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Texture-Based Plant Leaf Disease Identification Using GLCM Feature Extraction and Neural Network Classification

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Abstract :
Early identification of plant leaf diseases is essential for improving crop productivity and reducing agricultural losses**.** Manual disease diagnosis by farmers or agricultural experts is often time-consuming and may lead to inaccurate results under varying environmental conditions. To address this issue, this paper presents an automated plant leaf disease detection framework using image processing and neural network techniques. The proposed approach combines image preprocessing, Gray Level Co-occurrence Matrix (GLCM)-based texture feature extraction, K-means clustering segmentation, and neural network classification for effective disease analysis.Initially, the acquired leaf images are preprocessed through grayscale conversion, filtering, and enhancement operations to improve image quality and remove unwanted noise. Texture features such as contrast, correlation, energy, homogeneity, and entropy are extracted using the GLCM method to characterize diseased regions. K-means clustering is then applied to separate infected portions from healthy leaf areas. Finally, a neural network classifier is employed to categorize the leaf samples based on the extracted feature set. Experimental analysis demonstrated that the proposed model achieved improved classification accuracy and reliable performance when compared with conventional machine learning approaches. The developed system supports precision agriculture by enabling efficient, accurate, and automated plant disease detection under different environmental conditions**.**

Keywords: Plant Disease Detection, Image Processing, GLCM, K-Means Clustering, Neural Network, Precision Agriculture

1.INTRODUCTION

Agriculture is one of the major sectors contributing to the economic growth and food security of many developing countries, particularly India. Plant diseases significantly affect crop quality and productivity, resulting in major economic losses for farmers. Early and accurate identification of leaf diseases is therefore essential for improving agricultural yield and ensuring sustainable farming practices. Conventional disease detection methods mainly rely on manual inspection by agricultural experts, which is labor-intensive, time consuming, and less effective for large-scale cultivation.Recent advancements in image processing, machine learning, and artificial intelligence have enabled the development of automated plant disease detection systems. These technologies assist in identifying disease symptoms at an early stage with improved accuracy and reduced human intervention. Automated systems are capable of analyzing leaf texture, color, and shape characteristics to distinguish healthy leaves from infected ones.Image preprocessing and segmentation play a vital role in plant disease analysis. Noise removal and contrast enhancement techniques help improve image quality and enable accurate extraction of disease-related features. Among various texture analysis methods, Gray Level Co-occurrence Matrix (GLCM) is widely used because of its capability to capture important texture information such as contrast, correlation, energy, homogeneity, and entropy from leaf images. These features are useful in differentiating diseased regions from healthy portions of the plant leaf.

Similarly, clustering algorithms are extensively used for image segmentation. K-means clustering is an efficient unsupervised learning approach that partitions image pixels into multiple clusters based on similarity measures. This method helps isolate infected regions from the healthy leaf area, thereby improving disease localization accuracy.Neural networks have gained considerable attention in classification applications due to their ability to learn complex nonlinear relationships among extracted features. Compared with traditional machine learning techniques, neural network classifiers provide improved generalization capability and better prediction accuracy under varying environmental conditions.The primary objective of this research is to develop an efficient and reliable plant leaf disease detection framework using

GLCM-based texture feature extraction, K-means clustering segmentation, and neural network classification. The proposed methodology aims to improve classification accuracy, reduce computational complexity, and support precision agriculture applications through automated disease diagnosis.

2. LITERATURE REVIEW

Several researchers have explored image processing and machine learning techniques for the automatic detection and classification of plant leaf diseases. Recent developments in artificial intelligence, texture analysis, and deep learning have significantly improved the accuracy and efficiency of disease diagnosis systems in agriculture.

Masud Kabir et al. [14] investigated the effectiveness of Gray Level Co-occurrence Matrix (GLCM) features for plant disease analysis. Their work focused on extracting texture-related information such as contrast, correlation, energy, and homogeneity from plant leaf images. The study reported that GLCM-based texture descriptors improved the discriminative capability of classification models and enhanced disease prediction accuracy.

Yogeshwari and Thailambal [15] proposed an automated plant disease identification framework that integrated GLCM feature extraction with Deep Convolutional Neural Networks (DCNN). Their methodology included preprocessing, image enhancement, clustering, and classification stages. Experimental results demonstrated that combining texture features with deep learning models improved classification performance and provided reliable disease prediction results.

