A Review on Machine Learning to Detect and Classify Paddy Leaf Disease

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Abstract— **India's primary source of income is agriculture. Paddy is grown almost everywhere in the world but is most common in Asian nations where it serves as the main source of food to world's population. Several diseases attack it at various phases of its development. Fungi, nematodes, viruses, bacteria, nutritional deficits, temperature, and other environmental variables are the key biotic and abiotic elements that contribute to plant illnesses. Brown spot, bacterial blight and Leaf blast are all important paddy leaf diseases that destroy rice and drastically reduce yield. The saturation threshold is used to eliminate background from photographs, while the hue threshold is used to divide diseased regions. Bangladesh, one of the world's top ten producers and consumers, relies significantly on rice to maintain its economy and meet its food demands. To guarantee the healthy and appropriate growth of the paddy plants, it is critical to identify any illness early on and before the damaged plants receive the necessary treatment. Farmers and planting professionals have had to deal with a slew of persistent agricultural issues, such as different paddy illnesses, for decades. A fast, automated, less expensive, and accurate method of detecting Paddy illnesses is highly desired in the area of agricultural information since severe paddy leaf diseases might result in no crop harvest.**

Keywords— Paddy Leaf disease, Machine Learning, Image Processing, Feature Extraction, Pre-processing.

I. Introduction

Diseases in plant have a negative impact on agricultural productivity. Approximately 58 percent of rural residents rely on farming as their primary source of income [1] Plant pathogens include fungus, bacteria, viruses, and other organisms. People are becoming more aware of the harmful impact that extensive usage of chemical pesticides has on both human health and the environment. [4] Paddy is a pretty wide term because there are numerous varieties of paddy grown in different regions of the earth. Initial identification and treatment of these illnesses are crucial because they increase yield quantity and quality, which lowers the need for pesticides. The most well-known, affordable, and nutrient-dense food in Asia is paddy.

Maize is a major agricultural commodity farmed across the world. Only wheat and rice have a greater worldwide growing area and productivity than maize. Furthermore, grain is an important beginning point for the production of things used in small-scale manufacturing in order to be a superior source of feed for animals [2]. Nonetheless, the Northeast foliage blight mostly affects grain, and the decline in grain yield caused by networking has steadily increased over the last few decades. As a result, effective identification and diagnosis of crop leaf infection is crucial. Early signs of illness include water-stained cigar-shaped patches that extend to the leaf cover.

Artificial neural networks, the foundation of machine learning, are learning ability and making wise choices by a help of algorithms. The general populace, food security, and the national economy are all directly and negatively impacted by this loss of yield. Often, paddy disease is manually identified by specialists using their unaided eyes, which takes more time and is expensive on large homesteads. These economic results demonstrate unequivocally that Bangladesh places a high priority on proper paddy cultivation. Agricultural research aims to improve the quality and productivity of crops while lowering expenses and increasing output. A key factor in achieving steady economic growth and maintaining the desired goals is disease-free paddy production.

The novel method for identifying and diagnosing plant diseases is now available thanks to the quick development of image processing and pattern recognition technology. For these reasons, leaf disease detection is crucial. A farmer typically discovers the presence of a disease attacking his crop through direct field observation.

The Green Revolution brought several new industrial agricultural practices to India along with it. For laboratory investigations, chemical reagents are necessary, and there is a lengthy procedure. Because of the advancement of online and mobile technology, several applications are being developed to assist manufacturers [3]. Rice Doctor and Rice Expert are two such smartphone applications. A quiz is included in the Rice Doctor app to assist farmers. Rice Expert describes the unusual status of rice in a similar manner. Using these portable applications to identify rice ailments raises the probability of error and reduces the process's efficacy.

There are some applications that identify plant diseases using artificial intelligence. Treating these illnesses can help to ensure productive farming. To detect paddy leaf conditions early, automatic and expert systems are required.

When a crop is being grown, a farmer may not be aware of the illness that affects the crop at any one time. They can transmit illnesses or difficulties, which can result in larger output losses [4].

Crop damage by insects occurs practically at every stage, which has an impact on crop productivity. Bacterial leaf blight has been shown to impair output by up to 70%, according to the International Rice Research Institute. After achieving excellent accuracy in both trained and tested data/feature sets, the model is approved. Twenty-one publications from the previous eight years were taken into consideration for a survey from the years of 2012 to 2023 on paddy leaf and seedling diseases. For laboratory investigations, chemical reagents are necessary, and there is a lengthy procedure.

