iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: V Month of publication: May 2025

DOI: https://doi.org/10.22214/ijraset.2025.70857

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

A Comprehensive Survey on Rice Plant Diseases Detection and Classification

Moumita Chowdhury
Department Of Computer Science and Engineering, Institute Of Engineering and Management(IEM), Kolkata

Abstract: Detecting plant diseases through image analysis has emerged as a significant research domain in agriculture and computer science. This paper provides a comprehensive analysis of various image processing tasks and machine learning methods employed for identifying diseases in rice plants using image-based approaches. In addition to reviewing multiple methodologies, this study also highlights essential image processing concepts, machine learning concepts relevant to rice plant disease identification. A detailed analysis of 20 research papers is conducted, encompassing studies on rice plant diseases as well as diseases affecting other crops and fruits. The survey categorizes these studies based on key factors such as dataset size, number of disease classes, preprocessing methods, segmentation techniques, classification models, and their corresponding accuracy. The insights gained from this survey serve as a foundation for designing and developing an improved approach for rice plant disease identification and classification.
Keywords: image processing; disease classification; disease detection; machine learning; classification; clustering.

I. INTRODUCTION

Agriculture continues to be the backbone of India's economy, providing employment and sustenance to a significant portion of the population. Nearly 70% of India's population relies on agriculture either directly or indirectly[1], with over 58% of rural households depending on it as their primary livelihood source[2]. Among staple crops, rice holds immense importance due to its widespread consumption. However, various plant diseases are a major threat to rice production, causing yield losses of around 10% to 15% annually across Asia[3].

Diseases in rice crops are primarily caused by pathogens such as fungi and bacteria. Common diseases affecting rice plants include Leaf Blast, Tungro, Bacterial Blight, Brown Spot, and Leaf Scald[4]. If these illnesses are not identified and treated quickly, they can have a major effect on crop quality and quantity. Regretfully, many farmers lack the equipment or knowledge necessary to identify these illnesses early. Unfortunately, many farmers lack the tools or expertise to detect these diseases early. In some cases, they may misidentify symptoms or rely heavily on outdated manuals for diagnosis[5].

Every plant disease has different stages and needs a different approach to treatment. For example, using targeted fungicides to disrupt the pathogen's life cycle is are common way to treat fungal infections [4]. Without professional assistance, traditional manual monitoring techniques are laborious, erratic, and frequently ineffectual. Furthermore, incorrect pesticide use without a good diagnosis can exacerbate the issue or damage the ecosystem.

The incorporation of automated technologies for disease detection has drawn a lot of attention as digital agriculture has grown. More effective disease detection is feasible by placing camera sensors throughout the field to take pictures of possibly infected leaves, which are then automatically analysed. Real-time infection notifications from these systems allow farmers to take prompt, well-informed responses.

This survey study demonstrates the use of machine learning concepts as well as image processing concepts to automate the diagnosis of rice plant diseases. Taking pictures of leaves, preprocessing them, separating the diseased area, extracting pertinent features, and utilising machine learning techniques to diagnose the disease are all important steps in the general pipeline for automated detection. Fig. 1 depicts this procedure.

The effectiveness of such a system depends largely on the precision of both image processing steps and the classification algorithms used. Performance can be measured by evaluating the accuracy of classification models. However, existing systems often face challenges due to limited datasets, improper feature selection, or poor classifier choices. Factors like shadows in images, similar visual symptoms across different diseases, and variations in leaf appearance due to rice variety or environmental conditions also hinder accurate classification[5][6].

Because there are numerous techniques and choices at each stage of the disease detection pipeline, researchers have explored a wide range of methods.

This paper represents a comprehensive survey of existing techniques for rice disease identification, covering image processing concepts as well as machine learning techniques. Additionally, it includes a study on plant diseases to provide domain-specific insights. This paper structure follows:

- Section II explores various rice plant diseases.
- Section III outlines the general method of disease detection.
- Section IV reviews existing literature in the field.
- Section V discusses image processing techniques used for rice disease detection.
- Section VI focuses on machine learning methods applied to classification tasks.
- Section VII concludes the paper by summarizing key findings and future directions.

