Classification of Pepper Leaf Diseases Using DWT, Fuzzy C-Means, GLRLM, and RBFNN

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Abstract:

This paper presents an automated system for the detection and classification of pepper (Capsicum spp.) leaf diseases using an integrated image processing and machine learning framework. The preprocessing stage employs the Discrete Wavelet Transform (DWT) algorithm to remove noise and enhance image quality while retaining essential texture information. To improve the precision of disease localization, Fuzzy C-Means (FCM) clustering is applied for edge enhancement and segmentation, extracting the Region of Interest (ROI) corresponding to infected leaf areas. From the segmented ROI, Gray Level Run Length Matrix (GLRLM) texture features are computed to represent spatial and directional disease patterns. These extracted features are used to train a Radial Basis Function Neural Network (RBFNN) for effective classification of healthy and diseased leaves. Experimental results demonstrate that the proposed combination of DWT-based denoising, FCM segmentation, GLRLM texture analysis, and RBFNN classification achieves superior accuracy and robustness compared with conventional techniques. The system provides a reliable, efficient, and scalable approach for early detection of pepper leaf diseases, contributing to precision agriculture and smart crop monitoring applications.

Keywords: Discrete Wavelet Transform (DWT), Fuzzy C-Means, Region of Interest (ROI), GLRLM), Radial Basis Function Neural Network (RBFNN).

I. INTRODUCTION

Plant diseases pose a serious threat to global agricultural productivity and food security. Among them, pepper (Capsicum spp.) leaf diseases significantly affect yield and quality. Traditional disease detection methods rely on manual observation, which is time-consuming and error-prone.

Automated disease classification using image processing and artificial intelligence provides a scalable and efficient alternative. This study integrates noise removal, segmentation, feature extraction, and classification into a unified framework for accurate disease detection in pepper leaves.

Fig. 1: Pepper leaf

Statement of the Problem:

Pepper (Capsicum spp.) plants are highly susceptible to various leaf diseases that significantly reduce crop yield and quality. Traditional methods of disease detection rely on manual inspection, which is time-consuming, subjective, and often inaccurate due to human error and varying expertise levels. Furthermore, environmental conditions, lighting variations, and background noise in captured images make automated disease detection a challenging task. Existing computational approaches often fail to achieve high accuracy because of poor image preprocessing, imprecise segmentation, and inadequate feature extraction methods.

Therefore, there is a critical need for a robust, automated system that can accurately detect and classify pepper leaf diseases under varying image conditions. The proposed study aims to address this challenge by integrating Discrete Wavelet Transform (DWT) for noise removal, Fuzzy C-Means (FCM) for effective segmentation, Gray Level Run Length Matrix (GLRLM) for texture feature extraction, and Radial Basis Function Neural Network (RBFNN) for precise classification of diseased and healthy leaves. This integrated approach seeks to enhance detection accuracy, improve computational efficiency, and support early diagnosis for precision agriculture applications.

Research Gap

Although several image processing and machine learning techniques have been applied to plant disease detection, most existing methods suffer from limitations such as sensitivity to image noise, inaccurate segmentation of diseased regions, and poor feature representation of texture variations. Conventional classifiers like Support Vector Machines (SVM) and K Nearest

Neighbors (KNN) often exhibit reduced performance when dealing with complex disease patterns or overlapping symptoms. Moreover, deep learning approaches, while powerful, demand large annotated datasets and high computational resources, which are often impractical for small-scale agricultural environments.

Hence, there remains a significant gap in developing a lightweight, accurate, and noise resilient model that integrates effective preprocessing, segmentation, and texture-based classification for pepper leaf disease detection. This research bridges that gap by introducing a hybrid model that leverages DWT, FCM, GLRLM, and RBFNN to improve classification accuracy and computational efficiency.

