An Image Processing Method for Identifying Plant Diseases Based on Changes in Leaf Morphology

Article · September 2022

DOI: 10.14704/nq.2022.20.9.NQ44325

4 authors, including:

N. Krishnamoorthy
VIT University

An Image Processing Method for Identifying Plant Diseases Based on Changes in Leaf Morphology

Dr. Madasamy Raja. G[1], R.Deenadhayalan[2], Dr.N.Krishnamoorthy[3], Dr.S.Anandamurugan[4]

[1]Associate Professor, Department of Information Technology, Paavai Engineering College, Namakkal, Tamilnadu, India.

[2]Assistant Professor, Department of Information Technology, Paavai Engineering College, Namakkal, Tamilnadu, India.

[3]Associate Professor, Department of Computer Science and Engineering, Kongu Engineering College, Perundurai, Tamilnadu, India.

[4]Associate Professor, Department of Information Technology, Kongu Engineering College, Erode, Tamilnadu, India.

Abstract

The product quality control is an incredibly important necessity to get more value-added items. Numerous studies demonstrate the decline in agriculture product quality. Agrarian goods' quality might decline due to a variety of factors. Plant diseases are the primary cause of the decline in quality of it. As a result, a significant increase in product quality is made in order to reduce plant illnesses. A significant source of income for the world's expanding population is agriculture. Farmers hold the key to our nation's development. Numerous diseases damage plants as a result of environmental variables. Therefore, in order to ensure an adequate output, farmers feel pressure to detect plant illness early. Thanks to technology, identifying plant diseases has now become quite straightforward and easy. This study focuses on employing image processing to identify paddy leaf diseases at their earliest stages by examining the morphological changes in leaves. Additionally, utilising the Internet of Things, this technology informs farmers about illnesses that affect the paddy crops (IoT).

Keywords: *Plant, Diseases, IoT, Agriculture, Environmental and Factors.*

Number: 10.14704/nq.2022.20.9.NQ44325 **Neuro Quantology 2022; 20(9):2792-2804**

1. Introduction

There are several illnesses that affect many different plants throughout the nation [1], making it impossible to identify every disease that affects every plant. It is feasible to isolate a single plant and identify every illness that affects it. Therefore, the purpose of this study is to find illnesses that only affect paddy leaves[2]. Given its influence on the international food market, paddy is one of the most important crops in the world [3]. With a rising population, there is a greater than ever need for food items like rice. The effects of the environment (such as the soil and weather) on the cultivation of paddy have a substantial influence on the global production rate of rice [4]. The good control of paddy diseases and pests, however, has the next major impact on raising productivity [5]. Pests and illnesses cost farmers an average of 37% of their annual crop each year. Thus, quick detection and treatment of paddy illness are essential parts of managing rice production in order to achieve higher productivity and higher profitability. Originally known as Oryza Sativa, rice is a fantastically cultivated food crop that is native to Asia [6]. Because rice is the most common meal in the world, many people consume it. There is less rice produced due to a number of variables. One of the primary causes of such low productivity is paddy disease. A disease is an abnormal condition that harms a plant or causes it to malfunction. Paddy crops may get a lot of paddy illnesses. The paddy illness is identifiable by its symptoms [7]. The usage of image processing technologies is especially advantageous in the agriculture sector. The farmers may use this technology to increase paddy output in addition to detecting diseases early enough to prevent disasters. Numerous factors contribute to the poor productivity and sluggish pace of rice production. One of the biggest causes of productivity loss is paddy disease. The yield of rice is significantly reduced by disease [8]. They are mostly caused by viruses, fungus, and bacteria. Most of the time, infections manifest as shifting visual symptoms on the paddy leaf body, tip, or stem, such as spots or colour changes [9], [10]. Brown Spot, Bacterial Leaf Streak, Leaf Scald, Leaf Blast, Bacterial Blight, Narrow Brown Spot, False Smut, Rice Tungro, Red Stripe, Sheath Blight, and Stem Rot are the most prevalent paddy illnesses.

The parasite Helminthosporium oryzae causes a black mark (Figure.1.). The darker area has traditionally been mostly dismissed as being among the most. widespread and very damaging rice disease. The parasite disease known as diminish hidden spot infects the leaf sheath, coleoptiles, leaves, glumes, panicle branches, and spikelet. The most obvious damage is when numerous large spots on the leaves decimate the whole leaf. Unfilled grains, speckled, or discoloured seeds are produced when a disease affects the seed. It is particularly isolated with brown, round to oval which resembles sesame seed.

Figure.1. Brown Spot

By employing crop revolution, standard planting seed, and modified treatment, the dark coloured spot may be lessened. The inadequate amount of potash in the soil is corrected by adding potash muriate. On long-grain mixtures, foliar fungicides are ineffective at controlling the dark-colored leaf spot. Before the existence of early signs of infirmities, three to four splashes with 0.2 percentage of mancozeb and alternatives of 10 to 12 days at 75%WP or 0.2% of zinels may manage the maladies.

