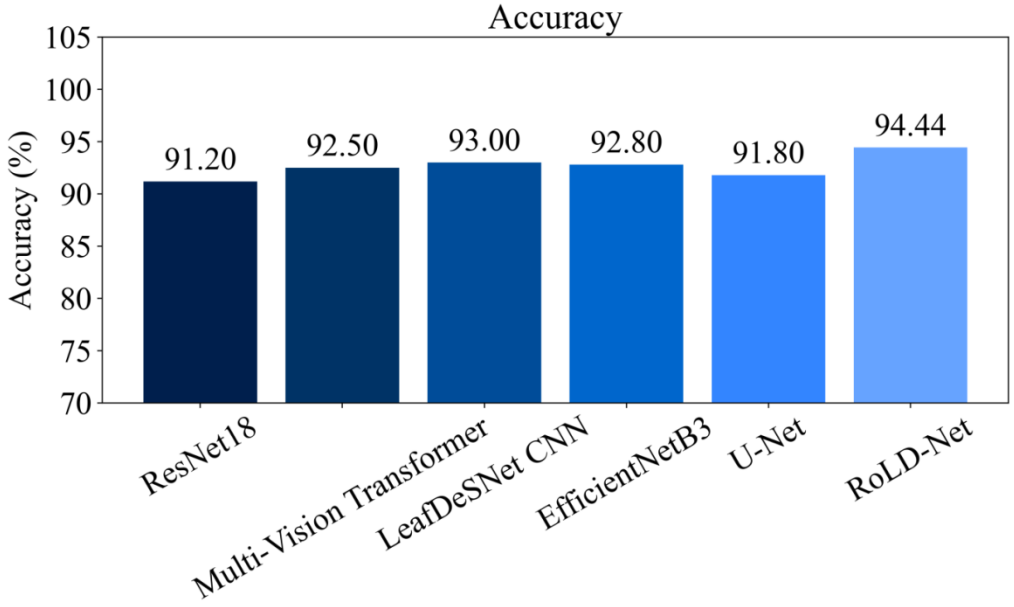


Figure 11: Accuracy Comparison

This above figure 11 shows the classification accuracy of six different models, including ResNet18, Multi-Vision Transformer, LeafDeSNet CNN, EfficientNetB3, U-Net, and the proposed RoLD-Net. RoLD- Net has the best accuracy of 94.44 %, which means that it has better general classification. The blue gradient shows how much each model is improved.

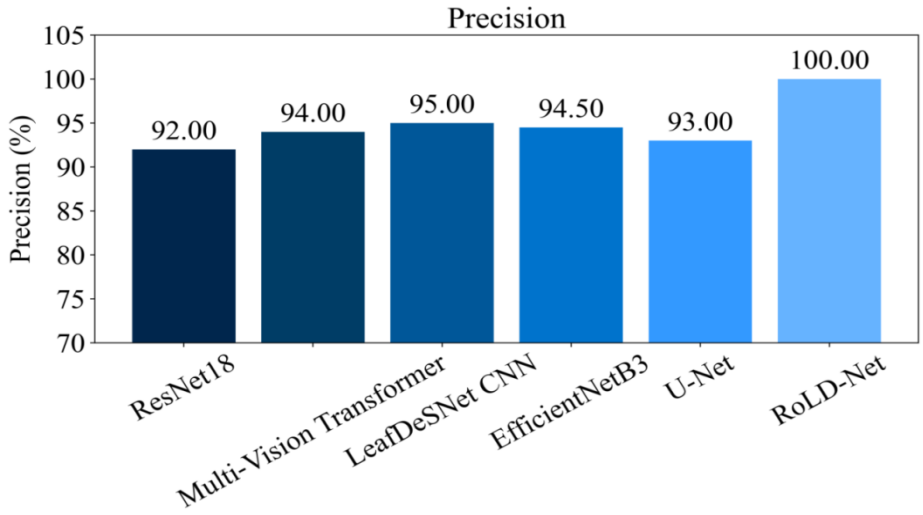


Figure 12: Precision Comparison

This above figure 12 shows the accuracy of the six algorithms in detection of plant leaf diseases. In proposed RoLD-Net has a 100 per cent accuracy, which is higher than that of all existing methods and this implies that it does not give false-positive predictions. The blue bars with gradients underline the incremental gains in the models.

