International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V70I12P237
Volume 70 Issue 12, 392-405, December 2022

Review Article

Machine Learning Approaches for Automatic Disease Detection from Paddy Crops - A Review

M. Karthick[1], D. Vijayalakshmi[1], Malaya Kumar Nath[1] and M. Mathumathi[2]

[1] *Department of ECE, NIT Puducherry, Karaikal, India.*
[2] *Department of CSE, K. Ramakrishnan College of Technology, Trichy, Tamilnadu, India*

[1]*Corresponding Author : karthickm.nit@gmail.com*

Received: 22 August 2022 Revised: 13 December 2022 Accepted: 20 December 2022 Published: 24 December 2022

Abstract - *Crop disease diagnosis is a significant area of concern which needs to be addressed for agricultural development and the flourishing nation's economy. Diagnosing plant disease with conventional methods is a long time-consuming task that necessitates a great deal of effort and knowledge. The prerequisite demand for developing nations is the automatic detection and categorization of crop diseases. Automatic detection of crop disease conditions aids in preventing damage at an early stage, resulting in increased yield efficiency. Advanced computer vision, digital image processing, deep learning and machine learning techniques deliver accurate results and information. The exact, accurate, and real-time data on crop health, disease categorization, and infection location pave the way for determining the best disease management strategy. This review has conducted an in-depth analysis to assess the feasibility of employing cutting-edge technologies of deep learning and machine learning models to identify rice plant diseases. Primarily, various potential infections and diseases, along with their causes and symptoms on the paddy crop, are investigated. The review paper elaborately focuses on a detailed examination of the various actions required for paddy crop disease diagnosis and classification using artificial intelligence-based machine learning and deep learning techniques. A number of online databases for paddy disease prediction have also been offered. Various obstacles and potential research directions in the use of machine learning and deep learning for crop disease detection are further discussed.*

Keywords - *Automatic disease detection, Deep learning and machine learning techniques, Rice leaf diseases, Paddy crop diseases.*

1. Introduction

Booming diseases and infections extremely affect the quantity and quality of crops, which negatively influence the nation's economy of agricultural dependant countries. Rapid diagnosis of crop disease conditions aids the prohibition of damages at the very earlier stage and further leads to improved yield efficiency. Around seventy percentage of the people in India depends on agribusiness, which subsidizes approximately 17 % of the overall gross domestic product of the nation [1]. India stands second in the world for paddy cultivation with 116.42 million metric tons yield [2]. Insects, weeds, microorganisms, and environmental conditions like biotic and abiotic stress are some of the causative agents of crop diseases and infections. Among the different factors, nearly 30 – 33 % of the overall loss of crop yield is due to pests [3]. The conventional technique of analyzing crop disease through a farmer's naked eye has several obstacles. Farmers can identify known crop diseases by their experience. However, they are limited to new infections, so following an unworthy control strategy leads to whole-crop deterioration. In addition, it is not possible for farmers to continuously monitor large-scale cultivations. Crop disease detection and classification by artificial intelligence (AI) based techniques is a prerequisite for society. The enriched technology helps detect new diseases and infections that are invisible to the naked eye through in-depth exploration. Advanced deep learning techniques provide accurate results and information to decide what, when, and how to act. Further, these novel techniques enhance the overall crop yield and quality by reducing labor costs and time consumption. The precise, accurate and real-time information related to crop health, disease classification and infection location paves the way for figuring out an optimized disease control strategy. This paper mainly focuses on various aspects of AI-based machine and deep learning technologies to diagnose paddy crop diseases. Section 2 discusses the different diseases found in paddy crops and their symptoms. This finds the route for detection and disease classification. The algorithm behind each step of deep learning techniques, from image acquisition to disease classification, is elaborated in Section 3. The AI-based crop disease detection and categorization are discussed briefly in Section 4. The datasets for rice plant disease detection are presented in Section 5. Various challenges behind each framework in the utilization of machine and deep learning technologies for automatic disease diagnosis are presented in Section 6. Section 7 provides future prospects, and Section 8 concludes the paper.

2. Common Types of Rice Plant Diseases

The most consumable food across India and all over the world is rice. More than forty types of genetically similar diseases infect rice plants. The most common diseases that easily spread and attack rice plants are rice blast, brown spot, narrow brown spot, bacterial leaf blight, leaf smut, sheath blight and tungro disease [4]. These diseases are represented in Table I. Fig 1 illustrates various diseases of paddy crops. For accurate detection and location of disease infection, it is much essential to understand the structural aspects of mature rice plants. The rice plant comprises grain particles, a sheath, a leaf, a stem, and a root [5]. Diseases associated with each part of the rice plant and the symptoms and causes are discussed below [6].

2.1. Rice Blast

The most common destructive disease of the rice plant is rice blast caused by the fungus *Magnaporthe Grisea* that occurs on the leaf and sheath. The infected leaf is noted with green-grey spots layered by a dark green outline [5]. During the late matured stage, the spots become the elliptical structure and the dark green color outline changes to reddish brown. Certain spots or lesions are diamond in shape. The spots or lesions at a later stage proliferate completely, leading to whole leaf deterioration.

2.2. Bacterial Blight of Rice

Xanthomonas Oryzae bacteria cause bacterial leaf blight. The leaf becomes pale yellow colour, and the occurrence of a translucent spot on the leaf is the most common symptom. As the infection progresses, death of the plant happens, preceded by cascading events such as rolling, drooping and withering of leaves [5].

2.3. Tungro Disease

Bacilliform virus affects the leaf and sheath of the rice plant and causes Tungro disease. The leaves appear yellow or yellowish orange in colour [7]. The tungro disease spreads extensively from the leaf's tip to the bottom. The rust-coloured spot and stripy appearance attract the plant hoppers, thereby decreasing the overall quality and yield of the crop.

2.4. Brown Spot

Brown spots usually affect the leaf and sheath of the rice plant. Brown spot in leaves mostly results due to nutrient-deficient and poorly drained soil [5]. At the seedling stage, tiny spherical yellowish-brown or brown-coloured lesions infect the coleoptile of the rice plant. The lesions at earlier stages appear dark brown, which later converted into reddish brown with grey-centered spots.

2.5. Narrow Brown Spot

A narrow brown spot (1-1.5 mm wide and 2-10 mm long) is caused by fungus. It infects the leaf, sheath and panicles of the rice plant. The lesions join together and get enlarged to make an entire region of infection [5]. The spots on the glumes are much larger when compared to leaves. The brown lesion and net-like pattern can be noticed at the leaf sheath.

2.6. Grain Discolouration

The grain's normal colour changes to brownish-white during the panicle initiation stage. Grain discolouration indicates poor quality, leading to decreased yield. Discoloured grains are much exposed to storage infection fungi such as *Fusarium spp and Aspergillus spp* [7].

2.7. False Smut

This disease is believed to indicate good crop production due to favorable weather nature and is caused due to fungus *Claviceps virens*. The disease infects only a few grains in the panicle, leaving the rest undamaged. The smut ball of velvety spores of diameter 1 cm occurs on the rice grain of the infected plant [7]. The development of the velvety spores leads to the enclosure of floral parts. Underdeveloped spores are concealed by a membrane and are characterized by flattened, smooth yellowish colour. Similarly, leaf smut caused by fungus is noted, with black spots all over the leaf [5].