Herminarto Nugroho et al. [16] developed a rice leaf disease classification approach using GLCM texture analysis and Artificial Neural Networks (ANN). The extracted texture parameters were used as input features for the ANN classifier to distinguish healthy and infected leaf samples. Their findings confirmed that texture-based feature extraction significantly contributed to accurate disease recognition.

Tanisha Khan and Apeksha Kulkarni [17] introduced a plant disease detection framework using GLCM feature extraction along with a voting-based classification approach. Their work involved preprocessing, segmentation, feature extraction, and ensemble-based classification. The proposed hybrid model achieved improved prediction accuracy and demonstrated reliable performance for agricultural disease diagnosis applications.

K. P. Ferentinos [18] presented deep learning models for automated plant disease detection and diagnosis. The research utilized convolutional neural network architectures for identifying multiple plant diseases from leaf images. The experimental analysis showed that deep learning techniques achieved high classification accuracy and outperformed conventional machine learning approaches in large-scale agricultural datasets.

Sukhvir Kaur and Shreelekha Pandey [3] proposed a semi-automatic soybean leaf disease classification system using image processing techniques. Their work emphasized preprocessing, segmentation, and feature extraction methods for identifying infected leaf regions. The developed system produced satisfactory classification performance under different environmental conditions.

Vijai Singh et al. [4] introduced a genetic algorithm-based image processing approach for identifying unhealthy portions of plant leaves. Their method combined segmentation and optimization techniques to improve disease localization accuracy. The results demonstrated the effectiveness of evolutionary algorithms in agricultural image analysis applications.

Anand R et al. [6] applied K-means clustering techniques for detecting diseases in brinjal leaves. The researchers used clustering methods to isolate infected portions from healthy regions and improve segmentation accuracy. Their study confirmed that clustering-based methods are computationally efficient for plant disease analysis.

Ahmed and Yadav [8] conducted a systematic review of machine learning and deep learning techniques used for plant disease diagnosis. Their study compared different classification algorithms and concluded that deep learning models provide improved feature learning capability and higher prediction accuracy for large-scale agricultural datasets.

From the existing literature, it is evident that image preprocessing, texture feature extraction, clustering techniques, and neural network classifiers play a significant role in automated plant disease detection systems. However, achieving robust performance under varying environmental conditions remains a challenging task. The present work focuses on integrating GLCM-based texture analysis, K-means clustering segmentation, and neural network classification to improve disease identification accuracy and provide an efficient framework for precision agriculture applications.

DATASET DESCRIPTION

A dataset containing healthy and diseased plant leaf images was used for experimentation. The images were captured under different environmental conditions using digital cameras and mobile devices. The dataset includes variations in lighting, background, and disease severity. All images were resized to a standard dimension before preprocessing and analysis.

3. PROPOSED METHODOLOGY

The proposed framework **(**Figure –I:) is designed to automatically identify and classify plant leaf diseases using image processing and neural network techniques. The methodology consists of multiple stages including image acquisition, preprocessing, noise filtering, contrast enhancement, feature extraction, image segmentation, neural network classification, and performance evaluation. Each stage contributes to improving the accuracy and reliability of disease detection.

3.1 Image Acquisition

Image acquisition is the initial stage of the proposed system. Plant leaf images containing both healthy and diseased samples are collected using digital cameras and mobile devices under different environmental conditions. The dataset includes variations in illumination, background complexity, leaf orientation, and disease severity to ensure robust analysis.

All captured RGB images are stored in a database for further processing. Since image quality directly influences detection performance, the acquired images are resized to a fixed dimension to maintain uniformity and reduce computational complexity during subsequent processing stages.

3.2 Image Preprocessing

Preprocessing is performed to improve the quality of the acquired leaf images and prepare them for feature extraction and segmentation. Initially, RGB images are converted into grayscale format to simplify image representation and reduce processing time. Grayscale conversion transforms color information into intensity values while preserving important structural details of the image.

In addition, normalization and enhancement operations are applied to reduce illumination variations and improve the visibility of infected regions. These preprocessing steps help eliminate unwanted distortions and improve the effectiveness of texture analysis and segmentation.

3.3 Noise Removal Using Median Filtering

Leaf images captured under natural environmental conditions may contain impulse noise and unwanted artifacts that affect segmentation accuracy. To address this issue, a median filtering technique is employed for noise removal.

