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Detection and classification of rice plant diseases based on the combination of deep learning and clustering algorithms: A survey

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Abstract

Rice, fed more than 50% of humans, rice is one of the most important plants in agriculture. Diseases can decrease the quantity and quality of this product, and crop losses from such diseases occasionally range between 30 to 60%. Plant diseases have always been one of the worst threatening situations for farmers. While the leaves of most plants have a unique disease characteristic, it still takes human eyes to spot them. This review also summarizes the outperformance of these approaches in solving various types of problems. This review discusses the constraints of existing studies and outlines prospective guidelines toward the significant enhancement of robust and well rice leaf disease detecting methods. Recent computer vision and Deep Learning developments introduced a disease classification system from leaf images, in modern agriculture. Identifying what type of disease the actual plant suffers from, a deep harvest cycle drives the world farmer to lose 37 percent of all the production due to non-accessibility of the details. (Source: ScienceDirect) The correct identification of disease for rice leaves is important as it can save on costs by enhancing the provision of noticed horticulture and managing the crop's future by maintaining a sound food-transferring system. This is done using a CNN model.

Keywords: Deep learning algorithms, Types of rice plant diseases, detection, and classification.

1. Introduction

Globalization is one of the more direct consequences of smart agriculture, which has become an essential lifeline for people worldwide. There are many farmers who grow crops according to the soil and weather parameters. Still, challenges like crop infection by pests & diseases, lack of water, and natural calamities will impact their yield. With the advancements in science and technology, various scientific technologies are increasingly being used to solve these problems. Other than that, it also helps to increase crop production without any need for intervention from experts, which is mainly used to detect plant diseases, especially leaf disease, at an early stage [1].

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A prediction of plant diseases under agriculture is one of the trends that need thorough research because of the growing need for disease forecasting in agriculture. Awareness of the significance of agriculture and food security has increased in recent years, resulting in an improved understanding of crop diseases and their classification. Rice is the third most consumed food in the world, being a staple food for billions of people in countries with a large population like China, India, and Pakistan. It is classified as being in the rice group, including wheat, corn, and cereal. Rice is the food for over 3 billion people owing to its vitamin, mineral, and nutrient richness [2]. While the rice grown in different regions varies from each other, all of them go through three separate growth stages before they can be harvested. Rice fields cover approximately 15% of all farmlands used for agriculture across the globe. Although its production is mainly in eastern Pakistan and India, production has sharply decreased in recent years due to several reasons such as the impact of diseases on rice plants which is one of the most important factors contributing to this decline [3]. These include some of the most devastating, Bacterial Leaf Blight, Leaf Smut and Brown Spot which significantly impact yield and grain quality (Rathore et al. Although different, these diseases appear as black spots on the plant leaves. Most of these diseases can be detected early to prevent damage. Unfortunately, the lack of follow-through with monitoring and general disease knowledge among newer farmers contributes to this problem [4]. These diseases can occur in rice plants at any stage, but continuous observation and monitoring are essential to prevent the transmission of this disease. Around the globe, smallholder farmers suffer from huge crop losses caused by plant diseases. Farmers can take necessary measures to avoid the spread of this disease and save their crops when they are predicted before spreading[5]. In this paper, we propose to develop an end-to-end model which predicts diseases on rice leaf images using a pre-trained VGG19 network and its residual blocks. We also investigate different pre-trained models like ResNet50 and InceptionV3, which use residual blocks to reach even better prediction accuracy than VGG19, which is used alone.

Residual blocks are an architecture that describes the difference between inputs and outputs of a convolutional neural network (CNN) layer typically used for image classification. This is a part of input where we can pass another convolution layer, and the network approximates the expected output better. Residual blocks also enable the prevention of overfitting and increase prediction accuracy. Thus, if you input a dog in our model, which was supposed to have learned how to take the features of a cat and produce an approximate output closer to what word is supposed to be attached, such as "cat", the residual block will help it come close enough [6]. Disease classification is useful for various aspects of humans, such as those in wheat and citrus fruits; However, this study implements rice, classifying leaf diseases. We chose VGG19 instead of ResNet50 and InceptionV3 because its architecture is much simpler than the other models since it has fewer layers. The VGG19 model does not predict diseases, however, the weights of the pre-trained VGG19 can be trained to detect the disease. Rice leaf disease photographs obtained from the UCI machine learning dataset are used in this research. Disease prediction is performed using the VGG19 network with pre-trained weights, and the input of a feature vector extracted from diseased leaf images is used as a region of interest (RoI) in the prediction model. Prediction of Rice leaf Disease with Higher Accuracy of the Mode[7].

Agriculture is a fundamental function of humans. It provides food for human beings, fiber, and other raw materials necessary for the various dimensions of subsistence network that support human function. Rice is one of the most important food crops in the world, and many physical factors like soil types, climate and weather conditions, irrigation, geography, seed type, and biological factors influence its yield [8].Plant diseases could significantly affect the environment and economy by reducing crop yields, losing food sources, or using chemical pesticides, damaging the ecosystem. Rice is susceptible to several diseases that reduce the quality and quantity of production. Bacteria, fungi, and viruses cause major crop diseases of rice; specific examples, such as Brown spot, Blast, Leaf Smut, and Bacterial leaf blight, are very destructive, leading to vast yield losses. As these diseases are rising, protecting these rice crops is vital for food security. Embracing cutting-edge technologies is crucial to improving rice yield [9].

Existing approaches for disease detection are reference-based, expert-dependent, labor-intensive, time-consuming, but error-prone. On the contrary, automatic methods for detecting rice leaf diseases afford many advantages[10]:

- Expert knowledge is required when using traditional methods which can sometimes result in mistakes, on the other hand automation provides consistent and reliable results with minimum human intervention.
- Because automation minimizes manual inspection processes, it cuts labor and equipment costs by depending on cheaper hardware and software.
- Disease identification before visual damage to crops helps farmers prevent damage, so automation in this area can help recognize the disease visually early.
- Automation encourages precision agricultural practices which target the situation instead of applying pesticides to all regions, minimizing their usage and environmental damage.
- In areas where agricultural specialists are scarce, automated systems help less-experienced farmers by providing practical advice[11].

2 Deep Learning offers the following benefits:

- Existing rice leaf disease identification methods lack expert knowledge and are most error-prone. Deep learning enables more competent results with lesser human intervention.
- Deep learning helps identify diseases before visible healthy symptoms appear, so it is critical to control diseases to get them under the early stages.
- In precision agriculture, deep learning assists in fending off diseases by using fewer pesticides on varied areas and illness-affected regions[12].

Different species of bacteria cause bacterial diseases of rice. Table 1 lists the most prevalent rice bacterial diseases, their causal agent, symptoms, and how they affect the rice plant.

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Table 1. Review on bacterial diseases of rice: etiology, symptoms, and importance[13]

Disease name	Causal bacterium	Symptoms	Impact
Bacterial Leaf Blight	Xanthomonas oryzae pv. oryzae	Necrosis with yellow halos due to soaking effect spread out into amorphous shapes	Affects photosynthesis
Bacterial Leaf Streak	Xanthomonas oryzae	Water-soaked lesions that are long and narrow. Gray-white centers also develop in lesions	Affects overall plant health
Bacterial Panicle Blight	Burkholderia glumae	Panicles that are infected, do not develop.	Reduced yield
Bacterial Wilt	Burkholderia gladioli	Discoloration of vascular tissues, Leaf wilting	Plant death in severe cases
Sheath Brown Rot	Pseudomonas fuscovaginae	Lesions on the sheaths that have absorbed water	Reduced grain filling

Several fungal diseases caused by fungal pathogens affect the different parts of the rice plant, such as seeds, leaves, stems, and grains, as in Table (2).

Table 2. An overview of rice fungal diseases: A review on its causes, symptom and effects [14]

Disease name	Causal virus	Symptoms	Impact
Narrow Brown Spot	Bipolaris oryzae	Roundish to oval patches on foliage	Reduced photosynthetic efficiency
Bakanae Disease	Gibberella fujikuroi	Breaking the impact of rice seedlings elongation by foolish seedlings	Reduced yield potential
False Smut	Ustilaginoidea virens	Smut balls on rice panicles	Reduced grain quality
Sheath Blight	Rhizoctonia solani	Irregular lesions on leaves, sheaths, and blades	Causing lodging, decreasing the quality of grains
Brown Spot	Cochliobolus miyabeanus	Lesions which are small and circular to oval	Affects photosynthesis

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Disease name	Causal virus	Symptoms	Impact
Leaf Scald	Rhynchosporium oryzae	Center of brown with yellow halos around the outside, colorless, oval shaped lesions on leaves	Affects photosynthesis
Neck Blast	Magnaporthe oryzae	Lesions on the leaves, sheaths and blades are irregular	Disrupts the development of healthy panicles
Stem Rot	Sclerotium oryzae	Dense small round to oval foci	Reduced nutrient transport, impacting plant stability
Foot Rot	Sclerotium oryzae	Please write in the English language. Oval lesions on leaf blades forming yellow halos around brown centers	Stem collapse and lodging, weakening plants and hampering nutrient uptake
Blast	Magnaporthe oryzae	Results in lodging, causes a reduction in grain quality	Severe leaf damage, sterility, grain losses

Several virus species cause viral diseases of rice and are transmitted by arthropod vectors, nematodes or mechanically by humans, as show in Table (3)

Table 3. An overview of rice viral diseases: A review on its causes, symptoms and effects [15]

Disease name	Causal virus	Symptoms	Impact
Black Streaked Dwarf	Black Streaked Dwarf Virus	Leaves with dark lines, elongated and slow growth	Shortened panicles, reduced yield
Yellow Mottle	Rice yellow mottle virus	Leaves turning yellow and mottled	Affects photosynthesis
Grassy Stunt	Rice grassy stunt virus	Stunting, yellowing of plants	Reduced tillering
Stripe	Rice stripe virus	Leaves with yellow strips, weakened plants	Reduced yield
Ragged Stunt	Rice ragged stunt virus	Stunting, reduced tillering,	Irregular growth of the plant
Tungro	Rice tungro spherical virus	Leaves turning yellow, dwarfism, and decreased panicle size	Reduced yield

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3 General Methodology of detection and classification of Rice disease:

The overall architecture of the rice plant disease detection and classification is as follows, to begin with. Image Acquisition First, the RGB color images are acquired from the digital camera with a necessary quality of pixels input Images Pre-Processing and Segmentation. The first step is improving the image data that potentially contain noise and other undesired distortions, in these processes, environment augmentation, Gaussian cloud reduction, and standardization concerning size. There are several Steps used in disease detection. The process starts with data acquisition, which means capturing diseased images utilizing apparent devices such as cameras, mobiles, and image sensors (Figure 1).

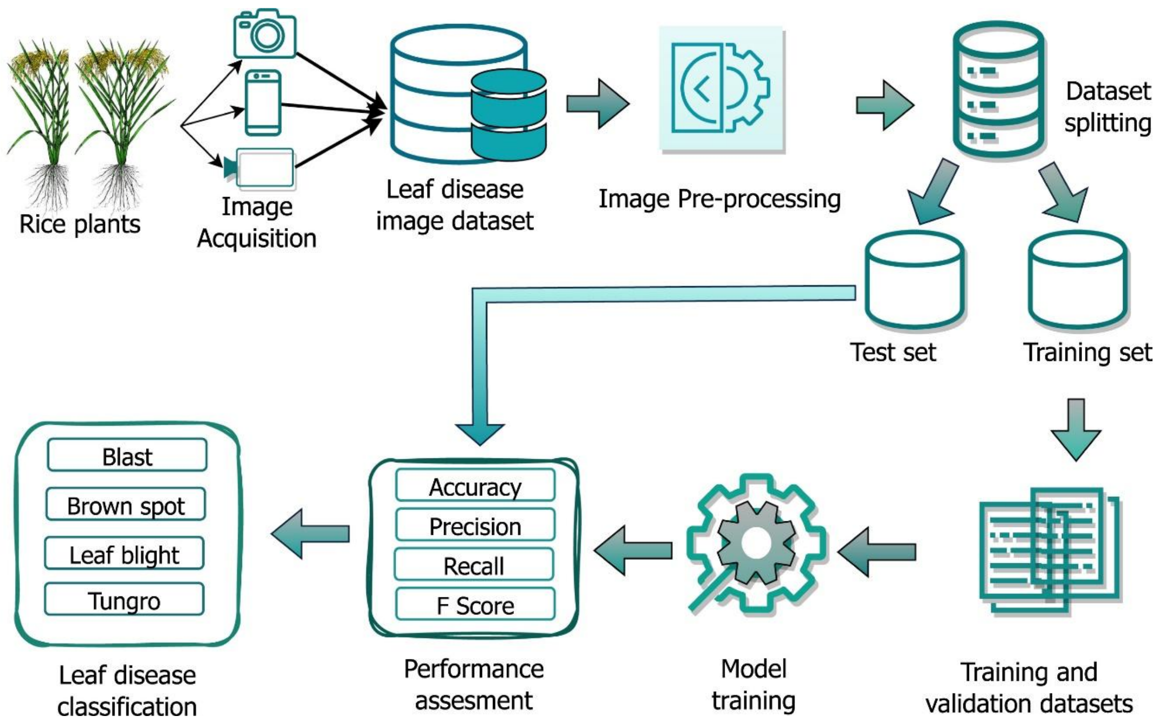

Fig. 1. Typical block diagram for rice disease detection and classification [16].

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4 Literature Review

To identify rice diseases, Phadikar and Sil (2008) used digital images of rice plants affected by disease in East Midnapur and South Bengal, India. Image Acquisition: Take snap images from the diseased rice plants with a digital camera. Preprocessing: Improving images increases brightness and contrast. Conversion to Hue, Intensity, Saturation (HIS) genotype for better segmentation. Segmentation: A bi-level thresholding method based on entropy is used to differentiate the parts of infected leaves, followed by an 8-connectivity algorithm for boundary detection to outline the area infected. Boundary Based: The dimensions of the segmented images ranged from 300 on 300 to 1500 on 1500 pixels. Spot Recognition: Recognizing spots on the affected leaves for disease severity assessment. SOM neural net-based classification for images using the RGB values of spots detected. With 92% accuracy in classifying rice diseases, the study highlights the potential of image processing and neural networks techniques to assist in agricultural diagnosis [17].

Takuya and Yutaka (2018) developed a rice disease classification system with artificial intelligence, focused on Rice Blast. They photographed healthy and infected rice leaves at 200x200 pixel resolution, resulting in a 40 k RGB (Red Green Blue) values dataset. Principal Component Analysis (PCA) was used to reduce the computational load and learning time by converting the data into two dimensions. This created two-dimensional features which proved helpful in learning and classification. Precision test was executed from leave-one-out cross-validation using a nonlinear Support Vector Machine (SVM) with RBF kernel to assess which learning information could be usefully integrated. Irrespective of features, the pixel values were extracted using the SVM classifier, which was 95% effective for rice leaves misunderstanding with Rice Blast[18].

Komal et al. Meanwhile, in 2019, a review paper was published on detecting and classifying images of rice diseases based on an image collection from the Rice Research Institute Lahore-Pakistan and different places in Punjab, India. It looked into three diseases – Bacterial Leaf Blight, False Smut and Brown Spot. Their methodology was to pre-process the acquired images and convert color images to greyscale using a function in EM GUI. They used Scale-Invariant Feature Transform (SIFT) both for feature detection and to obtain regions of the images. They developed a vocabulary through Bag of Words (BoW) where the BoW model makes words out of SIFT-detected features for image classification. Finally, K-means clustering was performed with the number of clusters as 80. A Brute-Force matcher [19] was then employed to determine and match each feature's descriptors (Closest Descriptor). A Support Vector Machine (SVM) was trained with training normalized histograms, optimizing parameters for efficiency or accuracy. Results are developed by tuning the values for Gamma and Nu parameters in the SVM to offer

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optimum results. The accuracy of classifying the three rice diseases using precision and recall metrics in the system reads 94.16%[20].

Sanyal and Patel (2008) suggested that rice leaf blasts and brown spots be used as study objects to detect rice leaf illness. For 400 photos used in this article, we had 80% for training and 20% for testing. A feature vector was computed for each pixel in an image based on its 7*7 neighborhood. The Multilayer Perceptron classifier was fed 70 hidden nodes of color characteristics and 40 hidden nodes of texture features. Both the color and texture features correspond with their classification results. Categories in MLPs and Quantitative analysis gave 89.26% accuracy[21].

Libo and Guomin (2009) rice bacterial blight disease survey, Brown Spot disease Related Tags:high -throughput, genomic, farm Apply: rice other activity Type field[01]Research on Rice Leaf Diseases Applied]]. Using the collected images, they converted from RGB color space to XYZ reference color space and then Lab color space. The R, G, and L components were calculated from the images, and they found that L displayed better background-kill effects than any of the above-mentioned three kinds of image component (specifically between lesions and their background), besides which it also had a strong noise reduction effect. As a result, R,G, and L values served as inputs for the layer neurons of the neural network containing a single output layer and three hidden layer neurons calculated by the method (upper limit on hidden neuronal) on multilayer perceptron. Using the images, they could identify Brown Spot on rice leaves. Over 400 images were analyzed, and an accuracy of 90% was achieved in classifying the disease [22].

Orillo et al. (2014) conducted a study using images of rice diseases obtained from the International Rice Research Institute in Los Baños, Laguna, Philippines. They focused on three specific diseases: Brown Spot, Rice Blast, and Bacterial Leaf Blight. Their methodology enhanced the images with noise reduction and contrast adjustment before being converted from RGB into HSV (Hue Saturation-Value) color space. The image intensity was optimized using Otsu's method. Subsequently, the processed images were thresholded to be made into binary images, employing Blob Extraction to filter out noise. Extracting Diseases from Leaves The segmented leaf images were transformed into LAB color space, and an A-color plane was used to extract the diseases. These images were then further converted into binary images using histogram equalization with two bins (black vs. white), constituting a mask that allowed for identifying and removing healthy parts of the leaf tissue. The diseased areas were then used for feature extraction. These extracted features were instrumental in training the backpropagation neural network, allowing the system to achieve an impressive 100% accuracy in identifying the rice diseases[23].

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Ramesh and Vydeki (2018) Pathogen detection and classification based on machine learning algorithm The study object is rice blast. The collected images have been processed, and the RGB color space needs to be changed to HSV for this study. K-means clustering is employed to calculate the mean distance of each cluster vs its corresponding mean and cluster means to facilitate photo segmentation. The averaged value, standard deviation, and GLCM were calculated during feature extraction to refine the ANN training. This work has used a 3 hidden layer ANN architecture with input layers as N and an output.[24].

Prajapati et al. VisionSati and Abiyw (2017) detailed detecting and classifying rice plant diseases. The images used in this study include images of three specific diseases, Leaf Smut(BH), Brown Spot(BD), and Bacterial Leaf Blight (BLB), which are obtained from Shertha(Gandhi Nagar, Gujarat, India). All acquired images were first changed from RGB color space to HSV color space and only the Saturation component of the HSV image was taken. Next, a mask was created from the initial image and masked onto the hue, value, and saturation of the HSV image, which makes up to RGB, thus helping remove/replace the background.

Following the background removal step, the image was transformed back to HSV colour space, and the K-means algorithm was applied to the hue channel. Finally, thresholding was applied to remove the green regions that could remain in the image so only the infected pieces of the leaf remained. Color, shape, and texture features were extracted from these infected parts. After calculating these features, Min-Max normalization was performed, and the Support Vector Machine (SVM) classifier was trained based on them. The classifier's performance was evaluated on its ability to identify dead leaves.

It also compares Differential segmentation using three techniques: color space-based K-means clustering, a statistical approach, the LAB color space, level-based statistics, and Otsu's segmentation algorithms[25]. Of these methods, K-means clustering based on HSV color space gave the best accuracy of 96.71%[26].

Chowdhury et al (2019) employed a convolutional neural network (CNN). This helped the researchers in selecting nine rice diseases and pests of interest, among which six major rice diseases viz, Brown Spot, Neck Blast, Bacterial Leaf Blight, Sheath Rot, False Smut and Sheath Blight; as well as three pest varieties: viz., Brown Plant Hopper (BPH), Stem Borer and Hispa. The study included nine classes: five for disease, three for pest, and one for healthy plants. Images were gathered from Bangladesh Rice Research Institute. A plant's condition is a healthy plant or a diseased plant; if diseased, the disease may be identified by logging onto the UCI machine learning repository domain. One of the significant advantages of this work is the identification of diseases both inside and out of the plant (e.g., in leaf, stem, and grain). The paper compares Five CNN architectures, VGG16, ResNet50, Inception V3, InceptionResNetV2, and Xception. VGG16 performed best with fine-tuning, transfer learning from scratch.

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But they are big and have too many parameters to run on mobiles. To overcome this, the paper introduced a new architecture of CNN called as Stack CNN. Stacked CNN was proposed to achieve small model size with still high accuracy classification by doing training in two steps. Stacked CNN using 95% classifying accuracy for both diseases and pests[27].

Lu et al. ten (2017) Specific Rice Disease Detection Out of Ten Bacterial Leaf number 4 (now a fourth classifier, where three had been before): Brown Spot, Rice Blast, False Smut, Bakanae, Sheath Blight, Sheath Rot and Bacterial Sheath any Seedling Blight any Bacterial Wilt any Among them, 500 images of these diseases were collected from Heilongjiang Academy of Land Reclamation Sciences in China.. We compressed the images to 512×512 pixels for speeding up the processing, the ZCA whitening method has been set to break the correlation between data. These images were then annotated with the ten diseases. In the preprocessing step, from these 500 images we randomly selected 10,000 patches of size (12x12), thus we have image patches with corresponding feature map. To extract low- and high-level features, the study created a three-layer hierarchical CNN architecture with layers following directly on top of one another using stochastic pooling to reduce variance. The multiclass classification problem was tackled using softmax regression, and a supervised learning algorithm was used to train the network. The experiments indicated that, when using a 10-fold cross-validation strategy, the stochastic pooling method achieved better recognition performance (95.48% accuracy) than mean pooling, max pooling and other techniques. The final part of the study focused on different convolutional filter lengths, evaluating 5x5,9x9,16x16, and 32x32 filters once again achieving optimal performance with a 16×16 filter (93.29%). With an accuracy of 95%, the proposed CNN (Convolution Neural Network) outperformed other models including BP Method, Support Vector Machine (SVM), and Particle Swarm Optimization (PSO)[28].

Bhagyashri and Gajanan (2017) Images used from Rice Research Center, Karjat, Maharashtra state of India. The effort was concentrated on two diseases, Brown Spot and Leaf blast, wherein 40 images of each disease were collected. All the images were pre-processed and converted from RGB color to Lab color space. K-means clustering algorithm was used for image segmentation to increase the accuracy. Following that, three features were extracted: area, grey level co-occurrence matrix (GLCM), and color moment. The genetic algorithm was implemented for feature selection to narrow down these features and streamline the computational complexity and dimensionality. We compared two classifiers: Support Vector Machine (SVM) and Artificial Neural Network (ANN). Results confirm that SVM classifier performed better than ANN classifier by achieving overall accuracy (92.5%) vs (87.5%) respectively[29].

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Wan-Jie et al. (2019) Sharik et al. has prepared the first data set of images for rice blast disease, maintained as the Rice blast disease image data set. Data Source o Institute of Plant Protection, Institute, Jiangsu, China & Agricultural Sciences Academy, Nanjing, China. This research determined Rice Blast as the work unit. In this work, the images are taken out by 128*128 pixels, padded into cut moves with a stride of 96 pixels, and rice blast lesions are charged with experience in the appropriate full scale. In total, they found 2906 positives and 2906 negatives. The paper includes a data set related to the study based on that data set, and a t-SNE qualitative rating from the experimental outcome. The results of the evaluation state that CNN is a more effective classifier, which has better discriminative and representative power than the (LBPH) Local binary pattern histogram, as well as the Haar-WT (Haar wavelet transform). More over, a qualitative comparison of CNN with SoftMax, CNN with SVM (Support Vector Machine), LBP (Local binary pattern)with SVM and Haar-WT with SVM for rice blast classification indicated that achieved accuracies accurately by two classifier model were 95.83%, 95.82% respectively which best than this two classifier Comparative study about the efficacy of different Suite image preprocessing methods using ML algorithm/S NLP scores posed in Arabic languages[30].

Taohodul et al. (2018) fetched images from the International Rice Research Institute, giving a topic. The study chose the subjects of rice blast, rice bacterial blight, and rice brown spot. The background and an unnecessary component of the obtained image are eliminated in this topic to limit processing time. to remove the leaf's green section (not affected), between the RGB pixels mask with a blue pixel on the green pixel. The next task on the leftover image is to focus on real RGB only, which were later used to obtain RGB percentages in the disease portions. We color the pixel to four classes: Color A, Color B, Color C, and Color D. We compute the proportion of each color class related to the Overall Number of Pixels under the diseased area[31].

Gayathridevi and Neelamegam (2018) published a limited survey of Rice diseases from Thanjavur, Tamil Nadu, concentrating on Leaf streak, Leaf blast, false smut, Brown Spot, and Bacterial leaf blight. The dataset was a quantifier dataset, comprising 500 fresh images of healthy and infected rice plants obtained from Tamil Nadu Rice Research Institute (TNRRI), Aduthurai, Thanjavur, India. Initially, the median filter denoised and resized images are smaller in file size. K-means clustering was employed to categorize the photos. Classifier training involved feature extraction using hybrid methods like SIFT, DWT and GLCM on the segmented images. In this paper, four classifiers (KNN, ANN, Bayesian classifier, and Multiclass SVM) were compared for their performance. It was observed that Multiclass SVM had the highest accuracy of 98.63% surpassing all other classifiers[32].

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Maohua et al. Rice blast disease recognition is based on images collected by Nanjing Agricultural University (2018). Principal component analysis and neural networks were employed to analyze the diseases. I created four typical rice blast lesions in the rice--Schizotrichum spp. To reduce noise and combat the effects of inhomogeneous lighting, both healthy and infected rice plants' images were processed by converting them. Both HSI and YCbCr are topological mappings from the RGB color space. Rice blast lesions of four types differ in color and morphology. In our approach, since various characteristics were exploited to find the optimal feature combination, a fusion combination of color feature extraction for segments, morphological feature extraction for leaves, and texture feature analysis was applied to substantiate classification for advanced precedes exactly treated with rice leaf segment affected by rice blast disease. After PCA for feature vector dimension reduction, we put those vectors into the Backpropagation Neural Network (BPNN). On the contrary, comparison of recognition rate between PCA − BPNN and PCA−SVM showed that the former has superior performance with an accuracy of 95.83%[33].

Faranak Ghobadifar et al. (2016) presented a sheath blight detection framework using SPOT satellite images as a primary data source. The RS-based approach for pest infestation detection can lower food production expenses, reduce environmental impact, and soften possible attempts to enhance natural enemies before the problem develops. SPSS software and ENVI4 were used for data analyses, considering applications related to precision agriculture. 8 -- Visualizer -- Environment for visualizing images. Comparing the image data from early growing seasons to the late growing season indicated differences between each class. Some specific indices like RVI14, SDI24 and SDI14 were successfully differentiated healthy from diseased rice plants and thus can be considered valuable indicators of sheath blight detection using remote sensing methods[34].

Shahzad Amir Naveed et al. (2010) Isolation of Bacterial Blight resistance in different Pakistani rice germplasm within Basmati rice varieties. Collection and sowing of seeds. Seeds were collected from other research institutes and sown in pots for analysis. The DNA was purified and screened for polymorphism with molecular markers linked to the xa5 gene. Of these 88 germplasm lines, 45 showed the presence of the xa5 gene (240bp amplification) like MB66, MB33, MB2, and MB57. However, amplification of expression was not seen in 43 lines. In another study investigating the xa5 gene, similar results were found when 10 Basmati varieties from Pakistan were tested, which also did not show positive for this gene[35].

What has been detailed in previous works will be summarized to focus on specific details, as in Table (4).

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Table 4. Table summarizing the entire review

Reference article	*Rice* Diseases	Total number of images	Image Pre-processing	Image segmentation	Feature extraction	Classifier	Accuracy (%)
Phadikar and Sil (2008)	Rice Blast and Brown spot	300	Contrast and Brightness enhanced, RGB Color space to HSI color space	Entropy-based bi-level thresholding	Boundary detection algorithm and Spot detection algorithm	Self-Organizing Map (SOM)	92
Takuya and Yutaka (2018)	Rice blast	167	RGB		Principal Component Analysis	Support Vector Machine	95
Komal et al. (2019)	Bacterial Leaf Blight, False Smut, Brown spot	400	RGB Color space to gray scale color space	K-means Clustering Method	SIFT algorithm, Bag of Words, Brute Force matcher	Support Vector Machine	94.16
Sanyal and Patel (2008)	Rice leaf blast and Brown spot	400	RGB		Color texture extracted	Multilayer perceptron classier	89.26
Libo and Guomin (2009)	Rice Brown Spot	400	RGB Color space to Lab color space		RGL components of images	Back Propagation Neural Network	90
Orillo et al. (2014)	Brown Spot, Rice blast, Bacterial leaf blight	134	RGB Color space to HSV color space, Histogram equalization	Otsu’s Method, Blob Extraction	Blob Extraction	Back Propagation Neural Network	100
Prajapati et al. (2017)	Leaf smut, Brown Spot and Bacterial Leaf Blight	120	RGB color space to HSV color space, Background removal	K-means Clustering Method	Min–Max Normalization, GLCM	SVM	96.71
Ramesh and Vydeki (2018)	Rice blast	300	RGB Color space to HSV color space	K-means Clustering Method	Mean Value, Standard Deviation, GLCM	Artificial Neural Network	99
Chowdhury et al. (2019)	Brown spot, Neck blast, Bacterial leaf Blight, Sheath Rot, False Smut, Sheath blight, Brown Plant	1426	RGB			Stacked CNN	95

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	hopper, Stem borer, and Hispa						
Lu et al. (2017)	Brown Spot, Rice blast, false smut, Bakanae, sheath blight, sheath rot, bacterial sheath, Seedling Blight, Bacterial wilt, Bacterial leaf blight	500	ZCA whitening method	PCA		Deep Convolutional neural network	95.48
Bhagyashri and Gajanan (2017)	Brown Spot, and Leaf Blast	80	RGB Color space to Lab color space	K-means Clustering Method	GLCM	SVM & ANN	92.5 & 87.5
Wan-Jie et al. (2019)	Rice Blast	5808	RGB		Haar-Wavelet LBPH	CNN (With Softmax) & CNN (With SVM)	95.83% & 95.82
Taohodul et al. (2018)	Rice blast, Rice bacterial blight, and Rice brown spot	60	RGB	Masking Green Pixels		Gaussian Naive Bayes	90
Gayathridevi and Neelamegam (2018)	Leaf streak, Leaf blast, False smut, Brown Spot, Bacterial Leaf Blight	500	Median Filter	K-means Clustering Method	SIFT, GLCM, DWT	Multi Class SVM	98.63
Maohua et al. (2018)	Rice blast lesions	387	RGB Color space to HSV and YCbCr color space	Otsu's Method	Principal Component Analysis	Back Propagation Neural Network	95.83

5 Discussion and comparison

The summary table provides some key insights, particularly regarding the significance of image acquisition and preprocessing. Captured images are in RGB space color, thus some preprocessing techniques are needed to get better results. Clearly, from this study, median filter selection for RGB images will profoundly impact the segmentation process. K-means clustering is the most widely applied segmentation algorithm among all the studies, and it shows the effects of other classifiers on accurately identifying rice diseases. For instance, the backpropagation neural network (BPNN) gained a 100% accuracy from Orillo et al. (2014), but this was a considerably smaller dataset (134 images only). From

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it is mentioned that for large datasets, BPNN works better and relatively provides higher accuracy. Furthermore, in Wan-Jie et al. (2020), the convolutional neural network (CNN) with Softmax was the best performing classifier reported in their study using a classification accuracy of 95.83%. 's (2019) study. What makes this study different is that the authors compiled their own dataset consisting of 5,808 images quite big compared to others reviewed. Their results also showed that CNN with Softmax gave a better result than CNN with SVM, and it is a benchmark for accurately classifying rice diseases.

6 Challenges in Diagnosing Rice Diseases

Laboratory methods are time-consuming and expensive. Conventional laboratory techniques, including biochemical analyses, are often insufficiently rapid and require specialized instruments and trained personnel. This creates inaccessibility for much of the farmer's population, especially in developing regions[36].

There are some main challenges in rice disease diagnosis, which are linked with the complexity and variability of diseases as well as the restriction of traditional diagnostic methods. Key Challenges: Dependence on Skilled Labor Conventional techniques rely heavily on skilled farmers or agronomists to visually identify symptoms. This methodology is subjective and can cause misdiagnosis, particularly in extensive disciplines where non-specific indications might be disregarded[37].

Detection of Limited Performances: Although helpful, existing optical sensing technologies suffer from large sample sizes and can lose accuracy in some complex environmental situations. In addition to noise suppression and feature extraction issues, accurate disease identification has become more complicated[38].

Data Explosion: The explosion of data generated through imaging and sensing technologies can overwhelm traditional methods of analyzing it. High-throughput data necessitates sophisticated computational methods to interpret and make disease predictions[39].

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7 Future Outlook Using Machine Learning

Deep learning (DL) and the associated ML technologies have potential ways to overcome these rice disease diagnosis-related problems: Improved Accuracy during Detection. In terms of identifying rice diseases from images, different types of models such as the Convolutional Neural Network (CNNs), have been implemented with high accuracy [81–83]. Studies show that R-CNN and other models can accurately detect diseases like rice blasts and brown spots over 96% of the time. Automated Diagnosis: ML algorithms can provide instant detection of diseases to mobile applications, allowing farmers to take a picture of their crop for immediate checking. It opens up access to expert level diagnostics, allowing non-specialists to identify issues earlier. Hybrid Approaches combining multiple methods allows for enhanced diagnostic functionality using more than one ML technique. Hybrid models, combining deep learning and traditional machine learning approaches, could advance recognition rates for several rice diseases. This method uses the best of several modalities to create a tool with higher diagnostic accuracy. Economical Alternatives: Low-cost multispectral imaging systems are being developed to provide cost-effective solutions for plant disease detection. This would help to minimize reliance on high cost laboratory tests while preserving the accuracy at high levels12. Widening Research: The use of ML to detect rice disease is an ongoing study whose research expansion has been made fast over the search. These studies aim to design and create novel lower-parameter models with better accuracy that have great potential to minimize the cost involved in deploying disease management strategies within the agricultural context.In summary, Rice disease diagnosis suffers considerable drawbacks such as dependency on skilled labor, time-consuming and traditional methods; however, the distant future of machine learning technologies looks bright. These innovations could revolutionise the way we manage diseases in rice, resulting in improved precision and automation, a blending of methodology and cost-saving solutions.

8 Conclusion

Rice disease diagnosis and detection for healthy crop production ensure food security. Methods of this type have a well documented lack of accuracy, efficiency, and scalability because the detection is performed using human personnel visualisation of symptoms and interpretation [8]. Such methods require a lot of time and money, which are not very accessible to most farmers; especially in regions with few resources.

New developments in machine learning (ML) and deep learning (DL) technologies appear to offer solutions to these issues. Research has shown that DL models attain a high degree of accuracy in identifying rice diseases, including leaf blast, brown spot, and bacterial blight. A case in point is the accuracy that some models have achieved, which varies between 91% and 96% on different datasets. This shows that these technologies can play a significant role in enhancing diagnostic accuracy.

This capability can be embedded in automated systems using ML and DL so that a disease can be detected quickly and accurately from an image captured by a smartphone or drone. This gives farmers access to timely information and reduces dependency on expert knowledge. Moreover, ensemble formation of different algorithms has become more apparent to improve diagnosis performance further.

Nevertheless, data quality and the generation of large datasets still put obstacles before perfect results. Such systems are still under development, for instance, to enhance their efficacy through improved data acquisition by employing high-resolution imaging and advanced spectral analysis capabilities.

To summarize, though conventional rice illness diagnosis approaches are constrained by the availability of in-abundance labour and assets, the future is set to change with machine learning and deep learning technologies. These innovations will transform the detection and management of rice diseases by providing farmers with precise, efficient, and affordable solutions globally. Further research in this area will likely lead to significant improvements in crop health monitoring and disease control.

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