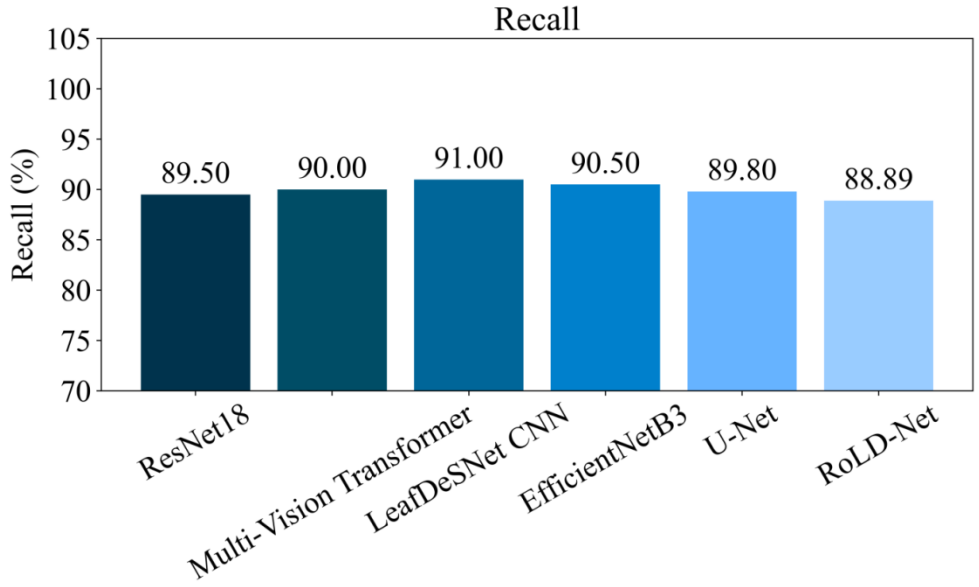


Figure 13: Recall Comparison

This above figure 13 shows how each model will be able to correctly identify true positive cases. Although RoLD-Net has a lower recall (88.89) than other models, it still has high overall performance. The color gradient blue enables a visual clarity of differences.

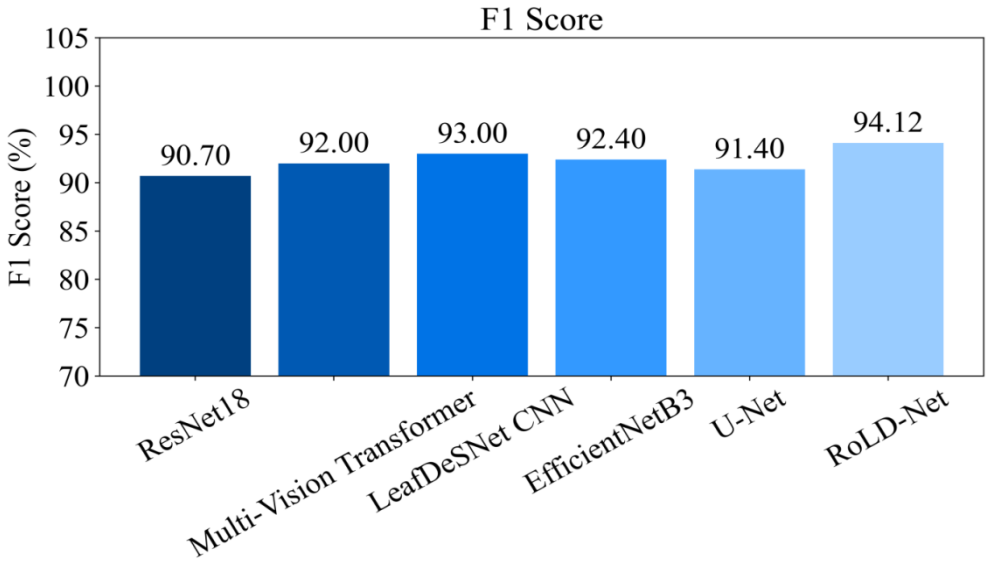


Figure 14: F1 Score Comparison.

This figure 14 above F1 scores of all methods, which is a combination of precision and recall in one single value. RoLD-Net has the best F1 score (94.12%), as it has equal precision and recall performance. The blue bars with gradation are a clear indication of the effectiveness of method compared to others.

