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ScienceDirect

Procedia Computer Science 167 (2020) 516-530



International Conference on Computational Intelligence and Data Science (ICCIDS 2019)

Image Processing Techniques for Diagnosing Rice Plant Disease: A Survey

Prabira Kumar Sethy^a*, Nalini Kanta Barpanda^a, Amiya Kumar Rath^b, Santi Kumari Behera^b

^aDepartment of Electronics, Sambalpur University, Jyoti Vihar, Burla and 768019, India ^bDepartment of Computer Science and Engineering, Veer Surendra Sai University of Technology, Burla and 768017, India

Abstract

Over the past decades, rice crops are crucially admitted as one of the powerful energy streams for the production of resources. Rice plant diseases are considered as a raising factor behind the agricultural, economic and communal loss in the upcoming development of the agricultural field. Since last 10 years diagnosis of plant disease in approach to image processing techniques have remained keen are of interest among the researcher. A number of disease detection, identification and quantification methods have been developed and applied in a wide variety of crops. This paper reviews related research papers from the period between 2007 and 2018 with a focus on the development of state of the art. The related studies are compared based image segmentation, feature extraction, feature selection and classification. This paper also outlines the current achievements, limitations, and suggestions for future research associated with the diagnosis of rice plant diseases.

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Peer-review under responsibility of the scientific committee of the International Conference on Computational Intelligence and Data Science (ICCIDS 2019).

Keywords: rice diseases; image segmention; feature extraction; feature selection; classification.

^{*} Corresponding author. Tel; +91-9439489214. *E-mail address*:prabirsethy.05@gmail.com

1. Introduction

Rice is deliberate as a major source of food among the rural population and also it is considered and the second most cereal crop cultivated over the world. Rice belongs to the family of Poaceae and correspond to two main subspecies i.e. Japonica and Indica. Rice is the most widely recognized low cost and effective nutrient food available in Asia. Rice crop is cultivated in five regions of the world i.e. Asia, Africa, America, Europe, and Oceania. As indicated by the Food and Agriculture Organization of the United Nations (FAOSTAT) overview, 91.05% of the world's rice is deliver and devour by Asian Countries [1]. The rest of the rice generation is partition between different locales of the world, for example, 2.95% by Africa, 5.19% by America, 0.67%byEurope and 0.15% by Oceania (See Fig. 1).

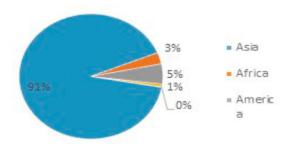


Fig. 1. Production of Rice World (Source FAOSTAT)

According to World Bank, the projected demand of rice consumption will increase by 51% by the year 2025, which is much more than the growth rate of population. Fig. 2 shows the projection of rice consumption in major countries in Asia, 1995-2015.

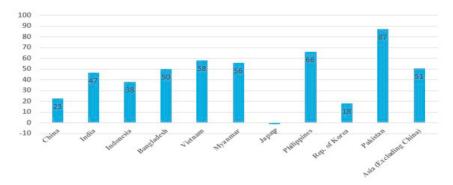


Fig. 2. Projection of Rice Consumption in Percentage of Asian Countries, 1995-2025. (Source World Bank Population Projection, 1995-2025).

Rice demand expected to grow faster than the production in most countries. In this situation, damage of rice crop by any cause is unacceptable [2]. Detection of rice plant disease and its severity has always been challenging. Earlier naked eye observation (visual analysis) was the only available technique to diagnosis the rice disease. This technique requires continuous monitoring of the crop field for the correct estimation of disease by expert of this field. As the visual analysis requires constant human observations, the process (visual analysis) tends to be very costly, cumbersome and time-consuming for large areas of plants. The exponential increasing population changes the demand of supply of food produce scenario rapidly. Such situation forces the society, as a whole, to think for, use of advanced technology so that early and accurate estimation of disease for the implementation of remedial measure can applied at the right time. Image processing techniques are prove one of the accurate and economic practices for measuring the parameters related to various plant diseases. Therefore, a rigorous survey and

comparative analysis of different image processing techniques have done in this paper, which are applicable for diagnosis of plant diseases. The Growing period of rice crop comprises: (1) Germination, (2) Vegetative Phase, (3) Reproductive phase, (4) Ripening phase [3]. In germination, at first root and shoot crop up from the seed [4]. The vegetative phase is from uprooting of plant to initiation of panicle. The reproductive phase includes the emergence of panicle from tiller to complete growth of panicle. Then in ripening phase, the panicle is mature enough so that the kernel inside the grain is completely grown. The disease can affect any part or any growing stage of rice crop.