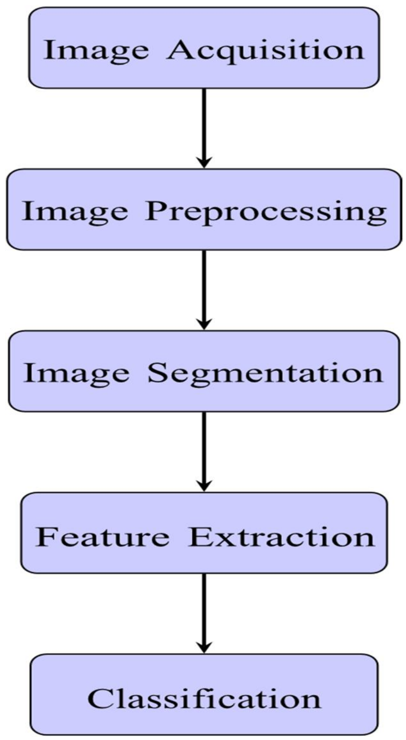


Fig. 1: Plant Disease Identification Methods

II. TYPES OF RICE PLANT DISEASES

This section provides a concise overview of common diseases that affect rice crops. The purpose of including this information is to help readers grasp the relevance of image processing operations and understand the types of visual features that should be extracted to build an effective disease detection system. Fig. [2] displays images of six major rice diseases that occur frequently. Below is a brief description of each. For more comprehensive details, readers may refer to [7].

1) Leaf Blast: This disease typically presents as dark or oval-shaped lesions with thin,crimson-brown edges and a light gray or whitish center[7].
2) Brown Spot: Found mainly on the leaves, this disease appears as circular to oval dark brown spots, potentially leading to reduced plant vigor[7].
3) Sheath Blight: This illness affects the stem and leaves, resulting in oval lesions with reddish-brown edges and a white or straw-colored core [7].
4) Leaf Scald: Distinguished by lengthy, slender reddish brown bands or streaks. Lesions with golden or yellow outlines can occasionally be seen along the leaf margins [7].
5) Bacterial Leaf Blight: The disease starts at the tips of the leaves and develops into lengthy lesions that can reach a length of several inches. Bacterial activity causes the infected regions, which are initially white, to eventually turn yellow [7].

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

III. PLANT DISEASE IDENTIFICATION

The general method for diagnosing plant diseases is described in this section and is usually broken down into two primary parts: (1) image processing, (2) machine learning.

A. Image Processing

1) Image Collection

While publicly accessible datasets, such as the International Rice Research Institute's (IRRI) dataset, are available [8], it is frequently required to generate a bespoke image dataset by gathering information from real rice fields. In this procedure, digital cameras are used to take pictures of sick rice plants straight from the farms. Since these photos are digitally preserved, they may be represented numerically, which makes other image processing tasks easier [9].

(a) Leaf Blast (b) Brown Spot

(c) Sheath Blight (d) Leaf Scald

(e) Bacterial Blight

Fig. 2: Sample images of common rice diseases

2) Image Preprocessing

Image preprocessing is essential to improve results in subsequent phases since dust, dewdrops, and insect excrement may exist on the plant, considered as picture noise [5]. Gathered photographs may have some shadow effects and water drop distortion, which could cause issues throughout the feature extraction and segmentation phases [5].

Various noise removal filters can be used to lessen or eliminate the effect of such distortion. Algorithms for contrast enhancement can be applied to captured images that have low contrast. In certain cases, techniques for background removal could be necessary in situations when a region of interest needs to be extracted.

A median filter can be applied to noise like salt and pepper. A blurring effect can be eliminated by applying the Weiner filter. Regarding the pictures that were taken. Using cameras with great definition may result in large images; hence, image size reduction is important. Additionally, image reduction helps with lowering the amount of memory used by computers [9].

