SEMARAK ILMU PUBLISHING
202103268166(003316878-P)

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Betel Leaf Diseases Classification using Machine Learning Algorithm: A Feasible Approach

Femi David[1,*], Manapakkam Anandan Mukunthan[1]

[1] Department of Computer Science & Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India

ARTICLE INFO

Article history:
Received 8 October 2023
Received in revised form 19 November 2023
Accepted 3 January 2024
Available online 19 February 2024

Keywords:
Betel leaf; Region of interest; Gray level cooccurrence matrix; Extreme learning machine

ABSTRACT

Even though the development in science and technology in various domains, agriculture is essential for humans to survive. It is mandatory to implement the development of science in the agriculture sector. There is a huge demand for agricultural workers because of lots of risk in production behind productivity. One of the major risks is diseases caused in plants. Our approach uses region of interest algorithms for image segmentation and feature extractions are done by GLCM and finally the diseases are classified with the help of ELM algorithm. These improvements in the classification of plant leaf diseases not only increase the precision and effectiveness of disease diagnosis, but also make it easier to accurately monitor vast fields of crops quickly. Due to its ability to precisely diagnose and categorize plant leaf diseases, the extreme learning machine technique is a novel strategy that has attracted a lot of attention. Additionally, this method has benefits over conventional image processing methods, which could find it difficult to categorize various plant leaf diseases. Research on betel leaf has received a lot of attention because of its possible medical benefits. Studies on its impact on dental health have been done because betel leaf extracts have antibacterial and anti-inflammatory properties. Approximately 1047 betel leaf images are captured to test our approach by taking five classes of diseases like Anthracnose, Phytophthora Foot Rot, Fusarium wilt, Bacterial Leaf Rot, Powdery Mildew. The model reports accuracy of 97%.

1. Introduction

An emerging field called agricultural image processing uses cutting-edge technology to transform conventional farming methods. There is an urgent need to improve agricultural processes for higher yields, lower resource consumption, and sustainable farming techniques given the world's continually rising population and decreasing amount of arable land. Agriculture image processing is crucial in this situation [16]. Farmers and researchers can gather enormous volumes of information regarding crop health, soil conditions, and environmental factors by using a variety of imaging tools, such as satellite and drone imagery, as well as ground-based sensors. Decisions including precision

* *Corresponding author.*
E-mail address: dfemi20@gmail.com

https://doi.org/10.37934/araset.40.1.7486

crop management, early disease identification, and yield prediction can all be made using this data after it has been processed and analysed.

It is impossible to overestimate the significance of leaf disease categorization in agriculture [14]. It functions as a crucial instrument for preserving crop health and guaranteeing food security. If left untreated, leaf diseases can result in considerable crop losses and financial difficulties for farmers. Farmers and researchers may quickly identify the precise infections or circumstances to blame by accurately identifying these diseases, enabling focused and timely responses. This information is useful for choosing disease-resistant crop varieties, making the best use of pesticides, and carrying out precise agronomic procedures [10]. Furthermore, by limiting resource waste and the environmental effects of excessive chemical treatments, leaf disease classification supports sustainable agriculture. Ultimately, it plays a pivotal role in enhancing agricultural productivity, reducing food supply risks, and supporting the global effort to feed a growing population while preserving natural ecosystems.

Betel leaves, known scientifically as Piper betel, hold a rich tapestry of cultural, traditional, and medicinal importance across Asia and beyond. These glossy, heart-shaped leaves have been cherished for centuries as symbols of hospitality, respect, and friendship in numerous rituals and social gatherings. Beyond their cultural significance, betel leaves offer a treasure trove of medicinal properties, thanks to their bioactive compounds. They possess antiseptic and anti-inflammatory qualities, often used to heal minor wounds and skin ailments. Additionally, their use in aiding digestion and freshening breath is well-established. While betel leaves contribute to an array of traditional remedies, it's crucial to note that certain practices, such as combining them with areca nut and slaked lime, come with health risks like oral cancer. Thus, betel leaves are emblematic of a vibrant cultural heritage intertwined with age-old remedies, all while urging caution and responsibility in their utilization.

Machine learning techniques, such as extreme learning machines, have shown promise in automating the detection and classification of plant leaf diseases [20]. Feature extraction is a crucial step in machine learning models for plant leaf disease classification [8]. It involves extracting relevant information from raw leaf images to identify important patterns and characteristics associated with different disease classes. By using deep learning models and feature extraction techniques, researchers and practitioners can effectively identify and classify plant leaf diseases.