2. Paddy Diseases and their Symptoms

The paddy diseases are due to many constraints such as pathogens, insect pest, deficiency of nutrients and unusual environmental condition [5-7]. Plant pathogens can be parasitic, bacterial, viral or nematodes and can harm plant parts above or underneath the ground. This section provide information about the paddy diseases with their appearance. So that, reader can understand what type image processing and feature needed to detect that particular disease.

2.1. False Smut

False Smut appears as silvery-white structures and later as orange smoke/dust, when infected later develops panicles. The disease cycle continue late into the growing season and has caused the loss of direct yield so far. Disease favors during the rainfall and high humidity; Land with extreme nitrogen content [8].

2.2. Sheath Blight

Sheath blight in rice plant caused by fungi Rhizoctonia solani Kuhn that infected the straw of rice. It occurs when sclerotia fall off the straw before or during the time of rice harvesting. Initial lesions on leaf sheaths, presence of sclerotia. It filled or empty grains, such that with the underneath panicles [9].

2.3. Rice Blast

Blast of rice is major disease since many decades in Middle Gujarat and since last two decade in South Gujarat. Pathogen attacks all the aerial parts of plants at any stage of crop growth right from germination to harvest [10-12]. The disease occurs as seedling blight, leaf blast, node blast, and neck or panicle blast and grain spot. Seed and soil borne infection during germination and thereafter on tender seedling cause, seedling blight leading to death of seedling. Leaf blast is characterized by production of large spindle shaped lesions with ashy grey centers with brown margins drastically reduce crop growth and tillering. The infected node or neck tissues became soft and rotted. The node or neck blast treated as an effective stage of the disease attacking prior or after flowering and grain formation, causing drastic reduction in grain quality and quantity of produce. The infection on grain produced dark brownish black spot [13-16].

2.4. Leaf Scald

The symptoms are narrow reddish-brown wide bands. Sometimes lesions are at leaf edges with yellow or golden borders [13-15].

2.5. Brown spot

This disease occurs on leaves of the rice plant. The symptoms of the disease are round to oval shape with dark brown lesions [13-15].

2.6. Bacterial leaf blight

Symptoms contain elongated lesions on leaf tip, lesions are several inches long and it turn into yellow from white due to effect of bacteria [13-15].

2.7 Rakane

The affected Rice plant may be of abnormal elongation in the seedbed and loss the actual development phase. Thus, the seed exist in the growing stage; they exhibit empty panicles field —with yellow shades leafs. Reduced tillering and drying of leaves at late disease - terminating the bucket seedlings at early phase. In part filled grains, sterile, or void grains for enduring plant at development. Infected seedlings are taller than ordinary plants and are thin and yellowish-green at the seedling stage, bakanae can be found in the vegetative stage, infected plants are taller than the typical plants and have a couple of tillers and yellow-green leaves [14,15].

3. Growth Phases of Paddy Crop and its Diseases

Rice crop take around 3-6 months for its cultivation and undergo three general growth phases: vegetative, reproductive, and ripening. Besides these three phase, there is another phase prior to development of radicle and

plumule from the seed known as Germination. After the embryo germinates, it grows out of the seed and known as a plantlet or seedling. The diseases appeared in different growth stage are illustrated in Table 1.

Table 1. Growth I	Phase of Rice	with Diseases
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Growth Phase of Rice	Diseases
Germination	Seed Rot
Vegetative Phase	Crown rotor foot rot (also known as Bakane),Leaf blast, Brown spot, Sheath blight,Leafscald,Leafsmut,StackburnorAlternarialeafspot,Whiteleafstreak,Whitetip,Bacteriall eafblight,Crownsheathrot,Collar blast, Node blast
Reproductive and Ripening Phase	Rotten neck blast, Downy mildew, White ear head, Panicle blast, Bacterial panicle blight.

3.1. Adaptive features of Paddy in germination phase and related dysfunction

Germination of seed depends on nature of soil, whether it is infected by microbes or not and environmental condition. Aiming to the problem the most common disease that appears in germination phase is seed rot and caused by fungal pathogen. The spore of fungi i.e. conidia carried by rice seed at the time of germination, the fungus grows which lead dead or weakening of seedling. Besides these factors, germination of seed is more confide in quality of seed use for seedling purpose. For satisfactory farming, germination test is needful in a certain degree [6, 7]. The measurement of seed quality or selection of good seeds is an important factor for successful farming. In Fig. 3 the germination of seed are specified which indicates one of the phase in the formation of plant.