3) Image Segmentation

Plant disease detection may benefit greatly from image segmentation. To divide up a picture is to separate it into specific regions or items. The main objective of segmentation is the process of examining visual data to identify the most valuable features. Image segmentation can be carried out in two ways: (1) using discontinuities, and (2) using similarities. The first way, such as edge detection, divides an image according to abrupt variations in intensity values. In contrast, the second method divides images according to a certain predetermined standard, such as Otsu's method for thresholding.

4) Feature Extraction

Finding the intrinsic qualities or characteristics of objects contained in an image is the main goal of the feature extraction component of image analysis.. These attributes help in distinguishing different objects or conditions. Typically, the extracted features fall under three broad types: color, texture, and shape. The color attribute is especially useful in distinguishing between various diseases. Furthermore, the shape of lesions may vary for each disease, making shape-related features useful for classification. Common shape characteristics include area, angle, and axis length. Texture describes how intensity and color patterns are distributed across an image [22].

B. Machine Learning Methods

1) Classification: Data is mapped into distinct groups or classes through classification. The term "supervised learning approach" is typically used to describe classification [12]. The method of classification involves two steps: The classifier model, which describes a predetermined set of classes, is first created. The classification algorithm builds the classifier in this stage, known as the learning phase (or training step), by "learning from" the data with its unique class labels. The model created in the first phase is used for classification in the second step [13]. Stated differently, test information is utilised to assess the trained model's performance on the test data to evaluate its accuracy. The characteristics taken from the photos are used to categorise the diseases in the plant disease classification. Support vector machines, neural networks, closest neighbours, and rule-based classifiers are some examples of classification models.
2) Clustering: Clustering means a technique to organize data points divided into groups according to their inherent similarities. It ensures that items with comparable characteristics are grouped, while those with distinct traits form separate clusters [14]. Often referred to as data segmentation, clustering divides large datasets into smaller, more meaningful subsets. It falls under the category of unsupervised learning methods. Clustering does not depend on predefined class labels. As a result, it is considered a form of “learning by observation” rather than “learning by example” [13]. In image analysis, clustering is frequently applied in the segmentation of color images, as different parts of an image may have distinct color intensities. It helps group pixels with similar intensities into one cluster and separates those with differing intensities into others.

IV. RELATED WORK

This section outlines a variety of research contributions made in multiple agricultural domains, such as plant classification, weed identification, fruit grading, and plant disease recognition.

Jayme Garcia et al.[15] provided an overview of various techniques used for identifying and categorizing plant diseases. Their work also examined how to determine disease severity. The study highlighted several image processing methods as well as machine learning approaches, including thresholding, fuzzy logic, neural networks, dual-segmented regression analysis, colour quantification, and region growing techniques.

Rashmi Pandey et al.[16] reviewed the integration of image processing as well as machine learning in automated fruit grading systems. In such systems, grading is performed based on parameters like shape, size, texture, color, calyx, and stem. Among these, color stands out as the most significant feature. The paper presented various color feature extraction techniques and included a comparative analysis of different machine learning algorithms, like rule-based systems, support vector machines, artificial neural networks, and nearest neighbor methods.

Anup Vibhute et al.[17] Conducted a survey focusing on how image processing techniques are applied in agricultural practices, particularly for weed detection and grading of fruits or food items. Since weeds negatively impact crop yields, their detection can be achieved using methods like color and edge detection, wavelet-based analysis, and fuzzy classification. In fruit grading, the use of segmentation and feature extraction techniques is emphasized.

A study on several image processing and also machine learning methods for plant disease identification using leaf pictures was published in [18]. Initial colour change structure is produced, and then that colour transformation structure is subjected to device-independent colour space transformation. The presentation includes pre-processing techniques such as histogram equalisation, image smoothing, image enhancement, and clipping.

A brief description is also given of segmentation methods such as Otsu's thresholding, K-means clustering, and border and spot detection. Important characteristics are also covered, including colour, texture, morphology, and edges. The working principle of ANN-based classification is examined.