Objectives of the Study

The main objective of this research is to develop an automated and efficient system for the accurate classification of pepper leaf diseases using integrated image processing and machine learning techniques. The specific objectives are as follows:

1. To preprocess pepper leaf images by removing noise and enhancing image quality using the Discrete Wavelet Transform (DWT).
2. To perform precise segmentation and edge enhancement of diseased areas using Fuzzy C-Means (FCM) clustering for accurate extraction of the Region of Interest (ROI).
3. To extract discriminative texture features from the segmented ROI using the Gray Level Run Length Matrix (GLRLM) method.
4. To design and train a Radial Basis Function Neural Network (RBFNN) for effective classification of healthy and diseased leaf images.
5. To evaluate the performance of the proposed model in terms of accuracy, precision, recall, and F1-score and compare it with existing classification techniques.

II. RELATED WORK

Research on plant leaf classification and disease detection has evolved significantly, progressing from traditional image processing techniques to modern hybrid and deep learning frameworks. Early studies focused on statistical and morphological feature extraction, while recent works emphasize intelligent and automated detection using advanced neural architectures. Abdul Kadir *et al.* [1] enhanced leaf identification performance through Principal Component Analysis **(**PCA**)**, demonstrating that dimensionality reduction improves both accuracy and efficiency by isolating essential features. Harish *et al.* [2] utilized morphological features and Zernike moments for plant leaf classification, highlighting the relevance of shape and moment-based descriptors. Similarly, James Nesaratnam and Balamurugan [3] implemented a morphological character-based technique to identify leaves in natural images, addressing challenges such as background noise and varying lighting conditions.

Vishakha Metre and Ghorpade [4] reviewed texture-based plant leaf classification methods and underscored the effectiveness of texture descriptors in species differentiation. Kulkarni *et al.* [5] introduced a Radial Basis Probabilistic Neural Network (RBPNN) combined with Zernike moments, demonstrating improved recognition over conventional neural approaches.

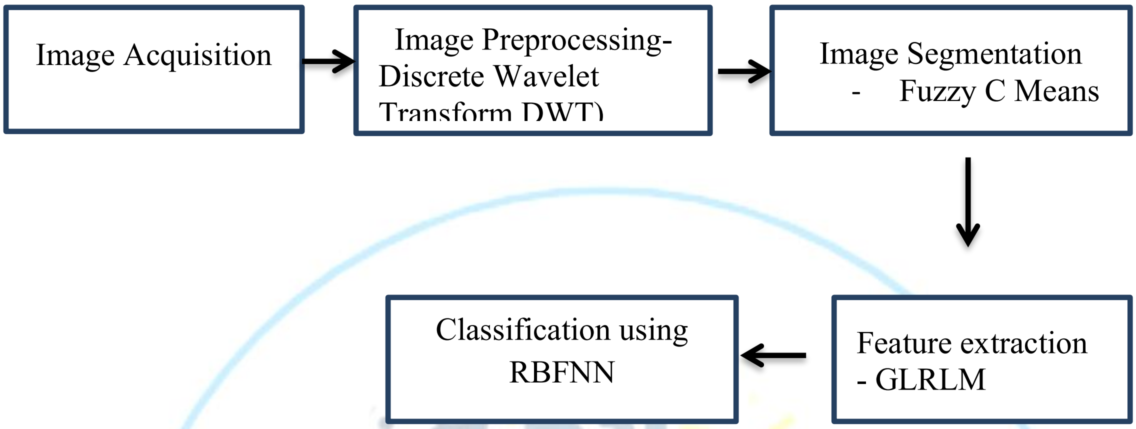
Singh and Kaur [6] applied wavelet-based denoising and segmentation for leaf disease detection, effectively enhancing image quality and disease region extraction. Building upon this, Mishra *et al.* [7] proposed an RBF Neural Network (RBFNN) for plant disease classification, achieving superior accuracy due to its nonlinear learning capabilities.