Fig. 3.Germination of Seed.



Fig. 4.Fungal infected Rice seeds.

Fig. 4 illustrates the fungal infection recognized in the rice plant seed. Assurance of harvest plants from pathogens and enhancement of plant efficiency are basic about expanding interest for sustenance to help the developing total population. Rice is a vital staple sustenance edit around the world.

3.2. Adaptive features of Paddy in Vegetative Phase and related dysfunction

Vegetative phase the rice crop is affected by various diseases caused by bacteria, fungi & virus i.e. Crown rot or foot rot (also known as Bakane), Leaf smut, Stack burn or Alternaria leaf spot, White leaf streak, White tip, Bacterial leaf blight, Crown sheath rot, Collar blast, Node blast. The sample image of different rice diseases appear in vegetative phase illustrated in Fig. 5. Besides different diseases, mineral deficiency is a major constraint factor that affect the growth of rice crop. Rice crop required favorable nutritional balance of mineral or macronutrient like potassium, magnesium, nitrogen, phosphorous and zinc for its proper growth. The deficiency of minerals observed in its leaves because of deformity in shape and Color appeared in leaves. The Fig. 6 depicts the mineral deficiency of rice plant like nitrogen, potassium, Magnesium, phosphorous and zinc.

3.3. Adaptive features of Paddy in Reproductive & Ripening Phase and related dysfunction

Reproductive phase starts with emergence of panicle from stem (known as Booting) and ends with full visible of panicle (known as heading). The ripening phase is time of transformation of flower to complete mature grain, suitable enough for harvesting and approximately take 15-40days [17]. In this two phase the diseases as rotten neck blast, White ear head, Panicle blast and Bacterial panicle blight are appear. The Fig.7 depicts the various set of disease that arise in the reproductive and ripening phase of the rice plant.

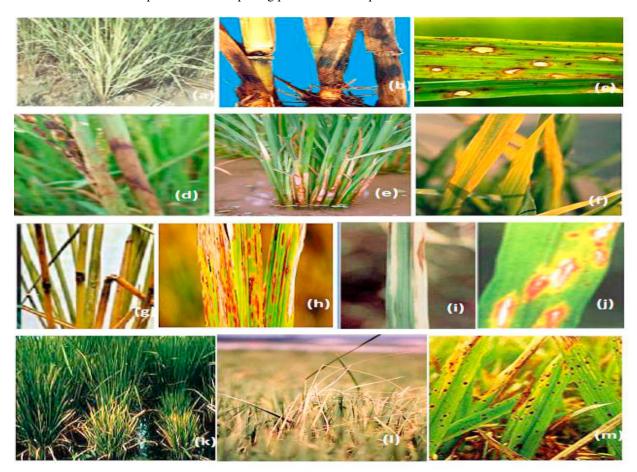


Fig. 5. Different rice diseases in vegetative phase (a) Yellow dwarf disease (b) stem rot (c) stack born (d) sheath rot (e) sheath blight (f) rice tungro (g) node blast (h) narrow brown spot (i) leaf blight (j) leaf blast (k) grassy stunt (l) foot rot (m) brown spot.

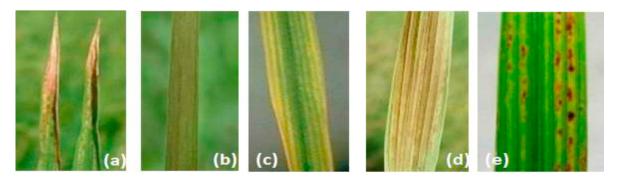


Fig. 6. Mineral Deficiency in Rice Plant (a) Nitrogen (b) Potassium (c) Magnesium (d) Phosphorous (e) Zinc.

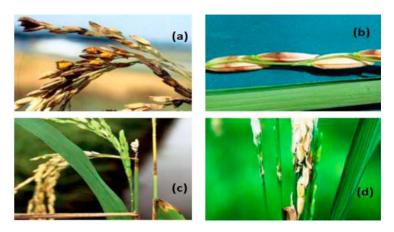


Fig. 7. Different diseases in reproductive and ripening phase (a) False Smut (b) Bacterial Panicle Blight (c) Rotten Neck Blast (d) Panicle Blast.