A median filter was applied to decrease noise, and for segmentation, K-means clustering was employed after RGB images were converted to CIE XYZ colour space, which was then transformed into the l*a*b colour model. The authors in [19] investigated the identification of plant diseases using images of grape and wheat leaves, consisting of 85 grape leaf images and 100 wheat leaf images. The images were compressed using the nearest neighbour interpolation without changing the resolution.

The study extracted features related to color, texture, and shape. Principal component analysis (PCA) was utilised to lower the dimensionality of the features that were extracted.

This dimensionality reduction contributed to minimizing the number of neurons required, thereby enhancing the performance velocity of the Backpropagation neural network.

The study in [20] suggested a study on identification regarding the categorisation of plant illnesses. Five diseases are taken into consideration. Tiny whiteness, ashen mould, late scorch, cottony mould, and early scorch. CIE L*a*b*, independent of device colour transformation, the structure is created from the RGB images.

The sick section of the leaf is extracted using K-means clustering. After being identified, green-colored pixels are masked in the original image. To extract features, the affected areas (clusters) are transformed into HSI colour space. The HSI model's hue and saturation planes are used to create spatial grey level dependence matrices. Lastly, categorisation is done using neural networks.

V. EXAMINING AND EVALUATING IMAGE PROCESSING OPERATIONS IDENTIFYING RICE DISEASES

The image processing methods utilised in several studies on rice disease identification are described in this part.. 13 publications on rice disease identification are surveyed in this section, with criteria including image dataset, number of diseases, preparation, segmentation, then edge detection, extraction of features, and also image processing.

The study of various articles on the identification of rice illnesses is shown in Table I. We use the following notations in the table: Examples of these situations include: Rice Blast (RB), Sheath Blight (SB), Brown Spot (BS), Bacterial Leaf Blight (BLB), Sheath Rot (SR), Red (R), Green (G), Blue (B), Hue (H), Saturation (S), Value (V), RGB (Red, Green, Blue), HSV (Hue, Saturation, Value), and HIS (Hue, Saturation, Intensity). Usually, two steps are needed to determine the illness from a leaf. The first duty is image processing, then the second is machine learning. There are various strategies accessible at every stage of the image processing operation. After reviewing various literature, we discovered that there isn't a publicly available dataset for this issue. The majority of authors [21], [5], [6], [11], and [22] have stated in their publications that they took pictures of rice fields for their studies. Some authors, for instance, used standard databases like IRRI (International Rice Research Institute) in [23], [24], and [25], and used another dataset that was accessible at shutterstock.com

TABLE I .IMAGE PROCESSING TECHNIQUE ANALYSIS

No	Ref	Dataset	Diseases	Preprocessing	Segmentation	Edge Detection	Feature Extraction	Background images	Color space
1	[21]	Picture of 50 diseases	RB, SB, and BS	Yes	Yes	Yes	Yes	Dark or	RGB
				Digitization, Quantization	Thresholding	Sobel	Two c space, area, roundness, complexity, longer axis, length concavity, and short axis differences		

2	[23]	Not mentioned	RB	Yes Enhancement of contrast with histogram equalisation and the Weiner filter	Yes K-means	No	Yes Mean, standard deviation	Not specified	RGB
3	[5]	72 pictures of each disease	BLB eSB RB	Yes Reducing resolution and eliminating noise with a median filter	Yes Otsu's method	No	Yes compactness, elongation, rectangularity, roundness, contrast, uniformity, entropy, area, perimeter, inverse difference, and linearity correlation	Non-uniform natural background	RGB
4	[25]	6 images	SR, RB, and BS	No	Yes Fermi energy base	No	Yes The standard deviation and mean of the infected background pixels are R, G, and B.	Not specified	RGB
5	[6]	500 images	RB, e BS	Yes mean filter for improving images	Yes Otsu's method	No	Yes hue dispersal radially from the spot's centre to its edge	Not specified r	RGB, Grayscale
6	[26]	60 images	BS, NBS, BLB, RB	Yes Binarization, median filtering, and green plan extraction	Yes 8-connected component Label	No	Yes PCA weight matrix, m of H, S, and V	White BG	RGB HSV