These advancements in plant leaf disease classification not only improve the accuracy and efficiency of disease diagnosis, but also aid in monitoring large fields of crops in a short time with high accuracy. Plant leaf disease classification using extreme learning machine is an innovative approach that has gained considerable attention due to its ability to accurately identify and classify plant leaf diseases. Moreover, this approach offers advantages over traditional image processing techniques, which may struggle to classify multiple disease types in plant leaves [17]. Instead, the use of artificial intelligence-based approaches like extreme learning machines allows for higher recognition accuracy through iterative learning without the need for specific features extracted by image processing techniques.

The use of extreme learning machines [9] in plant leaf disease classification represents a significant advancement in the field. This approach utilizes the power of machine learning to extract relevant features from raw leaf images, allowing for accurate identification and classification of different disease types of diseases like Anthracnose, Phytophthora Foot Rot, Fusarium wilt, Bacterial Leaf Rot, Powdery Mildew. For feature extraction, the grey-level co-occurrence matrix (GLCM) is used. Accuracy, error rate, precision, recall, F score, and AUC were used to assess the performance of the ELM classifier. Overall, this learning demonstrated that ELM was a reliable, low-cost, and precise method for detecting and classifying plant diseases.

2. Literature Survey

This section describes and reviews the most common machine learning and deep learning techniques.

Chouhan [1] introduced a method known as the Bacterial Foraging Optimizer-based Radial Basis Function Neural Network (BRBFNN) for the detection and classification of various infections affecting crop leaves' regions of interest (ROIs). Initially, the study employed a region-growing method to perform feature extraction by identifying and grouping seed points with similar characteristics. Subsequently, the RBFNN was trained using optimized weight values determined through the bacterial foraging optimizer, with the goal of improving both convergence speed and model efficiency. However, it's important to note that the study primarily focused on fungal diseases, and future research should consider incorporating datasets containing dissimilar diseases, such as bacteria and viruses, to enhance detection accuracy.

Zhang [2] introduced an innovative approach for segmenting crop disease leaves by employing a hybrid clustering method. Their method began by dividing a full-colour leaf image into multiple compact and nearly uniform super pixels through super pixel clustering. This division offered valuable clustering information, aiding in the acceleration of the Expectation-Maximization (EM) scheme's convergence. Subsequently, the EM scheme was utilized to accurately separate lesion pixels from all super pixels. However, a drawback of this approach was its tendency to inaccurately extract features.

Khan [3] introduced an innovative method for detecting and classifying apple diseases. Initially, they enhanced apple leaf spots using a hybrid approach that combined 3D box filtering, de-correlation, 3D-Gaussian filtering, and 3D-median filtering. Subsequently, they segmented the lesion spots using a robust correlation-based method, and these results were further improved by incorporating EM segmentation. Next, they extracted various features from the segmented images and combined them using a comparison-based parallel fusion technique. Additionally, they employed genetic algorithms to select relevant features, which were subsequently classified using the one-vs-all Multiclass SVM (M-SVM). However, the computational cost of this approach was relatively high due to the preprocessing step. To enhance accuracy, the study suggests the need for deep features from the segmented symptom areas.

Hou [4] introduced an automated method for leaf image segmentation utilizing the graph-cut algorithm. Initially, they extracted foreground seeds through Otsu thresholding and background seeds through colour statistical thresholding on the a* and b* components. To eliminate backgrounds with similar colours to the infected area, super pixels near the leaf's outline were iteratively removed if their entropies deviated significantly from those of the leaf's main portion. In the next step, they extracted colour characteristics from different channels of the Lab* colour space within the refined region of interest (ROI). Additionally, texture characteristics were acquired using the Local Binary Pattern (LBP) method. To identify potato disease, various classifiers like K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest (RF) were employed. However, challenges were encountered in feature extraction under conditions such as irregular illumination and overlapping leaves. Moreover, the study suggests that a larger dataset of potato disease leaf images is required to enhance accuracy.

Chouhan [5] developed a computer vision-based approach for segmenting and classifying leaf diseases in Jatropha Curcas L. and Pongamia Pinnata L. plants. The initial step involved segmenting the disease areas in leaf images using a hybrid neural network called Adaptive Linear Neuron (ADALINE), which was guided by super pixel clustering. Subsequently, various features encompassing colour, shape, and texture were extracted and employed with different machine learning algorithms to detect leaf diseases. However, a potential limitation of the approach was that network parameters, such as the connection weights between layers, were not optimized. This lack of optimization could have an impact on the segmentation performance of the system.