Because of the advancement of online and mobile technology, several applications are being developed to assist manufacturers. Rice Doctor and Rice Expert are two such smartphone applications. A quiz is included in the Rice Doctor app to assist farmers. Rice Expert describes the unusual status of rice in a similar manner [5]. Using these portable applications to identify rice ailments raises the probability of error and reduces the process's efficacy.

Many pathogens, including bacteria, viruses, nematodes, and fungi, cause paddy illnesses. Certain diseases may be brown in colour, whereas others may be yellow. When compared to healthy plants, affected plants produce paddy that is of lesser quality and quantity. Along with the loss of the farmers, it has a big effect on the economy of the nation. The majority of issues are reduced by offering some technical facilities. Nonetheless, recent times have seen some difficulties with the paddy crop. By the best of our understanding, this is the first study to look at the use of methods of transfer learning for rice illnesses.

II. RELATED WORK

A. *Different types of Paddy Plant diseases*

In this section, many diseases that affect rice plants are briefly explained. This section was included so that readers could understand the many image processing processes that would be required and the various features that would need to be given consideration in order to create such a disease detection system [6]. We have six pictures of common ailments and a brief description of each one. Further information on all rice plant diseases.

1. Leaf Blast (LB): Black to oval-shaped spots with reddish brown, grey, or white tips are a sign of the condition.

2. Brown Spot (BS): The illness spread to the rice plant's leaves. Round to oval lesions that are dark brown are a sign of illness.

3. Sheath Blight (SB): This infection makes a showing on the stems and leaves. The tell tale sign is an oval with reddish brown dots and a white or straw-colored centre.

4. Leaf scald (LS): Narrow, reddish-brown, wide bands are the symptoms. The border of the leaf may occasionally have a lesion; it may be yellow or gold [7].

5. Bacterial Leaf Blight (BLB): signs include multiple long, elongate lesions towards the tip of the leaf that become white to yellow as a result of the bacterium's activity.

6. Rice Blast (RB): Magna Porthe Oryza, a fungus, is to blame. The wounds range in hue from white to a gray-green and have a dark-colored border at first. The most prominent leaf lesions are oval or spindle-shaped, with a white to grey middle and a red to necrotic edge. The spots typically have two pointed ends and are long.

7. Sheath Rot (SR): Sarocladium Oryza and sacroladium tensum, two fungi, produced it. The upper sheath of the spikelet marks the beginning of the typical casing root. More spots are evident, these spots will grow, and they can eventually cover the majority of the leaf sheath. It appears as an oblong or asymmetrical stain with dark red, brown margins, grey midway, or brownish grey in most cases.

B. *Materials and methods*

The steps involved in paddy leaf classification are outlined in Figure 1.

1) *Data acquisition:*

About 500 images of the Paddy diseases of plants were collected from the experimental field of the Fujian University of Subtropical Botany's agricultural scientific innovation centre in Xiamen, China [8]. Images frequently contain complex backgrounds and varying levels of light. Using Photoshop tools, these photographs are reliably translated into the RGB model before being scaled down for the following computations [9]. Rice leaf scald, stack burn, white tip, leaf smut, and bacterial leaf streak belong to the rice illnesses seen in these images. Plants images in various environmental situations are taken in this stage to construct an effective detection algorithm.

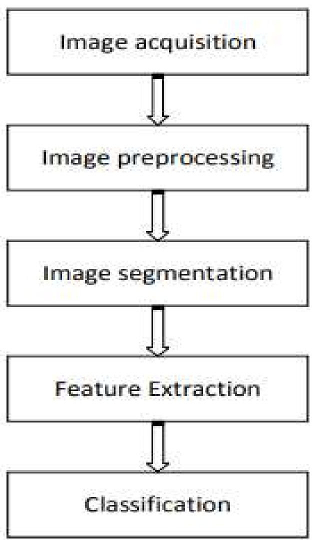

Fig. 1. Steps of paddy leaf classification

The collection is made up of numerous photos of varying resolutions. To picture plants, various technologies such as tablets, cellphones and standard

RGB cameras are utilized [10]. Other factors, such as lighting conditions at the moment of photograph snap, weather, and distinct biological regions, all contribute significantly to the dataset gathering. The images gathered are associated with various stages of plant growth. The symptoms of several rice leaf diseases are listed in Table I, and few envoy photos are shown in Fig.2.