7	[24]	RB-360 and BLB-409 Healthy - 239 BS-319	BLB, RB, and BS	Yes Crop the resized image's area (50* Smoothing).	No	Yes Canny	Yes shape, color	Non-uniform natural bg	RGB CIE LAB
8	[10]	20 samples	BS	No	No	No	Yes R, G, L element	Not specified	RGB, LAB
9	[27]	RB-42, BS-37, and BLB-55	BS BLB, RB	Yes Enhancement of Images, Otsu Method	Yes Thresholding, masking	No	Yes	Black	RGB, HSV
10	[11]	BS-37, NBS-47, RB-14	NBS	Yes Morphological operators and the median	Yes Otsu's method	No	Yes Number of spots, spot width and length, and colour difference between RGB and LAB	Not specified	RGB LAB
11	[22]	Not specified	Tungro, RB BS	Yes Cropping, greyscale conversion, and Laplacian enhancement	No	No	Yes Fuzzy entropy	Not specified	RGB
12	[28]	Not mentioned	RB Bs	No	Yes Cropping, greyscale conversion, and Laplacian enhancement	No	No	Non uniform Natural	HSI
13	[29]	500 samples	, RB, BS SR, BLB	No	Yes based on Fermi energy	No	Yes The central moment, mean, standard deviation, and the position of infection changes in the spot's pixel values	White	RGB

A variety of diseases can affect rice plants; however, the most common ones include Bacterial Leaf Blight [5, 26, 24, 27], Brown Spot [21], [25], [6], [26], and Rice Blast [21], [5], [25], [23], [6].

Once the images are collected, the first necessary step is image preprocessing, as outlined previously. Many researchers have implemented the median filter to diminish or eliminate noise from the images [5],[26],[11]. This filter employs a 3×3 kernel that scans across the image, replacing each pixel with the median value of its neighboring pixels. However, a limitation of this method is that if the infected regions on the leaf are too small, they might be distorted or even lost during the filtering process.

To further enhance image quality, various methods have been utilized, such as histogram equalisation [23], mean filtering [6], and the Laplacian filter [22]. For instance, in [26], researchers applied green plane extraction to emphasize the diseased parts of the leaf, as the green areas tend to be more visibly affected during infections. In [11], to eliminate irrelevant spots, a combination of median filtering and morphological operations was applied.

Different segmentation approaches have been employed depending on the study's goals. Table II offers a comparative overview of the segmentation techniques used for identifying diseased regions. One of the most frequently used methods is thresholding, which divides the image based on a predefined intensity value, as seen in [21],[27],[28]. Among thresholding approaches, Otsu's method is particularly notable because it automatically determines the optimal threshold. This technique was used in studies [5],[11],[6]. However, a drawback of Otsu's method is that its effectiveness relies heavily on the image content, meaning a suitable threshold for one image may not perform well on another due to varying grayscale distribution.

Another popular method is K-means clustering, adopted in [23]. This algorithm groups similar pixel colors into the same cluster, effectively separating areas with different color intensities, like healthy and diseased regions. Due to this feature, K-means is often more accurate than other segmentation methods when applied to leaf images.

In [21], the Sobel edge detection technique was utilized to highlight the leaf's edges. These detected edges were then used to calculate the image density by dividing the total edge pixels by the image area. The study in [24] tested various edge detection techniques like Prewitt, Roberts, Canny, and Sobel, ultimately finding that the Canny edge detector delivered superior results, as it was able to capture finer details on the leaf surface.

After identifying the diseased area, key features such as the mean, the standard deviation (R, G, and B)channels are extracted, as they vary with disease type [25],[23],[29]. For example, Brown Spot shows different color values than Bacterial Leaf Blight due to their distinct hues.