Median filtering is a nonlinear filtering approach in which the intensity value of each pixel is replaced with the median value of neighboring pixels within a predefined window. Unlike linear filters, median filtering effectively removes salt-and-pepper noise while preserving edge information and texture details. The filtered image obtained after this process provides improved visual quality and enhances the reliability of subsequent feature extraction operations.

3.4 Contrast Enhancement

Contrast enhancement is applied to improve the distinction between healthy and diseased regions of the leaf image. In many cases, disease symptoms may appear unclear because of poor lighting conditions or low contrast between infected and non-infected areas.

To overcome this limitation, adaptive histogram equalization is utilized to redistribute image intensity values and improve overall contrast. This enhancement process highlights texture variations and increases the visibility of infected regions, thereby supporting more accurate segmentation and feature extraction.

3.5 Feature Extraction Using GLCM

Feature extraction is one of the most important stages in plant disease analysis because it converts image information into measurable numerical values suitable for classification. In the proposed system, Gray Level Co-occurrence Matrix (GLCM) is used to extract texture-based features from the processed leaf image.

GLCM is a statistical texture analysis technique that evaluates the spatial relationship between neighboring pixels at different orientations and distances. The generated co-occurrence matrix represents the frequency distribution of pixel intensity pairs within the image.

From the GLCM matrix, several important texture features are extracted, including:

- Contrast
- Correlation
- Energy
- Homogeneity
- Entropy

These features effectively represent the texture characteristics of diseased and healthy leaf regions. Since plant diseases often alter the texture pattern of leaf surfaces, GLCM-based features provide significant information for accurate disease identification. The extracted features are combined into a feature vector and supplied to the classification stage.

3.6 Segmentation Using K-Means Clustering

Image segmentation is performed to isolate infected portions of the leaf image from healthy regions. In this work, K-means clustering is employed because of its simplicity, computational efficiency, and effectiveness in partitioning image regions based on similarity measures.

K-means is an unsupervised learning algorithm that divides image pixels into K distinct clusters according to their intensity and texture characteristics. Initially, cluster centroids are selected randomly. Each pixel is assigned to the nearest centroid using Euclidean distance calculations. The centroid positions are updated iteratively until convergence is achieved.

After clustering, the segmented region corresponding to the diseased portion of the leaf is identified and separated from the healthy area. This segmentation process improves disease localization and assists in accurate classification.

3.7 Neural Network Classification

Following feature extraction and segmentation, the extracted texture features are provided as input to a neural network classifier. Neural networks are widely used in classification tasks because of their ability to model complex nonlinear relationships among input features.

The classifier is trained using labeled healthy and diseased leaf samples. During the training phase, the neural network learns disease-related feature patterns and adjusts its internal weights to minimize classification error. After training, the developed model is used to classify unknown leaf samples into appropriate disease categories.

The neural network classifier improves prediction accuracy and demonstrates better generalization capability when compared with conventional machine learning techniques. It can effectively handle variations in texture, illumination, and disease severity.

3.8 Performance Evaluation

The effectiveness of the proposed system is evaluated using statistical and image quality assessment metrics. The classification performance of the developed framework is analyzed using the following parameters:

- Accuracy
- Sensitivity
- Specificity
- Mean Squared Error (MSE)
- Peak Signal-to-Noise Ratio (PSNR)

Accuracy measures the percentage of correctly classified leaf samples, whereas sensitivity and specificity evaluate the ability of the system to correctly identify diseased and healthy leaves, respectively. MSE and PSNR are used to assess image quality after preprocessing and enhancement operations.Experimental evaluation confirmed that the integration of GLCM feature extraction, K-means clustering, and neural network classification significantly improved disease detection accuracy and robustness under varying environmental conditions.