TABLE I. SYMPTOMS AND CHARACTERISTICS PADDY LEAF DISEASE

Disease Name	***Color***	***Shape***	***Junction***
Leaf scald	0ff-white or yellow	Watery stain form or strip	No
Rice stack burn	Yellowish-white macular	Circular or Ellipse	No
White tip	Centre: ashen; edge: brown	Strip	2 layers
Leaf smut	Black	Short strip	No
Rice false smut	Black	Spores (grain)	No
Bacterial leaf streak	Brown or russet	Long strip	2 layers
Rice stem rot	Black	Long strip (stem)	No
Rice blast	Brown	Circular punctate	2 layers
Rice sheath blight	White	Circular punctate	2 layers
Rice kernel smut	Black	Spores (kernel)	No
Grain spotting and peck	Centre: off-white to brown	Circular (grain)	2 layers
Rice sheath rot	Brown	Long strip (sheath)	No
Rice sheath spot	Centre: off-white to brown	Strip (sheath)	2 layers

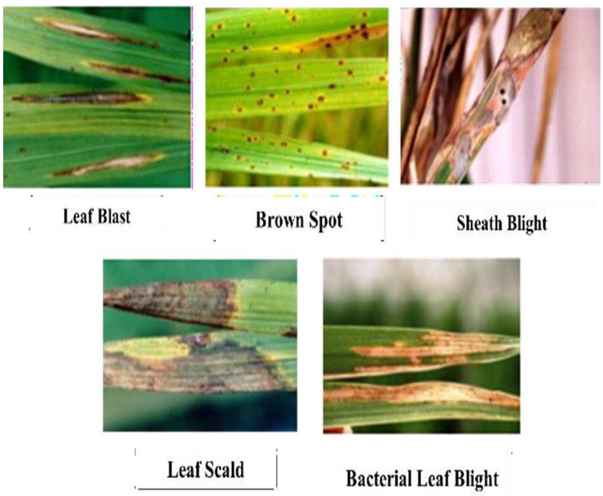

Fig. 2. Sample Images of Paddy leaf diseases

2) Pre-processing:

This is the technique of enhancing the aesthetic quality of plant images. picture pre-processing can improve the quality of the retrieved features as well as the findings of the picture research [11]. This stage includes many procedures such as noise removal, picture intensity balance, and object exclusion. The preliminary processing improves the appearance of picture data before it is digitally processed. To eliminate noise from photos or other objects, many processes for pre-processing are used. Picture cropping is used to eliminate unwanted picture sections and acquire the leaf image.

This stage likewise employs the smoothing filter to soften the picture. The picture Enhancement technique improves picture contrast and converts RGB images to grayscale images [12].

3) Segmentation:

Segmenting image is an essential step in feature extract and detection of plant illness disease. It is critical for locating and detecting infected plant leaves in hostile conditions [13]. As a result, picture segmentation entails distinguishing characteristics from the foreground.

A picture is divided into numerous non-overlapping, vocal, and similar areas throughout this method. The infection area of sick leaves of plants is of particular importance [14]. The division of a sick leaf image is an intrinsic step in recognizing the polluted imagery and the kind of infection that occurred. Image segmentation has a direct impact on consecutive processing of images and additionally determines its benefits and drawbacks. The following are most often used segmentation techniques:

- *Iteration technique:*

It is capable of calculating the threshold to a certain extent. To attain the best classification limit, the Grayscale averages are continually decreased [15].

- *Otsu thresholding:*

The most often used threshold segmenting technique is the biggest interclass variation strategy, additionally referred to as Otsu. A 2D Gray-level intensity functional, that is the grey level often represents the characteristics of an image.

4) Feature extraction using texture analysis.

A. Shape Feature Extraction

A crucial aspect of an image is its shape. Humans frequently use an object's shape to comprehend and distinguish it [10]. Its shape can be described using general descriptors like the quantity of the object, its width, and its length [16]. These traits are employed to derive features from the lesion. In this study, blob analysis is utilised to count the objects in various sections of a noise-free binary image. Spreads in the foreground and backdrop add up to a minimum.

B. General Discussion

The edges of the paddy leaf and the infected area are visible. In the input image, the backdrop is removed. Following the segmentation procedure. The segmented image's characteristics are extracted. Contrast, correlation, energy, and homogeneity are the characteristics that are extracted, and they are represented as values that will be compared to the trained dataset and used for classification [17].