Xanthomonas oryzae pv is the culprit behind Bacterial Blight (Figure. 2). Oryzae. It causes a blot on leaves, yellowish streaks on leaf tips, and seedling withering. Establishing in regions with damaged plant weeds and stubbles is very required. In particular, rain-fed lowland regions and flooded places are where it may be found in pairs, temperate, and tropical habitats. On seedlings, the damaged leaves curl up and become a grayish-green colour. The leaves turn from yellow to straw-colored as the illness worsens. The whole seedling dries up and dies as a result of wilting and yellowing. To reduce infection caused by this illness, field cleanliness techniques include removing weed hosts, using rice straws, volunteer seedlings, and using ratoons are crucial.

Figure.2. Bacterial Leaf Blight

The development of Pyricularia grisea accelerates the blast (Figure.3) (P.oryzae). It spreads throughout the whole surface of the rice plant, including the leaf, hub, neck, and panicle parts. Anywhere there are impact spores, the impact may occur. It occurs throughout the day in areas with little soil moisture and at a chilly temperature. The significant difference in temperature between day and night contrasts the way dew forms on leaves, and cold conditions encourage the spread of illnesses in highland rice. White changes to dim green dots with dim green borders to show the beginning of the negative effects. Older illnesses that affect leaves have curved or shaft-molded foci that range from white to black with reddish to caramel-colored or necrotic borders. Some of the specks have shapes like expensive stones. Spots may grow and obliterate the whole leaf.

Figure.3. Leaf Blast

Microdochium oryzae produces Leaf Burn (Figure.4), an infectious illness that gives leaves a burned look. On developing leaves, disease progression normally occurs late in the growing season. The humid environment encourages tight spacing and extensive nitrogen preparation. Compared to unwounded leaves, it advances more quickly in them. Single wounds may cover the whole leaf or measure 1 cm to 5 cm long and 0.5 cm to 1 cm broad. An extensive portion of the sharp leaf edge becomes damaged due to the continued development and accumulation of wounds. This illness manifests itself in arid, highland, and irrigated areas.

Figure.4. Leaf Scald

The Narrow Brown Spot is caused by the fungus Sphaerulina oryzina (Figure.5.). It develops in the late season and essentially has no negative effects on the yield. Influenced sheath injuries may grow to a few inches in length and are unpredictable in their formation. The parasite may infect tissue right above the hub or the hub area just under the panicle, resulting in a deeper, more drab stain. This disease, notably narrow dark coloured leaf spot, which taints leaves, sheaths, and panicles, may drown some spikelets and individual flowers. The spots are often on leafcutting edges, but they may also appear on leaf sheaths and glumes of rice bodies. They are brief, thin, and round to straight darker lesions. On variants that lack strength, the dull necrotic occurs. They are lighter and bigger in size.

Figure.5. Narrow Brown Spot

Image processing is now innovating swiftly thanks to its applicability in several domains [11]. Remote sensing, medical image processing, biometrics, industries, computer vision, data transfer, forecasting and fingerprint detection, face detection, argument reality, optical character recognition, etc. are some essential image processing tools in the scientific sector [12],[13]. Traditionally, analogue pictures were employed in study fields, but currently, digital technologies are being used instead. Visual processing refers to the use of a computer to process a two-dimensional image signal and apply common signal processing techniques to it. Picture processing may produce an image or an asset with features or characteristics connected to the image. The three distinct stages of image processing are picture capture, image processing, and output display. The first stage in every vision system is picture capture. It may be gathered via a scanner, a mobile device, a camera, or a satellite. Images acquired from various image capture devices are processed using a variety of image processing algorithms to extract the necessary high-quality information from the picture. As a result, the term "image processing" is defined more specifically as a means of connecting the human visual system to digital imaging devices [14]. It quickly transforms a picture into a more accurate representation of an item. In India, 60–70% of the population is dependent on agriculture. People are affected by plant diseases either directly or indirectly [15]. Plant diseases are putting a strain on the world's food supply and costing farmers a lot of money. It is very difficult to identify infections in agriculture at an early stage. In the current system, farmers consult a large group of specialists to identify plant illnesses [16]. It costs a lot to hire professionals, and it takes a long time. Disease signs may be seen in plant components such leaves, stems, roots, and fruits. A leaf exhibits a broad range of symptoms, including toned patches and streaks, when it becomes infected by any foliar disease. As a plant disease progresses, its consequences exhibit a constant variation in shade, form, and size [17]. Consequently, it is crucial to identify plant diseases in their early stages. The condition and development of the plant are shown by the leaves. By adding spots on the leaf, the appearance of the leaf change may induce changes in leaf colour. The morphology of the majority of plant diseases is used to identify them [18]. For disease identification by watching the appearance changes in plant leaves, an image processing-based approach is more comfortable and less expensive. This kind of image processing could be able to capture the finer details of visual reactions [19]. This method aids in the diagnosis of illnesses based on morphological variations that are unique to paddy leaves. Paddy is grown three times every year. Since snail, worm, and other species prey on them, a substantial portion of paddy ranchers have numerous difficulties while harvesting their crop. The other areas are likewise polluted when the paddy is assaulted or contaminated. As a result, it lowers the pay of paddy ranchers and brings about bad luck for the rancher. To determine the kind of sickness, a Paddy rancher must expend a lot of effort. It also requires an investment as the paddy ranchers physically check the malady since the paddy field is in the wide territory.