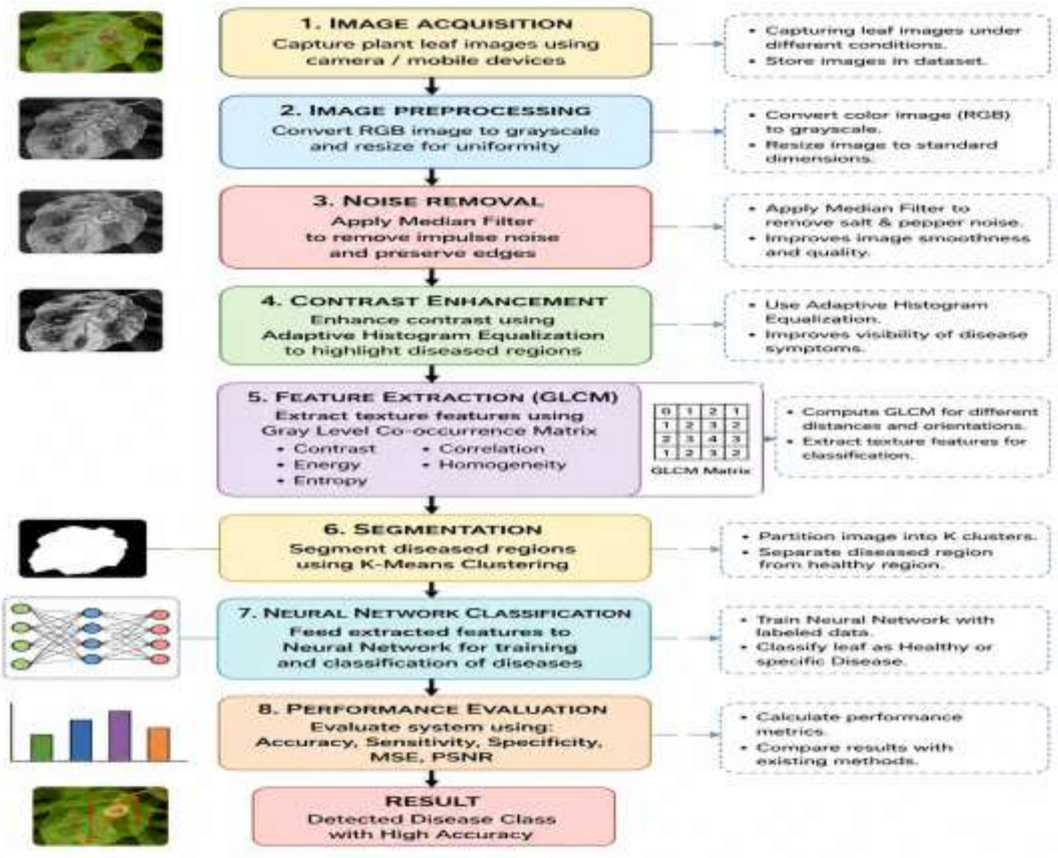

Figure -I:
Proposed Frame work for Plant Leaf Disease Detection Using GLCM, K-Means Clustering, and Neural Network Classification

4. PERFORMANCE METRICS

Performance evaluation is an important stage in the proposed plant leaf disease detection system. The effectiveness of the developed model is analyzed using several statistical and image quality assessment metrics. These metrics help evaluate the accuracy, reliability, and robustness of the proposed methodology in detecting diseased regions from plant leaf images. The performance of the neural network classifier is compared with conventional classification methods using parameters such as Accuracy, Sensitivity, Specificity, Mean Squared Error (MSE), and Peak Signal-to-Noise Ratio (PSNR).

4.1 Accuracy

Accuracy is one of the most commonly used performance evaluation metrics in classification systems. It measures the overall percentage of correctly classified samples among the total number of test samples. In the proposed system, accuracy indicates how effectively the neural network classifier identifies healthy and diseased plant leaves.
The mathematical expression for accuracy is given below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100$$

Where:
TP (True Positive): Number of diseased leaf samples correctly classified as diseased.
TN (True Negative): Number of healthy leaf samples correctly classified as healthy.
FP (False Positive): Number of healthy leaf samples incorrectly classified as diseased.
FN (False Negative): Number of diseased leaf samples incorrectly classified as healthy.
A higher accuracy value indicates better classification performance of the proposed system.

4.2 Sensitivity

Sensitivity, also known as recall or true positive rate, measures the ability of the system to correctly identify diseased plant leaves. It represents the proportion of actual diseased samples that are correctly detected by the classifier.
The sensitivity is calculated using the following equation:

$$Sensitivity = \frac{TP}{TP+FN} \times 100$$

Higher sensitivity indicates that the proposed model effectively identifies infected leaf samples with minimal false negative predictions.