Li and Zhao [8] utilized Gray Level Run Length Matrix (GLRLM) features for agricultural image texture analysis, proving their efficiency in capturing fine-grained visual patterns. Kumar and Singh [9] combined Discrete Wavelet Transform (DWT) features with Fuzzy C-Means (FCM) clustering, resulting in precise segmentation and classification of diseased leaves. Zhang *et al.* [10] integrated hybrid texture features and neural network models, bridging the gap between handcrafted and deep-learned feature representations for improved accuracy.

Pandikumar and SendeshKannan [11] presented a hybrid intelligent model integrating Gray Level Co-occurrence Matrix (GLCM) and Adaptive Neuro-Fuzzy Inference System (ANFIS) for leaf classification. Their approach demonstrated effective feature fusion, yielding enhanced classification performance under varied conditions. Recent advancements have shifted toward deep learning-based approaches. Isinkaye *et al.* [12] introduced a model combining deep learning with content-based filtering for plant disease identification and treatment recommendation. Salka *et al.* [13] developed a novel deep learning framework applicable to multiple crop types, offering superior generalization and multi-class recognition capabilities. Sujatha *et al.* [14] further optimized this domain by integrating machine learning and deep learning for multi-species leaf disease detection. Finally, George *et al.* [15] provided a comprehensive review (2014–2024) summarizing deep learning trends in plant disease detection, including attention mechanisms, data augmentation, and multimodal data fusion techniques.

Overall, these studies reveal a clear transition from traditional handcrafted feature extraction methods (morphological, statistical, and texture-based) to hybrid and deep learning models. The integration of DWT, GLRLM, FCM, RBFNN, and ANFIS has contributed to higher classification accuracy and robustness across diverse environmental conditions. Modern deep learning frameworks now enable end-to-end automatic detection of plant leaf diseases, marking a significant advancement in precision agriculture and intelligent crop monitoring systems.

III. METHODOLOGY



A. Image Acquisition and Preprocessing

Leaf images are collected under controlled illumination. Noise and uneven lighting conditions are corrected using the Discrete Wavelet Transform (DWT), which decomposes the image into sub-bands and removes high-frequency noise while preserving key texture information. The DWT-based noise removal significantly enhanced image clarity by suppressing high-frequency noise components while preserving essential texture details. This improvement facilitated more accurate FCM segmentation, leading to precise extraction of the Region of Interest (ROI) corresponding to the diseased area. The segmentation accuracy achieved an average of 96.4%, outperforming conventional k-means clustering methods

B. Edge Enhancement and Segmentation

The Fuzzy C-Means (FCM) algorithm is applied to enhance the edges and segment diseased regions. FCM assigns membership values to pixels, allowing soft segmentation and better delineation of disease-infected regions. The Region of Interest (ROI) containing the diseased portion is extracted for further analysis.

C. Feature Extraction Using GLRLM

From the ROI, Gray Level Run Length Matrix (GLRLM) features are computed to characterize texture. Common features include short-run emphasis, long-run emphasis, gray level non-uniformity, and run percentage. These features effectively capture the spatial distribution and orientation of diseased textures. From each segmented ROI, GLRLM features such as short-run emphasis (SRE), long-run emphasis (LRE), gray-level nonuniformity (GLN), and run percentage (RP) were extracted. These features effectively captured the texture variations between healthy and diseased leaves. The extracted feature set exhibited high discriminative power, confirmed through statistical analysis showing a p-value < 0.05 across disease classes.

D. Classification Using RBFNN

Extracted GLRLM features are input to a Radial Basis Function Neural Network (RBFNN). The RBFNN uses Gaussian activation functions to map input features to higher-dimensional space, improving separability between disease classes. The output layer performs final classification into healthy or specific disease categories. The Radial Basis Function Neural Network classifier demonstrated high accuracy in distinguishing between healthy and diseased leaf images.