2. Literature Survey

In the last three decades, a variety of methods for detecting plant diseases have been suggested. Preprocessing, segmentation, feature extraction, and classification are the crucial four processes of an autonomous image processing system. This part displays the research's conclusions and its critical analysis in a more advantageous manner.

The preprocessing stage is crucial for improving an input image's contrast. The input pictures with greater noise are acquired using cameras and sensors. Noises often compromise the segmentation accuracy in addition to the unfavourable background. The preprocessing increases the visibility of the sick areas of an image in comparison to the acquired picture. An automated approach incorporating lesion-based identification and classification was suggested in [20]. Utilizing HSI colour space conversion, intensity correction, and histogram analysis, the collected pictures are altered. The segmented picture is then used to calculate the size, shape, and colour attributes. They came to the conclusion that their approach is acceptable for illness identification in leaves after performing classification using an artificial neural network (ANN) classifier.

A technique for disease spot identification using colour transform was developed in [21]. Here, a median filter and otsu thresholding are used to enrich and segment the data. The illness spot is then calculated based on the findings to determine the crop loss. Calculating the disease spot area is important to estimate yield loss.

For the purpose of diagnosing paddy leaf diseases by histogram and preventing their substantial effects, [22] suggested an image processing approach. This technique involves processing the paddy leaf that was caught initially for improvement. The techniques of image processing are then used to fully identify the diseases. Additionally, provide advice on how to lower these illnesses with the help of an agronomic. The colour transformation strategy for processing the input RGB picture was suggested in [23]. The texture statistics features were used to calculate the features in this case. With this procedure, the categorization of illnesses is done with a 94% accuracy rate.

[24] presented a colour transformation-based approach that converts RGB to HSV to identify plant illnesses. It is a colour descriptor, and the green pixel removal process uses a certain

threshold. The texture characteristics are then extracted from the picture segmentation using SGDM matrices. By comparing the collected texture information with the texture characteristics of a healthy leaf, the illnesses in the leaves are detected.

Picture segmentation is the division of an image into several components. Segmentation is used to find any disease-related regions in the picture. By merging comparable pixels during segmentation, the area of interest is created. Numerous diseases in agriculture harm the leaves and fruits. The literature review includes a variety of segmentation techniques to address these problems, making it simple to spot the sick area of the picture.

The fundamental concept of leaf disease diagnosis utilising leaf pictures was put out in [25]. When the illness manifests itself on the leaf, the suggested approach may detect it early. Segmentation is done using Otsu thresholding. In the next step, a support vector machine classifier is used to categorise the retrieved colour and texture data. As a result, it helped farmers by somewhat protecting them from loss. In. [26] provided a technique to estimate the amount of disease severity caused by fungus in sugar cane leaves. It carries out the two segmentation procedure. The leaves were first separated from the background using a straightforward thresholding technique. The second segmentation employed RGB to HSI colour conversion and a binarization to identify the area of interest. The infection ratio is calculated using the binary picture after binarization using the Triangle thresholding approach. An improved K-means clustering technique was developed in [27] to investigate the prediction of leaf disease at an inopportune period. To distinguish the sick zone, the scientists employed a color-based segmentation technique. On test picture samples, experimental analyses are performed based on the temporal complexity and the sick area. The authors offered ways to spot plant illnesses as well as treatments to protect plants from them. The technique for identifying illnesses in plant leaves was proposed in [28]. The results showed that their approach was more effective in identifying sick leaves. The contaminated area of the supplied leaf picture was located using automatic methods. The grouping of photos was then obtained using the K-means technique. This method helped farmers avoid suffering significant losses.

The specifics of several picture segmentation approaches were covered in [29] along with a comparison of the techniques. The in-depth segmentation methods used in this study are appropriate for item recognition and identification in medical imaging applications. In the medical profession, these methods are used to identify cancer, and in satellite photos, they are used to identify roads and bridges. Authors came to the conclusion from this survey that no one approach is sufficient for every picture and that no method is appropriate for a particular image. Depending on the application the image segmentation was selected. The choice of segmentation technique is a herculean undertaking.

[30] outlined a method to determine the effects of the K-means clustering algorithm using a variety of computation parameters, including centroid, distance, split method, epoch, attribute, and iteration. It also considered the identification of parameter combinations with the potential to produce accurate clustering. By contrasting human and machine vision approaches, [14] built the system to determine the severity degree of rust disease in coffee leaves. Two different imaging technologies are used in the system testing. The segmentation for both systems is carried out using a straightforward thresholding method. Finally, the authors claim that digital image processing is a more accurate way than visual methods for obtaining findings. They also observed that colour imaging has a significant impact in differentiating between rusty and non-rusted vegetation.