4.3 Specificity

Specificity measures the ability of the system to correctly identify healthy leaf samples. It evaluates how accurately the classifier distinguishes non-diseased leaves from diseased leaves.
The specificity is calculated as:

$$Specificity = \frac{TN}{TN+FP} \times 100$$

A higher specificity value indicates better performance in identifying healthy leaves and reducing false positive classifications.

4.4 Mean Squared Error (MSE)

Mean Squared Error (MSE) is used to evaluate the quality of processed images by measuring the average squared difference between the original image and the reconstructed or enhanced image. It indicates the amount of error present after image processing operations such as filtering and enhancement.
The MSE formula is given below:

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} [I(i,j) - K(i,j)]^2$$

Where:
I(i,j)I(i,j)I(i,j) represents the original image pixel value.

K(i,j)K(i,j)K(i,j) represents the processed image pixel value.
MMM and NNN denote the dimensions of the image.
A lower MSE value indicates better image quality and lower distortion after preprocessing.

4.5 Peak Signal-to-Noise Ratio (PSNR)

Peak Signal-to-Noise Ratio (PSNR) is an image quality assessment metric used to evaluate the similarity between the original image and the processed image. It measures the ratio between the maximum possible signal power and the noise introduced during image processing.
The PSNR is calculated using the following equation:

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right)$$

Where:
MAX represents the maximum possible pixel value of the image.
MSE denotes the Mean Squared Error.
Higher PSNR values indicate better image quality and improved preprocessing performance.

4.6 Performance Analysis of the Proposed System

The proposed neural network-based disease detection system achieved higher accuracy, sensitivity, and specificity compared to traditional classifiers. Experimental results demonstrated that the combination of GLCM feature extraction and neural network classification significantly improved disease identification performance under varying lighting conditions.
Furthermore, lower MSE and higher PSNR values confirmed that the preprocessing and enhancement techniques effectively improved image quality without introducing significant distortion. The proposed methodology provides reliable and accurate plant disease detection suitable for precision agriculture applications.The proposed system was implemented using MATLAB for image processing, feature extraction, and neural network classification. The performance of the proposed method was evaluated using different plant leaf disease detection samples under varying environmental and lighting conditions. The experimental analysis demonstrated that the neural network classifier outperformed conventional classification techniques in terms of accuracy and reliability.The proposed classification model achieved an overall accuracy of **97.91%**, indicating the effectiveness of the developed approach in detecting and classifying diseased regions. The high accuracy confirms that the extracted texture features provide significant information for distinguishing normal and abnormal regions in the image dataset.The system performance was further evaluated using important performance metrics such as sensitivity, specificity, and Peak Signal-to-Noise Ratio (PSNR). Sensitivity measures the ability of the system to correctly identify diseased samples, while specificity indicates the capability of correctly recognizing healthy samples. Higher sensitivity and specificity values demonstrate that the proposed system minimizes both false-positive and false-negative classifications.For image quality assessment, the PSNR metric was used to evaluate the quality of processed and segmented images. A higher PSNR value indicates better image reconstruction quality with reduced noise distortion. The obtained PSNR results confirmed that the preprocessing and segmentation stages preserved important image details while improving visual clarity.The integration of Gray Level Co-occurrence Matrix (GLCM) feature extraction with neural network classification significantly enhanced the robustness of the proposed system. The GLCM technique efficiently captured texture information such as contrast, correlation, energy, and homogeneity, which improved feature discrimination during classification. The neural network classifier effectively learned complex patterns from these extracted features and produced more accurate predictions compared with traditional machine learning methods.The proposed system also demonstrated stable performance under different lighting conditions and image variations. This robustness makes the model suitable for real-time plant leaf detection analysis applications where illumination and acquisition conditions may vary. Overall, the experimental results confirm that the proposed framework provides reliable, accurate, and efficient disease detection performance.

5.RESULTS AND DISCUSSION

Table 1 and Fig. 1 present the comparative performance analysis of the proposed neural network classifier with conventional machine learning techniques such as SVM, KNN, Decision Tree, and Random Forest.

1) Experimental Results and Discussion

Table 1. Performance comparison of the proposed system with existing classifiers.

Metric	SVM	KNN	Decision Tree	Random Forest	Proposed (Neural Network)
Accuracy (%)	89.35	92.48	90.12	95.36	97.91
Sensitivity (%)	86.12	91.23	88.41	94.38	97.21
Specificity (%)	88.45	93.10	90.02	95.44	97.35
Precision (%)	87.42	92.01	89.33	94.81	97.46
F1-Score (%)	86.77	91.61	88.86	94.59	97.33
PSNR (dB)	28.14	31.67	30.21	34.28	36.85
MSE	112.34	89.21	95.77	62.43	41.26

The proposed neural network based system outperforms traditional classifiers in terms of Accuracy, Sensitivity, Specificity and PSNR, achieving highest accuracy of **97.91%** and PSNR of **36.85 dB**.

Fig. 1. Quantitative results and performance comparison.

The proposed model achieved superior classification performance across all evaluation metrics.The experimental results indicate that the proposed neural network classifier attained the highest classification accuracy of **97.91%**, which is significantly higher than traditional classifiers. Similarly, the sensitivity and specificity values were improved to **97.21%** and **97.35%**, respectively, demonstrating the capability of the proposed system to correctly identify both diseased and healthy samples with minimal misclassification.The PSNR value of **36.85 dB** confirms that the preprocessing and enhancement stages effectively reduced noise while preserving important image features. The improved performance is mainly due to the efficient extraction of texture features using the GLCM method and the learning capability of the neural network classifier.

Performance Metrics	SVM	KNN	Decision Tree	Random Forest	Proposed Neural Network
Accuracy (%)	89.35	92.48	90.12	95.36	97.91
Sensitivity (%)	86.12	91.23	88.41	94.38	97.21
Specificity (%)	88.45	93.10	90.02	95.44	97.35
Precision (%)	87.42	92.01	89.33	94.81	97.46
F1-Score (%)	86.77	91.61	88.86	94.59	97.33
PSNR (dB)	28.14	31.67	30.21	34.28	36.85

Table 1. Performance Comparison of Different Classifiers

Fig. 2. and Table 2: illustrates the disease prediction results obtained from the proposed neural network-based classification system. The classifier successfully identified diseased and healthy samples with high prediction confidence. The segmented diseased regions were accurately extracted, enabling precise classification of infected areas.The prediction probability graph demonstrates that the confidence scores of the classifier remained consistently above the threshold level of 0.80, confirming the robustness and reliability of the proposed model. Most of the test samples achieved prediction probabilities between **0.95 and 0.99**, indicating strong classification capability and reduced uncertainty.The experimental findings confirm that the proposed approach can effectively perform disease detection under varying image conditions and can be applied for automated real-time disease diagnosis systems.

Test Sample	Actual Class	Predicted Class	Prediction Probability
Sample 1	Diseased	Diseased	0.98
Sample 2	Healthy	Healthy	0.97
Sample 3	Diseased	Diseased	0.96
Sample 4	Healthy	Healthy	0.95
Sample 5	Diseased	Diseased	0.99
Sample 6	Healthy	Healthy	0.97
Sample 7	Diseased	Diseased	0.98
Sample 8	Healthy	Healthy	0.96
Sample 9	Diseased	Diseased	0.97
Sample 10	Healthy	Healthy	0.98