Extracting features entails translating raw image into meaningful representations for a certain categorization function. Conceptual features, that is, an analytical depiction of the picture conveying information relating to the categorization problem and removing redundant ones, are computed to reduce this big imagery. Among the most prevalent approaches for obtaining informative characteristics are GLCM and hue moment [18]. Feature extraction technique is then applied over it for the classification described in Figure 3.

- *GLCM features*

GLCM is used to remove texture characteristics that have been retrieved. This technique reveals critical information about the geographical distribution of grey stages in a leaf texture picture. The correlation, contrast level, homogeneity and energy parameters of this technique are utilized to build the co-occurrence framework, which requires 8 bits to Grayscale grade to every stage is equal to sixty-four attributes to describe the image texture in leaf.

- *Hu moment invariants*

The invariants of Hu moment are seven moment qualities that may be used to define forms and are constant under translation and rotation. Invariants are determined from an image's contour of an item. After Hu moments, the pictures' central moment and gravity are calculated and recorded in vector form as a result.

5) Classification:

Following image processing and feature extraction, the pictures must be categorized based on their target features. It is largely concerned with the creation and application of classifiers. Extraction of features typically yields a vector as output [19]. A machine learning algorithm is used to convert this vector to a confidence score. Depending on the programmed being used, the score is assessed in relation to either a single threshold that determines whether an object appears or not, or it is evaluated to additional scores to classify other types of items.

- *Disease identification based on machine learning model*

Using cutting-edge machine learning techniques has made it easier to reliably identify disease types at an early stage. This section presents the most recent solutions that outperform for diagnosing various O. Sativa crop diseases, along with their performance metrics (Table II).

TABLE II. ML TECHNIQUES PERFORMANCES

Author Name & Year	***ML/DL Technique***	***Diseases Identified***	***Performance Measure and score***
Prabira Kuar (2020)	Deep feature based SVM	BLB, LB, BS, and Tungro	0.98 F1 score and 0.97 accuracy
Yang et al (2017)	Deep CNN	False smut, LB, Bakanae disease, SB, BS, SR, Bacterial sheath rot, BLB, Bacterial wilt and Seeding blight	Accuracy: 0.95
Long Tian et al (2021)	SVM-SFFS	LB	Mean Accuracy:0.91
Lei Feng et al (2020)	CNN model with high level fusion	BLB, LB, and SB	Accuracy: 1.0
F. Jiang et al (2020)	CNN with SVM	SB, Stripe blight,Red blight, and LB	0.96 Accuracy
Li-Wei Liu et al (2021)	PNN	LB	Accuracy: 0.91 F1 score: 0.92
Muhammad Anwarul Azim et al (2020)	Extreme gradient boosting (XGBoost)	LS, BLB and BS	0.87 F1 score and 0.86 accuracy
Md. Mafiul Hasan Matin et al(2020)	AlexNet neural network	BS, BLB and LS	Accuracy: 0.99
Kawcher Ahmed et al(2019)	Decision Tree(j48)	BS, BLB and LS	F Score and 0.97 accuracy
Junde Chen et al (2020)	Deep_Transfer Learning	Bacterial leaf streak, Stackburn, SB, Kernel smut, Sheath spot, Stem rot, LB, White tip, Leaf scald, LS and False smut	0.98 Accuracy
P A Gunawan et al (2021)	ANN	BS and LS	0.79 Accuracy
Shreya Ghosal et al (2020)	CNN_Transfer Learning	LB, BLB and BS	Accuracy: 0.92
Bari et al (2021)	Faster_ RCNN	Hispa, BS and LB	0.987 Accuracy
Vikas Sharma et al (2020)	Minimum Distance Classifier (MDC)	Stem Rot, BS, False Smut, LB, and SB,	Accuracy: 0.81
Ramesh et al (2019)	DNN _JOA	BLB, LB, BS and SR	Mean Accuracy: 0.95

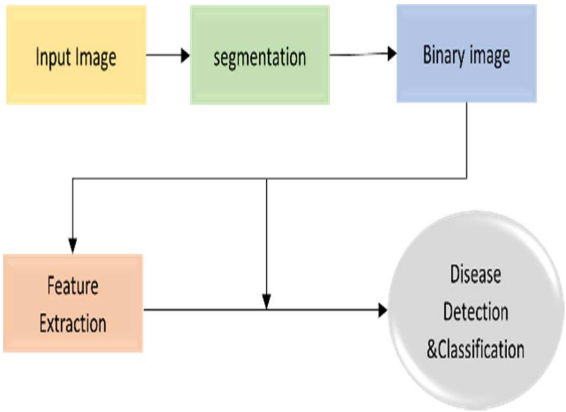

Fig. 3. Feature extraction technique is then applied over it for the classification.