4. Role of Image Processing in Detecting and Identifying Paddy Diseases

Agriculture industry go about as a significant job in the economic parts. A large portion of the plants infected by variant fungal and bacterial illnesses [18]. Because of the exponential tendency of population, the climatic conditions additionally cause the plant sickness. The significant difficulties of maintainable improvement is to lessen the utilization of pesticides, cost to spare the earth and to build the quality. Exact, precise and early conclusion may diminish the utilization of pesticides. Rice is one of the significant crops developed in India. These days, innovation generally utilized for plant disease expectation. The idea of image processing with information mining advances helps us in following purposes:

- Recognizing infected leaf and stem
- Measure the influenced region
- Finding the shape of the infected area
- Determine the color of infected area

The manual classification and recognizable proof strategies which are being utilized to recognize diverse sorts of leaf disease that are concerned with the human resource. Thereby it exposed to some sort of mistakes since these systems engaged by human contribution. Therefore, advance automated technique like image processing and machine learning is needful to implement for diagnosis of paddy diseases. The systematic steps of image processing are briefing in following sub-section. The content of sub-section includes comparative study on image segmentation, feature extraction, feature selection and classification applicable for plant disease diagnosis. It also outlines the current achievements and limitations.

4.1. Image Acquisition

Image acquisition is the principal central advance in image processing which gives an idea regards to the root of digital images. In addition, this stage includes the pre-processing undertaking, for example, image scaling. Acquisition of image is very testing challenge [19,20]. It require proper gadget like scanner or good resolution camera.

4.2. Image Pre-Processing

Image processing is a procedure to change an input image onto digital frame and performed a couple of process, with the true objective to get a redesigned picture or to separate some significant data from it. It is a sort of signal dispensation which input is image, like video edge or photo and result may be picture or characteristics related with that image [21, 22]. The image pre-processing include filtering, color conversion and detail enhancement of image [23-31]. As per the recent researches that has been conducted over the related image pre-processing techniques carried out for diagnosis of paddy diseases are mentioned in Table 2.

Reference	Year	Objective	Methodology	Parametric Measure	Result
[32]	2018	Noise Reduction	Gaussian Filtering	Accuracy	98.63%
[33]	2017	Detection of plant disease over cotton plant	Machine Learning Regression-Median Filtering	Accuracy	83.26%
[34]	2017	Detection of infected and healthy leaf	Image processing-Weiner filtering	Accuracy	80-99%
[35]	2017	Automated crop disease identification	HSV color extraction	Accuracy	Sensitivity= 98.91% Precision= 99.04%
[36]	2017	Diagnosing plant disease	Gaussian smooth approach	Accuracy	90.96%

Table 2. Comparative Analysis of Different Techniques applied in Pre-Processing Stage.

T. Islam et al. (2018) [32] reported a faster rice disease detection technique. The green pixel masking with Naïve Bayes' classifier used for detection of bacterial blight, rice brown spot & rice blast with accuracy of 89%, 90% & 90% respectively. Sarangdhar et al. (2017) [33] illustrated a SVM of regression system for detection and characterization of different cotton leaf disease. After identification, the name of an infection with its control measures listed to the ranchers utilizing android application. The general arrangement precision of the framework is 83.26%. Rewar et al (2017) [34] introduced a research on the detection and classification of plant disease at its initial stage over the agricultural engineering. This paper proposes an algorithm to diagnosis the diseased leaf using Weiner filtering with different window size i.e. n=10, 20, 30 out of which n=20 gives better detection efficiency and adaptive histogram equalization is used to remove background noise. Different edge detection techniques used to detect the edges of infected and healthy leaf parts in which canny gives 80-99% of accuracy. Hamuda et al 2017 [35] proposed an algorithm which dependent upon color space feature and morphological disintegration and expansion is proposed. This procedure portions cauliflower image from weeds and soil under common light. The proposed calculation utilizes the HSV color space space for segregating yield, weeds and soil. The execution of the calculation evaluated by contrasting the acquired outcomes and corresponding techniques. A sensitivity of 98.91% and accuracy of 99.04% accomplished separately. Nti et al 2017 [36] illustrated a study on the detailed observation of the plant disease validation and the possible preventive measures which are being adapted. The discovery of plant leaf is an imperative factor. Most plant dysfunctions caused by microscopic organisms, parasites, and infections. A framework designed for diagnosis of plant disease in approach of Gaussian smooth filtering and results 90.96% of accuracy.

4.3. Segmentation

Image segmentation meant way toward sectioning default image into its tremendous sections or objects. It is a standout amongst the most troublesome errands in computerized image processing. It used to find desired objects. Segmentation implies segment of picture into assorted piece of same skin tone or having some resemblance analysis implies distributing image into various piece of same components or having some similarity. The segmentation ought to be conceivable using distinctive Algorithms like Otsu' methodology, k-means clustering, conversion of RGB image into HIS model [37, 38]. The following will deliberated as the various possible algorithms to acquire to perform the segmentation parameter in the image processing technique.