The diagnosis of illnesses based on size, texture, form, and colour is greatly aided by feature extraction approaches. Through feature extraction, the item is classified into the appropriate class. The many feature extraction approaches are used to extract the characteristics in agriculture. A method for the early and precise identification of illnesses in pomegranate leaves was published in [15]. They applied K-means clustering for segmentation after preprocessing the image with median filtering. The writers took the colour and textural qualities from the outcomes.

[16] suggested a Local Binary Pattern-based computerised approach for the categorization of fungal infections affecting vegetable crops (LBP). To distinguish the sick areas from the background and foreground noise in this study, a segmentation approach based on clustering was applied. Artificial Neural Network (ANN) and Neuro KNN classifier, which employs features derived using the combined LBP and Principal Component Analysis, are used to classify the disorders (PCA). The findings demonstrate that the neural k-NN provided superior classification accuracy than the ANN. A comparison of the powdery mildew disease on squash leaves with leaves from other plants is shown in [17]. Sunflower and oat leaf comparisons are employed in this investigation. In order to contrast this squash leaf illness with sunflower and oat leave diseases, several segmentation and classification techniques are applied. Utilizing the leaf's average pixel value, the disease severity is calculated. Additionally, the instructional and actual outcomes are contrasted. Additionally, they contrasted the outcomes depending on the kind of capturing instrument.

The feature extractions are used by classifier-based approaches to identify images. This section discusses a number of classifier techniques, including SVM, ANN, PNN, BP, RBF, KNN, and NB. A machine vision-based approach to identify plant diseases using their visible symptoms in coloured photographs was presented in [5]. Images of the cotton crop that were obtained are improved and segmented. The Support Vector Machine then classifies the illnesses based on the attributes that were extracted. Other categorization techniques are used to cross-validate the given findings. The authors claim that their approach successfully distinguishes between damaged and healthy portions for a variety of circumstances and plant species.

The six kinds of mineral deficits in rice harvests were suggested in [6]. The suggested approach was used to extract the texture and colour information. The appropriate MLP neural network was then given each kind of feature. The final categorization was then generated by combining the findings from the two networks. [8] discussed the use of several computer vision algorithms to identify plant diseases. In this study, the colour cooccurrence texture characteristics are analysed using SGDM. With the improved colour feature extraction, larger databases provide better results. The survey of plant disease detection utilising various image processing approaches was published in [9]. Different classifiers, including K-Nearest Neighbour (KNN), Back Propagation Neural Network (BPNN), Spatial Gray-level Dependence Matrices (SGDM), and Support Vector Machine are used to evaluate the disease kind in plant leaves (SVM). The different illness categorization techniques were reviewed in [10]. The results shown that the K-nearest neighbour classifier is seen to be appropriate for prediction among all the classifiers. In [11] surveyed different diseases classification methods for disease detection from the segmented images.

3. Proposed Method

The suggested technique for detecting paddy illness involves a number of image processing phases, including picture capture, image enhancement, image segmentation, image feature extraction, and image classification [3]. The acquired RGB image is first resized and given a median filter and contrast enhancement boost. The improved picture is segmented using the Otsu thresholding technique and K-Means clustering. The features are then retrieved using the DWT-GLCM feature extraction technique, SIFT, and GLCM. Finally, to characterise the paddy disorders, classifiers like Naive Bayesian, K-Nearest Neighborhood (KNN), Artificial Neural network (ANN), and Multiclass SVM are utilised. MATLAB is used to accomplish the suggested job. Figure.6. demonstrates a block architecture for the identification and categorization of paddy diseases using image processing.