Mukhopadhyay [6] developed a novel framework for the automatic identification of diseases in tea leaves using image processing techniques was introduced. Initially, an image clustering method based on the Non-dominated Sorting Genetic Algorithm (NSGA-II) was applied to effectively segment the diseased regions in tea leaf images. Subsequently, Principal Component Analysis (PCA) and Multiclass Support Vector Machines (M-SVM) were employed to select the most relevant features and classify the various types of diseases present in the segmented images, respectively. However, it's important to note that the framework did not address the issue of class imbalance. To enhance segmentation efficiency, there is a need to incorporate a clustering algorithm with an improved fitness function that can better handle the class imbalance problem.

3. Plant Leaf Diseases and Symptoms

Plants can be infected by a variety of diseases that are affected by fungi, bacteria, or viruses. Typically, the infected portion of the plant's leaf will be visible and easily identifiable [21]. For example, crop colour changes, Common signs of plant diseases include the presence of dark spots on leaves and wilting of the leaves [7]. These signs and symptoms play a crucial role in identifying plant diseases. The plant diseases [11] which to addressed in our work are Anthracnose, Phytophthora Foot Rot, Fusarium wilt, Bacterial Leaf Rot, Powdery Mildew is shown in Figure 1.

2.1 Anthracnose

A variety of betel leaves (Piper betel) can be affected by the fungus anthracnose. It is brought on by several Colletotrichum fungus species. Anthracnose often appears as tiny, rounded, depressed lesions on the plant's leaves, stems, and occasionally even fruits. These lesions frequently feature reddish or dark brown borders, as well as dark, necrotic interiors. Lesions can emerge as the disease worsens and cause significant plant damage.

2.2 Phytophthora Foot Rot

Betel leaf (Piper betel) is susceptible to the dangerous fungal disease known as Phytophthora foot rot. Different Phytophthora species are responsible for this disease, which typically damages plant roots and lower stems. The lower leaves of the betel leaf plant begin to yellow and wilt as the first signs of the disease.

2.3 Fusarium Wilt

Fusarium wilt is a fungus that affects a variety of betel leaves (Piper betel) and is brought on by different species of Fusarium. This illness predominantly affects the plant's vascular system, causing wilting, yellowing, and ultimately death in affected plants.

2.4 Bacterial Leaf Rot

Betel leaves (Piper betel) are susceptible to the common illness known as bacterial leaf rot. Numerous bacterial species, such as Xanthomonas campestris and Pseudomonas spp., are to blame.

This illness often starts with water-soaked sores on the leaves and can develop into damaged plant tissue rotting and decaying.

2.5 Powdery Mildew

Plants that are susceptible to the fungal disease powdery mildew include betel leaves (Piper betel). The formation of white, powdery-looking spots on the leaves and other plant parts is its defining feature. These patches are made up of mycelium and fungus spores.

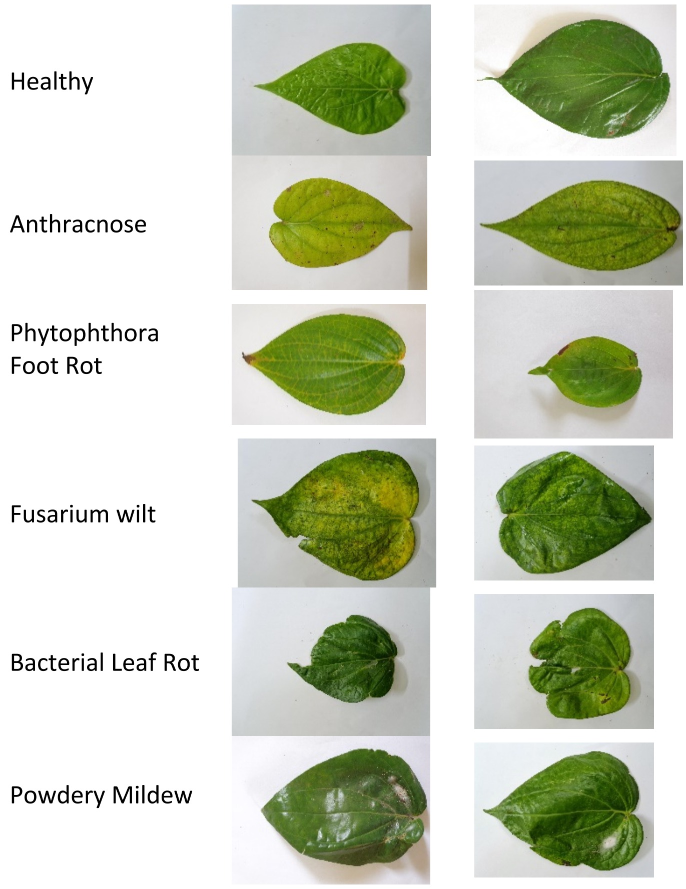

Fig. 1. Classes of Betel leaf Diseases

3. Proposed Methodology

Figure 2 shows the architecture diagram of the suggested strategy.