Fuzzy C Mean: Fuzzy C-Means is a variation on Q-means, which allows each datum partial membership in each cluster, similar to a mixture model. Segmentation of the affected image is for the most part partitioned the image into various clustering portion, resulting pixels of every locale have comparable dim esteem. The theory of fuzzy sets gives an arrangement of essential speculations and strategies to depict and control dubious or uncertain things. Accordingly, the fuzzy clustering algorithm is likely to consider as an effective strategy that is appropriate for the segmentation of rice leaf diseased image [37-39]. Among them, the fuzzy C-mean clustering algorithm (FCM) is an unsupervised learning algorithm.

K-Means Clustering: Using k-means algorithm at first random two centers or pixels chosen from the infected leaf. The centers represent the faulty and faultless regions of the leaf. It based on similar kind of featured weights. It is to identify the infected cluster by a specific type of disease, of the sample leaf. Now for all the pixels the nearest center is calculated and assigned to the corresponding centers. At this stage, the new two centers calculated using the assigned pixels and the algorithm goes back to the previous step. This iterative process followed until the centers stabilize [37-39].

Thresholding: Thresholding is the basic strategy of segmentation. Segmentation is finished utilizing the thresholding esteems accomplished by the histogram of the input data set. Consequently, on the off chance that the edge discovery is right, limit esteems are right. The downside of this segmentation philosophy is that it is not useful for the intricate pictures. The corresponding segmentation and the optimization process carried out by initiating two processes: image processing and image analysis. In pre-processing stage, the picture converted to a Gray scale and sifted to eliminate false range. The plant is viewed as infected if this number is over the threshold, which, after observational validation.

Accordingly, over the basis of the concurrent study of diagnosing the paddy field diseases many researchers applied various segmentation techniques, illustrated in Table 3.

Reference	Year	Objective	Methodology	Parametric Measure
[37]	2017	Identification of mineral deficiency	Fuzzy C mean and K- Mean Clustering	Accuracy (FCM)= 92%, Accuracy(K-Mean)=85%
[38]	2017	Cucumber leaf spot disease detection	Fuzzy C mean	Average segmentation error=0.12% and exhibited an efficiency accuracy in the detection of the disease
[39]	2012	Segmentation of leaves	K-mean clustering	Higher accuracy rate
[40]	2009	Diagnosis of paddy disease	Variable, Global And Automatic Threshold Based On Otsu Method	Accuracy= 87.5%
[41]	2012	Classification of rice plant dysfunctions	segmentation by Otsu method	Accuracy= 78%
[42]	2015	Detection and classification of plant diseases	Image processing	Higher accuracy
[43]	2018	Rice leaf blast detection	Color image thresholding	The severity of the disease is adequately classified

Table 3. Comparative Analysis of Different Segmentation Techniques for Plant Disease Diagnosis.

P K. Sethy et al. (2017) [37] reported a mineral deficiency identification method for rice crop by use of SVM in association with two feature extraction method such as K-means clustering and FCM clustering. Here the overall identification accuracy of N, P, K, Mg & Zn deficient rice leaf by use of SVM with K-means clustering and FCM are 85.05% and 95% respectively. Bai et al 2017 [38] illustrated a research to extend the classification of cucumber leaf spot disease over distinctive condition. An improved FCM algorithm implemented in the process to detect the presence of corresponding disease symptom over the leaf. Results demonstrate that normal segmentation error was just 0.12%. Valliammal et al 2012 [39] Proposed an examination on plant image segmentation by including nonlinear K-means algorithm. Appropriately, the segmentation procedure starts clustering technique for high-resolution image to raise the accuracy and processing time. Test result demonstrates this new methodology disentangles the procedure to extract shape related highlights and estimations of the leaf for higher precision. Kurniawati et al 2009 [40] presented an examination on diagnosing the system to perceive the paddy diseases. The strategy may incorporate the element extraction techniques focuses on removing paddy includes through disconnected image. The methodology includes changing over the RGB images into binary image utilizing variable, worldwide and automatic threshold dependents on Otsu strategy. Later on S. Phadikar and A.K. Das (2012) [41] reported a methodology for

classification of rice leaf diseases based on leaf complexion. The image samples of 1000 number both healthy & disease affected leaf were collected using Nikon COOLPIX P4 digital camera in macro mode. Then classification is done in two phase. First healthy and affected rice leaf are classified. Then brown spot & leaf blast are classified. The classification is done by two classifier i.e. Bayes' classifier and SVM with tenfold cross validation and achieved accuracy of 79.5% and 68.1%respectively. Rishi *et al* 2015 [42] discussed a technique based on heterogeneous plant disease with feasible and apprehension respectively. Otsu method, image compression, image cropping and image denoising including K-means clustering are the techniques involved in the articulation of the disease images. Bakar *et al.* 2018 [43] proposed a methodology to detect RLB and classify into three category according to its severity. It includes the image pre-processing, image segmentation and image analysis where Hue Saturation Value (HSV) colour space is used. To extract the region of interest, image segmentation is applied, and pattern recognition based on Multi-Level thresholding approach is used.