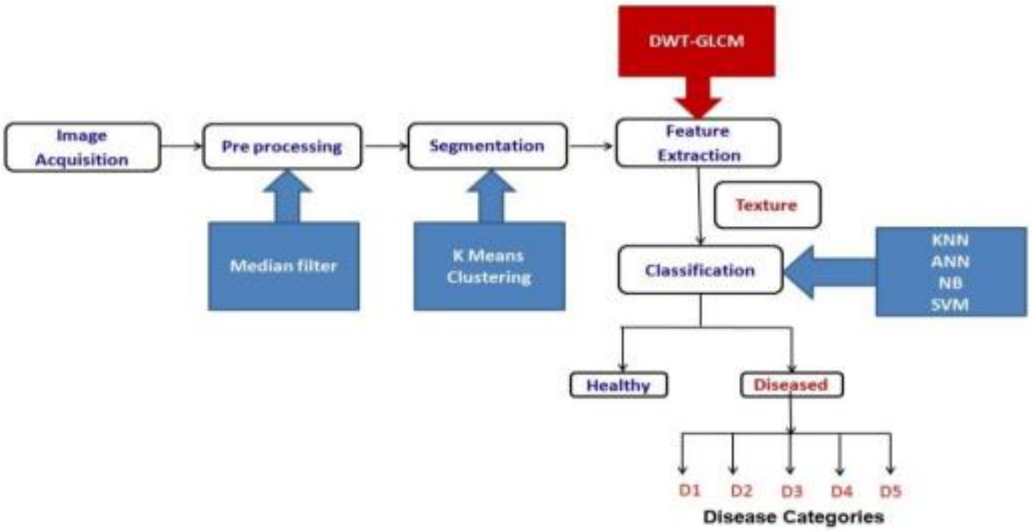


Figure.6. Block Diagram of Paddy Disease Detection

Using a digital camera, the input photos of the leaf sample are collected. The subsequent phases of image processing are then applied to these pictures [6]. Images of both healthy and sick leaves are included in the database. Images that are being collected may have noise in them. To lessen this noise, several noise reduction methods are used. Denoising is done in this work using the median filter and contrast enhancement methods. The acquired picture is smoothed using a median filter. Three elements make up the colour space. Utilizing digital segmentation to assess these components is challenging. The black and white pixels are separated using the contrast enhancement approach. Contrast enhancement makes advantage of the capacity of human vision. It is the most important step in the picture processing process. The main idea is to widen the image's spectrum of grey levels. The contrast of the picture is increased using linear and nonlinear approaches.

A nonlinear filter is the median filter. It helps to eliminate sounds during the pre-processing process. Further image processing steps provide better results as a consequence of the noise reduction. The margins of the pictures are well preserved while the noise is being extracted. The median filter's primary job is to go pixel by pixel through the picture. Each pixel's noisy value is swapped out for the median value of its neighbours. The window [7] refers to the layout of the surrounding pixels. The grey levels of the window's pixels are used to classify them. The stored noisy value is then substituted for the median value [8]. The window may have an apparent linear, cross, round, square, etc. form.

Using similar features, segmentation separates the picture into identically relevant parts [9]. There are several methods for segmenting images. Otsu thresholding segmentation and K-Means clustering are nonetheless used in this study.

Using this technique, the picture is divided into the same varieties of regions. Similar pixels are recognised and gathered into similar types of areas. Region expanding, region splitting, and region merging are the three region-based segmentation techniques. A technique for grouping pixels into bigger areas is called region growth. Calculations for region splitting begin with the overall picture and divide it up until each subarea is uniform. A technique for integrating comparable picture regions is region merging.

The segmentation approach used is clustering. It is a method where a picture is converted to a histogram and clustering is then carried out on it [3]. The K-Means clustering method is one of the basic clustering computing techniques. It is the division of the photos into groups of pixels that have a similar look [4]. The input photos are divided into a number of groups or clusters with a comparable set of pixels using the K-Means Clustering method [5]. There are two steps to this approach. calculate the k centres first. The locations of these centres are widely apart. Every point in the cluster and its neighbours to the nearest centre are taken into account in the second phase. Euclidian distance is used to get the nearest centroid [6]. After then, the recomputation of every cluster's new centroid is carried out. The supplied data is converted into a feature set via image feature extraction. Investigating a picture for a particular application is part of the image feature extraction process [7]. Color, shape, and texture information is often included in features. There are several methods for extracting features. In this study, feature extraction techniques including SIFT, GLCM, and hybrid DWT-GLCM are applied. Figure.7. provides information on the various kinds of retrieved characteristics and Figure 8. outlines the many feature extraction algorithms that are employed.

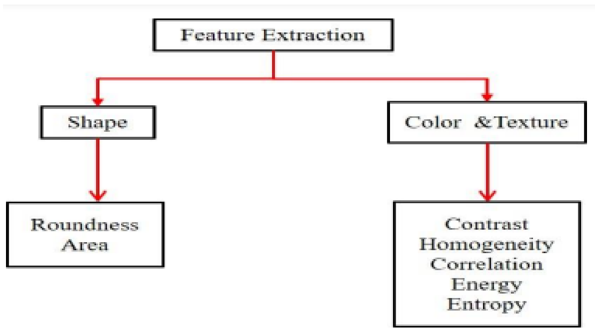


Figure.7. Feature extraction of paddy diseases detection

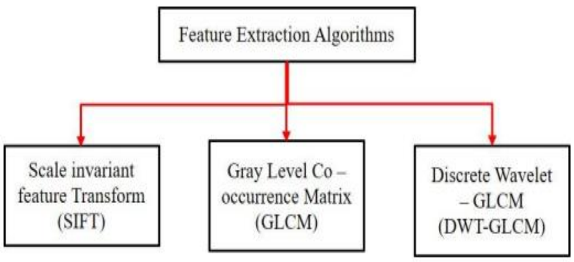


Figure.8. Feature extraction algorithms

With the help of the retrieved features, SIFT is used to match comparable photos from various perspectives. The tiered filtering approach is used to find these traits. Any modifications to the size, rotation, transformation, and lighting have no effect on the retrieved features [18]. To identify the precise picture, the extracted SIFT characteristics from the input photos are saved in a database and compared with the new image. To get the individual colour bands, the input query picture or the captured image is submitted for feature extraction. In order to match photos from a database, this technique leverages key points.