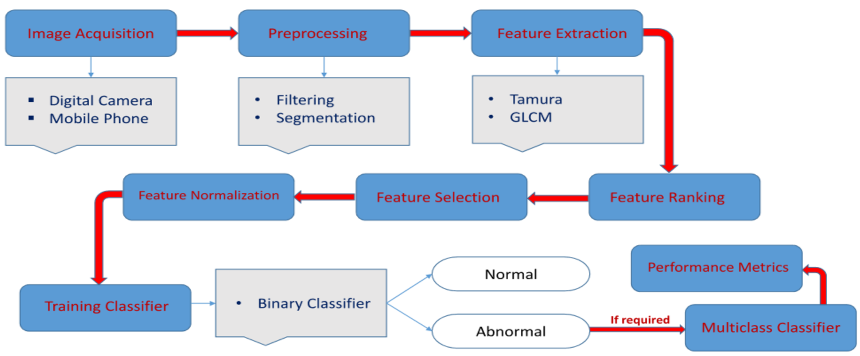

Fig. 2. System Architecture

Figure 3 depicts the proposed approach's workflow. The first part of the suggested approach starts with an image acquisition task of plant leaves (healthy and unhealthy) [18]. The second stage of our technique focuses on carrying out duties connected to input picture preprocessing and segmenting the sick area. The texture features are then calculated and extracted from the segmented area of the infected part of the plant leaf image based on specific traits of the pixels in the images or their texture [13]. These retrieved attributes will be necessary for additional research. The process of selecting features that best depict the provided image came next to eliminate feature redundancy. These traits are later used to identify the disease's name. The developed methodology's last step uses a classification technique to locates the affected plant leaf.

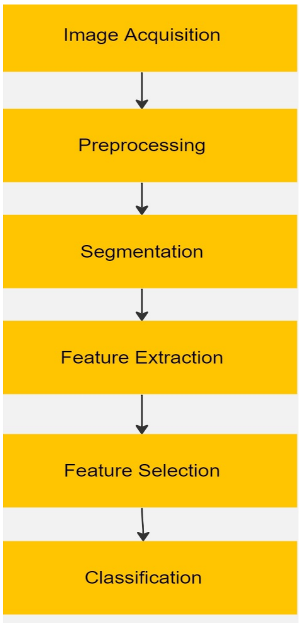

Fig. 3. Flow Chart

3.1 Image Acquisition

Image acquisition is the process of capturing visual data, converting the real world into digital representations, essential for fields like photography and medical imaging. It involves sensors or cameras capturing light information to create visual images [19]. Nearly 1050 samples of both diseased and healthy leaves were collected from various betel farms. The image was taken from normal camera and then it was pre-processed to remove noise and images were made into equal size. In specific 308 healthy leaves and all others are unhealthy leaves depending on their diseases like anthracnose (130 samples), Bacterial Leaf rot (238 samples), Fusarium wilt (130 samples), Phytophthora Foot Rot (231 images), Powdery Mildew (13 Samples).

3.2 Image Preprocessing

The bilateral filter is a popular image filtering technique used in computer vision and image processing. It is employed to enhance and denoise images while preserving important edges and fine details. Unlike traditional smoothing filters like Gaussian blur, which treat all pixels equally, the bilateral filter considers both spatial and intensity differences between pixels. It applies a weighted average to neighbouring pixels, where the weights depend on both spatial proximity and similarity in intensity values [22]. This allows the bilateral filter to smooth an image while preserving edges and fine structures, making it particularly useful for applications like image denoising and stylization.

From Figure 4 it seems that as the proportion of Gaussian noise rises, the PSNR falls, signifying a decline in image quality brought on by increased noise levels. On the other hand, as noise levels rise, SSIM and IQI tend to get better, indicating that the images are becoming closer to the original. It's crucial to remember that there is a trade-off between maintaining image information and decreasing noise. The elapsed time, which indicates the computing cost of processing or analysis for each noise level, may also be a significant aspect to consider.

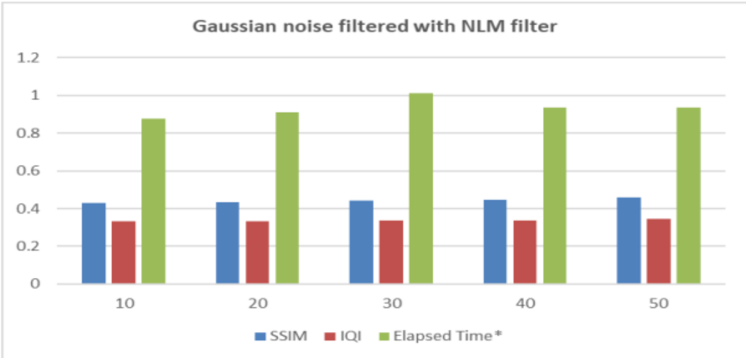

Fig. 4. Noise removal using Bilateral Filter

The Non-Local Means filter is another image denoising technique that gained popularity due to its effectiveness in preserving image details while reducing noise. Instead of considering only local neighbourhoods of pixels, as in traditional filters, the NLM filter looks at the entire image to find similar patches of pixels. It computes the weighted average of pixel values based on the similarity between these patches. Figure 5 shows the removal of gaussian noise using NLM filter.