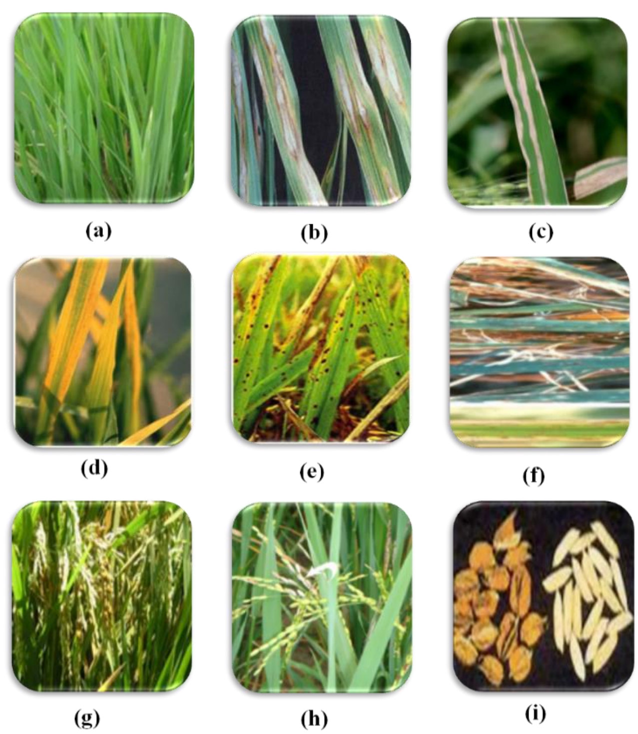
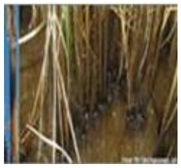


Fig. 1 Images of various paddy crop leaf diseases: a) healthy leaf, b) rice blast, c) bacterial leaf blight, d) tungro disease, e) brown spot, f) narrow brown spot, g) Healthy grain, h) grain discolouration, and i) false smut.

Table 1. Common types of rice plant diseases

S.NO	Disease	Image	Nature	Effect	Affected part
1	Rice blast		Green grey spots layered by dark green outline, Elliptical spots and dark green to reddish brown in later matured stage	Whole leaf deterioration	Leaf and sheath
2	Bacterial blight		Pale yellow leaf, translucent spot on leaf	Rolling, drooping and withering of leaves	Leaf
3	Tungro disease		Yellow or yellowish orange leaf, rust colored spot with stripy appearance	Decrease the overall yield and quality	Leaf tip and lower part
4	Brown spot		Tiny spherical yellowish brown, brown colored lessions	Decreases the yield	Leaf and Sheath
5	Narrow brown spot		1-1.5 mm wide and 2-10mm longnarrow brown spots,net like pattern on the discolored leaves	Leaf discoloration, decreased crop growth and yield	Leaf, sheath and panicles
6	Grain Discolouration		Brownish white color during panicle initiation stage	Decreased headrice recovery and yield	Rice Grain
7	False smut		Velvety spores on the rice grain, underdeveloped spores characterised enclosure by flattened, smooth yellowish color, later into greenish black color	Occurs during reproductive and ripening stage, enclosure of floral parts, both grain qulity and yield gets affected	Grain
8	Stem blast		Greyish brown lesions in the nodes	Grain loss at milky stage and poor quality grains, collapses the panicles, cause stem litting	Above ground parts, stemnodes, neck, collar and panicle

9	Stem rot		Small black reting strcture named scletoria appears during tillering stage, black lesions on the sheath leaf, Sheath die and slough off, culmpenetration	Grain quality and panicle size gets reduced	Leaf sheath, culm
10	Stem dwarf and grassy shunt		Stunting, excess tillering, rusty leaf spots, leaf turn yellowish green to whitish green, later become soft and droop	Reduced leaf size, small panicles with unfilled grains	Stem, Leaves, panicle and grains
11	Root rot		Root Lessions, abnormal thin and tall plants	Infected Seedings, yellowish green leaves, crop death	Lower part and above ground part of plant

2.8. Stem Blast

Node infection causes grayish-brown lesions in the nodes and collapses the panicle. These infections result in grain loss at the milky stage and poor-quality grains at the later stage [5]. The blast does not cause stem splitting. Stem borers cause it at the boring point. Both the stem borers and the blast led to the occurrence of whiteheads.

2.9. Stem Rot

The infected culms get accumulated by several black and white tiny sclerotia and mycelium. Chalky grain and unfilled panicles are produced because of the infected culms [7]. The leaf sheath close to the water level contains small black colour lesions that expand as the disease progresses. Tiller death arises when the infection becomes severe.

2.10. Stem Dwarf

Stem dwarfism makes the affected plant leaves change into pale green and undersized plants. The leaves further become soft and droop slightly due to excessive tillering [7]. The growth of the root is drastically affected, and chlorosis happens that spreads to the leaf sheath. Towards the vein, parallel shape leaf streaks are noted.

2.11. Stem Grassy Shunt

The infected plants have upright stunted growth with grassy and rosette tiller appearance. The leaf size is greatly reduced and appears yellowish green even after adequate nitrogen fertilizer application [7]. Panicle production is lost due to tiny rusty leaf spots. These patches altogether merge and result in the formation of mottled leaf blotches.

2.12. Root Rot

Root rot causes the infected plants to look abnormal, thinner and slightly taller than the normal ones. Infected seedlings die at an earlier stage, even before transplanting, due to excess root lesions [5]. The leaves are yellowish-green and pale in appearance. White chalky growth is developed at the lower part or above the ground node of the plant.

3. Image Processing Stages for Automatic Crop Disease Detection

As mentioned above, crop diseases reduce the productivity of rice fields. So there is demand for the detection of these diseases at early stages. But manually detecting/identifying the diseases by the farmer is tedious, time-consuming and sometimes inaccurate due to ignorance. So automatic detection of paddy crop diseases and infections is the most demanded research to enhance crop yield and quality. Automatic detection, the most significant tool for close and continuous monitoring of infections, greatly reduces labour requirements. Computer vision, DL, and ML techniques are utilized for automatic disease detection techniques that rely on image processing. IoT sensor-based image acquisition from the farm field and image processing for feeding computer vision machine-learning models involve several sequences of stages [8]. Fig. 2 represents the various stages associated with automatic disease detection, which are discussed further below.

3.1. Image Acquisition

Image acquisition or image capturing is the most crucial step necessary for feeding machine-learning models to train automatically and detect paddy crop infections. Visual images obtained from the paddy field using a high-resolution digital camera are transformed into an array of binary records [9].

Fig. 2 Automatic detection and classification techniques for paddy crop diseases

Other variants, like smartphones, are also utilized nowadays for image acquisition. Desired image formats like png, jpg and tiff are frequently obtained and used for the next level stage of image preprocessing. Image enhancement techniques are further carried out to meet the requirements of machine feeding. Optical system-based energy generation, energy reflection from the target object surface, and sensor-based energy measurement are the three steps commonly associated with image acquisition [10, 11].

The overall performance depends on the quantity and quality of the image captured from IoT devices [8]. Training the models for paddy disease detection and classification can also be performed using a freely available and paid version of existing datasets containing healthy and unhealthy images of paddy crops. The available dataset for obtaining rice diseases image is the kaggle dataset and research center that provide the path to cross-refer other datasets IRRI and BRRI [12]. Further hyperspectral imaging systems can be used for obtaining image data.

3.2. Image Preprocessing

Pre-processing of images is performed to meet the requirements of benchmark standard features on machine learning models. Image size, colour and resolution adjustment are the most common preprocessing tasks carried out for benchmark standardization and computational cost reduction[13]. A mathematical or statistical method is generally incorporated in preprocessing stage to enhance image appearance and its geometric characteristic. Image preprocessing is trailed by image segmentation and feature extraction to improve system performance [14]. The prominence of the target area by augmenting image intensities is also an added benefit of preprocessing stage [15].

Image cropping, image colour enhancement, image colour space alteration, removal of noise, minimization of distortion, and hue saturation value (HSV) conversion methods are some of the extensively used preprocessing techniques [16, 17, 18]. To improve the speed and efficiency of preprocessing, screening and background exclusion method is performed [19]. To emphasize the human sensing feature, the hue saturation intensity technique is developed for subsequent analysis [20]. Switching between desired pixel values for obtaining precise information is tinted based on intensity gradient adjustment by several filters like the Laplacian filter, Fourier transforms filter, and minimal and maximal filters [21, 22]. Gaussian dispersion enables picture smoothening using average local pixel values [23]. Diseased plant images are upgraded by the histogram equalization technique to maximize the image quality by stressing shaded areas [1]. To identify the diseased part of leaves, image segmentation is performed prior to feature extraction [18].

Image processing is critical in agriculture for crop disease prediction, weed identification, classification of vegetables and fruits, precision agriculture, and animal monitoring. Numerous factors affect the image quality acquired, includ- ing non-uniform light, environmental variations, and relative motion. Image enhancement is necessary to maximise the quality of images to extract the finest information for further disease diagnosis and yield improvement. Numerous ways to increase the overall image contrast have been discussed in the literature. Several examples are brightness-preserving histogram equalization [24], recursive sub-image histogram equalization [25], contrast-limited adaptive histogram equalization [26], and residual spatial entropy-based contrast enhancement [27].

Histogram equalization (HE) is prone to over-stimulation, noise amplification, and undesired artefacts. By clipping the histogram at a predetermined value, contrast-limited adaptive histogram equalization overcomes the constraints of HE [28]. Two-dimensional histogram-based approaches enhance contrast by considering spatial information in addition to pixel intensities [27]. Among the numerous techniques, the gradient-based enhancement algorithm (GCE) performs the best in terms of visually distinguishing features [29]. The performance of CE approaches is evaluated using a variety of performance metrics. GCE approaches are superior because they minimize artefacts, retain high-frequency regions (edges), and avoid over-enhancement. Enhanced agricultural photos enable access to the most minute facts about a crop, animal, or piece of land.

3.2.1. Segment by Otsu Threshold

The threshold value from grey-level images is converted into binary images using the Otsu threshold algorithm. The pixel value above the threshold is considered 1, and the pixel value below the threshold is regarded as 0. The Otsu algorithm involves threshold setting, pixel clustering based on a threshold value, median calculation of each cluster, median difference squaring, and obtaining the product of pixel numbers in a single and another cluster [2, 31].

3.2.2. Region Growing Segmentation

The prime step of region-growing segmentation is seed point selection that processes at the pixel level. Pixel intensity, similarity, colour, greyscale, and adjacency are the most common factors affecting region growth. Region-growing segmentation involves following steps such as entire image segmentation to obtain pattern cells, developing pattern cell relation with adjoining cells, Region addition based on the intensity value similarity, and Continuous region development by examining adjacent regions [32]. The aforementioned steps are further repeated until all cells are added to the corresponding Region [2].

3.3. Image Useful Feature Extraction

Feature extraction is the most significant process behind automatic disease detection. Texture, morphology and colour are the important feature descriptors retrieved from pictures. Better results are obtained using morphological features compared to texture and colour features [14]; colour histogram, colour moment and colour correlogram are the techniques followed to generate colour features like gabor texture and colour moments [2]. GLCM provides desired properties like a moment of inertia, entropy, energy, homogeneity, and contrast [33].

Wavelet packet decomposition method, discrete cosine transform, FT difference operator, speed up robust feature (SURF), scale-invariant feature transform (SIFT), histogram of oriented gradients (HOG), and pyramid histogram of visual words (PHOW) are other techniques, generally incorporated to enhance the effectivity of AI-based disease diagnosis [8]. Similarly, genetic algorithms (GA), modified self-organizing feature maps (MSOFM) and back propagation neural networks (BPNN) also generate promising output in automatic crop diseases identification based on the colour feature [34]

4. Techniques used for Automatic Crop Disease Detection

Disease detection is a simple process, whereas a complex disease classification process is many prerequisites. Electing appropriate classifiers relevant to the problem is the critical stage for disease classification. This involves using various classifiers categorized into supervised and unsupervised methods. [2, 8]. Table 2 represents the various techniques associated with automatic paddy disease detection and classification and the datasets used in the literature.

It is observed from the literature that the researchers classified a maximum of 4 paddy diseases. Except few, the publicly and locally available datasets have limited images. Optimized deep neural network with Jaya optimization algorithm proposed by Ramesh et al. attains the highest accuracy of range 90.57 – 98.9% for various rice plant diseases. Various techniques and datasets are used in the literature to detect and categorise paddy crop disease automatically. The techniques available in the literature are discussed below.

Prajabati et al. [52] developed a system for identifying rice diseases in three classes (leaf smut, brown spot, and bacterial leaf blight). Centroid-based K-means clustering is utilized for portioning the affected sides of the leaf. The segmented outputs were further enhanced by eliminating the green pixels from the diseased part. This information was fed into the support vector machine for classification. The method attains an accuracy of 93.33% and 73.33% for the training and testing dataset, respectively.

Yang Lu et al. [51] proposed DCNN that uses Alexnet architecture for automatic rice disease classification for 10 classes and displayed 95.48% accuracy. Suresha et al. [50] developed a global threshold method and KNN classifier to classify two classes (rice blast and brown spot of rice disease). For segmentation, the RGB images are transformed into HSV images, and attributes like area, perimeter, major axis and minor axis were considered. An accuracy of 76.59% was achieved with this method.

Ghyar et al. [48] used GLCM, area, and color moment for feature extraction. Selected features were extracted using a genetic algorithm and segmentation by K- means clustering algorithm that provides higher accuracy and fast computation. Accuracy of 92.5% and 87.5% was achieved for SVM and ANN classifiers.

Ramesh et al. [47] preprocessed the disease images by performing the color conversion using Lab and HSV color space. They used K-means clustering for segmentation. From the segmented image, the features are extracted by finding the mean, standard deviation, and GLCM. ANN is used for classification. The authors obtained an accuracy of 90%. Kodama et al. [4] proposed automatic disease detection for rice blasts. PCA was used to improve the learning rate and classification by the SVM classifier. An accuracy of 90% was achieved.

Islam et al. [46] proposed a technique for automatic disease detection in which the acquired images are preprocessed, followed by green pixel masking, RGB percentage extraction, and finally, classification using Naive's Baye classifier. Classification accuracy of 89%, 90%, and 90% was achieved for rice blast, bacterial blight and brown spot classes, respectively. Sethy et al. [45] compared the performance of 13 CNN models in transfer learning for classifying rice diseases such as tungro, bacterial blight, brown spot and rice blast. Resnet50 with SVM is used for classification. This method attains an F1 score of 0.9838 with a training time of 69 seconds.

Table 2. Techniques and datasets used for automatic detection and classification of paddy crop diseases

S. No	Reference	Technique used	Dataset	Performance accuracy (%)	Remark
1	Shrivastava et al., 2021. [51]	Support vector machine	619 images collected from the paddy field Chhattisgarh – India	94.65	Rice blast, Bacterial leaf blight, sheath blight
2	Sharma et al., 2020. [52]	Analysis of colour, morphology, structure and texture using baye's and minimum distance classifier	150 images collected from the paddy field	Baye's:81.06 MDC:69.53	Sheath blight, stem rot, False smut, leaf blast
3	Ramesh et al., 2020 [53]	DNN, along with Jaya optimised algorithm	650 images of paddy leaf collected from a paddy field, Tamilnadu-India	98.9	Sheath rot, bacterial blight, rice blast and brown spot
4	Sethy et al., 2020 [46]	Transfer learning and support vector machine	5932 images of rice leaf captured from a paddy field, Odisha-India	SVM:98.38 ResNet50:98.38	Tungro disease, brown spot, bacterial blight and rice blast
5	Li et al., 2020 [54]	Faster Region-based and deep convolutional neural network (Faster RCNN and DCNN)	5320 images collected from a paddy field in China	65.9 -87.2	Brown spot, sheath blight and rice stem borer
6	Rath et al., 2019 [55]	Radial basis function neural network	300 images obtained from the paddy field	95	Rice blast and brown spot
7	Shrivastava et al., 2019 [56]	Convolutional neural network, SVM	619 images collected from the paddy field	91.37	Bacterial leaf blight, Sheath blight, rice blast and healthy leaf
8	Hasan et al., 2019[50]	Deep convolutional neural network, SVM	1350 images collected from BRRI, BRKB, plantix and IRRI datasets and paddy field	97.5	Tungro disease, red stripe, sheath blight, leaf smut, brown spot, bacterial leaf blight and false smut
9	Zhou et al., 2019 [31]	Faster Region-based convolutional neural network	3010 images collected from Hunan rice research institute	98.26	Rice blast and bacterial blight
10	Chen et al., 2019 [57]	Convolutional neural network	5267 images collected using the Internet of Things	89.4	Rice blast
11	Jie liang et al., 2019 [58]	Deep convolutional neural network and SVM	5808 images captured from a paddy field in China	95.82	Rice blast
12	Sethy et al., 2018 [59]	Support vector machine	16 images from the paddy field	86.35	Leaf blast, bacterial blight and brown spot
13	Islam et al., 2018[60]	Gaussian naive baye's method	60 images captured from rice field	90	Bacterial blight, brown rice spot and rice blast
14	Kodama et al., 2018 [4]	Support vector machine	167 images collected from the paddy field	90	Rice blast and healthy crops
15	Ramesh et al., 2018 [61]	Artificial neural network	300 images captured from a paddy field, Tamilnadu-India	90	Rice blast and healthy crops
16	Ghyar et al., 2018[62]	Support vector machine	60 images collected from rice fields, Maharashtra-India	92.5	Brown spots, rice blast and healthy crops
17	Prajapati et al., 2017 [47]	Support vector machine	120 images collected from a paddy field, Gujarat-India	73.33	Bacterial leaf blight, leaf smut and brown spot

18	Suresha et al., 2017 [63]	K-nearest neighbourhood	330 images collected from a paddy field, Karnataka-India	76.59	Brown spot and rice blast
19	Lu et al., 2017 [64]	Deep convolutional neural network	500 images captured from a paddy field in China	95.48	Brown spot Bacterial blight, bacterial sheath rot, false smut, rice blast
20	Prajapati et al., 2016 [65]	Support vector machine	145 images obtained from a paddy field, Gujarat-India	-	Leaf smut, bacterial blight, brown spot and healthy crops

Cheng et al. [43] have discussed the ricetalk method for diagnosing rice blast disease. Ricetalk incorporates IoT and artificial intelligence for disease detection and management strategy. The working model consists of the weather input device, agritalk engine, agritalk server, and agritalk GUI. Sensors connected through IoT gather data and are processed by the ricetalk engine, and the prediction results can be accessed through mobile phones. In the agritalk architecture, database and machine learning cyber devices communicate through the ricetalk engine. The cyber databank device preprocesses the data, and execution of the AI model is performed by the machine learning cyber device. The prediction results of the artificial intelligence model will be sent to the alert device. The farmers will decide on control measures based on the alert message received. This method utilizes a spore germination mechanism for feature extraction. An accuracy of 89.4% was achieved using CNN.

Zhou et al. [31] proposed rapid rice disease detection based on FCM-KM and a faster R-CNN method. An accuracy of 96.71%, 97.53%, and 98.26% was obtained for detecting rice blast, bacterial blight, and sheath blight disease. Hasan et al. [42] proposed a hybrid network using DCNN integrated with SVM to classify nine types of rice diseases and obtained a prediction accuracy of 97.5%. Shrivastava et al. [41] proposed color feature-based rice disease classification. The performance of seven classifiers was evaluated, and an accuracy of 94.65% was obtained using SVM. Four classes (rice blast, leaf blight, sheath blight and healthy crops) were classified.

Rath et al. [40] proposed a rice disease detection technique for two classes (brown spot and rice blast) using a radial basis function neural network. The captured images were preprocessed, and features were extracted using the gabor filtering method. Performance measures were found to be 95%, 97%, and 95% for accuracy, precision, and recall, respectively. Li et al. [39] proposed a DCNN backbone network for video detection of rice disease classification for three classes (brown rice spot, rice stem borer, and sheath blight). High-defined videos were captured from the paddy field and were converted into frames. These still images are used by faster RCNN for detection. The custom DCNN system provided better recall and precision than YOLO v3.

Sethy et al. [38] proposed a deep feature of Resnet50 with SVM for rice disease classification of three classes (bacterial blight, brown spot, tungro and rice blast). This method provides an F1 score of 0.9838. Also, they compared the performance with 11 CNN models using transfer learning. The proposed system of the in-depth feature of Resnet50 with SVM outperformed significantly.

Ramesh et al. [37] proposed a deep neural network along with Jaya's optimised algorithm for the classification of sheath rot, bacterial blight, rice blast and brown spot diseases. Initially, the captured images are preprocessed, converting RGB to HSV images. The binary images were extracted for the affected and unaffected parts of the leaf. Comparitive analysis was done using ANN, DAE, and DNN. The authors obtained an accuracy range of 90.57 – 98.9% for various rice plant diseases.

Researchers mainly used K-NN, GA, SVM, DT, ANN, and CNN for disease classification of paddy crops. The description about the above classification methods is mentioned below.

K-NN: The conventional non-parametric algorithm that can resolve classification and regression problems is K-NN. The comparability measure between each stored accessible case and the characterized new case is calculated for the K-NN technique. Euclidean equation is used to calculate the K-NN distant function [53]

Genetic Algorithm: This method is established by the imitations of natural selection and genetics [2]. The principle of the fittest surviving is the foundation of GA. GA technique is normally engaged to provide the best solution for search and optimization issues. The unfit generations are forced to stay out. The result named to chromosome is expected to be the corresponding source of solution to solve the existing issue. Fitness is measured based on the degree of correctness, quality and accuracy of the solution generated. The average fitness usually improves as the generation evolves, and the most suitable is selected among various generations. GA increases the classifier performance, decreases the computations, and is used for feature extraction [54]. The most desired chromosomes from the ancestor genetic code to the following generation aid enhancement of ancestor chromosome fitness.

SVM: A non-probabilistic algorithm generally employs hyperplane separation used for regression and classification purposes [55]. SVM utilizes the kernel method for a broader range of applications in classification problems. Sev- eral classification problems use familiar kernel functions like linear, polynomial, nonlinear, RBF, and Gaussian kernel functions [56]. There are two types of SVM, known as linear SVM and nonlinear SVM. Linear or straight-line SVM segregates the available image into different classes. Nonlinear SVM is employed when the images cannot be classified employing linear lines [2]. A multi-class SVM classifier is employed when the number of classes is more.

Decision tree: It is the most powerful and efficient algorithm for regression and classification problems and widely finds its applications in medical diagnostics, recognising character and speech [57]. Multiple decision trees are used in the random forest for classification and regression problems. By using the value-test attribute and by dividing the source into subsets, a tree is said to be learnt. The derived subsets are partitioned repeatedly and hence called recursive partitioning. The recursion is performed till the segment has the same parameter without altering the parameter estimates [2]. The random forest, which uses multiple decision trees, summarises all its outcomes during training time for classification and regression problems.

4.1. ANN

It comprises several nodes called neurons connected together, which act as parallel distributed processing systems. ANN, a feedforward network, uses a learning algorithm to adjust weights and biases to produce the required network output [58]. The neurons can either be fired or not fired based on the activation function. ANN comprises three layers: input layer, hidden layer and output layer.

4.2. CNN

For each upcoming problem, deep learning reduces the mission of creating a new feature extractor. Without human intervention, CNN-based classifiers are easily trained using raw images. CNN, the feedforward neural network, provides noteworthy results in artificial intelligence, robotics, automation, agriculture, audio, and video and image recognition. The data gets transferred from the input to the output layer. The architecture of CNN is comprised of input, hidden and output layers. The output layers are fully connected to each other. Rectified linear unit, Convolution and Pooling are the hidden layers stacked together to develop each individual network. The input layer is fed with an array form of the image pixel value [59]. Hidden layers, like the convolution layer, act as the feature extractor and perform the feature extraction task independently. Between the filters and the image matrix, the convolution operation is executed. Rectified linear unit sets all the negative pixels to zero, thereby imposing non-linearity by an activation function. Various filters minimize the dimensionality of the features in the pooling layer. The dimensionality reduction is performed and forwarded to the output layer. The fully connected output layers classify the images into various predefined groups.

The number of Epochs, learning rate and batch size, are some parameters on which CNN depends. The CNN model's learning pace and training performance can be enhanced using an optimizer such as Adam. The drawback of CNN includes over-fitting due to fewer training data points. Data augmentation or multiple image generation from a single image is introduced to overcome the obstacles. The CNN model enactment is highly dependent on architectures such as GoogleNet, ResNet, MobileNet, SqueezeNet, AlexNet, Inception and Xception [60, 61]. GoogLeNet architecture is recommended for better classification of plant diseases. [62].

5. Rice Disease Image Datasets

To achieve effective results, deep learning necessitates more training images [63]. Various publicly and locally available databases test the classification accuracy of different paddy crop disease detection methods. These databases mainly consist of paddy crop diseases Bacterial blight, blast brown spot, and tungro are four types of rice leaf diseases represented in the mendeley data collection, which has 5932 number images [38]. Kaggle is one of the largest databases comprising images related to rice and its diseases, around 13GB. 120 jpeg photos of diseased rice leave added in the Kaggle dataset mentioned in the literature authored by prajabathi et al., 2017, the images are divided into three categories: leaf smut, bacterial leaf blight, brown spot, based on the ailment. Each class contains 40 photos [49]. Many research also used the Plantvillage dataset, which includes images that were primarily acquired via a systematized approach to help produce homogeneous backdrops [64]. 1 to 24 MPixels resolution images were captured using a variety of digital cameras and smartphones. An NVIDIA Quadro K620 Graphics Processing Unit was used for the studies (GPU). Two distinct CNNs were instructed, one using the original unedited pictures and the other using full images with the background manually removed, to examine the effect of the background on the outcomes [63]. A repository of 33,026 rice disease images were collected to construct a computer-aided diagnostic model. 9,354 photographs depicted rice leaf blast, 6,417 images depicted rice sheath blight, 6,727 images depicted rice bacterial stripe, 4,876 images depicted false rice smut, 3,894 images depicted rice neck blast, and 1,758 images depicted rice brown spot illnesses [65].

Table 3. Rice Disease Datasets And Their Weblinks

S. No	Name of the dataset	Classes of rice disease
1.	Rice leaf diseases dataset	Bacterial leaf blight- 40, Brown spot- 40, Leaf smut- 40
2.	Rice plant diseases image dataset	Brown spot-523, Healthy leaf -1488, Hispa-565, Leaf blast-779
3.	Leaf rice disease	Rice blast-80, Bacterial blight-80, Tungro-80
4.	Rice disease	Brown spot-523, Healthy-523, Hispa-523, Leaf blast-523
5.	Rice leaf diseases	Bacterial leaf blight- 40, Brown spot- 40, Leaf smut- 40
6.	Rice disease	Stem rot-500, Apex blast-500, Leaf blast-500, Leaf burn-500, Neck blast-500
7.	Rice leafs	Brown spot-523, Healthy-1494, Hispa-565, Leaf blast-779
8.	Rice plant dataset	Healthy seeds-501, Unhealthy seeds-506
9.	Rice-leaf-disease	Brown spot-40, Leaf smut-40, Blast-80, Blight-80, Tungro-80
10.	Rice Leaf Disease Image Samples	Bacterial blight-1584, Rice blast-1440, Brown spot-1600, Tungro-1308
11.	Bangladeshi Local Rice dataset	Brown spot-139, Leaf scaled-217, Rice blast-272, Tungro-195, Sheath blight-283
12.	Rice Leafs Disease Dataset	Bacterial blight-438, Brown spot-438, Healthy-438, Leaf blast-438, Leaf scald-438, Narrow brown spot-438
13.	Rice leaf diseases	Bacterial Blight-80, Brown spot-100, Healthy-100, Rice blast-80
14.	Paddy-leaf-disease-UCI	Bacterial blight-55, Brown spot-54, Leaf smut-55
15.	Rice_disease	Brown spot-100, Healthy-100, Hispa-100, Leaf blast-100

1350 images were collected from Bangladesh Rice Research Institute (BRRI), Bangladesh Rice Knowledge Bank (BRKB), Plantix and International Rice Research Institute (IRRI) datasets and paddy fields [50]. The detailed description of the dataset and their weblinks are further represented in Table 3.

6. Challenges of Automated Crop Disease Detection

A machine learning model is a potential tool for automatically detecting crop diseases. However, several factors can degrade the efficiency of these tools. Those performance-quenching challenges to focus on with attention are discussed below.

6.1. Dataset Size

Previously published pieces of literature had shown only a limited dataset source (i.e., thousand images) for training their model, leading to over-fitting. Data augmentation is the only solution available to enhance the learning dataset size [63]. The large dataset training provides accurate disease detection at a minimal cost [2]. The distribution between training data and the data applied must be monitored, and the difference must be noted.

6.2. Disease Symptom Variations

Colour, size, and shape variations ultimately change the disease symptom characteristics. Disease detection becomes complex when different symptoms under different conditions occur. Disease characteristics are highly influenced by factors such as sunlight exposure, humidity, wind, temperature, plant genotype, and healthy plant colour [66]. A practice of capturing images at different stages should be followed.

6.3. Diseases of Similar Patterns

The accuracy of disease detection and classification is greatly reduced due to the existence of multiple diseases with similar symptoms and patterns [66]. The complexity of segmenting and differentiating disease symptoms varies greatly, and the approaches used have an impact. The conventional technique uses a visible spectrum in the detecting sensor, which fails to classify diseases with similar symptoms. Meanwhile, sensors developed based on the infrared spectrum are found to be costly, challenging and error-prone. It's also worth noting that some discrepancies cannot be addressed even though multiple spectral bands are being used. The training requirement for large datasets can be drastically minimized using newer techniques [63].

6.4. Symptom Segmentation

Disease with similar symptoms makes the segmentation process complicated. In digital image processing, an intrinsic factor of symptom segmentation is commonly used. However, unclear edge symptoms, diseases with time-varying symptoms and overlapping disease symptoms hinder the segmentation process [66]. To overcome this challenge, an alternative segment symptom correction method must be intertwined with the existing model. Background noise in crop image: Segmentation is relatively easy if the crop image contains a black-and-white background. However, the process is quite challenging due to the presence of an image background with multiple colours, leaves, grass, soil, etc. [66]. The unnecessary noise in the image background has to be adequately removed to obtain the necessary attributes.

6.5. Image Background Criteria

The dataset images mentioned in the previously published pieces of literature were captured in a controlled environment. It is quite challenging to obtain similar images due to several factors like light intensity, humidity, wetness, temperature, and image angle. Hence, it is a prerequisite to capture images at different times of the day, environment conditions, and angles for enhancing the training dataset—the higher the training dataset, the greater the accuracy and performance [66]. The collected image samples are the most desired element that determines the accuracy of the training model. Hence, it should be collected carefully and with caution.

7. Future Prospects

Early disease detection prevents major loss due to crop damage and improves yield. A model incorporated with deep learning must be developed to monitor the large-scale cultivation and early prediction of diseases. Image processing techniques allow the user to identify the diseased segment from an image by handling noise and removing the undesirable background. Progress in machine learning and deep learning techniques will become a new hotspot of exploration in the domain of automatic crop disease detection. Therefore, the current state of the art and need of the hour is to examine and develop these intelligent models for real-time and continuous monitoring of crops subjected to infection. Machine learning and deep learning-based techniques can be developed to determine required chemicals based on soil fertility, mineral availability, and crop uptaking rate. Crop diseases can be easily diagnosed by closely monitoring leaves that act as nutrient deficiency and water scarcity index. A crucial requirement is for refined, cost-effective automatic models to address the abovementioned limitations.

8. Conclusion

This paper investigated the various AI-based disease diagnosis and categorization techniques for paddy crops. Various paddy crop diseases, their symptoms and their impact on crop productivity were discussed elaborately. The steps associated with the techniques, the challenges involved in automatic crop disease detection and the solutions for overcoming those challenges are also elaborated. Among the various techniques available in the literature, Ramesh et al. achieved the highest classification accuracy of range 90.57 – 98.9% for various rice plant diseases in the year 2020. The authors proposed an optimized deep neural network with the Jaya optimization algorithm (DNN-JOA). Though several rice diseases existed, it is evident from the literature that the researchers classified only a few rice diseases. There is necessary to build a deep learning model to classify all the rice diseases with higher accuracy and less prediction time. Deep learning-based real-time monitoring of large-scale cultivation aids in the prediction of crop diseases at the earlier stage. So farmers can take proper control measures to avoid the disease's spread and minimize productivity loss. Hence, leading research for accuracy improvement, real-time monitoring, and disease-based pesticide and chemical recommendation is important. This work can be further extended to monitor soil parameters, nutrition deficiency, weed control, and pest control.

Acknowledgement

This work has been supported by the department of ECE, National Institute of Technology Puducherry, Karaikal, India.

References

[1] S. D. Khirade, and A. Patil, "Plant Disease Detection Using Image Processing," *2015 International Conference on Computing Communication Control and Automation*, pp. 768-771, 2015. *Crossref*, https://doi.org/10.1109/ICCUBEA.2015.153

[2] J. A. Wani et al., "Machine Learning and Deep Learning Based Computational Techniques in Automatic Agricultural Diseases Detection: Methodologies, Application and Challenges," *Archives of Computational Methods in Engineering*, vol. 29, no. 1, pp. 641-677, 2022. *Crossref*, https://doi.org/10.1007/s11831-021-09588-5

[3] A. Kumar, S. Sarkar, and C. Pradhan, “Recommendation System for Crop Identification and Pest Control Technique in Agriculture,” *2019 International Conference on Communication and Signal Processing*, pp. 0185-0189, 2019. *Crossref*, https://doi.org/10.1109/ICCSP.2019.8698099

[4] T. Kodama, and Y. Hata, “Development of Classification System of Rice Disease using Artificial Intelligence,” *2018 IEEE International Conference on Systems, Man, and Cybernetics*, pp. 3699-3702, 2018. *Crossref*, https://doi.org/10.1109/SMC.2018.00626

[5] T. Bera et al., “A Survey on Rice Plant Disease Identification Using Image Processing and Data Mining Techniques,” *Emerging Technologies in Data Mining and Information Security*, vol. 814, pp. 365-376, 2019. *Crossref*, https://doi.org/10.1007/978-981-13-1501-5_31

[6] R. Shivappa et al., “*Emerging Minor Diseases of Rice in India: Losses and Management Strategies*,” Integrative Advances in Rice Research, 2022. *Crossref*, https://doi.org/10.5772/intechopen.99898

[7] S. Raghu et al., “Grain Discoloration in Popular Rice Varieties (Oryza sativa L) in Eastern India, Associated Mycoflora, Quality Losses and Management using Selected Biocontrol Agents,” *Journal of Stored Products Research*, vol. 88, 2020. *Crossref*, https://doi.org/10.1016/j.jspr.2020.101682

[8] S. Kaur, S. Pandey, and S. Goel, “Plants Disease Identification and Classification Through Leaf Images: A Survey,” *Archives of Computational Methods in Engineering*, vol. 26, no. 2, pp. 507-530, 2019. *Crossref*, https://doi.org/10.1007/s11831-018-9255-6

[9] D. Sugimura et al., “Enhancing Color Images of Extremely Low Light Scenes Based on RGB/NIR Images Acquisition with Different Exposure Times,” *IEEE Transactions on Image Processing*, vol. 24, no. 11, pp. 3586-3597, 2015. *Crossref*, https://doi.org/10.1109/TIP.2015.2448356

[10] S. Shrivastava, and D. S. Hooda, “Automatic Brown Spot and Frog Eye Detection from the Image Captured in the Field,” *American Journal of Intelligent Systems*, vol. 4, no. 4, pp. 131-134, 2014. *Crossref*, https://doi.org/10.5923/j.ajis.20140404.01

[11] A. Akhtar et al., “Automated Plant Disease Analysis (APDA): Performance Comparison of Machine Learning Techniques,” *2013 11th International Conference on Frontiers of Information Technology*, pp. 60-65, 2013. *Crossref*, https://doi.org/10.1109/FIT.2013.19

[12] P. Sanyal et al., “Color Texture Analysis of Rice Leaves Diagnosing Deficiency in the Balance of Mineral Levels towards Improvement of Crop Productivity,” *10th International Conference on Information Technology*, pp. 85-90, 2007. *Crossref*, https://doi.org/10.1109/ICIT.2007.40

[13] S. V. Militante, B. D. Gerardo, and N. V. Dionisio, “Plant Leaf Detection and Disease Recognition Using Deep Learning,” *2019 IEEE Eurasia Conference on IOT, Communication and Engineering*, pp. 579-582, 2019. *Crossref*, https://doi.org/10.1109/ECICE47484.2019.8942686

[14] Q. Yao et al., “Application of Support Vector Machine for Detecting Rice Diseases using Shape and Color Texture Features,” *2009 International Conference on Engineering Computation*, pp. 79-83, 2009. *Crossref*, https://doi.org/10.1109/ICEC.2009.73

[15] A. Camargo, and J. Smith, “An Image-Processing Based Algorithm to Automatically Identify Plant Disease Visual Symptoms,” *Biosystems Engineering*, vol. 102, no. 1, pp. 9-21, 2009. *Crossref*, https://doi.org/10.1016/j.biosystemseng.2008.09.030

[16] H. Al Hiary et al., “Fast and Accurate Detection and Classification of Plant Diseases,” *International Journal of Computer Applications*, vol. 17, no. 1, pp. 31-38, 2011. *Crossref*, https://doi.org/10.5120/2183-2754

[17] L. Wang et al., “Improved Rotation Kernel Trans- Formation Directional Feature for Recognition of Wheat Stripe Rust and Powdery Mildew,” *2014 7th International Congress on Image and Signal Processing*, pp. 286-291, 2014. *Crossref*, https://doi.org/10.1109/CISP.2014.7003793

[18] J. Hang et al., “Classification of Plant Leaf Diseases Based on Improved Convolutional Neural Network,” *Sensors*, vol. 19, no. 19, pp. 41-61, 2019. *Crossref*, https://doi.org/10.3390/s19194161

[19] S. S. Sannakki et al., “Diagnosis and Classification of Grape Leaf Diseases using Neural Networks,” *2013 Fourth International Conference on Computing, Communications and Networking Technologies*, pp. 1-5, 2013. *Crossref*, https://doi.org/10.1109/ICCCNT.2013.6726616

[20] M. Wiwart et al., “Early Diagnostics of Macronutrient Deficiencies in Three Legume Species by Color Image Analysis,” *Computers and Electronic in Agriculture*, vol. 65, no. 1, pp. 125-132, 2009. *Crossref*, https://doi.org/10.1016/j.compag.2008.08.003

[21] M. Aubry et al., “Fast Local Laplacian Filters: Theory and Applications,” *ACM Transactions on Graphics*, vol. 33, no. 5, pp. 1-14, 2014. *Crossref*, https://doi.org/10.1145/2629645

[22] T. A. Ell, and S. J. Sangwine, “Hypercomplex Fourier Transforms of Color Images,” *IEEE Transactions on Image Processing*, vol. 16, no. 1, pp. 22-35, 2007. *Crossref*, https://doi.org/10.1109/TIP.2006.884955

[23] J. S. Lee, “Digital Image Smoothing and the Sigma Filter,” *Computer Vision, Graphics, and Image Processing*, vol. 24, no. 2, pp. 255-269, 1983. *Crossref*, https://doi.org/10.1016/0734-189X(83)90047-6

[24] Yeong-Taeg Kim, “Contrast Enhancement using Brightness Preserving Bi- Histogram Equalization,” *IEEE Transactions on Consumer Electronics*, vol. 43, no. 1, pp. 1-8, 1997. *Crossref*, https://doi.org/10.1109/30.580378

[25] K. Sim, C. Tso, and Y. Tan, “Recursive Sub-Image Histogram Equalization Applied to Gray Scale Images,” *Pattern Recognition Letters*, vol. 28, no. 10, pp. 1209-1221, 2007. *Crossref*, https://doi.org/10.1016/j.patrec.2007.02.003

[26] K. Zuiderveld, "*Contrast Limited Adaptive Histogram Equalization*," Graphics gems IV, pp. 474-485, 1994.
[27] T. Celik, and H. C. Li, "Residual Spatial Entropy-Based Image Contrast Enhancement and Gradient-Based Relative Contrast Measurement," *Journal of Modern Optics*, vol. 63, no. 16, pp. 1600-1617, 2016. *Crossref*, https://doi.org/10.1080/09500340.2016.1163427
[28] J. Mun et al., "Edge-Enhancing Bi-Histogram Equalisation using Guided Image Filter," *Journal of Visual Communication and Image Representation*, vol. 58, pp. 688-700, 2019. *Crossref*, https://doi.org/10.1016/j.jvcir.2018.12.037
[29] D. Vijayalakshmi, and M. K. Nath, "A Novel Contrast Enhancement Technique using Gradient-Based Joint Histogram Equalization," *Circuits, Systems, and Signal Processing*, vol. 40, no. 8, pp. 3929-3967, 2021. *Crossref*, https://doi.org/10.1007/s00034-021-01655-3
[30] M. Islam et al., "Detection of Potato Diseases using Image Segmentation and Multiclass Support Vector Machine," *2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering*, pp. 1-4, 2017. *Crossref*, https://doi.org/10.1109/CCECE.2017.7946594
[31] G. Zhou et al., "Rapid Detection of Rice Disease Based on FCM-KM and Faster R-CNN Fusion," *IEEE Access*, vol. 7, pp. 143190-143206, 2019. *Crossref*, https://doi.org/10.1109/ACCESS.2019.2943454
[32] Shrivastava, and Gyanesh, "Review on Emerging Trends in Detection of Plant Diseases using Image Processing with Machine Learning," *International Journal of Computer Applications*, vol. 174, no. 11, pp. 39-48, 2021. *Crossref*, https://doi.org/10.5120/ijca202192099
[33] U. Mokhtar et al., "SVM-Based Detection of Tomato Leaves Diseases," *Intelligent Systems'2014*, vol. 323, pp. 641-652, 2015. *Crossref*, https://doi.org/10.1007/978-3-319-11310-4_55
[34] A. Meunkaewjinda et al., "Grape Leaf Disease Detection from Color Imagery using Hybrid Intelligent System," *2008 5th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology*, vol. 1, pp. 513-516, 2008. *Crossref*, https://doi.org/10.1109/ECTICON.2008.4600483
[35] V. K. Shrivastava, and M. K. Pradhan, "Rice Plant Disease Classification using Color Features: a Machine Learning Paradigm," *Journal of Plant Pathology*, vol. 103, no. 1, pp. 17-26, 2021. *Crossref*, https://doi.org/10.1007/s42161-020-00683-3
[36] V. Sharma, A. A. Mir, and D. A. Sarwr, "Detection of Rice Disease using Bayes' Classifier and Minimum Distance Classifier," *Journal of Multimedia Information System*, vol. 7, no. 1, pp. 17-24, 2020. *Crossref*, https://doi.org/10.33851/JMIS.2020.7.1.17
[37] S. Ramesh, and D. Vydeki, "Recognition and Classification of Paddy Leaf Diseases using Optimized Deep Neural Network with Jaya Algorithm," *Information Processing in Agriculture*, vol. 7, no. 2, pp. 249-260, 2020. *Crossref*, https://doi.org/10.1016/j.inpa.2019.09.002
[38] P. K. Sethy et al., "Deep Feature Based Rice Leaf Disease Identification using Support Vector Machine," *Computers and Electronics in Agriculture*, vol. 175, p. 105527, 2020. *Crossref*, https://doi.org/10.1016/j.compag.2020.105527
[39] D. Li et al., "A Recognition Method for Rice Plant Diseases and Pests Video Detection Based on Deep Convolutional Neural Network," *Sensors*, vol. 20, no. 3, p. 578, 2020. *Crossref*, https://doi.org/10.3390/s20030578
[40] A. K. Rath, and J. K. Meher, "Disease Detection in Infected Plant Leaf by Computational Method," *Archives of Phytopathology and Plant Protection*, vol. 52, no. 19-20, pp. 1348-1358, 2019. *Crossref*, https://doi.org/10.1080/03235408.2019.1708546
[41] V. K. Shrivastava et al., "Rice Plant Disease Classification using Transfer Learning of Deep Convolution Neural Network," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, pp. 631-635, 2019. *Crossref*, https://doi.org/10.5194/isprs-archives-XLII-3-W6-631-2019
[42] M. J. Hasan et al., "Rice Disease Identification and Classification by Integrating Support Vector Machine with Deep Convolutional Neural Network," *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology*, pp. 1-6, 2019. *Crossref*, https://doi.org/10.1109/ICASERT.2019.8934568
[43] W. L. Chen et al., "Rice Talk: Rice Blast Detection using Internet of Things and Artificial Intelligence Technologies," *IEEE Internet of Things Journal*, vol. 7, no. 2, pp. 1001-1010, 2020. *Crossref*, https://doi.org/10.1109/JIOT.2019.2947624
[44] W. j. Liang et al., "Rice Blast Disease Recognition using a Deep Convolutional Neural Network," *Scientific Reports*, vol. 9, no. 1, p. 2869, 2019. *Crossref*, https://doi.org/10.1038/s41598-019-38966-0
[45] P. K. Sethy et al., "Measurement of Disease Severity of Rice Crop Using Machine Learning and Computational Intelligence," *Cognitive Science and Artificial Intelligence*, pp. 1-11, 2018. *Crossref*, https://doi.org/10.1007/978-981-10-6698-6_1
[46] T. Islam et al., "A Faster Technique on Rice Disease Detection using Image Processing of Affected Area in Agro-Field," *2018 Second International Conference on Inventive Communication and Computational Technologies*, pp. 62-66, 2018. *Crossref*, https://doi.org/10.1109/ICICCT.2018.8473322
[47] S. Ramesh, and D. Vydeki, "Rice Blast Disease Detection and Classification using Machine Learning Algorithm," *2nd International Conference on Micro-Electronics and Telecommunication Engineering*, pp. 255-259, 2018. *Crossref*, https://doi.org/10.1109/ICMETE.2018.00063

[48] B. S. Ghyar, and G. K. Birajdar, "Computer Vision Based Approach to Detect Rice Leaf Diseases using Texture and Color Descriptors," *2017 International Conference on Inventive Computing and Informatics*, pp. 1074-1078, 2017. *Crossref*, https://doi.org/10.1109/ICICI.2017.8365305

[49] H. B. Prajapati, J. P. Shah, and V. K. Dabhi, "Detection and Classification of Rice Plant Diseases," *Intelligent Decision Technologies*, vol. 11, no. 3, pp. 357-373, 2017. *Crossref*, https://doi.org/10.3233/IDT-170301

[50] M. Suresha, K. N. Shreekanth, and B. V. Thirumalesh, "Recognition of Diseases in Paddy Leaves using knn Classifier," *2nd International Conference for Convergence in Technology*, pp. 663-666, 2017. *Crossref*, https://doi.org/10.1109/I2CT.2017.8226213

[51] Yang Lu et al., "Identification of Rice Diseases using Deep Convolutional Neural Networks," *Neurocomputing*, vol. 267, pp. 378-384, 2017. *Crossref*, https://doi.org/10.1016/j.neucom.2017.06.023

[52] B. S. Prajapati, V. K. Dabhi, and H. B. Prajapati, "A Survey on Detection and Classification of Cotton Leaf Diseases," *2016 International Conference on Electrical, Electronics, and Optimization Techniques*, pp. 2499-2506, 2016. *Crossref*, https://doi.org/10.1109/ICEEOT.2016.7755143

[53] Okfalisa et al., "Comparative Analysis of k-nearest Neighbor and Modified k-nearest Neighbor Algorithm for Data Classification," *2nd International Conferences on Information Technology, Information Systems and Electrical Engineering*, pp. 294-298, 2017. *Crossref*, https://doi.org/10.1109/ICITISEE.2017.8285514

[54] N. S. Patil, "Identification of Paddy Leaf Diseases using Evolutionary and Machine Learning Methods," *Turkish Journal of Computer and Mathematics Education*, vol. 12, no. 2, pp.1672–1686, 2021. *Crossref*, https://doi.org/10.17762/turcomat.v12i2.1503

[55] J. S. Prakash et al., "Multi Class Support Vector Machines Classifier for Machine Vision Application," *2012 International Conference on Machine Vision and Image Processing*, pp.197-199, 2012. *Crossref*, https://doi.org/10.1109/MVIP.2012.6428794

[56] B. Yekkehkhany et al., "A Comparison Study of Different Kernel Functions for SVM-based Classification of Multi-Temporal Polarimetry SAR Data," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, pp. 281-285, 2014. *Crossref*, https://doi.org/10.5194/isprsarchives-XL-2-W3-281-2014

[57] M. A. Azim et al., "An Effective Feature Extraction Method for Rice Leaf Disease Classification," *TELKOMNIKA, Telecommunication Computing Electronics and Control*, vol. 19, no. 2, p. 463, 2021. *Crossref*, https://doi.org/10.12928/telkomnika.v19i2.16488

[58] Hamit Taner Unal, and Fatih basciftci, "Evolutionary Design of Neural Network Architectures: a Review of Three Decades of Research," *Artificial Intelligence Review*, vol. 55, pp. 1723-1802, 2022. *Crossref*, https://doi.org/10.1007/s10462-021-10049-5

[59] R. R. Patil, S. Kumar, and R. Rani, "Comparison of Artificial Intelligence Algorithms in Plant Disease Prediction," *Revue D'Intelligence Artificielle*, vol. 36, no. 2, pp. 185-193, 2022. *Crossref*, https://doi.org/10.18280/ria.360202

[60] S. Barburiceanu et al., "Convolutional Neural Networks for Texture Feature Extraction. Applications to Leaf Disease Classification in Precision Agriculture," *IEEE Access*, vol. 9, pp. 160085-160103, 2021. *Crossref*, https://doi.org/10.1109/ACCESS.2021.3131002

[61] K. He et al., "Deep Residual Learning for Image Recognition," *2016 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 770-778, 2016. *Crossref*, https://doi.org/10.1109/CVPR.2016.90

[62] G. L. Grinblat et al., "Deep Learning for Plant Identification using Vein Morphological Patterns," *Computers and Electronics in Agriculture*, vol. 127, pp. 418-424, 2016. *Crossref*, https://doi.org/10.1016/j.compag.2016.07.003

[63] J. G. A. Barbedo, "Impact of Dataset Size and Variety on the Effectiveness of Deep Learning and Transfer Learning for Plant Disease Classification," *Computers and Electronics in Agriculture*, vol. 153, pp. 46–53, 2018. *Crossref*, https://doi.org/10.1016/j.compag.2018.08.013

[64] S. P. Mohanty, D. P. Hughes, and M. Salathe, "Using Deep Learning for Image-Based Plant Disease Detection," *Frontiers in Plant Science*, vol. 7, p. 1419, 2016. *Crossref*, https://doi.org/10.3389/fpls.2016.01419

[65] R. Deng et al., "Automatic Diagnosis of Rice Diseases using Deep Learning," *Frontiers in Plant Science*, vol. 12, p. 701038, 2021. *Crossref*, https://doi.org/10.3389/fpls.2021.701038

[66] J. G. A. Barbedo, "A Review on the Main Challenges in Automatic Plant Disease Identification Based on Visible Range Images," *Biosystems Engineering*, vol. 144, pp. 52-60, 2016. *Crossref*, https://doi.org/10.1016/j.biosystemseng.2016.01.017