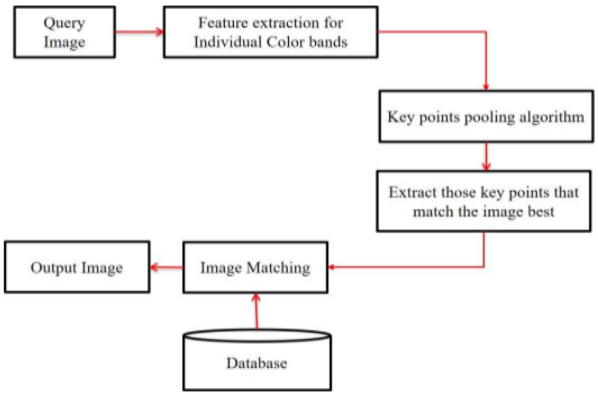


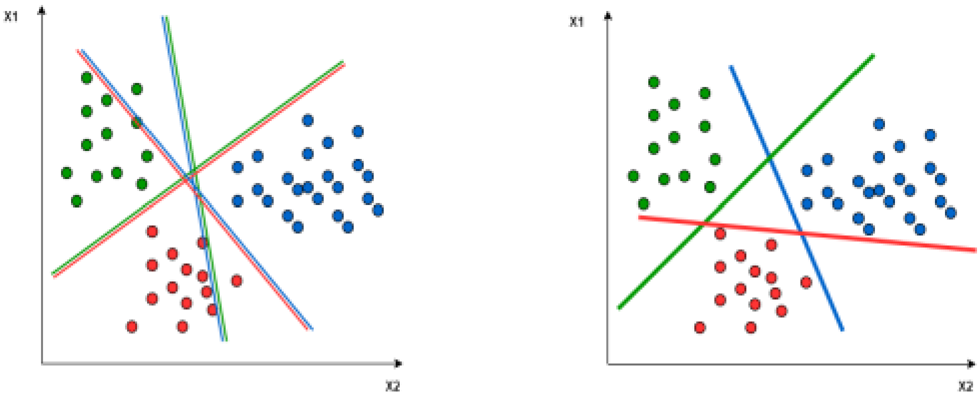
Figure.9. Flow model of SIFT algorithm

By specifying the gradient information, such as picture size, position, and orientation to each keypoint, keypoint descriptors are formed. At each keypoint in this region, measurements of the local image gradients are made at the set scale. Through suitable transform representation, the considerable local shape distortion levels and lighting variations are made possible. A local region's SIFT descriptor is created by weighting the gradient norms as they accumulate in a 3D histogram. to give gradients that are far from the keypoints' centres less weight. Additionally, Gaussian keypoints are employed.

The gray-level co-occurrence matrix (GLCM), often referred to as the gray-level spatial dependency matrix, is a statistical technique for analysing texture that takes into account the spatial connection of pixels. It calculates the combined likelihood that the specified pixel pairings will occur. The texture properties that maintain the spatial connectivity of pixels are investigated using the Gray Level Co-occurrence Matrix (GLCM) [80]. Texture is the irregularity that is dispersed across the picture. These textural orientations are unique for each class and increase classification accuracy [1]. Mean, Standard Deviation, Skewness, and Kurtosis are the retrieved first-order features, whereas Variance, RMS, Correlation, Contrast, Energy, Entropy, and Homogeneity are the extracted second-order features [8]. The selected GLCM features are calculated using only the GLCM Values [23].

4. Classification

The classifiers receive the retrieved characteristics and categorise the pictures using those features [7]. In this study, the classification of paddy leaf diseases is examined using classifiers including Naive Bayesian, KNN, ANN, and SVM. Naive Bayesian Classifier Based on the specifics of the prior event, the Bayesian classifier is used to generate inferential statistics. This classifier predicts the other feature value if the class is known [8]. If the class is unknown, the Bayes rule is used to forecast the class. The assumption-based classifier is this one. Each layer in an artificial neural network is separated by space. Neurons are present in each stratum [9]. Using the weighted connection of neurons from the preceding and next layers, these neurons are connected to all other layers. The network's structure and the quantity of input determine accuracy. A non-parametric technique is ANN. In this technique, the input categorization happens quickly, but the training procedure takes a while. It's difficult to choose the right architectural [19]. A straightforward classifier is KNN, or K-Nearest Neighbor. It carries out categorization based on the closest neighbourhood point and the provided point with the least distance or similarity function [11]. When a huge amount of training data is utilised, it is more effective. It is the most appropriate solution for basic recognising issues. Large training dataset, however, makes it sluggish throughout the training process [12]. In a high dimensional space with excellent separation, the SVM classifier creates a collection of hyperplanes for classification. In order to effectively handle additional input data, this classifier uses a non-parametric binary classifier technique. Accuracy is determined by hyperplane selection [23]. Naturally, multiclass classification is not supported by the SVM classifier. As a result of classifying the data points into two groups, it only enables two-class classification. After breaking the multiclass classification issue down into a large number of binary classifications, the same two class concept is employed in multiclass classification [24]. This classifier works on two methods. They are one-to-Rest and One-to-One method.