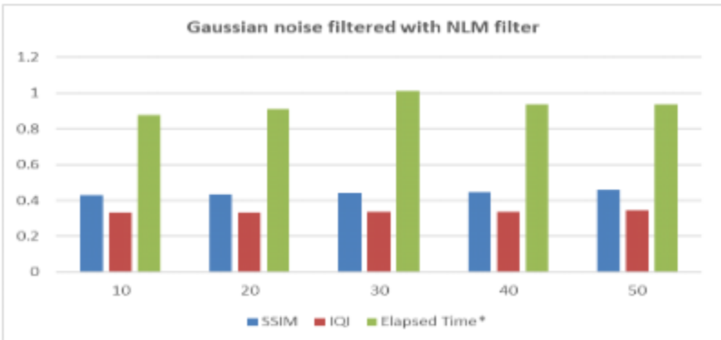

Fig. 5. Noise removal using NLM filter

From the above data appears that as the percentage of Gaussian noise increases, the PSNR decreases, which is expected because higher noise levels lead to lower image quality. Conversely, SSIM and IQI generally improve as noise levels increase, suggesting that the images become more like the original as noise levels rise. It's important to note that while higher SSIM and IQI values are generally desirable for image quality, there may be a point at which excessive noise degrades the image to the point where it is no longer visually meaningful, even if these metrics continue to improve.

3.3 Image Segmentation

Masking segmentation is a vital technique in leaf disease classification, a critical application in agriculture and plant pathology. This technique is employed to isolate the diseased regions on plant leaves from the healthy background, enabling accurate disease detection and classification. To create the mask, a thresholding technique is commonly used. This involves setting a pixel intensity threshold, above which pixels are considered part of the disease-affected area, while those below it is considered healthy. Figure 6 shows the ROI of the betel leaf after applying masking.

Fig. 6. Segmentation

3.4 Feature Extraction

In machine learning feature extraction refers to the process of transforming data into a useful and meaningful format usually in the form of a set of relevant features. These features contain information from the data while also reducing complexity and unwanted variations resulting in performance of the model.

The Gray Level Co-occurrence Matrix (GLCM) is a method for examining textures in image processing and computer vision. It measures the connections between pixel intensity values in an image by determining how often pairs of pixels with intensity differences occur at certain relative positions. GLCM is particularly useful for tasks like classifying textures segmenting images and extracting features as it allows us to understand the texture patterns within an image through properties of intensities and their arrangement, in space. In the process of extracting features, from plant leaf images we consider both colour and texture. Initially we convert the RGB images to grayscale by removing hue and saturation information. Then we create a Gray Level Co-occurrence Matrix (GLCM) to measure image texture. The GLCM helps us determine how often a pixel with a grey level value shows close to another pixel with a value. From the GLCM we extract textural properties related to shape and texture.

The extracted feature values for each class are given in Table 1. In the proposed work we have taken only four features like contrast, energy, entropy, homogeneity is taken for classification. The optimal of using contrast, energy, entropy, and homogeneity as features for betel leaf disease classification using an Extreme Learning Machine (ELM) is likely based on their ability to capture important information about the images or data relevant to distinguishing between healthy and diseased betel leaves. These are commonly used texture features in image analysis and classification tasks, particularly in the context of texture and pattern recognition.