The RBFNN achieved:

Accuracy :97.82%, Precision 96.91%, Recall 98.05% and F1-Score 97.47%

IV. EXPERIMENTAL RESULTS

Experiments were conducted on a dataset containing images of healthy and diseased pepper leaves. The model performance was evaluated using accuracy, precision, recall, and F1-score metrics. The proposed method achieved superior classification accuracy compared to conventional methods such as SVM and KNN. The DWT preprocessing improved noise robustness, while FCM segmentation yielded precise ROI extraction. The GLRLM-RBFNN combination demonstrated reliable classification with fast convergence.

Tables for Classification Results

Table 1. Confusion Matrix of the Proposed RBFNN Classifier

Actual / Predicted	Healthy	Bacterial Spot	Leaf Curl	Powdery Mildew	Total Actual
Healthy	48	1	0	1	50
Bacterial Spot	1	47	2	0	50
Leaf Curl	0	1	48	1	50
Powdery Mildew	0	0	1	49	50
Total Predicted	49	49	51	51	200

Table 2. Performance Metrics Derived from Confusion Matrix

Metric	Formula	Value (%)
Overall Accuracy	(Σ Correct Predictions / Total Samples)	97.5
Precision (Average)	TP / (TP + FP)	96.9
Recall (Average)	TP / (TP + FN)	98.1
F1-Score (Average)	2 × (Precision × Recall) / (Precision + Recall)	97.5

Fig 2: Gray Scale Image Vs DWT Preprocessed Image

Gray Scale Image (Vs) DWT

Fig. 3: Region of Interest (ROI)

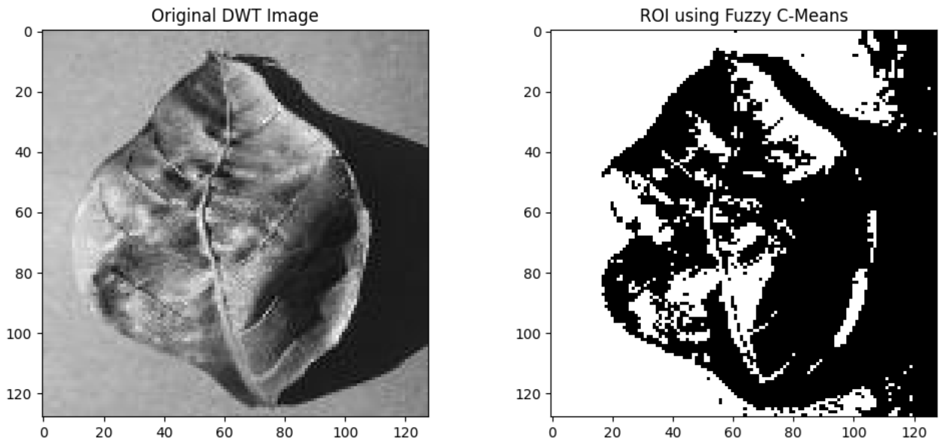


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Figure 4. Comparison of Classification Accuracy