5. Discussion

This section breaks the proposed RoLD-Net down to understand its effectiveness in the context of overall quantum-hybrid of plant disease detection. It measures the contribution of each part denoising, segmentation,

and lesion detection to the improvements in performance. The outcomes are discussed in contrast with the latest state-of-the-art approaches with emphasis improvements in precision and strength. In addition, the discussion offers information on the strengths, weaknesses of the model and how it can be applied in real-life agricultural situations.

Table 10: Comparative Analysis of PD Methods of State-of-the-Art and proposed framework.

Author (Year)	Method / Model	Key Idea	Limitations	Comparison with Proposed Method
Ali, A. H., et al. (2024) [11]	Ensemble CNN	Combines multiple DL models for better classification	No lesion localization, only classification	Proposed method includes lesion detection (RoLD-Net) + segmentation + denoising
Shafik, W., et al. (2025) [16]	Inception-Xception Hybrid CNN	Hybrid architecture improves feature extraction	Lacks lesion detection and disease severity analysis	Proposed method provides lesion-level detection and multi-stage processing
Naveed, F., et al. (2025) [19]	ResNet18 Few-shot Learning	Works with limited data	No localization, no segmentation, limited analysis	Proposed model supports full pipeline (denoising + segmentation + detection)
Baek, E. T. (2025) [20]	Vision Transformer (Attention-based)	Captures global features effectively	High computational cost, no lesion localization	Proposed method is efficient and includes region-based lesion detection
Alsuhaibani, A., et al. (2026) [21]	LeafDeSNet + Feature Selection	Optimized feature selection improves classification	High complexity, lacks preprocessing and localization	Proposed method integrates preprocessing + detection for better real-world performance
Proposed Method	Quantum-Hybrid Framework (Q-ANLMF + ASS-Net + RoLD-Net)	End-to-end pipeline with denoising, segmentation, and lesion detection	—	Addresses all limitations: noise handling, segmentation, lesion localization, and classification

This table 10 above provides a comparison of the recent methods of plant disease classification, the approaches and limitations of the methods. It emphasizes the fact that the proposed quantum-hybrid framework provides a better performance compared to the current models because it incorporates denoising, segmentation, and lesion-level detection to improve the performance and resilience of the framework.

Table 11: Ablation Experiments of Proposed RoLD-Net.

No	Configuration	Accuracy	Precision	Recall	F1 Score
1	Without RoLD (Baseline CNN)	90.12	91.30	88.20	89.70
2	+ Lesion Detection Only	92.05	94.10	89.50	91.70
3	+ Region Filtering	93.20	96.50	87.80	91.90
4	+ Feature Optimization	93.85	98.20	88.30	93.00
5	Full RoLD-Net (Proposed)	94.44	100.00	88.89	94.12

This above table 11 analyses the contribution of each part in the RoLD-Net architecture by ablation analysis. The findings indicate that the combination of lesion detection, region filtering, and multi-scale feature extraction can greatly improve overall performance, as compared to baseline model.

5.1 Outcomes

The outcome of this research demonstrates proposed quantum-hybrid system can improve in detection of PD significantly by incorporating denoising, segmentation and lesion-level analysis. The model has high levels of accuracy and precision, thereby making sure that there is good identification of diseased regions in complex real

world conditions. It also efficiently removes noise and maximizes features extraction and results in improved classification performance than current methods. The framework in general presents a comprehensive and viable method of precise and effective diagnosis of PD in precision farming.

6. Conclusion

This research introduces a hybrid quantum-based approach to detecting plant leaf diseases, comprising denoising, segmentation and lesion detection in a single pipeline. The Q-ANLMF approach proposed is efficient to eliminate noise and retain key structural and disease-related characteristics to improve the quality of images to be further processed. The ASS-Net model is able to accurately de-noise leaf areas and removes background distraction; this guarantees the accurate extraction of region-of-interest. MoreoverRoLD-Net improves the detection of diseases through lesion location and reliable classification results. Experimental findings prove that the proposed strategy is better than the current options in terms of accuracy, precision and general robustness in various datasets, such as Moringa, Spinach and Curry leaves. Quantum-inspired mechanisms coupled with DL can considerably improve the performance in real-world settings. The framework can be expanded into larger quantities of crops and field datasets in future work. Also, it can be considered deploying in real-time with the help of edge devices and integration with smart farming systems based on the IoT.

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