Table 1
Extracted Feature Values

Features	Anthracnose	Bacterial leaf rot	Fusarium wilt	Phytophthora foot rot	Powdery mildew	Normal image
Autocorrelation	182.62701	163.834251	156.190909	155.212232	167.111801	153.362469
Contrast	1791.72863	4587.55172	2455.66088	3198.88044	5139.23389	5267.74309
Correlation	0.01420089	0.01142547	0.01373411	0.01000572	0.0120592	0.01338602
Cluster Prominence	-0.58355264	-0.50516824	-0.40631928	-0.58701483	-0.1036783	-0.08060455
Cluster Shade	1.77097495	1.63140866	1.51198424	1.70753487	1.29851342	1.26211602
Dissimilarity	155.09523	161.514249	173.504291	168.254055	145.21792	176.085144
Energy	2971.91568	4086.67262	2209.73116	4452.72406	5310.10788	3168.27836
Entropy	0.01185994	0.00899986	0.01480279	0.01511455	0.01376849	0.01518889
Homogeneity	-0.58249637	-0.35519367	-1.21407348	-0.66334681	0.0749668	-0.85737749
Maximum Probability	1.8548199	1.53101442	3.0956727	1.66285181	1.22731805	2.1835289
Sum Of Squares	189.072043	186.226503	160.492577	151.871935	152.178662	180.977543
Sum Average	2296.62331	3392.38006	4579.27592	4714.90967	5250.19398	2244.74539
Sum Variance	0.02216064	0.0157619	0.00871221	0.0132419	0.0111068	0.01658971
Sum Entropy	-1.1125454	-0.74680784	-0.21673796	-0.08603123	-0.05883048	-0.8153228
Difference Variance	2.48062919	1.73851123	1.45833774	1.4042512	1.27789756	1.94879349
Difference Variance	201.54691	191.950449	156.094878	160.030355	162.079751	167.631673
Difference Entropy	3186.29896	3593.77891	3220.70208	4828.55301	4410.2328	4097.38492
Information Measure of Correlation 1	0.02204613	0.01916828	0.01177417	0.01405701	0.0126947	0.01556651
Information Measure of Correlation 2	-1.11840306	-0.90354849	-0.42712114	-0.30369175	0.02447112	0.16217554
Inverse Difference	2.48904479	2.01390986	1.61894895	1.41954961	1.26682327	1.1813552
Inverse Difference Normalized	0.02017216	0.02342711	0.01458622	0.01285152	0.01012705	0.01227428
Inverse Difference Moment Normalized	-1.22361353	-1.23753709	-0.7428142	-0.49	-1.02631616	-0.61844639

3.4.1 Contrast

Calculates the density contrast throughout the entire image, including adjacent and neighbouring pixels.

Contrast=$\sum_{i,j=0}^{N-1}(i,j)^2$.GLCM(i, j) (1)

3.4.2 Energy

Represents the orderliness of the image.

Energy= $\sum_{i,j=0}^{N-1}(GLCM(i,j))^2$ (2)

3.4.3 Entropy

Measures the randomness or uncertainty in the image.

Entropy=$\sum_{i,j=0}^{N-1} GLCM(i,j)$.log(GLCM (i, j) + € (3)

(Where ε is a small constant to prevent taking the logarithm of zero)

3.4.4 Homogeneity

Evaluates how closely the GLCM diagonal is matched by the distribution of its elements.

Homogeneity= $\sum_{i,j=0}^{N-1} \frac{1}{1+|i-j|}$ (4)

3.5 Feature Selection

Linear Discriminant Analysis (LDA) is a powerful technique used in plant leaf disease classification. It helps reduce the dimensionality of leaf image data while maximizing the separation between different disease classes. By transforming feature vectors, LDA enhances the accuracy of disease detection models. Calculate the mean feature vector for each disease class by averaging the feature vectors of samples in the same class. Calculate the covariance matrix for each disease class separately and sum them to obtain the within-class scatter matrix.

$S_W = \sum_{i}^{C}(X_i - \mu_i)(X_i - \mu_i)^T$ (5)

where C is the number of classes, X_i is the feature vectors of class i, and μ_i is the mean vector of class i.

3.6 Disease Classification

ELM [12] is a feedforward neural network with a single hidden layers where the number of neurons or hidden nodes need to be selected in this layer as a hyperparameter. Initialize the weights and biases connecting the input layer to the hidden layer with random values. These weights are typically initialized only once and kept fixed during training. The activation function for the hidden layer neurons, such as the sigmoid or ReLU (Rectified Linear Unit) function. ELM doesn't employ iterative optimization algorithms like gradient descent. Instead, it directly calculates the output weights using a pseudo-inverse approach. Given the feature vectors (X) and corresponding labels (Y) from your training data, compute the output weights (beta) as follows:

$\beta = (H^T H + \lambda I)^{-1} H^T Y$ (6)

where

H is the hidden layer output matrix, with each row corresponding to the output of a hidden neuron for one input sample

λ is a regularization parameter
I is the identity matrix
Y is the matrix of labels

4. Results and Discussions

In this proposed work 70% of data is used for training and 30% are used for validation. There are totally six classes of classification i.e healthy, Anthracnose, Phytophthora Foot Rot, Fusarium wilt, Bacterial Leaf Rot, Powdery Mildew. The performance of the system is measured through accuracy, precision, recall, Fscore and error rate [15]. The ROC graph is plotted using false positive and true positive rates using the confusion matrix which is given in Table 2.

Table 2
Confusion Matrix

anthracnose	117	5	3	3	2	
bacterial_leaf_rot	4	204	2	19	9	
fusarium_wilt	1	1	125	2	1	
normal_image	1	2	1	300	2	
phytophthora_foot_rot	4	3	4	10	210	
powdery_mildew				1		12
	anthracnose	bacterial_leaf_rot	fusarium_wilt	normal image	phytophthora_foot_rot	powdery_mildew

When the class distribution is balanced, accuracy is a common criterion for assessing classification models. It gives a logical knowledge of how effectively the model functions.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

The error rate complements accuracy by providing information about the proportion of incorrect predictions. It is a more robust metric for imbalanced datasets because it explicitly accounts for misclassifications.

$$\text{Error Rate} = \frac{FP+FN}{TP+TN+FP+FN} \tag{8}$$

Precision measures the model's ability to correctly forecast outcomes. It measures the proportion of accurate positive predictions to all the model's positive predictions.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{9}$$

Recall measures the ability of the model to identify all relevant instances of the positive class. It is the ratio of true positive predictions to all actual positive instances.

$$\text{Recall}=\frac{TP}{TP+FN} \tag{10}$$

Higher values of the Fscore indicate greater model performance, which runs from 0 to 1. It is especially helpful when you want to strike a balance between recall and precision, especially when false positives and false negatives have different costs.

$$\text{Fscore}= 2.\frac{Precision.Recall}{Precision+Recall} \tag{11}$$

Training classification accuracy for the ELM classifier was 97%.

5. Conclusion and Future Works

This paper underscores the pivotal role of integrating science and technology into agriculture, an essential sector for human survival. It addresses the pressing issue of plant diseases through a sophisticated approach that combines image processing, feature extraction using the Gray-Level Co-occurrence Matrix (GLCM), and classification powered by the Extreme Learning Machine (ELM) algorithm. Testing this approach on a dataset of 1047 betel leaf images, covering five distinct disease classes, resulted in an impressive accuracy rate of 97%. Moving forward, potential future directions include extending the methodology to other crops, implementing real-time disease monitoring systems, incorporating Internet of Things (IoT) devices, augmenting the dataset, exploring advanced algorithms, and collaborating closely with agricultural experts and farmers to ensure practical applicability. This research demonstrates how technology can significantly contribute to disease management in agriculture, thereby enhancing crop productivity and sustainability.

Acknowledgement
This research was not funded by any grant.

References
[1] Chouhan, Siddharth Singh, Ajay Kaul, Uday Pratap Singh, and Sanjeev Jain. "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 Access* 6 (2018): 8852-8863. https://doi.org/10.1109/ACCESS.2018.2800685

[2] Zhang, Shanwen, Zhuhong You, and Xiaowei Wu. "Plant disease leaf image segmentation based on superpixel clustering and EM algorithm." *Neural Computing and Applications* 31 (2019): 1225-1232. https://doi.org/10.1007/s00521-017-3067-8

[3] Khan, Muhammad Attique, M. Ikram Ullah Lali, Muhammad Sharif, Kashif Javed, Khursheed Aurangzeb, Syed Irtaza Haider, Abdulaziz Saud Altamrah, and Talha Akram. "An optimized method for segmentation and classification of apple diseases based on strong correlation and genetic algorithm based feature selection." *IEEE Access* 7 (2019): 46261-46277. https://doi.org/10.1109/ACCESS.2019.2908040

[4] Hou, Chaojun, Jiajun Zhuang, Yu Tang, Yong He, Aimin Miao, Huasheng Huang, and Shaoming Luo. "Recognition of early blight and late blight diseases on potato leaves based on graph cut segmentation." *Journal of Agriculture and Food Research* 5 (2021): 100154. https://doi.org/10.1016/j.jafr.2021.100154

[5] Chouhan, Siddharth Singh, Uday Pratap Singh, Utkarsh Sharma, and Sanjeev Jain. "Leaf disease segmentation and classification of Jatropha Curcas L. and Pongamia Pinnata L. biofuel plants using computer vision based approaches." *Measurement* 171 (2021): 108796. https://doi.org/10.1016/j.measurement.2020.108796

[6] Mukhopadhyay, Somnath, Munti Paul, Ramen Pal, and Debashis De. "Tea leaf disease detection using multi-objective image segmentation." *Multimedia Tools and Applications* 80 (2021): 753-771. https://doi.org/10.1007/s11042-020-09567-1

[7] Barburiceanu, Stefania, Serban Meza, Bogdan Orza, Raul Malutan, and Romulus Terebes. "Convolutional neural networks for texture feature extraction. Applications to leaf disease classification in precision agriculture." *IEEE Access* 9 (2021): 160085-160103. https://doi.org/10.1109/ACCESS.2021.3131002

[8] Femi, D., T. D. Chowdary, and Nallanukala Anilkumar. "Early detection of plant disease using machine learning." *International Journal of Innovative Technology and Exploring Engineering (IJITEE)* (2019): 950-952.