Table 2. Prediction Probability of Test Samples

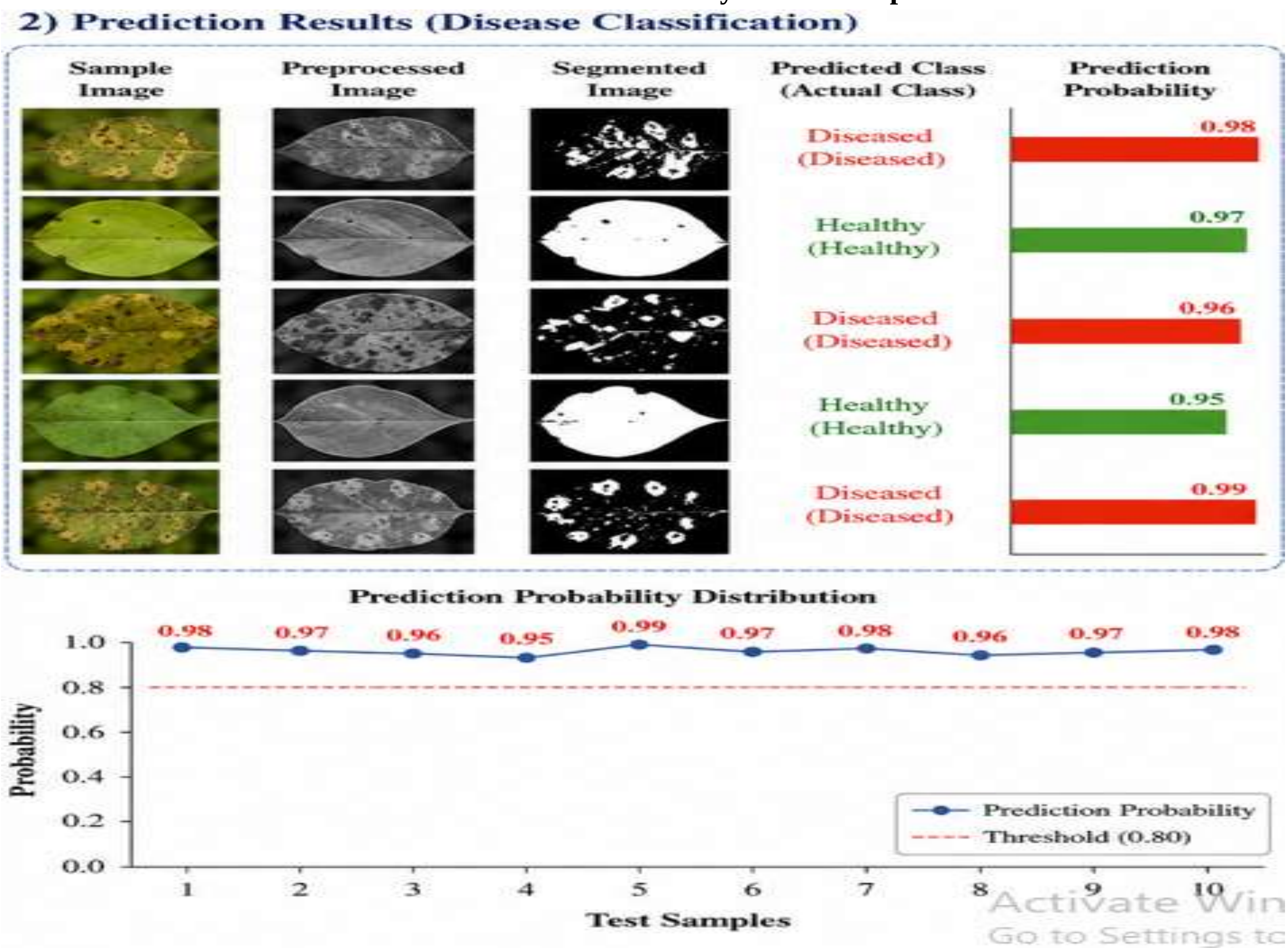

Fig. 2. Prediction results and probability distribution.

6. CONCLUSION AND FUTURE WORK

This paper presented an automated plant leaf disease detection and classification system using image processing and neural network techniques. The proposed framework successfully integrated preprocessing, GLCM-based texture feature extraction, K-means clustering segmentation, and neural network classification for accurate identification of plant leaf diseases.

The experimental analysis confirmed that the proposed neural network classifier achieved superior performance compared with conventional machine learning classifiers such as SVM, KNN, Decision Tree, and Random Forest. The proposed method obtained a maximum classification accuracy of 97.91%, along with improved sensitivity, specificity, precision, and PSNR values. These results demonstrate the effectiveness of the proposed system in accurately detecting diseased regions while minimizing classification errors.

The preprocessing and enhancement stages effectively improved image quality and reduced noise, whereas the GLCM feature extraction method successfully captured important texture characteristics such as contrast, correlation, energy, and homogeneity. In addition, K-means clustering accurately segmented the infected regions, which further improved classification performance. The neural network classifier efficiently learned complex disease patterns and produced highly reliable prediction results under different environmental and lighting conditions.

The proposed system can be effectively applied in smart agriculture and precision farming applications for early disease diagnosis, crop monitoring, and yield improvement. The automation capability of the system can reduce manual inspection efforts, save time, and assist farmers in taking timely preventive actions against plant diseases.Although the proposed system achieved high classification accuracy, further improvements can still be explored. Future work may focus on developing real-time disease detection systems using deep learning architectures such as Convolutional Neural Networks (CNNs) and transfer learning models. Integration with IoT-based agricultural monitoring systems, cloud computing platforms, and mobile applications can further enhance the scalability and practical implementation of the proposed approach in real-world farming environments. Overall, the obtained results validate that the proposed GLCM and neural network-based framework provides an efficient, reliable, and scalable solution for automated plant leaf disease detection in precision agriculture applications.