One-to-One approach   One-to-Rest approach

Figure.10. Multiclass SVM Methodologies

Because of its supervised learning method, the SVM is mostly favoured for recognition and classification [17]. The parameter selection and kernel design are used to enhance the SVM classifier's performance. With the use of a separate multiclass data set, SVM is utilised to resolve real-world issues. SVM enhances the geometric margin while lowering the empirical classification error.

5. Results and Discussion

MATLAB R2021b is used to implement the complete procedure. I used five distinct illness categories and 100 photos in total to process. A select handful of the picture samples are used as examples. In table.1, which displays the output from the preprocessing processes of RGB to Gray Conversion, Contrast Enhancement, and Median Filter, a sample of the results of the preprocessed photos are tabulated. The desk.2. demonstrates the segmentation outcomes for the relevant data from the K means Clustering and Otsu thresholding algorithms.

Table.1. Pre-processing Results for the sample images

Table.2. Segmentation Results for the sample images

This table.3. displays the characteristics for the example photos that were taken from the GLCM Method. The classifier will then use these extracted characteristics as input to classify the images.

Table.3 GLCM Extracted Feature vectors for the sample images

Paddy Disease	Contrast	Correlation	Energy	Homogeneity	Entropy
Bacterial Blight	1.295	0.883	0.536	0.922	1.63
Leaf Blast	1.342	0.852	0.688	0.941	1.62
Leaf Streak	0.798	0.849	0.767	0.965	1.97
Brown Spot	1.33	0.827	0.57	0.955	1.29
Tungro	0.81	0.882	0.751	0.978	1.72

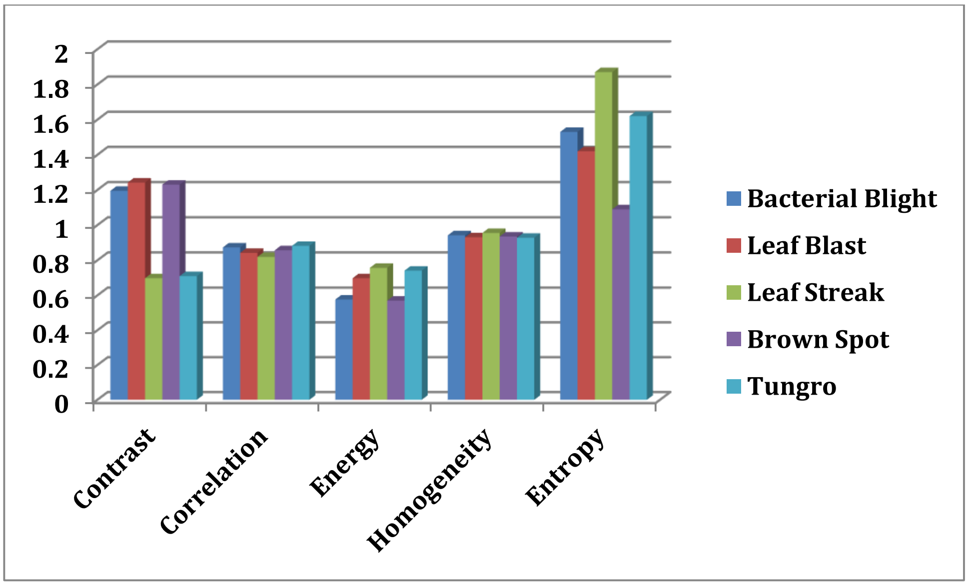


Figure.11. GLCM Extracted Feature vectors for the sample images

6. Conclusion

A prototype system for the early identification of illnesses based on the morphological changes in plant leaves may be created using the suggested methodology. This study aims to identify the five paddy diseases that primarily cause major production loss, including bacterial blight, blast, brown spot, leaf strake, and rice tungro. The results of this study may help individuals detect illnesses that affect paddy at an early stage, preventing significant loss and enhancing farmers' economies. Five paddy diseases were the main emphasis of the suggested strategy. There may be added many more illnesses in the future. Therefore, not only can this method be used to anticipate paddy illnesses but also other plant diseases. The disease's symptoms must be examined while other plant illnesses are being considered. Revolutionary innovations are destroying traditional agriculture practises and opening up new, difficult options. Cloud services help precision agriculture. Access to customer databases, supplier networks, and billing systems increase its effectiveness.