[9] Aqel, Darah, Shadi Al-Zubi, Ala Mughaid, and Yaser Jararweh. "Extreme learning machine for plant diseases classification: a sustainable approach for smart agriculture." *Cluster Computing* (2022): 1-14.

[10] Varshney, Divyanshu, Burhanuddin Babukhanwala, Javed Khan, Deepika Saxena, and Ashutosh Kumar Singh. "Plant disease detection using machine learning techniques." In *2022 3rd International Conference for Emerging Technology (INCET)*, pp. 1-5. IEEE, 2022. https://doi.org/10.1109/INCET54531.2022.9824653

[11] Dey, Amar Kumar, Manisha Sharma, and M. R. Meshram. "Development of ANN and ANFIS classifier for betel leaf pathogen detection." *Journal of The Institution of Engineers (India): Series B* 103, no. 5 (2022): 1555-1562. https://doi.org/10.1007/s40031-022-00743-5

[12] Hasan, Md Zahid, Nahid Zeba, Md Abdul Malek, and Sanjida Sultana Reya. "A leaf disease classification model in betel vine using machine learning techniques." In *2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST)*, pp. 362-366. IEEE, 2021. https://doi.org/10.1109/ICREST51555.2021.9331142

[13] Hu, Gensheng, Cunjun Yin, Mingzhu Wan, Yan Zhang, and Yi Fang. "Recognition of diseased Pinus trees in UAV images using deep learning and AdaBoost classifier." *Biosystems Engineering* 194 (2020): 138-151. https://doi.org/10.1016/j.biosystemseng.2020.03.021

[14] Harakannanavar, Sunil S., Jayashri M. Rudagi, Veena I. Puranikmath, Ayesha Siddiqua, and R. Pramodhini. "Plant leaf disease detection using computer vision and machine learning algorithms." *Global Transitions Proceedings* 3, no. 1 (2022): 305-310. https://doi.org/10.1016/j.gltp.2022.03.016

[15] Zamani, Abu Sarwar, L. Anand, Kantilal Pitambar Rane, P. Prabhu, Ahmed Mateen Buttar, Harikumar Pallathadka, Abhishek Raghuvanshi, and Betty Nokobi Dugbakie. "Performance of machine learning and image processing in plant leaf disease detection." *Journal of Food Quality* 2022 (2022): 1-7. https://doi.org/10.1155/2022/1598796

[16] Sai Reddy, B., and S. Neeraja. "Plant leaf disease classification and damage detection system using deep learning models." *Multimedia Tools and Applications* 81, no. 17 (2022): 24021-24040. https://doi.org/10.1007/s11042-022-12147-0

[17] Kumar, Raj, Anuradha Chug, Amit Prakash Singh, and Dinesh Singh. "A Systematic analysis of machine learning and deep learning based approaches for plant leaf disease classification: a review." *Journal of Sensors* 2022 (2022). https://doi.org/10.1155/2022/3287561

[18] Vasavi, Pallepati, Arumugam Punitha, and T. Venkat Narayana Rao. "Crop leaf disease detection and classification using machine learning and deep learning algorithms by visual symptoms: A review." *International Journal of Electrical and Computer Engineering* 12, no. 2 (2022): 2079. https://doi.org/10.11591/ijece.v12i2.pp2079-2086

[19] Talasila, Srinivas, Kirti Rawal, Gaurav Sethi, and M. S. S. Sanjay. "Black gram Plant Leaf Disease (BPLD) dataset for recognition and classification of diseases using computer-vision algorithms." *Data in Brief* 45 (2022): 108725. https://doi.org/10.1016/j.dib.2022.108725

[20] Javidan, Seyed Mohamad, Ahmad Banakar, Keyvan Asefpour Vakilian, and Yiannis Ampatzidis. "Diagnosis of grape leaf diseases using automatic K-means clustering and machine learning." *Smart Agricultural Technology* 3 (2023): 100081. https://doi.org/10.1016/j.atech.2022.100081

[21] El-Gamil, Nancy S., Sherin M. Youssef, and Marwa ElShenawy. "Computer-Aided Model for Abnormality Detection in Biomedical ECG Signals."

[22] Mohamed, Khaled H., Safa M. Gasser, Mohamed S. El-Mahallawy, and Mohamed Waleed W. Fakhr. "Large scale image retrieval for remote sensing images using low level features."