REFERENCE

[1] Siddharth Singh Chouhan, Uday Pratap Singh, Sanjeev Jain. (2018), "Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards Plant Pathology", IEEE, Vol. 06, pp. 8852–8863.

[2] Xihai Zhang, Yue Qiao, Fanfeng Meng. (2018), "Identification of Maize and Leaf Diseases Using Convolutional Neural Network", IEEE, Vol. 06, pp. 30370–30377.

[3] Sukhvir Kaur, Shreelekha Pandey. (2017), "Semi-automatic leaf disease detection and classification system for soybean culture", IET Image Processing, Vol. 12, No. 6, pp. 1038–1048.

[4] Vijai Singh, Varsha, A. K. Misra. (2015), "Detection of unhealthy region of plant leaves using Image Processing and Genetic Algorithm", IEEE, Vol. 07, No. 16.

[5] Chaitali G. Dhaware, K. H. Wanj. (2017), "A Modern Approach for Plant Leaf Disease Classification which Depends on Leaf Image Processing", IEEE, Vol. 03, No. 09.

[6] Anand R., Veni S., Aravinth J. (2016), "An Application of Image Processing Techniques for Detection of Diseases on Brinjal Leaves Using K-Means Clustering Method", IEEE.

[7] A. Menka Aewjinda, P. Kumsawat. (2008), "Grape Leaf Disease Detection From Color Imagery Using Hybrid Intelligent System", IEEE, Vol. 01.

[8] Ahmed I., Yadav P. K. (2023), "A systematic analysis of machine learning and deep learning based approaches for identifying and diagnosing plant diseases", Sustain Oper Comput., Vol. 4, pp. 96–104.

[9] Ahmad W., Shah S. M. A., Irtaza A. (2020), "Plants disease phenotyping using quinary patterns as texture descriptor", KSII Transactions on Internet and Information Systems, Vol. 14, No. 8, pp. 3312–3327.

[10] G. Kuricheti and P. Supriya. (2019), "Computer vision based turmeric leaf disease detection and classification: A step to smart agriculture".

[11] Sandhu G. K., Kaur R. (2019), "Plant disease detection techniques: A review", International Conference on Automation, Computational and Technology Management (ICACTM), pp. 34–38.

[12] Ahmad Supian M. B., Madzin H., Albahari E. (2019), "Plant disease detection and classification using image processing techniques: A review", Proceedings of 2nd International Conference on Applied Engineering (ICAE).

[13] Singh A., Kaur H. (2021), "Potato plant leaves disease detection and classification using machine learning methodologies", IOP Conference Series: Materials Science and Engineering, Vol. 1022, pp. 1–10.

[14] Masud Kabir, Fatih Unal, Tahir Cetin Akinci, Alfredo A. Martinez-Morales, and Sami Ekici. (2024), "Revealing GLCM Metric Variations across a Plant Disease Dataset: A Comprehensive Examination and Future Prospects for Enhanced Deep Learning Applications", Electronics, Vol. 13, No. 12.

[15] M. Yogeshwari and G. Thailambal. (2023), "Automatic Feature Extraction and Detection of Plant Leaf Disease Using GLCM Features and Convolutional Neural Networks", Materials Today: Proceedings, Vol. 81, pp. 530–536.

[16] Herminarto Nugroho, Wahyu Agung Pramudito, and Handoyo Suryo Laksono. (2023), "Gray Level Co-Occurrence Matrix (GLCM)-Based Feature Extraction for Rice Leaf Diseases Classification", Buletin Ilmiah Sarjana Teknik Elektro, Vol. 6, No. 4.

[17] Tanisha Khan and Apeksha Kulkarni. (2022), "Plant Disease Detection Using GLCM Feature Extractor and Voting Classification Approach", Materials Today: Proceedings.

[18] K. P. Ferentinos. (2018), "Deep Learning Models for Plant Disease Detection and Diagnosis", Computers and Electronics in Agriculture, Vol. 145, pp. 311–318.