4.4. Feature Extraction

The feature extraction technique plays an important role in image classification. The features are the main parameter that are involved for classification of image.

Texture Extraction: Texture extraction is determined as the example of information or course of action of the structure with random interval. Accordingly, texture attributes and appearance of object size, shape, thickness, characterization, extent of its basic properties. A fundamental stage to accumulate such features through texture extraction called as texture component extraction. Sequentially, the importance of texture data, texture component extraction is a core limit in various image-processing applications like remote detecting, biomedical imaging and object based image [44].

Color Extraction: Color extraction is an important factor of distinctive classes. Digital image processing produce color estimations which extremely useful when researching the sore for early determination [45]. An image pixel typically addressed in the RGB space, in which the color space at each pixel addressed as a combination of RGB. Other color spaces like the HIS and CIE color space model mostly used in various other segmentation procedures where their benefits and constraints analysed announced and examined. It understood that Euclidean separation of the distinct color are proportional to the variation that human visual impact over CIE Lab color space [46].

Shape Extraction: General descriptors, for example, object count, region of the shape, image dimension, and zone of picture, are essential object to depict the shape of an image. Those qualities are utilized to remove include the sore and level of the injury. Mass Analysis utilized in this examination to compute insights for marked regions in a denoised data, for example, quantity of the protest, region, and edge [47].

Edge Detection: Edges in image are the portions with solid boundaries and object with one pixel then onto the following can make genuine assortment in the picture quality. Edge detection is an image processing strategy for finding the limits inside the corresponding image. It works by distinguishing discontinuities in brightness. Edge recognition utilized for image segmentation and information extraction in regions, for example, picture processing, computer vision, and machine vision [48]. Accordingly, the specific edges used for limit estimation and extraction in the scene. The Table 4 illustrates the existing feature extraction techniques that conducted by many researchers for diagnosis of plant diseases.

Reference	Year	Objective	Methodology	Result
[44]	2007	Texture Extraction	Image Processing	Accuracy= 88.56%
[45]	2013	Detecting unhealthy leaf portion	Texture feature	Accuracy= 94%
[46]	2018	Evaluation of soybean leaf defoliation	Color Extraction	Accuracy= 96%
[47]	2017	Identification of infected leaf	Image extraction- leaf color	Higher accuracy
[48]	2018	Detection of Leaf Disease	Feature extraction-Edge detection	Accuracy= 82%

Table 4. Comparative Analysis of Different Feature Extraction Techniques for Plant Disease Diagnosis.

P. Sanyal et al. (2007) [44] tried to identify different mineral deficient rice leaf by used of multilayer perceptron neural network (MLP-NN) based on color& texture feature. For experimentation the image of healthy & mineral deficient rice leaf were collected (IRRI, Philippines) and 80% sample used for training & 20% for testing. The MLP-NN classifier have 40 hidden layer for texture feature and 70 hidden layer for color feature. The proposed technique successfully identified five types of mineral deficient rice leaf such as boron, iron, magnesium, manganese, nitrogen & potassium with overall accuracy of 88.565. Arivazhagan et al 2013 [45] initiated a study on the significant drop down of agricultural industry with the increasing plant disease. Accordingly, the process is constituted with a four phases of methodologies to be followed such as creation of input color transformation, masking of pixels, threshold removal and finally the segmentation process with 94% accuracy. Liang et al 2018 [46] proposed a research to attain corresponding approaches to evaluate the soybean overhang and leaves utilizing RGB pictures taken in the field. The segmentation results demonstrated an execution of 96% for soybean leaves utilizing Mahalanobis separate characterization. The models used edge detection methodologies to give an appraisal of soybean defoliation. The approval of soybean overhang defoliation and comparing trifoliate leaves defoliation likewise given sensible relationship (R2 = 0.96 and RMSE = 1.85%). Tamilselvi et al 2017 [47] induced a research on categorizing the plant leaf disease based on the color present over the corresponding leaf body. The affected images processed through image pre-processing, segmentation, feature-extraction and clustering. This cluster as a training set for the leaf classification induced to the extensive research. Gajanan et al 2018 [48] proposed a research on the identification of and recognition of plant disease. The diagnosis of the process carried out with respect to an intellectual system induced in the method. Subsequently, the color space, area and the quantity of these spots can determine, as it were, the illness that has humiliated a plant.