References

1. Phelps R.H and Shand C.R. Brown leaf spot disease and fertilizer interaction in irrigated rice growing on different soil types. In: Nitrogen Economy in Tropical Soils. 1995:117–121.
2. Bhadane G, Sharma S and Nerkar VB. Early Pest Identification in Agricultural Crops using. Image Processing Techniques, Int. J. Electr. Electron. Comput. Eng (2013); 2: 77–82.
3. Zhihao N and Zhang M. Detection of rice sheath blight for in-season disease management using multispectral remote sensing. International Journal of Applied

Earth Observation and Geo information 2005; 7(2): 115-128.
4. Ahmad IS, Reid JF, Paulsen MR and Siclair JB. Color classifier for symptomatic soybean seeds using image processing. Plant Dis 1999; 83(4): 320-327.
5. Shergill D, Rana A and Singh H. Extraction of Rice Disease using Image Processing. International Journal of Engineering Sciences and Research Technology(IGEST) 2015; 4(6):135-143.
6. Jayamala K and Raj Kumar P. Advances in Image Processing for detection of plant diseases. JABAR 2011; 2(2): 135-141.
7. Martin DP and Rybicki EP.Microcomputer-Based Quantification of Maize Streak Virus Symptoms in Zea mays. Phytopathology. 1998; 88(5):422-427
8. Sankarana S, Mishra A, Ehsani R, et al. A review of advanced techniques for detecting plant diseases. Comput. Electron Agric 2010; 72: 1-13.
9. Jonna SK, Badarinath VS and Saibaba J. Digital image processing of remote sensing data for water quality studies. Journal of the Indian Society of Remote Sensing 1989; 17(2):59-64.
10. Sabah B and Navdeep S. Remote area plant disease detection using image processing. IOSR J Electron Commun Eng 2012; 2(6):31–34.
11. Al-Bashish D, Braik M and Bani-Ahmad S. A framework for detection and classification of plant leaf and stem diseases. International conference on signal and image processing 2010: 113-118.
12. Artizzu B,Xavier P, et al. Analysis of natural images processing for the extraction of agricultural elements. Image and Vision computing 2010; 28(1): 138-149.
13. Barbedo, J.G.A. Digital image processing techniques for detecting, quantifying and classifying plant diseases. Springer Plus 2 2013; 1-13.
14. Goodwin P H and Hsiang T. Quantification of fungal infection of leaves with digital images and Scion Image software. Methods Mol Biol 2010;638:125-135.
15. Phadikar S, Sil J, and Das AK. Classification of Rice Leaf Diseases based on Morphological Changes. International Journal of Information and Electronics Engineering 2012; 2(3): 460-463.
16. Vibhute A and Bodhe SK. Applications of image processing in agriculture. A survey. International Journal of Computer Applications 2012 20. Pranjali BP and Anjali AY. SVM Classifier Based Grape Leaf Disease Detection. IEEE, 2016; 9-11.
17. Neha M, Priyanka BR, Sowmya GH and Pooja R. Paddy leaf disease detection using image processing and machine learning. International journal of innovative Research in electrical and electronics, instrumentation control engineering 2019; 7(2): 97-99.
18. Patil AB and Khirade SD. Plant Disease Detection using Image Processing Techniques. International Journal of Innovative Research in Science Engineering and Technology (IJIRSET) 2015; 4(6):295-301.
19. Sannakki SS, Rajpurohit VS, Nargund VB and Kumar A. Leaf disease grading by machine vision and fuzzy logic. Int J 2011; 2(5): 1709-1716.
20. Saradhambal G, Dhivya R, Latha S, and Rajesh R. Plant Disease Detection and its Solution using Image Classification. International Journal of Pure and Applied Mathematics 2018; 119: 879-884.
21. Chaudhari S, Mayuri SP, Haral S and Sogeshwari M. A Survey on Detection of unhealthy Region of Plant Leaves by using Image Processing. International Research Journal of Engineering and Technology (IRJET) 2016; 3(9): 1318-1320.
22. Sowmya GM, Chandan V and Sampath Kini. Disease Detection in Pomegranate Leaf, using Image Processing Technique. International Journal of Science, Engineering and Technology Research (IJSETR) 2017; 6(3): 396-400.
23. Pujari JD, Yakkundimath R and Byadgi AS. Neuro-kNN classification system for detecting fungal disease on vegetable crops using local binary patterns. Agric. Eng. Int. CIGR J 2014; 16(4):299-308.
24. Moya EA, Barrales LR and Apablaza GE. Assessment of the disease severity of squash powdery mildew through visual analysis, digital image analysis and validation of these methodologies. Crop Protect 2005; 24(9): 785-789.
25. Suresha M, Shreekanth K. N and Harisha Naik T. Identification of healthy and

diseased paddy leaves using classifier. International Journal of Advanced Research in Computer Science 2017; 8(9):705-709.

26. Revathi P and Hemalatha M. Classification of Cotton Leaf Spot Diseases using Image Processing Edge Detection Techniques. IEEE, 2012: 169-173.
27. Kiran RG and Gawndw U. An overview of the research on plant leaves disease detection using image processing techniques. International journal of pure and applied mathematics 2014; 16: 10-16.
28. Ghaiwat Savita N and Arora P. Detection and classification of plant leaf diseases using image processing techniques, a review. Int J Recent Adv Eng Technology 2014; 2(3):2347–812.
29. Halder M, Sarkar A, Bahar A, et al., Plant Disease Detection By Image Processing: Journal of Food Science and Technology 2019; 3(6); 534-538.
30. Sujeet Varshney and Tarun Dalal. Plant Disease Prediction using Image Processing Techniques - A Review. International Journal of Computer Science And Mobile Computing 2016; 5(5): 394-398.