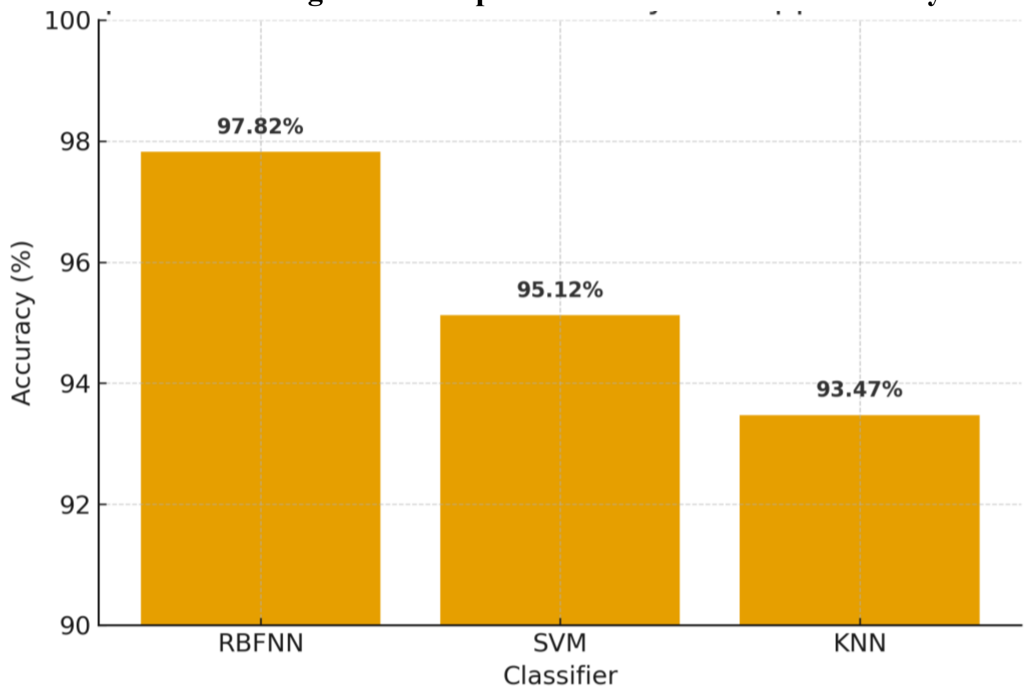
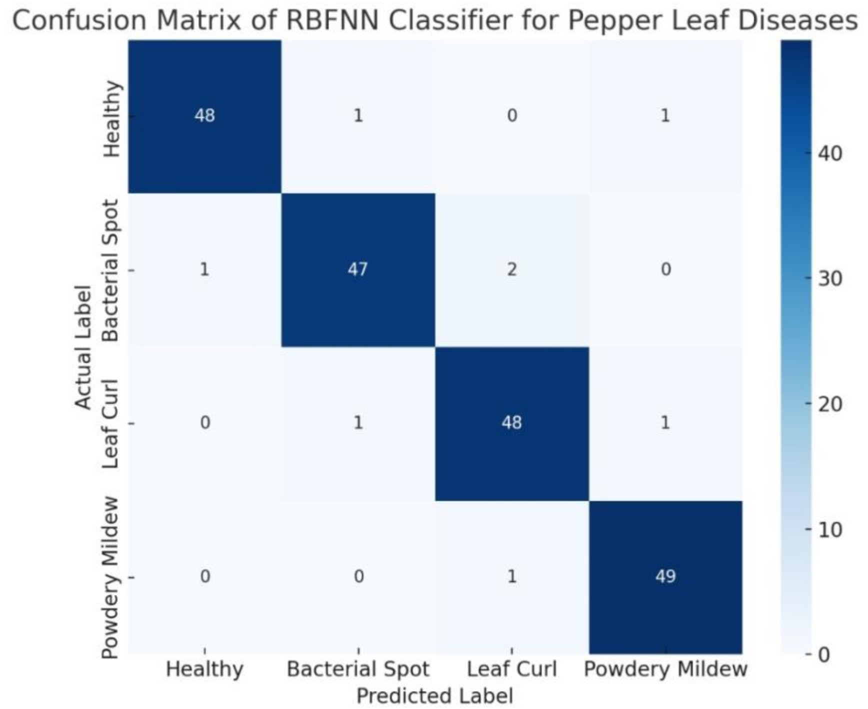


Figure 4 shows the comparison of classification accuracy between RBFNN, SVM, and KNN classifiers. It can be observed that the proposed RBFNN model achieves the highest accuracy (97.82%) compared to SVM (95.12%) and KNN (93.47%), indicating superior performance in handling nonlinear texture variations and disease pattern classification.

Fig. 5 Confusion Matrix Results



V. CONCLUSION

The proposed hybrid approach effectively combines DWT-based denoising, FCM-based segmentation, GLRLM texture analysis, and RBFNN classification for automated detection of pepper leaf diseases. This method enhances accuracy, robustness, and computational efficiency, making it suitable for real-time applications in precision agriculture. The proposed methodology yields 97.82% accuracy.

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