4.5. Classification

In a typical classification system image captured by a camera and then processed. In Supervised classification, most importantly preparing occurred through known gathering of pixels. The trained classifier used to group different pictures. The Unsupervised order utilizes the properties of the pixels to bunch them, these gatherings known as group, and process called clustering [49, 50]. The numbers of clusters decided by users. When trained pixels are not available, the unsupervised classification is used.

Support Vector Machine: SVM is a powerful discriminative parallel classifier that models the choice limit between two classes as an isolating hyper-plane. This hyper-plane endeavors to part, one class comprises of the objective-preparing vector, and alternate class comprises of the preparation vectors from an impostor (foundation) population [51, 52]. Utilizing the named preparing vectors, SVM analyzer finds an isolating hyper-plane that reduce the edge of segmentation between these two classes.

Probabilistic Neural Network: PNN dependent on the statistical methodology called Bayesian classifiers. PNN is a feed-forward system involving input, covered up and yield layers. The hidden layer otherwise called example layer. Specifically, design layer comprises of Bayesian classifier. PNN worked after using a non-parametric estimator to acquire multivariate probability and density function. At present, PNN remains the most fitting neural design for discovery of rice leaves contaminated eventually rice leaf roller. PNN design over noticeable and Shortwave Infrared (SWIR) ghostly groups. PCA utilized to change unmistakable and SWIR groups into primary component range. PNN anticipated both ailment and irritation disease. The combinational PCA and PNN results as best indicator of disease infected in rice plant [53-55].

Convolutional Neural Network: CNN is deliberated as an important unsupervised profound learning design that learns 'filters performing convolution' in the image domain. A measure distinction among CNN and ordinary NNs is that CNN roused from retinal fields in the vision framework. Sequentially, CNN is a coordination of natural vision and neural framework. CNN is an intricate design which sets aside impressively greater opportunity to prepare the neurons. Regardless, it has astounding order accuracy is very high. [56].

The Table 5 depict the various researches that performed to mention the possible classifiers implemented to classify the disease over the rice plant. The comparative study proves the efficiency of the implemented methodology over some related parametric measures.

Table 5. Comparative Analysis of Different Classification Techniques for Plant Disease Diagnosis.

Reference	Year	Objective	Methodology	Parametric Measure	Result
[49]	2012	Leaf disease detection	Color extraction	Accuracy I	Disease spot accurately detected.
[50]	2017	Detect the classification of leaf disease	K-Mean Clustering	Accuracy	FCM=95% K-Mean=85.05%
[51]	2009	Detection of rice seed disease	Support Vector Machine	Accuracy	97.2%
[52]	2015	Identification of rice panicle	Principal Component Analysis and Support Vector Machine	Accuracy Raw Reflectar Spectra First Reflectar Spectra Spectra Reflectar Spectra	99.14% a d nce 96.55%
[53]	2018	Rice disease determination	Principal Component Analysis and Neural network	Accuracy of BP ne network	eural 95.83%
[55]	2014	Detection of rice plant disease	Back Propagation And Artificial Neural Network	Accuracy	100%

Chaudhari et al 2012 [49] initiated a research on the disease spot segmentation with corresponding image processing technique respectively. Finally, edge distinguished by executing Otsu strategy on color space to recognize the affected portion. An optimization methodology initiated over the research to establish confusion, plant type and infected spot color space. Subsequently the technique with various infection spots are recognized precisely and results are not influenced by foundation, sort of leaf, and camera. P K. Sethy et al. (2017) [50] reported a mineral deficiency identification method for rice crop by custom of Support vector machine (SVM) in association through two article extraction method i.e. K-means clustering and Fuzzy C-means gathering. Here the overall identification accuracy of N, P, K, Mg & Zn deficient rice leaf by use of SVM with K-means clustering and FCM are 85.05% and 95% respectively. Liu et al. (2010) [51] introduced a crop health detection condition to attain the high quality production at the late growth stage. PCA started to get the past subordinate and crude spectra to diminish the variable reflectance measure. Support Vector Classification (SVC) used to exhibit the strong, empty, and corrupted panicles. The general rightness of SVC with PCS got from the crude first, second reflectance spectra for the testing dataset were 96.55%, 99.14%, and 96.55%, and the kappa coefficients were 94.81%, 98.71%, respectively. Yao et al. (2009) [52] consider an examination on recognizing rice infection, an extensive utilization of image preparing systems and SVM for distinguishing crop disease. The SVM induced to portray rice bacterial leaf scourge, rice sheath revile and rice affect. The results exhibited that SVM could effectively recognize and aggregate these ailment spots to an accuracy of 97.2%. Xiao et al. (2018) [53] initiated a research on the detection of rice blast disease by applying major constituent examination and back propagation neural network (PCA-BP). Initially, the research conducted by processing the harvested image and morphological features extracted respectively. The experimental outcomes demonstrate that the average detection rate of rice shoot dependent on foremost segment identification and