Shape-based features, like the area of infected spots, are also used, calculated from binary images [21],[5]. Additionally, disease differentiation is aided by textural characteristics such as contrast, homogeneity, and linear correlation [5]. Using uniform backgrounds improves accuracy and reduces processing time, which is why many studies have used them [26],[21],[29].

TABLE II. SEGMENTATION TECHNIQUES

	Technique	Thresholding method	Segmentation method	Complexity analysis	Segmentation effect	Merit	Demerit
1	Otsu’s method	Global	Thresholding method	Extremely High	stable	It functions on real-world photos regardless of homogeneity and shape measurements.	Need extra processing time.
2	Fermi energy-based	Global	Thresholding method	Low range	More superior to k-means and Otsu	Overcomes the constraint of choosing the appropriate threshold value.	Only functions in the presence of uneven illumination.

3	K-means	Local	Clustering method	Low range	Recognise diseased plant areas and those that are not	Reduces the total squared distance between the centroid and the item.	Predicting k with a set number of clusters is challenging. .
4	Grey-level thresholding	Global	Thresholding method	Normal range	More precise in contrast to Otsu's approach	Grey level transition (2G-R-B) creates contrast between the background and the illness area. .	The right threshold value must always be chosen to improve segmentation results. .
5	Fuzzy c means	Local	Clustering method	High range	More superior to k-means and Otsu	Utilises partial membership, making it more beneficial for actual issues. .	sensitive to the cluster number and cluster centre initialisation conditions .

.

TABLE III. MACHINE LEARNING METHOD IN RICE DISEASE IDENTIFICATION

	Ref.	classifier	classification	Inputs	Accuracy
1	[21]	Nearest Neighbour	Shape, diameter, length, width, and RGB range	Membership Function	80% Rice Blast 60% of rice sheath blight 85% of spots are brown.
2	[5]	Support Vector Machine	Radial Basis Kernel Function	Features of images	Models 1 and 2: 97.2% and 88% Model 3-11.1%
3	[30]	Neural networks, ensemble learning, support vector machines, and quantitative discriminant analysis	Default Parameters	Features of images	NN-80%, SVM, EL, and QDA-85%
4	[23]	Support Vector Machine	Not Specified	Features of images	Accuracy 82%
5	[25]	IF-Then Classifier	Shape nd color features	Features of images	Accuracy 75%
6	[6]	Support Vector Machine Bayes Classifier	Not Specified	Features of images	68.1% for Support Vector Machine, 79.5% for Bayes classifier
7	[10]	Backpropagation Neural Network	hidden layers -3	R, G, and L pixels	Accuracy 90%
8	[27]	Backpropagation Neural Network	9.7909e-13 is the minimum gradient needed for Epoch-87.	Features of images	Accuracy 100%
9	[31]	Production Rule with forward	Not specified	Features of images	Local Entropy about 100%

VI. EXAMINING AND EVALUATING MACHINE LEARNING TECHNIQUES USED FOR RICE DISEASE IDENTIFICATION

Researchers have employed various classifiers based on their specific requirements. Support Vector Machine (SVM) is commonly utilised for rice disease classification, as seen in [5], [6], [23], [30], due to its effectiveness with high-dimensional and distorted data [16]. SVM offers different kernel functions; the linear kernel is suitable for binary classification, while the radial basis function (RBF) is preferred for multiclass problems.

Some studies have utilized neural networks for classification [10], [22], [24], [27], especially when dealing with large datasets. However, neural networks typically demand more computational resources and training period [16].

The rule generation method, although less commonly used, classifies data based on predefined production rules. For example, if the shape and color features of a test image are similar to those from the training data, it is classified under the corresponding disease category. The classifier input is usually feature vectors extracted from infected regions, although some works, such as [10], [28], use raw image pixels as input.