- *Detection and classification*

The normally distributed subpopulations within the overall population are represented by GMM. The subpopulations are allowed automatically because it does not require the mixture model. This are supervised approach that classifies a wide range of data and is utilized as well in recognition of patterns due to its superiority. It produces data points based on parameters of Gaussian distribution. GMM parameters are well trained. The modeling data from several groups are used by GMM [20].

Consider, K clusters, and is estimated for each k. It estimated only by using maximum-likelihood method. The probability density function is defined by k clusters with the densities of all k distributions. GMM is defined by [21],

$$r(Z) = \sum_{k-1}^{K} \delta_k G(Z \mid \alpha_k, \beta_k) \tag{1}$$

Where, k is a coefficient. The estimation parameter of log-likelihood method is $r(Z \mid \alpha, \delta, \beta)$. In this study, GMM is used for the classification of paddy leaf from feature database. The categorization is made up of four, eight, sixteen, and twenty-two levels of Gaussian component. The GMM is also used in other fields like voice activity detection and video foreground separation [22].

III. Discussion

The performance is measured by using 50 normal and 50 infected paddy leaves. The images in the database are taken from digital camera. The paddy leaf images in the database are shown in figure 4.

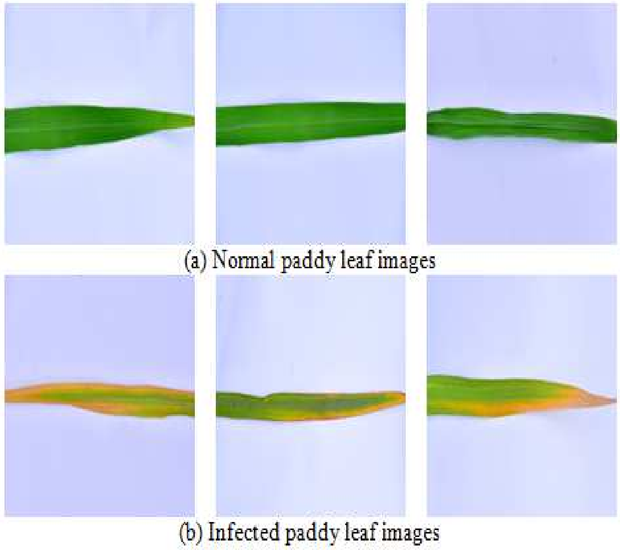

Fig. 4. Sample paddy leaf images in the database

Initially, the input paddy leaf images are given to color model, LBP and wavelet-based energy features are combined to form Multiple modalities of Feature (MMoF) extraction. The collected characteristics are then categorized using the GMM classifier and its components. For classification, the GMM classifier with four, eight, sixteen, and thirty-two levels of Gaussian component is utilized. Table III displays the performance of GMM.

TABLE III. GMM PERFORMANCES

MMoF wavelet levels	Gaussian component levels			
	G4 (%)	G8 (%)	G16 (%)	G32 (%)
1	73.00	75.00	79.00	77.00
2	78.00	80.00	85.00	83.00
3	84.00	86.00	90.00	87.00
4	82.00	84.00	87.00	86.00

The work effectiveness is carried out with the help of various parameters as well as various performances and comparative analyses are carried out. This paper presents a ML approach for diagnosing many rice leaves diseases, including bacterial leaf blight, leaf smut, and brown spot sickness. Table IV summarizes the ML model's assessment of performance.

TABLE IV. THE PERFORMANCE EVALUATION OF THE MACHINE LEARNING

Paddy Plant Diseases	**Precision**	**Recall**	**F-score**
Sheath blight	0.45	0.45	0.49
Leaf blast	0.57	0.57	0.59
Brown Spot	0.70	0.70	0.74
Sheath rot	0.62	0.62	0.60

From table III, it is observed that, the Gaussian component 16 (G16) produces the higher classification accuracy of 90% at 3rd level of MMoF. Also, the Gaussian components G4, G8 and G32 produce 84%, 86% and 87% of classification accuracy. The Receiver Operating

Characteristics (ROC) curve using GMM Gaussian component 16 is shown in figure 5.