BPNN is 95.83%, which is 7.5% higher than the accuracy rate utilizing BPNN and 2.5% higher than the current SVM technique with high precision in distinguishing rice impact. It can distinguish rice blast rapidly and successfully. To evaluate the sickness propaganda John. Willam Orillo *et al.* [55] proposed a Matlab based model for identification of rice leaf disease using BPNN. The proposed model comprises Image enhancement, image segmentation, and feature extraction. The BPNN used to group distinctive leaf illnesses of rice. The database of the system included 134 diseased image and 94 of these used for training, 20 image for validation and 20 image for testing. Overall, the program proven 100% accurate.

5. Findings and Future Direction for Diagnosis of Paddy Diseases

The manuscript summarizes various studies to automate detection and classification of paddy leaf and panicle dysfunction using Machine learning and image processing techniques. The survey shows, most of the researcher work on leaf disease diagnosis of paddy with a common acceptable framework depicts in Fig.8.Here are some research points, which may help to enhance current state-of-the-art.

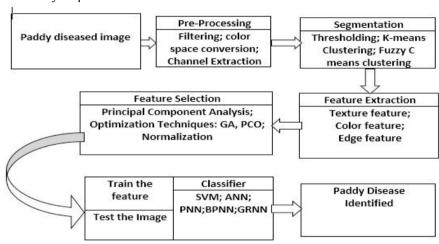


Fig. 8. Suggested Framework for Paddy Disease Diagnosis.

5.1. Development of Real-time Application

To the best of our knowledge, almost all solutions related to paddy disease diagnosis have taken off line images and none of the studies performs in real world scenario with acceptable accuracy. Again very few Web portals and mobile-based applications are accessible to provide an online assistance for a specific disease set of a particular culture for public purpose i.e. Leaf Doctor, Leaf Coder and atLeaf+. However, all the application are only provide the knowledge about some limited dysfunction of paddy. Therefore, it is needful to develop mobile Application and web portal, which directly predict the diseases with on-line images.

5.2. Pros and Cons of Recent Techniques

Since the last decade, all research based on image processing and machine learning are going on paddy leaf disease detection and identification with maximum five variety of diseases. To the best of our knowledge, there is no significant research on diseases appear on other part of rice plant such as panicle and stem. Huang, S. et al. (2015) [57] is only the researcher have work on panicle blast grading using hyperspectral imaging. Besides, conventional imaging, Bhakta, I. et al. (2018) [58] detect the bacterial blight disease of paddy using thermal imaging. The hyperspectral and thermal image capture devices are costly and only meant for research. Again, these devices need a capturing setup and use offline image. Again, Lu. Y. et al. (2017) [56] work on disease identification of paddy by use of convolutional neural network (CNN) and achieved better accuracy with maximum ten variety of diseases. The CNN approach is directly relates to computational complexity and memory requirement issues. Even if adaptation of new imaging devices and new learning technique if it not accessed by public with user-friendly mode,

it is useless. Therefore, one possible solution to this is to design full automatic system, keeping availability specification of mobile & web.

6. Conclusion

This paper review almost all paper between the years 2007 to 2018. This survey help researcher for collecting knowledge about different dysfunction of paddy with respect to their growth stage. Again, this paper give brief idea about pre-processing, segmentation, feature extraction, feature selection and classification techniques. Various issue related to paddy diseases diagnosis discussed and a common acceptable framework suggested. Here also briefing the other imagining techniques like hyperspectral and thermal imaging. These imaging systems directly depend on quality of image, number of training images and features of sample. If any inappropriate in setup of capturing system, it directly hamper its performance. Again, adaptation of CNN requires advance architecture with computational and memory resources. One possible solution to this is an intelligent blend of the expert system concept into the computer vision and machine learning techniques. An attempt to develop such a system may also be of great interest to researchers in this domain.

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