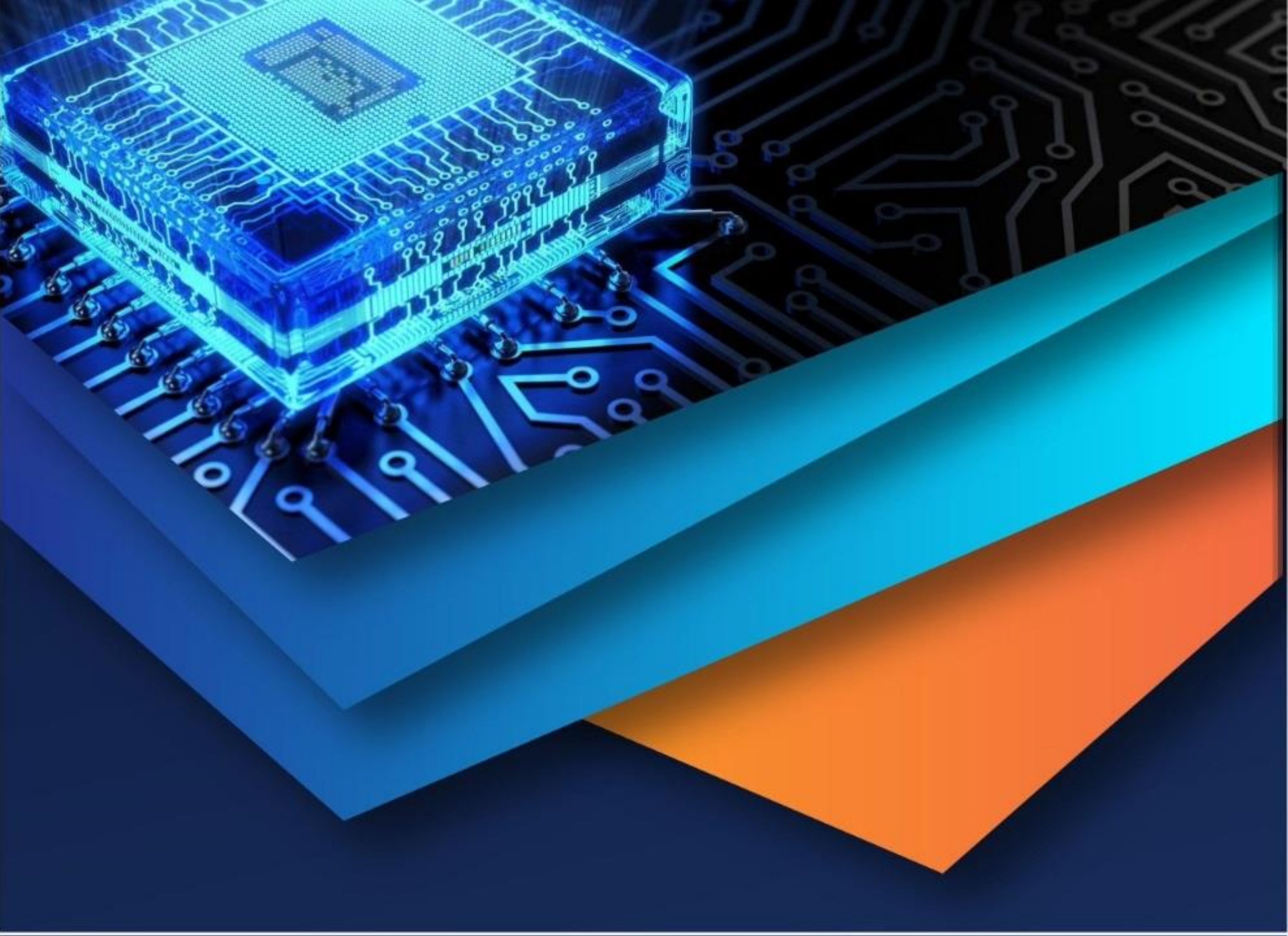
VII. CONCLUSION

The findings in this survey highlight the tremendous advantage that arises when integrating image processing and machine learning methods to significantly increase the accuracy in rice plant disease identification. Image collection is the initial step, and frequently involves creating datasets targeting rice fields using customized collection activities. Major pre-processing techniques, such as noise reduction, contrast enhancement, are very important in solving problems of dust, shadowing, and water drops on leaves. When researchers use techniques such as edge detection and thresholding for segmentation, they can easily isolate important parts of the image, allowing for precise feature extraction. By considering such features as color, texture, and shape, the system can discriminate among several diseases properly.