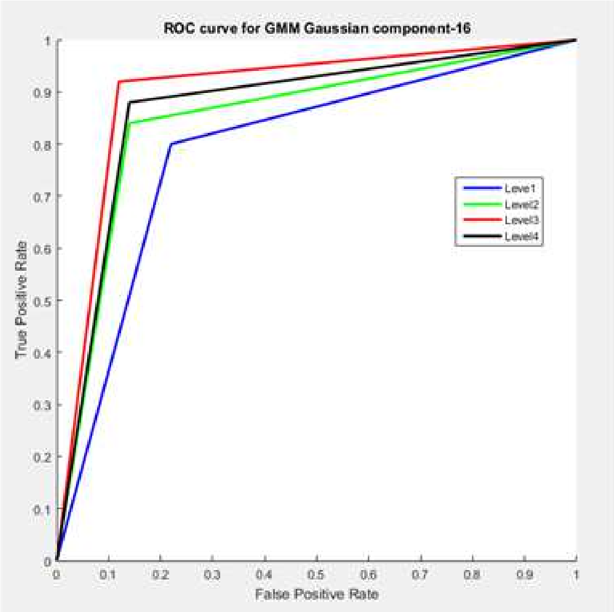

Fig. 5. ROC curve performances

From the figure 5, it is observed the maximum area under the curve is 0.9 and the minimum area under the curve is 0.79. The MMoF features are also compared with SVM and K-Nearest Neighbor (KNN) classifier is exposed in table V.

TABLE V. EVALUATION OF GMM AND DISSIMILAR CLASSIFIERS WITH MMOF

Classification techniques	**Accuracy (%)**
MMoF + SVM	75 %
MMoF + KNN	85 %
MMoF + GMM	90 %

According to the table previously mentioned, MMoF + GMM offer a greater classification accuracy of 90% when compared to SVM and KNN.

IV. CHALLENGES

There are numerous approaches for identifying rice illnesses, including edge detection, cluster, water separation, active contour, sale, limit, and so on. The method of discovery is essentially identical in all ways. The most significant approach for obtaining image functions is categorization, which involves separating the picture into sections of special interest.

Texture, form, color, and motion-related qualities are represented by the distinctive image attributes. Classification is a categorization result that is based on recently picked characteristics. A few studies on automated indicators of leaf disease offered.

- The elimination of backgrounds accomplished through the use of segment and elimination of backgrounds algorithms. They color segment using green pixel masks before they use Otsu thresholding algorithms on infected photos.
- A different study covered eleven plant diseases and slightly explored image-oriented plant separation algorithms. CNN defines shadows and their branches to distinguish the types of sickness using similarities.
- We discovered that availability of data continues to be restricted in several literature studies. Since the natural variance in each image is incorporated indirectly when splitting into smaller portions, the suggested technique not only considerably improves the amount of the image collection, but it also improves the variety of the data.
- This technique has certain disadvantages as well, but in the situation of restricted availability of data, it is bound to end in outcomes that are more reliable.
- Image pre-processing before executing a training of ML model will be a helpful approach of getting excellent results.
- Any enhanced approach may be utilized to get the greatest results by eliminating false categorization to enhance the identification and categorization of rice plant diseases.
- Improve the rice illness dataset and create a complete rice disease detection system. When the sample size is insufficient, data enhancement approaches are utilized to create good learners.
- The classification accuracy may be enhanced by additionally including more photographs in the dataset and modifying the ML parameters. Finding appropriate variables to ML models, on the other hand, remains an area of difficulty.

V. CONCLUSION

In light of the topic, it may be noted that paddy leaf in south India is afflicted by a number of diseases, the most significant of which are blast and blight. Damage from disease can significantly lower paddy output. They are primarily brought on by bacteria, viruses, and fungus. The simplest and frequently most economical method of managing illnesses is to plant resistant varieties. Then MMoF is used as input for classification. GMM component levels 4,8,16 and 32 are used for classification. The Gaussian component level 16 produces the higher classification accuracy of 90% using MMoF comparing with other Gaussian components. The GMM is also compared with SVM and KNN, 75% accuracy produced by using SVM and 85% accuracy produced by using KNN. The proposed GMM produces better classification accuracy comparing with SVM and KNN.

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