Classification tools in machine learning, such as SVMs and k-NN, are used for these features to be able to secure effective disease categorization and diagnosis. No need for specific assumptions about the data, as it is possible to organize data points by their inherent similarities using clustering algorithms. The combination of these techniques has significantly enhanced the capability of detecting diseases early, which has encouraged rapid measures and increased crop yields.

REFERENCES

[1] “Agriculture Economics and Importance of Agriculture in National Economy,” AgriInfo, [Online]. Available: http://agriinfo.in/?page=topic&superid=9&topicid=185. [Accessed: Nov. 23, 2015].
[2] “Agriculture Sector in India.” [Online]. Available:http://www.ibef.org/industry/agriculture-india.aspx. [Accessed: 23-Nov-2015].
[3] L. P. Gianessi, “Importance of Pesticides for Growing Rice in South and Southeast Asia," pp. 30–33, 2014.
[4] “Rice Production (Peace Corps): Chapter 14 - Diseases of rice.”[Online]. Available: http://www.nzdl.org. [Accessed: 23-Nov-2015].
[5] Q. Yao, Z. Guan, and Y. Zhou, "Application of support vector machine for detecting rice diseases using shape and color texture features," in International Conference on Engineering Computation, pp. 79-83, 2009.
[6] S. Phadikar, J. Sil, and A. K. Das, "Classification of Rice Leaf Diseases Based on Morphological Changes," International Journal of Information and Electronics Engineering, vol. 2, pp. 460-463, May 2012.
[7] D. Groth and L. S. U. Agcenter, “Rice Disease Identification Photo Link.”
[8] “IRRI - Rice science for a better world.” [Online]. Available: http://irri.org/. [Accessed: 23-Nov-2015].
[9] A Fakhri, A Nasir, M Nordin, A Rahman, and A R. Mamat, "A study of image processing in agriculture application under high performance computing environment," International Journal of Computer Science and Telecommunications, vol. 3, no. 8, pp. 16-24, August 2012.
[10] L. Liu and G. Zhou, "Extraction of Rice Leaf Disease Image Based on BP Neural Network," in Computational Intelligence and Software Engineering, Wuhan, 2009.
[11] N. N. Kurniawati, S. Norul, H. Sheikh, and S. Abdullah, "Investigation on image processing techniques for diagnosing paddy diseases," in Soft Computing and Pattern Recognition, 2009.
[12] P.L. Sahu, A. Singh, and K.L. Sinha, "A survey on data mining techniques for classification," vol. 2, no. 1, pp. 65-70, 2015.
[13] J. Han, M. Kamber, and J. Pei. Data mining: concepts and techniques: concepts and techniques. Elsevier, 2011.
[14] K.I. Rahmani, N. Pal, and K. Arora. "Clustering of Image Data Using K-Means and Fuzzy K-Means." International Journal of Advanced Computer Science and Applications 5, no. 7 (2014): 160-163.
[15] J. G. A. Barbedo, "Digital image processing techniques for detecting, quantifying and classifying plant diseases," SpringerPlus, vol. 2, pp. 660, 2013.
[16] R. Pandey, S. Naik, and R. Marfatia, "Image Processing and Machine Learning for Automated Fruit Grading System: A Technical Review," International Journal of Computer Applications, vol. 81, no. 16, pp. 29–39, Nov. 2013.
[17] A. Vibhute and S. K. Bodhe, "Applications of image processing in agriculture: a survey," International Journal of Computer Applications, vol. 52, no. 2, pp. 34–40, Aug. 2012. Academia
[18] S. D. Khirade and A. B. Patil, "Plant Disease Detection Using Image Processing," in Proc. Int. Conf. Computing Communication Control and Automation (ICCUBEA), Pune, India, Feb. 2015, pp. 768–771.



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY