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Review

Application of artificial intelligence techniques to addressing and mitigating biotic stress in paddy crop: A review

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A R T I C L E I N F O

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A B S T R A C T

Agriculture provides basic livelihood for a large section of world's population. It is the oldest economic activity in India, with two third of Indian population involved in crop production. India is second largest producer of rice and biggest exporter globally, with rice which is most common staple crop consumed in country. However, there are several challenges for paddy production including small production yield, soil quality, seed quality, huge volume of water needed and biotic stress. Of these, biotic stress drastically affects yield and susceptibility to other diseases in paddy production. It is caused by pathogens such as bacteria, viruses, fungi, nematodes, all of which severely affect growth and productivity of paddy crop. To mitigate these challenges, infected crops are identified, detected, classified, categorized, and prevented according to their respective suffering disease by using conventional methods which are not effective and efficient for growth of paddy crop. Thus, use of artificial intelligence (AI) and a smart agriculture-based Internet of Things (IoT) platform could be effective for detecting the biotic stresses in very less time or online mode. For this, deep learning, and convolutional neural networks (CNN) multi-structured layer approach were used for diagnosing disease in rice plants. Different models and classifiers of CNN were used for detecting disease by processing high-spectral images and using logistic and mathematical formulation methods for classification of biotic paddy crop stresses. Continuous monitoring of stages of infection in paddy crop can be achieved using real-time data. Thus, use of AI has made diagnosing paddy crop diseases much easier and more efficient.

1. Introduction

India is an agricultural country since agriculture is primary activity of its population, of all crops, rice is most produced and consumed grain over whole country. In India, the production of rice utilizes largest area of agricultural land ~43.86 million hectares of land, with a productivity of about ~2390 kg/h which may be decreased owing to urbanization (Sethy et al., 2020a). As population and food demands are steeply increasing which led the global food security that poses a huge challenge for food production and for rice production. It has highest rate of consumption when compared to other crops, with current demand of ~524 million tons expected to increase to over ~700 million tons. Furthermore, it accounts for approximately 60 % of global food consumption. Studies have shown that, rice production needs to be increased by >40 % from 2023 because of its high demand (SaberiKamarposhti et al., 2024)[3]. Since rice is a staple food, demand for it is high globally and thus, to meet these demands, an increase in its production is one of the most important concerns at present. Changing environmental conditions

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and increasing human population have led to the overexploitation and destruction of land used for its production (Verma et al., 2024). Along with this, there are still challenges in agriculture related to less awareness in farmers, improper policies, plant related diseases related to biotic stress are still concerned of interest (Talaviya et al., 2020).

According to a survey by the Food and Agriculture Organization (FAO), United States of America (USA) (Wang et al., 2021), it has been estimated that plant diseases cost around ~220 billion dollars annually on a global economic scale. An average loss of 20–40 % occurs due to various diseases caused by biotic stress. Paddy (rice) crops are affected by various pathogens such as bacteria, fungi, viruses, and nematodes along with insects, weeds, and other pests, which are ultimately a major factor in hindering the growth, development, and production of rice in paddy fields. To detect these issues, conventional methods are being used to lower the effect of biotic stress on production of rice. The conventional methods have several disadvantages such as less accuracy and precision; time consuming and prone to human errors. The implementation of artificial intelligence (AI) holds significant potential to address challenges related to agricultural management and productivity, particularly in developing countries like India. By integrating AI, it is possible to reduce costs associated with energy consumption, time, and equipment, thereby enhancing overall agricultural efficiency (Jackulin and Murugavalli, 2022). With technological advances, the AI is supposed to have significant impact on the agricultural outputs by its proper integration with the farming system (Parbat et al., 2021). AI is a part of the computer science field which seeks to create an intelligent and highly accurate machine. Such a machine works by learning from experiential data (Talaviya et al., 2020). By integrating the Internet of things (IOT) (Wicaksono et al., 2021) with AI, “thing-to-thing" communication has been much easier and more efficient. Deep learning, convolutional neural networks (CNNs), artificial neural networks (ANNs), support vector machine (SVM), k-NN (Behmann et al., 2015), K-clustering, and machine learning are all sub-domains of AI (Tejaswini et al., 2022). Machine learning uses experiential data and statistical logistics to make the process of solving a specific task faster and with better accuracy. Data science and big data have advanced using machine learning, utilizing mathematical and logistical approaches/models to build an ‘intelligent’ machine with quick and accurate outcomes.

Of all the sub-classes of AI, neural networks are the most commonly and consistently used for machine learning. CNNs basically have three layers. The input layer is the input layer into which the input data is fed and processed. Data are split and used to create training and testing models (Wang et al., 2021; Debnath and Saha, 2022). The second layer is a set of layers into which the processed input data are received and processed, based on optimized CNN models and respective classifiers through its multi-level architectural layers. These multi-structured CNN layers are referred to as the convolutional layer, pooling layer, and fully connected layer (Jackulin and Murugavalli, 2022; Altinbilek and Kizil, 2022) The convolutional layer extracts the required data from the input and optimize the values into a weight matrix. Logistic analysis is carried out using a data map obtained from machine learning. The max pooling layer segregates the input data and transmits the obtained maximum value using a mathematical approach to the next preceding layer at a specific field location on the data map. The fully connected layer processes the output from the interconnected multiple architecture convolutional and pooling layers, and uses high-level mathematical reasoning functions to produce the final output. The third layer is the output layer which processes the resultant values from the other layers and uses probabilistic and logistic approaches to convert the class output into an equivalent score. Neural networks are efficient at predicting biotic stresses involving complex mapping of agricultural land, detecting disease in crops at an early stage, infection prediction at every stage of a diseased plant’s development, and identification of fungal infection in the leaves of the plants (Fontana et al., 2021). Neural networks can also be used to predict the harmful effects of both weeds, and attacks by insects and pests on the plants that are detrimental to crop plant growth and production (Hoang Trong et al., 2020). Detection and classification of the bacterial, viral, and fungal pathogens, as well as nematodes that cause plant diseases have been made much easier, faster, and efficient (Çakir et al., 2023). This multi-structured CNN technique uses mathematical and logistic approaches for each layer to process the input data at each stage and produce the final output result (Sharma et al., 2022).

This review examines the applications and advantages of using AI in rice production. Smart agriculture approaches and various fields of artificial intelligence, such as deep learning and machine learning have resulted in easier, faster, more cost-effective, and highly layered efficient processes for experts and farmers to monitor their rice crop fields in a much more effective manner (Çakir et al., 2023). AI helps in diagnosing disease, level of infection and its causative agents such as pathogens and pests in the rice plant. Thus, AI will help humans to take appropriate actions for the protection of rice crops from various types of biotic stress and, subsequently, play a major role in enhancing the productivity of rice fields.

2. Current state-of-the-art of detection of biotic stress in paddy crops

Plants have evolved to survive various types of environmental stresses at the expense of their productivity. One of the major stress types is biotic stress, which is defined as the detrimental effects of living

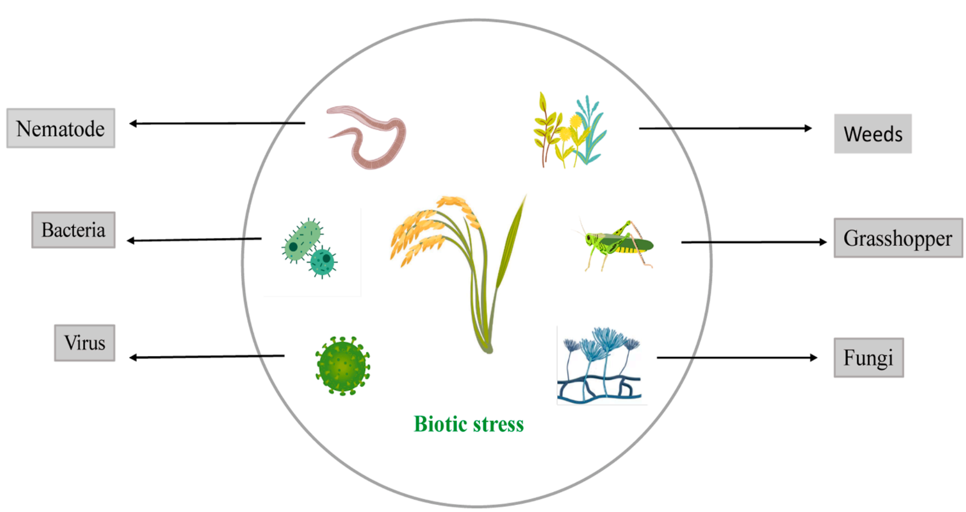


Fig. 1. Various pathogens that cause biotic stress.

organisms such as pests, pathogens, insects and weeds on a plant's growth and productivity (Çakir et al., 2023). Bacteria, fungi, viruses, and nematodes are some of the pathogens that attack crops and hinder their growth, by reducing their yield and affecting both their quantity and quality as shown in Fig. 1 (Kaur and Gautam, 2021). Biotic stress severely affects plants' physiological processes and biochemical pathways, thus causing huge damage to their development process. Pests, such as insects, mites and even mammals, can cause harm by ingesting the plant's tissues and spreading infection further throughout the plants (Deng et al., 2021). AI techniques such as deep learning, neural networks, clustering and SVM are extremely useful because of their ability to utilize big data and make use of a variety of processes to identify, detect and classify different causative factors that are responsible for biotic stress in plants (Houetohossou et al., 2023). Deep learning is the most well-known AI technique and uses large structured multi-layered networks. It achieves multi-level abstraction by analyzing hierarchical data from images of the diseased crop. Deep learning algorithms have much higher potential to train variable deep learning models, offering greater efficiency in identification and classification of diseased plants (Altinbilek and Kizil, 2022). Deep learning optimizes its sub-class, CNN, for fast learning and more efficient generation of the output. CNNs use an image-based AI technique, consisting of image acquisition, manipulation, segregation, multiple feature extraction, analysis and finally image optimization for detection and categorization of different plant diseases these models such as "VGG-16 (Swain and Tripathy, 2024), VGG-19 (Cao et al., 2022), Dense Net, Alex Net and LeNet-5 (Al-Salman and AlSalman, 2024)", which help in recognition, classification and categorization of crop stresses and identification of plant disease, can run on any device (Vardhini et al., 2020). CNN models consist of multiple image classifiers such as SVM (Kumar et al., 2021), Back Proportion Neural Network (BPNN) (Lu et al., 2024) and k- nearest neighbors (KNN) (Nasser Shah et al., 2019) operating on the multi-layered network structure of CNNs.

2.1. Early disease detection in paddy crop production

Paddy crops are very prone to infections caused by pathogens such as bacteria, fungi, nematode and viruses (Deng et al., 2021). For early detection of the disease, monitoring rice fields is a crucial preliminary measure. Visual inspection of the field enables the identification of infected leaves. Without timely intervention to manage the disease, the infection can spread rapidly throughout the entire paddy field, resulting in significant losses for the farmer (Sethy et al., 2020a). A system is required to assist farmers in the early detection of rice diseases, enabling timely intervention to protect paddy fields and mitigate reductions in rice production at an early stage. To achieve this, deep learning and big data analysis can be employed to process images of paddy fields, simulating the human brain by optimizing artificial neural networks to address common diseases in rice crops effectively (Çakir et al., 2023; Sharma et al., 2022). In the past, visual observations by experts were carried out for diagnosing disease in plants, but the risk of error was high and the results were inaccurate. Then, various spectroscopic and imaging techniques were used which required sensors and instruments equipped with cameras and inbuilt electronic equipment but they were costly and were quite inefficient. Finally, automatic plant disease detection and diagnosis using machine learning was introduced, based on an unsupervised learning K clustering method and SVM technique, but the complex preprocessing and feature detection image technology ultimately reduced the efficiency of this system (Sharma et al., 2022). Plant imaging captures detailed plant visuals for health analysis, but relies on time-consuming human interpretation. Machine learning (ML) automates disease detection by analyzing large image datasets, improving accuracy over time. While plant imaging requires high-quality images, ML can utilize various image types, transforming them into actionable insights through algorithms. Table 1 describes the comparison between traditional and AI rice disease detection techniques.

However, deep learning and CNN have yielded much more relevant and accurate results then machine learning models because they directly extract the features of plants automatically and input the images therefore avoiding complex preprocessing steps (Debnath and Saha, 2022). Mostly, rice blast, bacterial and brown spot diseases are found on rice leaves which cause severe infection to all the other crops very quickly.

Brown spot disease is a major chronic fungal disease which produces small brown spots on the surface of leaves and can be detected at an early stage using deep learning. A real-time image of the disease was taken by the deep CNN application, then stored, processed, and analyzed on a cloud server of an IoT-based system (Tejaswini et al., 2022). Then, the data from the file were labeled and the final image processed and stored on a shared network. Finally, a smart customized farming app was designed and connected to the cloud networking server from which a farmer could easily visualize the diseased crop on their mobile phones. Thus, they can easily observe and quickly take the required measures to prevent damage to the paddy crop field. The basic functions of this image processing include identification of infected sections of plant such as stem and leaf, measuring the affected area of the field, recognizing the shapes of the infected zone, and detecting the infected colored regions (Venkatamohan et al., 2023). The image is captured using sensors, cameras, drones, and scanners. Then the changes in images are found to the images by using robotics and remote sensing. The image quality is analyzed and edited using techniques such as filtering, normalization, resizing and cropping to obtain the desired image. The image and its background are improvised for better clarity by using k-clustering, text, shape and color changes (Venkatamohan et al., 2023). Features in the image are optimized by using techniques such as pattern extraction, texture, shape, coloring of the infected section in the final image, as shown in Fig. 2.

Evaluating the classification and prediction model performance in terms of its accuracy, recall and precision uses true and false parameters in the following equations (Dhiman and Saroha, 2022) :

$$\text{Model Accuracy (A)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \tag{1}$$

$$\text{Model Recall(R)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{Model Precision (P)} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

where the true and false parameters are defined as:

TP - true positive (correctly classified, expected result)
TN - true negative (wrongly classified, expected result)
FP - false positive (wrongly classified, unexpected result)
FN- false negative (correctly classified, unexpected result)

Alongside disease detection, severity estimation is also an important topic of concern which can be easily resolved by using mainstream deep learning architecture models such as VGG16 (Houetohossou et al., 2023), ResNet101 (Patil et al., 2023), Mobile Net (Anami et al., 2020) and EfficientNet-B0 (Patil et al., 2023). Precisely quantifying the degree of disease in the paddy leaf helps farmers to take preventive steps against that respective disease at the correct time. Deep learning approaches that can be used to identify the diseases here are RCNN, SSD and YOLO. EfficientNet-B0 (Patil et al., 2023) and RCNN produce the most accurate output model. The real-time image datasets of rice leaves are collected and administered with the public web database to eliminate the present robustness. The record is kept using the colored charge couple device with optimized required image acquisition distance.

Image annotation is an important step in disease severity quantification as it highlights the exact region where the infection is present, as

Table 1
Comparison between traditional and AI rice disease detection techniques.

Refs.	Disease	Traditional techniques	Use of AI techniques	Remarks
(Tejaswini et al., 2022)	Rice leaf blast	Visual analysis	Deep Learning models	Continuous monitoring of infected leaves gives ineffective and inaccurate results whereas DL models produce efficient, accurate results in a faster time
(Latif et al., 2022)	Brown spot disease	Visual monitoring	CNN	Highly precise and accurate datasets for diseased rice leaf
	Phytophthora black fungal disease	Visual assessment, Pathogen -inducesystem, Laboratory identification	SVM	Detection algorithm used by SVM yields good rice leaf recognition and classification performance
(Nasser Shah et al., 2019)	Brown plant hopper infection	Manual detection	K-clustering	Classification of segmented images using K-clustering has much better performance in detecting BPH infected rice crop
(Rifa'I and Mahdiana, 2020)	Bacterial leaf blight	Camera	Fuzzy system	Fuzzy system produces highly accurate images for diagnosis of rice disease
(Sethy et al., 2020a)	Rice Leaf smut disease	Hyperspectral and Thermal imaging	CNN	It gives more accurate image processing and segmentation techniques for identifying rice leaf disease
(Haridasan et al., 2023)	Rice sheath rot	Visual assessment	CNN	More accurately diagnoses the disease
(Islam et al., 2021a)	Leaf scald	Visual monitoring	Deep CNN	Using a deep learning algorithm to optimize high precision and accuracy in tests validated using ResNet-V2 network architecture

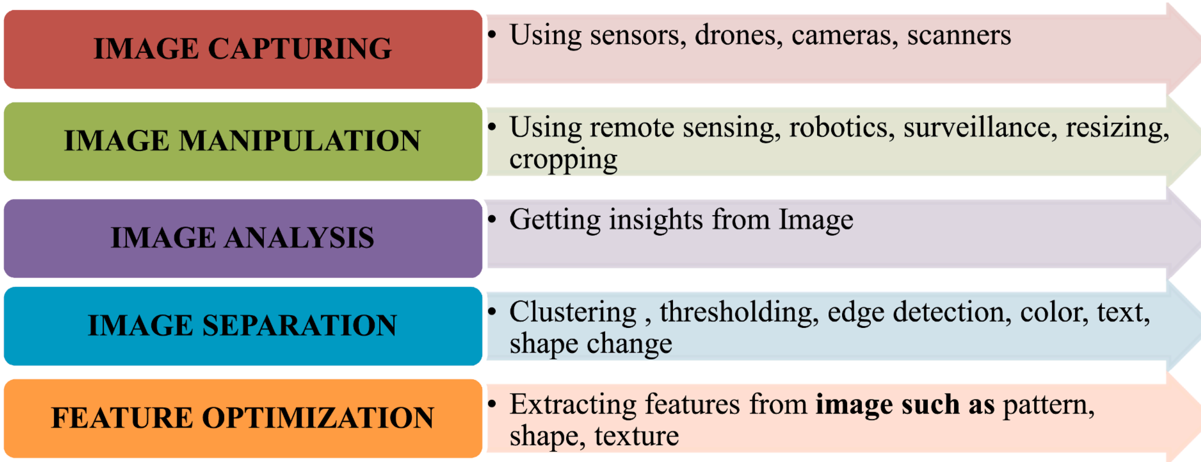


Fig. 2. Functions of the deep convolutional network used.

shown in Fig. 3. Graphical tools such as VCC annotation and Make Sense can be used to mark the place of infection in the diseased leaf image accurately (Doğan and Ergen, 2022). Mostly, a pink colored polygon shape is used to mark the diseased area. A polygon shape provides a more accurate and defined technique for inspection of complex spots and calculation of the affected area (Doğan and Ergen, 2022). The annotated image is exported in single COCO JSON file format as this provides information about the class category of image and dimensions of bounding box. Image resolution, depth layers, count of channels to obtain width of images are set and analyzed by the EfficientNet-B0 deep learning model. It is based on Mobile Inverted Convolution (MBCnvl) (Doğan and Ergen, 2022), with a convolutional layer which is composed of seven consecutive blocks thus minimizing the calculations.

This method of object detection in deep learning is used to locate the precise area of leaf infection. It is composed of three layers. The first, the regional proposal network (RPN) labels the possible leaf infected region by determining the spot anchor boxes which accurately detect the diseased leaf region on the image. This results in a feature map which is the input to the second layer, the region of interest (RoI), which further manipulates the resultant variable sized anchor boxes of the feature map into standard data. Finally, the third layer is the region-based CNN which is composed of two sub-layers, the Softmax layer and the regressor layer. The Softmax layer is also called the classifier layer, and detects the nature of the infection spot and checks for its background. The regressor layer searches for the coordinates of the bounding box and matches those to the location of the infection detected by the Softmax layer.

The training of the neural network is achieved using a training dataset, testing the deep learning model outcomes, and examining the test results. A multi-task loss function for classifying and bounding box regression losses is shown in Eq. (4) (Patil et al., 2023):

$$Loss\left(\{l_{\_i}\},\{p_{\_i}\}\right) = \frac{1}{N\_cls}\sum Loss\_cls(P\_i, GT\_i*) + \lambda * \frac{1}{N\_reg}\sum P_{\_i} * Loss\_reg(p\_i, gt\_i*) \tag{4}$$

L_i = Likelihood factor that region will include an object or not
GT_i* = Ground truth value for determining presence or absence of an object
p_i = Predicted factor coordinates
gt_i = Ground truth coordinates for bounding boxes
$Loss\_cls$ = Classifier loss
$Loss\_reg$ = Regression loss

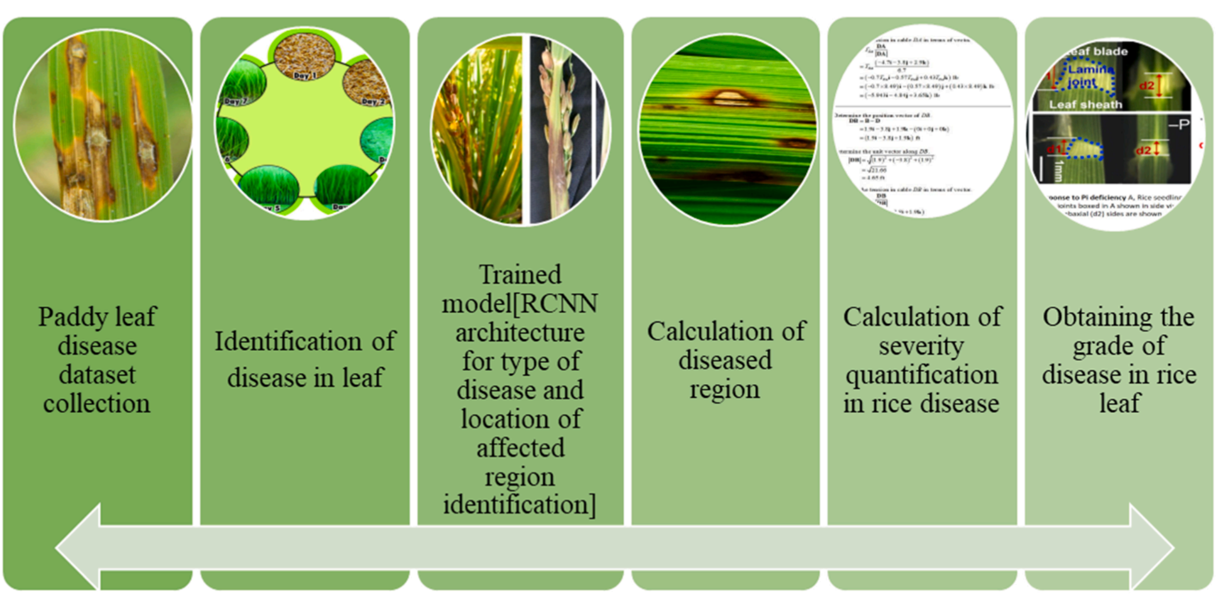


Fig. 3. Paddy disease severity detection process using CNN.

N_cls = Classification normalization parameter
N_reg = Regression normalization parameter

The severity quantification of rice disease is estimated after the RCNN algorithm is run, with the total infected area and total surface area covered by the leaf calculated. The percentage of rice disease severity is calculated using the ratio of diseased region (TDA) to leaf surface area (TLA) as given in Eq. (5) (Patil et al., 2023):

$$Severity\ quantification(\%) = \frac{\sum Disease\ affected\ bounding\ box\ area\ (TDA)}{\sum Total\ leaf\ bounding\ box\ area\ (TLA)} * 100 \tag{5}$$

It has been suggested that the implementation of deep learning with its model will help farmers improve the quality and efficiency of rice production (Patil et al., 2023). The early detection of disease in rice is helpful for farmers since they can easily identify the major cause of disease by using the early disease detection system. Then there would be good chance that farmers could destroy the root cause of the disease and take prevention against that disease at a very early stage.

2.2. Rice disease detection using a neural network

The diagnosis of the disease has, in the past, been carried out manually, ultimately giving rise to errors. Paddy fields are extremely prone to infections caused by bacteria, fungi, and viruses. Such infections are highly contagious once contracted and endanger the entire crop in the field. AI uses algorithms to identify and analyze data relating to the symptoms of disease and infection. CNN is a sub-class that uses deep learning algorithms (Behmann et al., 2015; Lu et al., 2024) as shown in Fig. 4. It can process much greater volumes of data much quicker, making it a much simpler way to identify diseases in plants. It works astonishingly well for disease detection based on image identification and categorization as either diseased or healthy.

Furthermore, these models comprise a multiple layer system which identifies each single detail needed for image processing from the source image using convolutional filters. The first layer is called the input layer into which input is fed an image. At this stage, the count of neurons and features are similar, that is, the number of pixels in the image is equivalent to the number of features in that image. Most of the data input to the first layer are optimized for the training model, with the rest being optimized for the testing model. There is then a series of hidden layers which use the output from the input layer. These are completely dependent upon the data and size of model, so includes the variable number of neurons or pixels in the image.

The last layer is the output layer that utilizes the data taken from both the input and hidden layers. It changes the output score of a class into an appropriate equivalent probability score by converting the result of every class using logistic functions.

Image edge detection is defined as a technique for determining the edges and borders in an image after processing using convolutional filters (Dhiman and Saroha, 2022). It is used to reduce image content and undesired information, thus allowing for the quick selection of relevant features. Also, it helps with compression and resizing of the image. The edges are detected by determining the intensity gradient function which focuses on the local maxima and minima of the image. A smoothing process is used to blur an image to minimize unwanted noise. The area where the highest level of gradient exists is determined by utilizing the non-maxima suppression methodology (Joshi et al., 2022).

A deep learning framework has been optimized to work with a sensor system, operated with smart phones, called Rice Bios (Joshi et al., 2022). This system aims to reduce the need for training, decrease computational time and minimize data storage. It is a user-friendly, quick, and accurate sensing system which identifies biotic stress in crops. The diagnosis of stress-inducing conditions in crops by continuous monitoring of the field has made farmers aware of the need to take prompt action to mitigate such problems with their crops to help in maintaining the gross productivity of the farm. This system helps farmers predict the current state of the rice crop by identifying the disease and classifying the crop as either healthy or diseased. The smart phone shows whether disease is present, and whether it is bacterial or fungal, alerting the farmer to take quick remedial actions, as shown in Fig. 5 (Joshi et al., 2022).

To begin, an RGB image is captured with dimensions 256×256×3 (height x width x number of channels). The ideal situation for the image is no background noise, which is achieved by minimizing the distance at

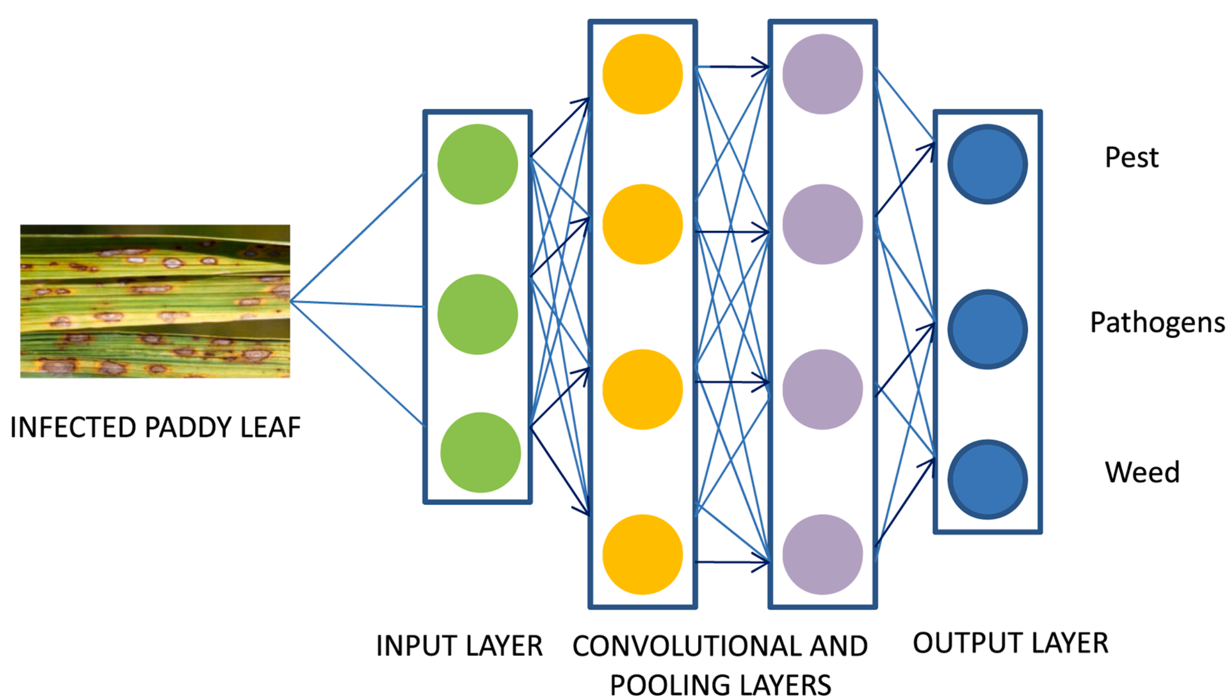


Fig. 4. Layer architecture of CNN.

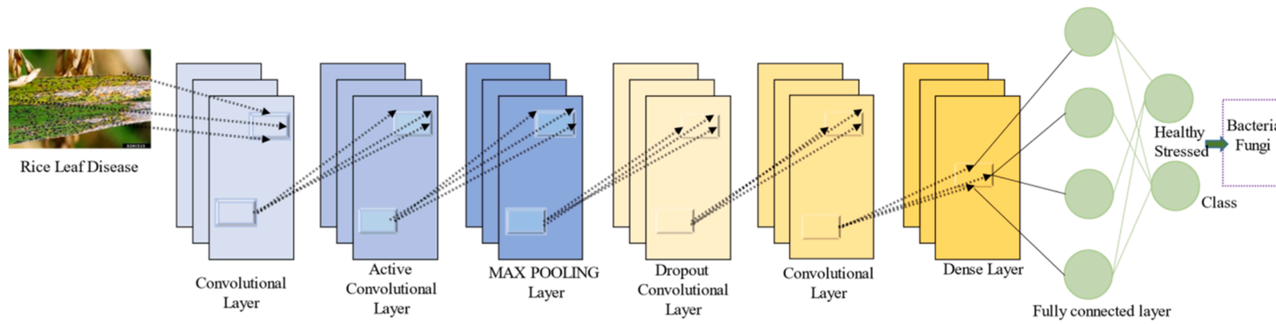


Fig. 5. Categorization of rice leaf disease using neural network.

regular angles and maintaining ideal light conditions. The enhancement of the image of an infected leaf is achieved by using RGB (red, green, blue), HSV and CIELAB color space values to eliminate unwanted features and noise in the background of the image. The pixel intensity is measured by using the variance formula given in Fig. 6. with the final output image dilated using the 2D Otsu adaptive threshold technique.

The convolutional layer integrates the features in the image which are of low quality, such as colors, gradient orientation, and edges. The primary layers extract the high-level features such as leaf texture, and color coding in the infected portion of the leaf. Subsequently, further layers extract the low-level features from the input image. The input image is fitted over a kernel matrix to ensure correct functioning of the convolutional operation, a straight forward propagation using Eq. (6):

$$q^{(k)}{}_{ij} = \sum_{i=1}^{m} \sum_{j=1}^{n} W_r^k y(i+r)(j+h) + b \tag{6}$$

where qij includes the sum of weight bias b and product of $W_r^k y$, and $y(i+r)$ $(j+n)$ is the propagation path and the input features (Haridasan et al., 2023).

The features of the input image are extracted automatically, thus avoiding the complex processing procedures of disease detection in plants using a traditional approach. CNN is the best model for image processing, with an accuracy rate of 93.5 % over fully connected multi-structured networks when used for classification purposes (Tejaswini et al., 2022).

2.3. Pest management using artificial intelligence

Pests are one of the main threats to paddy crop production. Farmers across the country face huge losses every year from reductions in quality and quantity of rice due to pest attack in their fields (Yao et al., 2020). In the past, farmers have continuously monitored their crops manually which is a tedious and labor-intensive process. It is a very difficult task for farmers to protect their crops from pests during and even after production. Pesticides are mainly used to control the number of pests in the field. Conventionally, sticky traps were used to trap insects, which were then identified and counted manually in laboratories. Finally, a targeted pesticide could be produced to kill a specific pest in the field (Yao et al., 2012). Eventually, such a process became significantly error-prone, taking up a good deal of time due to the inaccurate assessment of the pests present in the rice crop field. As a result, the chances of incorrect detection of the pesticide were also common thus causing null effect to the pest in the paddy field. Machine learning and CNN have been used to create a much easier, faster and more efficient method of detection and identification, by using image processing. This combination of techniques is one of the most promising of all the deep learning techniques, providing end-to-end learning and input image processing without any prior knowledge (Koshariya et al., 2023).

The equations used to create such a CNN are as follows (Koshariya et al., 2023):

$$Yj = f(wj * x) \tag{7}$$

where Yj = Feature map y (jth output) f = Non-linear function

w = Jth Feature map
j = Convolutional operator
x = Input image

The pool layer reduces the feature space resolution for optimizing high input distortion. It passes the average input image value to the next image. The max pool value is passed to the next layer.

$$Y_{jik} = (p, q) \in R_{ik}^{max} X_{jpq} \tag{8}$$

where $Yjik$ = jth feature map

$xjpq$ = Elements at point $(p,\ q)$
Rik = Field at location (i, k).

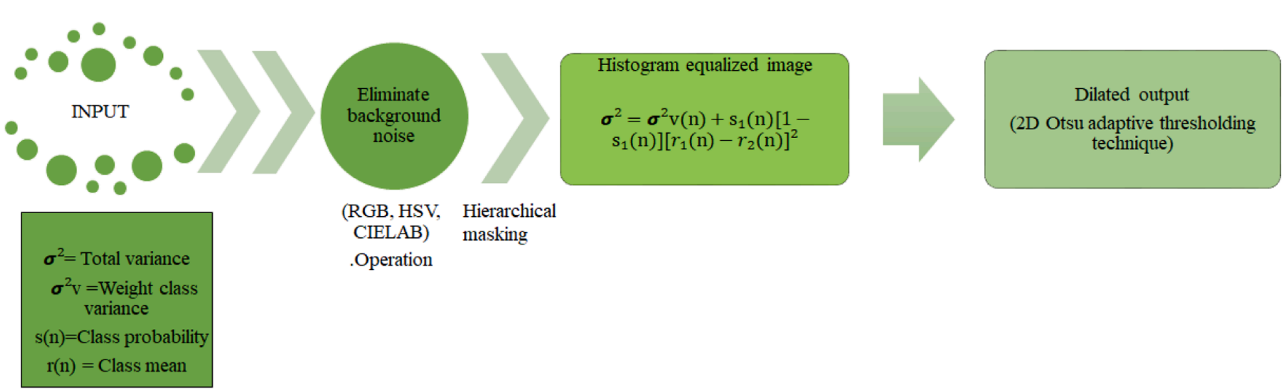


Fig. 6. Image processing using CNN operations.

The connected layer translates the output of the convolutional and pool layers, and applies a high-level reasoning function. In the past, the operator Softmax was used for resolving the classification problems in deep CNN but a SVM method is now frequently used as it produces more accurate, faster results. However, this method carries a high computational cost, which is a problem that can be solved by using a global average pool layer.

The insect light trap system was used before the use of sticky traps. It takes images of more than one insect and their features from top to bottom of the trap by using more than one camera. It is based on machine vision, comprising a cloud server and client platform such as a computer or mobile phone. It initially traps, kills, or releases insects by taking pictures and saving them on the server. The comparison uses approximately six color features, 18 shape features, and 54 texture features from a single image of each insect. A total of 156 features comprising images from the top to the bottom of the trap are analyzed and further used for training and testing of the SVM classifier. However, there is a major problem with the selection of just targeted insects and thus the results are inaccurate. An automated system using image processing and AI has been developed to identify and count the Brown Plant Hopper (BPH) (Nasser Shah et al., 2019) present in a paddy field. It comprises image capture, image distortion, feature extraction, object segmentation and detection. For image capture, an image was first taken of the sticky traps by attracting insects to a light for about 4 h to avoid multiple insect collection and trapping only those insects with a similar size to BPH. A rectangular image of approximately 2490×1800 pixels was captured after 4 h and saved in JPG format. For image distortion, the image data are changed by using a transformation from RGB color to the HSI model, which is a color model based on human color perception. Each color in an image is defined in terms of Red (R), Green (G), Blue (B), hue (H), saturation (S) and intensity (I).

The HSI model is created from the RGB color model using Eqs. (9)–(11), as given in Fig. 7:

$$H = \cos^{-1}\left(\frac{[1/2(R-G)+(R-B)]}{\left[(R-G)^2+(R-B)(G-B)1\big/2\right]}\right) \tag{9}$$

$$S = \frac{1-\min(R,G,B)}{1} \tag{10}$$

$$I = \frac{(R+G+B)}{1} \tag{11}$$

Image segmentation is a crucial step as it enables counting of insects. It processes the image by separating the objects from the background.

The k-mean clustering classification is much more accurately based on features extracted between the edge and background, and the foreground/background ratio and their difference. The k-mean algorithm is based on k number classes that are generated after choosing a center k cluster either randomly or heuristically, assigning a pixel value to the image and recomputing the cluster center. The undesired regions in the images are known as noise, which is variation in brightness or color data. Most noise appears much smaller than the target object and can be eliminated using appropriate filters. Image linearization (Liundi et al., 2019) converts the image of the BPH to a binary black and white image which has brightness as two levels, 0 and 1. Smaller unwanted objects are eliminated when their pixel values are less than the standard set pixel value. Additionally, image feature extraction identifies objects and determines their features dependent on color, texture, size, and morphology thus finding the type of insect. Insect detection and counting in an image is achieved using the kNN classification method.

2.4. *Identification of fungal and bacterial infections in rice using a neural network*

Fungal and bacterial diseases such as rice blast, bacterial leaf blight, sheath rot of rice, potato late blight and gray tomato mold are some of the more common fungal diseases that have been problematic for paddy crop production, as shown in Table 2. They cause immense damage, hindering the growth of rice and destroying productivity (Liundi et al., 2019). Some of the common fungal pathogens are *Magnaportheoryzae, Botrytis cinerea, Phytophthora infestans* and *Sclerotinia sclertiorum*. They are responsible for a significant reduction in rice production of 40–50 %. Identification of a fungal disease depends on first detecting the deteriorating health of the plant. However, since different fungal infections have the same symptoms, and can co-exist in the same field, it can be difficult to identify which fungal infection is present (Tejaswini et al., 2022; Haridasan et al., 2023).

The most problematic disease of rice is false smut, caused by the fungus *Ustillaginoidea virens*. The pathogen is small and can be observed between the glumes. It spreads to be >1 cm in diameter, encircling the plants' florets and releasing toxins which are dangerous to humans and livestock. Ultimately, this pathogen destroys the rice crop completely. Conventionally, detection of fungal disease was completely based on three methods namely, the observation method, symptom induction or

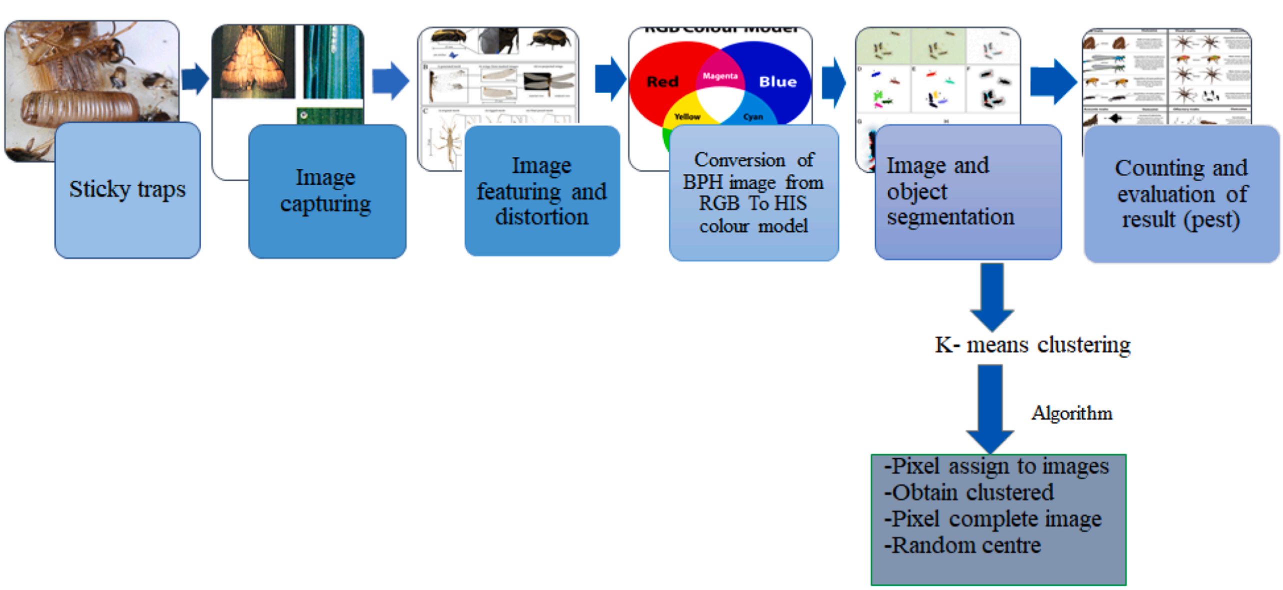
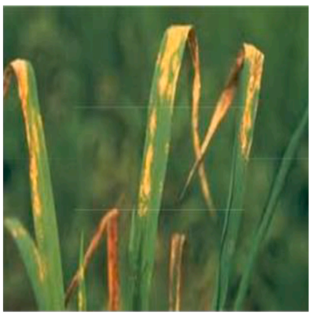


Fig. 7. Detection and counting of pests in paddy fields.

Table 2
Details of various fungal and bacterial diseases in paddy leaves.

Affected Leaf	**Scientific Name of Disease**	Common name of Disease	**Affected area**
	*Cochliobolusmiyabeanus*	Brown spot	Fungal disease affects mainly the leaves, leaf sheath, panicle branches, glumes and spikelet
	*Xanthomonas oryzae*	Bacterial leaf blight	This type of bacteria can survive the winter in plant detritus, but cannot endure a long time in just soil or water. These sores are frequently caused by insects. *
	*Magnaporthe grisea*	Rice Blast	The crop is afflicted by a fungus. This disease affects rice kernels, leaves, collars, nodes, necks, panicle pieces, and leaf sheaths.
	*Sarocladiumoryzae*	Sheath rot of rice	Rotting occurs on the leaf sheath that encloses the young panicles. Infected panicles and grains are sterile, shriveled, unfilled and discolored.

determining pathogen type at a laboratory scale (Arinichev et al., 2021). When using the observation method, incorrect and inappropriate disease detection results are likely. Due to many diseases having similar symptoms, the identification of disease is often incorrect. On the other hand, laboratory identification using pathogen cultivation is a very tedious process and it always requires highly skilled professions who are not available in smaller laboratories (Ouhami et al., 2021). The classic approaches followed by scientists to identify fungal diseases include optical techniques, microscopic techniques, biological approaches, culturing methods and genetic approaches as given in Fig. 8 (Ramesh and Vydeki, 2019). The basic steps behind all these approaches are first to take a picture of an affected region using cameras or scanners, isolating the affected section from the background, then analyzing the difference in the image by comparing its features after extraction of colors, textures, and shapes with the help of classification techniques such as neural networks, SVM, and k-NN (Haridasan et al., 2023).

The optical approach helps in detecting the physical symptoms of the disease and how much it has affected the plant. The microscopic technique analyzes the changes in the infected tissue of the plant and identifies the causative agent of that pathogen and its sporulation cycle. The biological approach uses AI to predict the degree and range of damage to the affected tissue as a percentage. The culturing method involves the isolation of fungus in a nutrient medium and observation of its external and cultural characteristics and pattern of growth. The genetic approach uses molecular genetics techniques such as polymerase chain reaction (PCR) for diagnosing the fungi. By combining PCR with the ANN method (Liu et al., 2008), the level of infection in rice panicles can be determined, the main objective being to determine the different infection levels in diseased rice panicles (Liu et al., 2008). In relation to artificial neural networks, learning vector quantization (LVQ) is a supervised learning technique, based on vector quantization differentiate variable input vectors. It also consists of input, hidden and output layers used to compare normal, mild and serious infection levels in the rice panicles (Liu et al., 2022). The input layer data is interpreted using the hyperspectral data processing technique. Trained weights having a mean square error < 0.01 are optimized in the hidden layer, with the

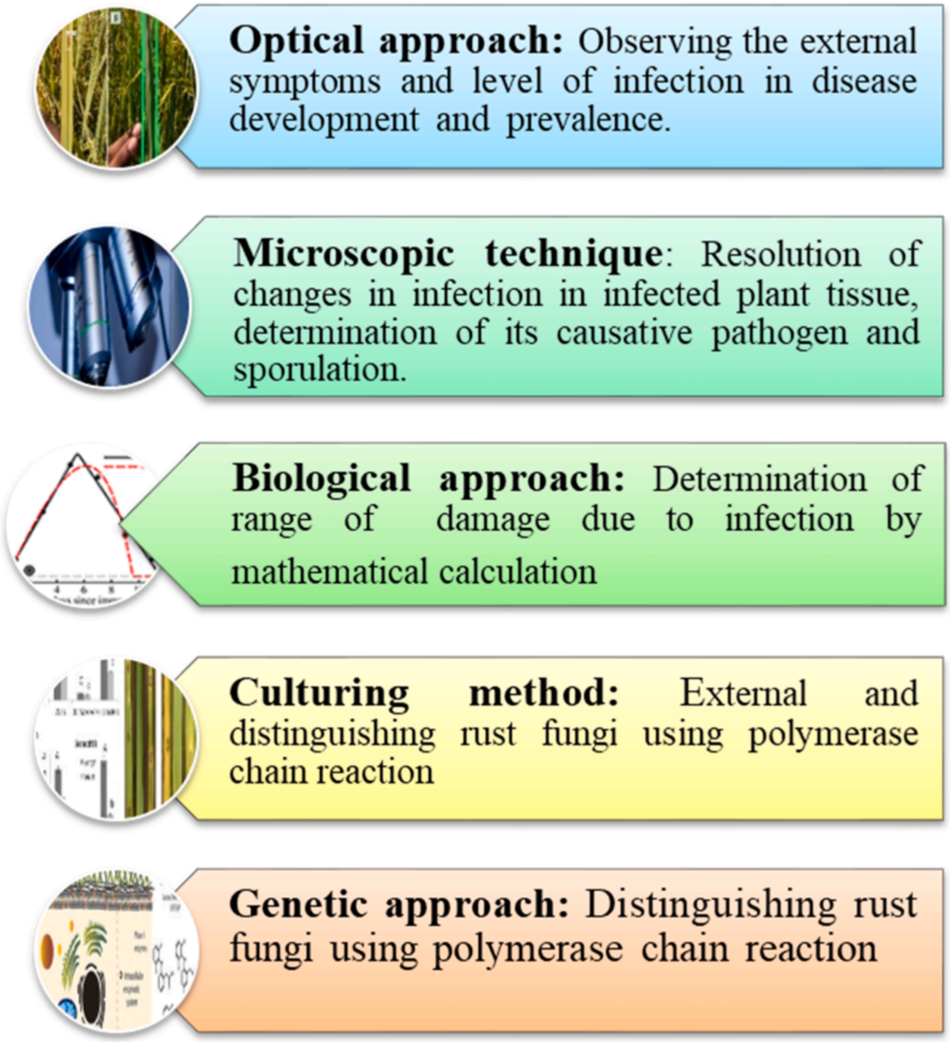


Fig. 8. Classic methods of identification and classification of fungal disease in rice.

output layer node producing the final categorization of infection as normal, mild or serious.

Magnaportheoryzae (Galhano and Talbot, 2011) is another serious fungal disease-causing rice blast in a paddy crop. The physical symptoms that appear are lesions on leaves, stems, peduncle, panicle, seeds and roots. One of the most common signs is a diamond-shaped lesion on the affected leaves that are brown in color initially, but become black at a later stage. Sometimes, the affected leaves form spores called conidia on them. The branches become brittle and are easy to break off. The pedicle on the infected leaves do not produce seeds. It is a highly labor-intensive and tedious process to monitor and detect rice blast infection in rice fields for the farmers. However, AI and the Internet of Things can be combined to detect this disease efficiently. The spot color on plant parts can be detected using deep learning CNNs (Sethy et al., 2020b). The neural network approach uses hyperspectral data for detecting plant disease. Using an AI-based model and an IoT platform, AgriTalk created an application called Rice Talk, which used sensors for resolving field issues. They used non-image data for training, using a real-time AI mechanism integrated into an IoT platform (Sharma et al., 2020).

The application uses weather information from the central bureau of weather through software, and other real-time data, such as temperature, humidity, barometric pressure sensor and rainfall. from micro weather stations using AgriTalk sensors (Chen et al., 2020a). The AgriTalk server comprises the AgriTalk Engine, which inputs the information from weather stations, and the AgriTalk graphical user interface (AgriGUI), which provides the user with an AI-based IoT platform to create projects. The input data are sent to computer or smartphone and can be accessed on the web alert dashboard after being completely processed by the AgriTalk Engine. The AI training model also receives its input for labeling from an input device called Infection. The AI AgriTalk weather station gives the users real-time features, where a farmer can also check for diseases such as rice blast in its training feature. The web dashboard has an alert system which provides real-time information about the sensor outputs which is easily accessible on the smartphones. The application displays icons for showing barometric pressure (BARP-I), checking temperature (Temp-I), showing relative humidity (Humidity-I) and checking the growth rate of spore germination (Spore-I). The AgriTalk Engine is also connected to two cyber devices, namely the DataBank cyber device and ML cyber device. The DataBank cyber device receives data from the weather input device for pre-processing, while the ML cyber device helps the AI models to produce outputs for the alert system in the web-based dashboard available on smartphones as shown in Fig. 9 (Yao et al., 2012; Koshariya et al., 2023).

2.5. Weed detection in paddy fields using artificial intelligence

Weeds are one of the most important factors that reduce rice production. They not only increase costs but also affect the quality of the rice crop. They are undesired, fertile, competitive and deplete the crop

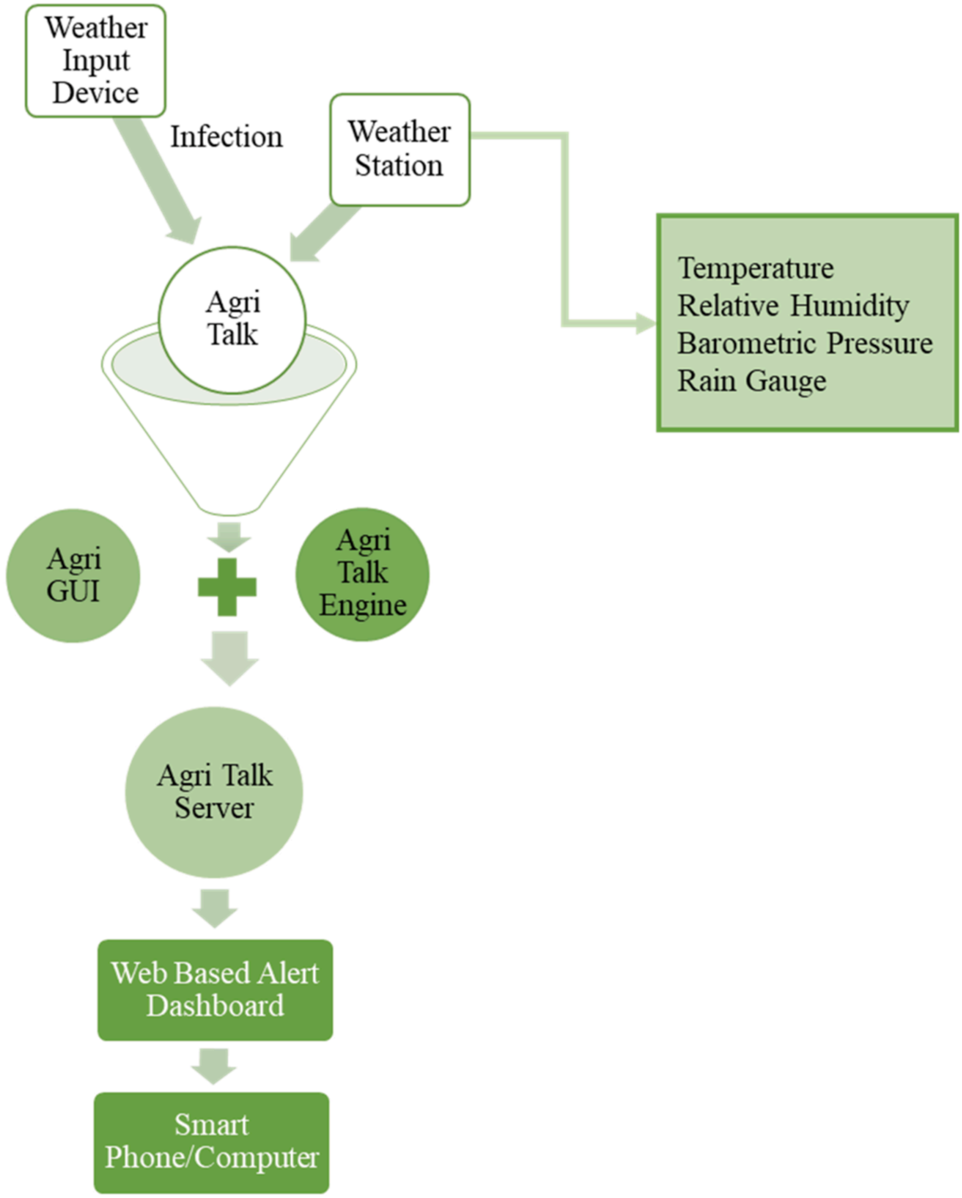


Fig. 9. Functioning of AgriTalk using web-based server.

environment by growing in every field, thus they are also known as a plant that grows irrespective of time and place. Weeds affect crops at any growing stage by competing for water, sunlight and nutrients (Aggarwal et al., 2022; Kamath et al., 2020), thus threatening their productivity. Hence, it is a main biotic constraint whose early control is a major need which is estimated to prevent the losses of rice crop up to 34 % and limits the use of chemicals and prevent from the pest attacks and diseases.

In the past, weeds were managed by cultural or non-chemical methods (Dinesh Kumar et al., 2021) such as hand-pulling and weeding, puddling and flooding using manual labor which, ultimately, used to take about 7 to 10 days, depending on the area of the field, climatic conditions and workforce, to complete (Zhang, 2003). More recently, the time-consuming labor-intensive non-chemical manual method (P and Eagan, 2014) of weed control shifted to the use of chemicals. However, chemical methods significantly affect the soil's properties such as pH, salinity, and the macro and micro nutrient level. They also affect the growth and grade of the rice crop in the field because of the herbicides sprayed (Partel et al., 2019) on to the crops directly over the entire field without understanding the distribution of weeds (Shibayama, 2001). It was an expensive approach but, more than that, it caused severe environmental pollution and risk to human life.

The combination of machine learning and digital images of weeds helps in recognizing the precise locations of weeds present in the paddy field with much higher accuracy (Cheng and Matson, 2015). Different weed detection models based on deep learning algorithms can apply the selection criteria that help in discrimination between the rice crops and the unwanted weeds based on feature detection and extraction from the image. Images of weeds can be collected in the paddy field by using cameras, polarization spectroscopy, hand-held spectroradiometers and satellites. An Unmanned Aerial Vehicle (UAV) is the most common research platform because of its availability, high quality data transfer and easy processing used to identify weeds in the rice field crop. UAVs use different types of data collection sensors such as Red Blue Green (RGB), multispectral and hyperspectral sensors (Eugenio et al., 2023). The RGB sensor is most commonly available and utilized in commercial cameras. It produces high-quality images, is low cost and has easy operational processes for object recognition, disease detection and phenology. optimizing machine learning (Barrero and Perdomo, 2018). A multispectral sensor is mainly used because it detects multiple RGB bands. The various multispectral images are captured and processed for input and output errors and unidentified data by using radiometric and atmospheric correction (Roslim et al., 2021). The sensor can be combined with machine learning algorithms for Site-Specific Weed Management (SSWM). The drawback of these sensors is that they are inefficient at producing a good quality high-resolution spectral images and handling overlapping images.

The third sensor is the hyperspectral sensor (Sulaiman et al., 2022) which detects visible light but split across many more bands than just red, green and blue. It has a variable number of radiometric spectral bands, ranging from visible to infrared or sometimes microwave. It is much more complex than a RGB or multispectral sensor because of radiometric and atmospheric correction. It comprises of different image sizes and its data storage and quality assessment of image.

Image masking consist of the creating a binary mask to isolate specific regions of interest within the hyperspectral image, facilitating focused analysis and reducing computational complexity. A binary mask is essentially an image where the pixels of interest are marked with a value of 1 (white), and all other pixels are marked with a value of 0 (black). This binary information helps in filtering out irrelevant data, enabling more accurate and efficient processing of the hyperspectral data. By applying a mask, we can, for instance, concentrate solely on a crop field within a larger image, ignoring surrounding areas like roads or buildings. This targeted approach not only enhances the precision of subsequent analyses, such as vegetation health monitoring or soil property assessment but also significantly reduces the data volume to be processed. A masking process is carried out after that image is converted into a format such as an RGB image. Binary information can then be extracted by converting the three component RGB image into a gray scale. It eliminates the unwanted background from the foreground object and reduces unwanted data in the image. The weeds and crops are classified using machine learning algorithms such as SVM, KNN and USL based on parameters such as size, shape, and color. The machine learning algorithms identifies and discriminates between the weed and crop more precisely by optimizing a deep neural network (DNN) (Sen Debleena and Barnwal, 2020). Feature selection and extraction are carried out to classify the images with higher accuracy to identify features such as shape, color, position and size (Kamath et al., 2020). The features that detect the weeds are categorized as spectral features, visual features, spatial features, and morphological features. Specifically, the color features and spectral features are mainly used when there is a significant difference in color between the weed and crop.

Overall, the sensors that were previously covered each have pros and cons that make them appropriate for a variety of uses. While multispectral and RGB sensors provide more information, they only record a portion of the electromagnetic spectrum. Their main advantages are cost and simplicity of use, which makes them perfect for applications like vegetation assessment of health and agricultural surveillance that call for rapid and generic analysis. But their low spectrum resolution makes it difficult to distinguish between related elements. On the contrary, hyperspectral sensors record hundreds of consecutive spectral bands, providing fine-grained spectrum data capable of identifying even the smallest variations in the composition of the material. They are useful in applications like as ecological surveillance, precision agriculture, and mineral prospecting due to their excellent resolution of spectral information. The drawbacks include their high price, intricacy, and massive data quantities, which call for a lot of processing power and knowledge. UAVs, offer flexibility and high spatial resolution. They may collect data from low-level locations by deploying a variety of sensors, including as RGB, multispectral, and hyperspectral ones. In situations like disaster response, precision farming, and structural inspection that need for regular, focused, and high-resolution data collecting over difficult or unreachable regions, they perform better than alternative approaches. The limits of UAVs include limited flying durations, regulatory restrictions, and weather sensitivity. UAVs, as opposed to manned or satellite aircraft, provide unmatched on-demand data collecting, but they have operational and logistical limitations that need to be addressed.

To obtain the green segment region and object part, and eliminate the soil background from the image, the following equation for the RGB third sensor is the hyperspectral sensor is used (Sohail et al., 2021):

$$I_{Plant}\left(X_{Pixel,}Y_{Pixel}\right) = I_{G\_S} \tag{12}$$

$$I_{Plant}\left(X_{Pixel,}Y_{Pixel,}G\right) - I_{Gray}\left(X_{Pixel,}Y_{Pixel}\right) \tag{13}$$

where $I_{Plant}\left(X_{Pixel,}Y_{Pixel,}G\right)$ represents the green segment region and $I_{Gray}\left(X_{Pixel,}Y_{Pixel}\right)$ denotes the rest of the background region.

To reduce the noise, a 3 × 3 filter mask is applied for median filtering, maintaining edges, and differentiating objects of interest with a specific threshold value. The threshold is estimated by using Otsu's method of selecting the appropriate histogram according to the following equation (Sohail et al., 2021):

$$Ibin(x,y) = \begin{cases} 0, Imedian(x,y) < t \\ 1, Imedian(x,y) \geq t \end{cases} \tag{14}$$

Classification of the image is finally achieved using machine learning and deep learning algorithms to differentiate the weeds from the rice field by evaluating the accuracy assessment quality of the classified output image. The comparison of the classified pixels of the image with the ground truth pixel is carried out using a confusion matrix in terms of the producer accuracy and overall accuracy. The producer accuracy is defined as the probability of identifying a pixel accurately as class X where X is known as the ground truth class. The final calculation uses the following equation (Rosle et al., 2021):

$$Producer\ accuracy = \frac{c_{aa}}{c_{\cdot a}} \times 100\% \tag{15}$$

where: c_{aa} = Element at a position aTh row and aTh column

$c_{\cdot a}$ = Columns sums

Overall accuracy is defined as the total correctly identified percentage of pixels and is calculated by using (Gandhi et al., 2016):

$$Overall\ accuracy = \frac{\sum_{a=1}^{U} c_{aa}}{Q} \times 100\% \tag{16}$$

where:

Q = Total number of pixels.
U = Total number of classes.

Weed detection accuracy is given by the area of observed weeds that intersect with areas of weeds detected by the algorithm divided by the area of observed weeds. This ratio is multiplied by 100 to give a percentage of area correctly identified as containing weeds. It can be calculated by using the following equation (Rosle et al., 2021):

$$WdA\ (\%) = \frac{Area\ ofobserved\ weed\ objects\ intersecting\ Detected\ weed\ Objects \times 100}{Area\ ofObserved\ Weed} \tag{17}$$

CNN is a well-used deep learning algorithm that can be used to identify the significant elements without the need for human assistance. This algorithm requires an input image structured such that its height (m) is equivalent to the width (m). Its depth (r) is called the channel number and, for an RGB image, is three.

The kernel filter for the convolutional layer is denoted by the letter k (n x n x q) where n is less than m, and q is less than or equal to r. The convolutional layer calculates the dot product between the input and weights by using (Rosle et al., 2021):

$$h_k = f\left(W^k * x + b^k\right) \tag{18}$$

where:

h_k = Feature maps in size (m – n – 1).
W^k = Weightage.
b^k = Bias.

Deep learning can be used to classify weeds in paddy crop fields with a higher accuracy than suitable weed map (Tiwari et al., 2019). To accurately recognize weeds using deep learning algorithms, a large training dataset is required which contains data about weeds in a variety of environmental conditions. Once trained, such a system can achieve an accuracy of around 85–99 % detection of weeds in images of paddy crop fields (Bal and Kayaalp, 2021).

3. Application of artificial intelligence for predicting biotic stress in paddy crops

Biotic stress in paddy crops represents a major threat to their development and production. It is caused by various pathogens, pests and weeds and is a serious challenge for farmers and scientists as it can result in huge losses in crop production. The use of artificial intelligence, through sub-classes such as AI, has reduced the issues associated with identification, detection, and classification of diseases by using images of the affected parts of the rice plant. Multi-structured CNN models, such as VVG-16, VGG-19, Dense Net (Gandhi et al., 2016) and CNN classifiers such as SVM, back proportion neural network and k-NN, have been used for identification, diagnosis, and classification of diseases in paddy fields. Detection and classification of disease and the level of infection caused by the pathogens can be optimized and analyzed by using multi-layered neural networks (Al-Amin et al., 2019). Image datasets can be analyzed using variable image augmentation methods and categorization can be achieved by optimizing the training, validation, and testing processes for different CNN models (Kaundal et al., 2006). Smart agriculture in combination with AI can be used to create an application to detect and classify pests in paddy fields. The Line Bot application uses deep learning dataset training and testing processes with disease classification CNN models such as YOLOv3 to predict and diagnose a disease and its pathogen efficiently. Therefore, the application of AI helps in solving issues related to paddy crop diseases and, thus, in improving productivity.

3.1. Prediction of paddy cultivation using deep learning

Deep learning CNNs can be used for identification and classification of biotic stresses and diseases in paddy crop plants. The production of rice can be improved by using technologies such as machine learning, Big Data, and the Internet of Things to enhance productivity. Multi-layered CNNs (Chen et al., 2020b) with specific classifiers have been implemented to solve the multi-level problems associated with diagnosing biotic stress in paddy crops. There are various well-known CNN models that work well at recognizing, classifying and categorizing paddy crop stresses and their associated diseases, as shown in Fig. 10 (Anami et al., 2020; Sudar et al., 2022; Latif et al., 2022). SVM, Back proportion neural network (BPNN), K- nearest neighbor (k-NN) are CNN image classifiers (Atole and Park, 2018) that are used in CNN models for classification of objects in an image.

The average accuracy of every model has been found to be greater than 90 %.

The operation of CNN models is shown in Fig. 11 (Islam et al., 2021b). First, image datasets are obtained by capturing images of the rice field using high-resolution cameras during daytime. Images are enhanced using multiple augmentation methods such as scaling, shearing, and translation. The image dataset comprises three sub-datasets: training, validation, and testing. Finally, they are resized to reduce the number of pixels to optimize computational time.

Transfer learning models are used for improving the use of CNN to process image datasets. These are easily editable using MathWorks' Deep Network Designer application. VGG-16, Inception-V3, ResNet-50, and DenseNet-128 are some of the most common models that have the greatest potential for image processing since they are pre-trained. Testing the CNN models (Lu et al., 2017) involves using a paddy crop stress image dataset to produce batches of images to use as a training

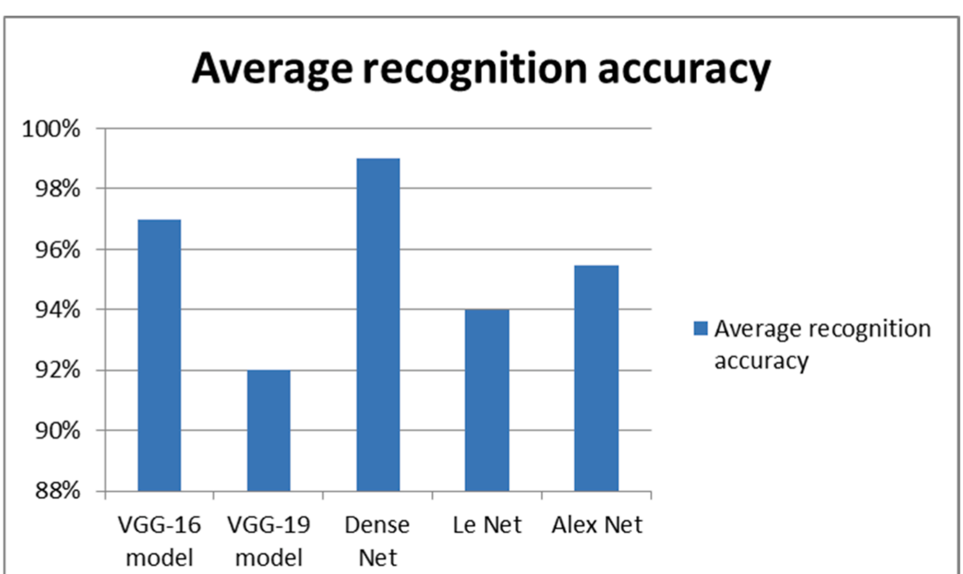


Fig. 10. Average recognition accuracy of different CNN models.

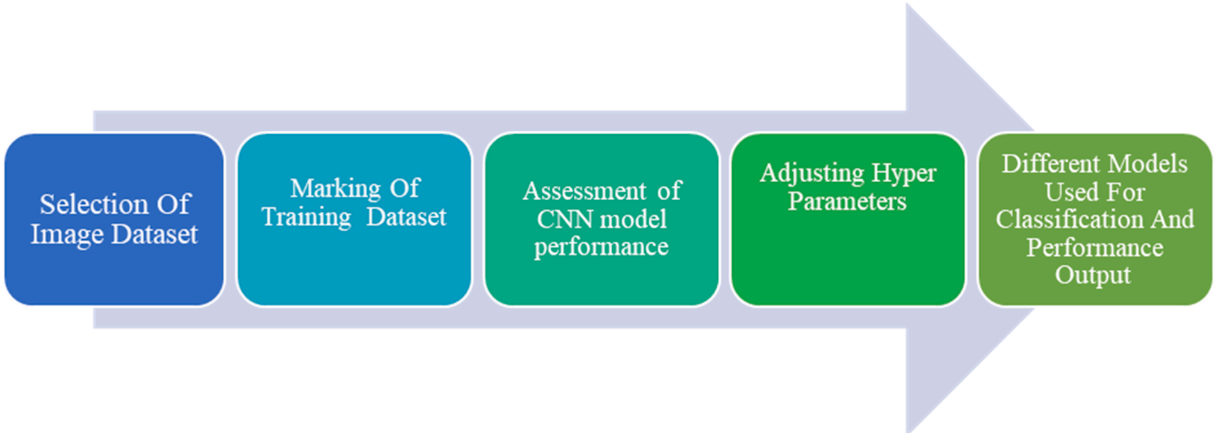


Fig. 11. Functioning of variable CNN models.

dataset. After training, a validation process of comparing the outputs with known images helps determine which models perform best. Precision, updating and F1 score evaluation matrices are formed which are used for comparing the performance of all CNN models (Bhupendra et al., 2022). Thus, these models were compared to find highest average percentage for identification, classification, and categorization of paddy crops. The highest average accuracy of all the models was 92.61 %. The DenseNet CNN model showed the highest classification accuracy at 99.75 % so can be used to make a much-improved model for classification of diseases in images of paddy plants (Vellaichamy et al., 2021).

3.2. Application-based model for diagnosing paddy crop disease

There is lack of technological resources that helps in predicting the threats, pests and leaf diseases in paddy crop production (Firdaus et al., 2020) for the farmers and experts. Thus, AI-based application helps in diagnosing paddy plant disease that are designed to provide real time day to day monitoring information about infected paddy crop (Poornappriya and Gopinath, 2020). The Line Bot application is made where an automatic chatbot is designed in collaboration with LINE account. Chatbot is designed as an automatic IoT robot that perform as a communication tool partner for the other person (Jain et al., 2022). The disease diagnosing engines are the main center hub that receives and store the information shared by the LINE Bot to it and further image processing is performed inside it and thus finally detects the disease objects in the paddy field images (Temniranrat et al., 2021). This application system is easy and practical in use even for the rice farmers to find out the area which is infected in the paddy leaves since, it uses images taken from the rice field directly using mobile LINE application. Starting with the image collection of infected rice paddy fields by clicking photographs from the fields, where physical symptoms were easily observed in the images (Chandolikar et al., 2022).

It was investigated the UAV multispectral remote sensing images and spatial-context-attention network (SCANet) to classify the nematode disease in pine with high precision and accuracy. SCANet achieved an overall accuracy of 79 % and enhanced capability of detection system of measurement over other methods (Qin et al., 2023). Furthermore Ma et al. (Zhu et al., 2023) employed the UAV equipped with cameras of multispectral and visible that united with YOLOv5 algorithm optimized for high-speed and high-accuracy detection. The model illustrates a precision of 98.1 % and accuracy of 97.3 %, showing it highly effective for detection infected plants. AI detects nematode diseases through a combination of remote sensing technologies, machine learning, and deep learning algorithms. Firstly, UAVs (drones) equipped with multispectral and visible light cameras capture high-resolution images of the forest canopy. Multispectral imaging involves capturing light in multiple wavelengths, which aids to detect the subtle changes in vegetation health that are indicative of disease. Then images are preprocessed to enhance the quality and extract relevant features. Vegetation indices like NDVI (Normalized Difference Vegetation Index) and NDRE (Normalized Difference Red Edge Index) are computed to highlight differences between healthy and infected trees based on their reflectance properties in different spectral bands. Then, deep learning models such as YOLO, SCANet, and GoogLeNet are trained using labeled datasets. These datasets consist of images of both healthy and infected trees, annotated by experts. The models learn to identify the patterns and landscapes related with nematode infestation (Qin et al., 2023). To improve feature extraction, advanced techniques like spatial-context-attention mechanisms, Convolutional Block Attention Modules (CBAM), and Coordinate Attention (CA) mechanisms can be employed. These methods help the model focus on relevant areas of the image and enhance detection accuracy for small-scale infestations. In further stage, models are assessed employing different metrics mainly precision, recall, and overall accuracy. Precision measures the proportion of true positive detections among all positive detections made by the model, while recall measures the proportion of true positives identified out of all actual positives. High precision and recall indicate effective detection capability. Once trained, these models can be deployed in UAVs for real-time monitoring of forests. The UAVs scan large areas, and the models process the images to detect and classify infected trees, facilitating timely intervention and control measures. The application steps as follows: preparation of training data is the next step and comprises three stages namely, training, validation and testing. The training and validation datasets together teach the deep learning model, while the testing dataset is used to evaluate its output. The algorithms used for training include Faster R-CNN, RetinaNet, YOLOv3and MaskR-CNN (Nawaz et al., 2022). These can be used to train a CNN to classify paddy crop diseases such as blast, blight, brown spot and narrow brown spot, bacterial leaf streak and rice stunt virus. The accuracy of object detection and location can be compared between deep learning models. Results can be categorized as either True Positive (TP), False Positive (FP), True Negative (TN) or False Negative (FN). The final precision (P) is calculated using the formula (Altinbilek and Kizil, 2022) :

$$P = TP / (TP + FP)$$

The CNN YOLOv3 can be used to predict limiting bounding boxes of objects and class probabilities using only one deep learning neural network with multiple enlarged layers in a single evaluation (Yumang et al., 2022). It can identify objects much faster and thus makes it more applicable for real-time applications. It utilizes binary cross-entropy for determination of objects class and mean squared errors bounding box regression. To use the Line Bot system, a user first must set up an official account to allow communication with the Line Bot platform. This gives them access to online groups that specialize in aspects of the Line Bot application. For example, there is a rice disease group. Images from users are shared to an object prediction deployment GPU server. The final output image contains objects that are labeled with their classification and prediction confidence, and is sent as a detection result image to the LINE Bot server. The LINE Bot server shares the predicted result images and text using the LINE Messaging API and LINE's service platform to the LINE Bot group and every user. Feedback logs are saved to use as data to improve the detection model. Thus, a smart application-based model using an AI server system and the Internet of Things together can easily, quickly, and much more accurately diagnose disease and its stages of infection in paddy crop plants.

3.2.1. Data preparation and training

For initiation of any systems, data preparation is the first stage which needs a lot of care and systems. The process of detection of biotic stress starts with the collection of images from infected rice fields, where physical symptoms are easily detected in the pictures captured directly from the grounds using the mobile LINE application. These descriptions are indispensable for structure a complete dataset to train AI models efficiently. Deep learning algorithms, such as YOLOv3, Faster R-CNN, RetinaNet, and Mask R-CNN, are also used in the training phase to categorize several paddy diseases that affect crops, such as rice stunting virus, bacterial leaf streak, blast, blight, brown spot, and narrower brown spot. These models are trained on labeled datasets, which are expert-annotated photos of both healthy and diseased trees. Using cutting-edge methods like spatial-context-attention mechanisms, Convolutional Block Attention Modules (CBAM), and Coordinate Attention (CA) strategies to improve feature extraction, the models are trained to recognize patterns and landscapes linked to nematode diseases.

3.2.2. Validation and testing

In the validation step, the model is adjusted and its training performance is evaluated using a subset of the training dataset. This guarantees the model's good generalization to fresh, untested data. Measures like recall, precision, and total accuracy are used to assess how well the model works. Recall indicates the percentage of genuine positives found out of all real positives, whereas precision measures the percentage of true positive identifications among all positive detections produced by the model (Altinbilek and Kizil, 2022). Lastly, the output of the model that was trained is assessed using the testing dataset. After comparing the models' precision in locating and detecting objects, the outcomes are divided into four categories: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) (Yumang et al., 2022). For example, in a single assessment, YOLOv3 may use a single deep learning neural network with numerous layers to forecast class probabilities and restricting bounding boxes of objects. To calculate the ultimate precision, use the formula. After testing, these models may be used in unmanned aerial vehicles (UAVs) to track forests in actual time. The models analyze the photos taken by the UAVs to identify and categorize sick trees, which allows for prompt intervention and management actions.

3.3. Challenges and opportunities related to using AI for biotic stress analysis

As discussed previously, rice is a basic food consumed around the world and the high demand for it presents major challenges for its production. Biotic stress negatively affects the growth and production of paddy crops. Developing an AI system which can accurately recognize paddy crop diseases caused by the fungi, bacteria, viruses, pests is a significant challenge. New data must consider the fact that the growth of paddy crops is related to parameters such as the cause of disease, the weather conditions, and its effects on the crop field. Training AI models to predict, analyze, and handle data with precision is highly time-consuming, complex, and expensive. It requires highly trained people who can easily help in identification, classification, and diagnosis of rice crop diseases. Also, farmers have trust issues with technological advancements, limited computational access, poor internet connectivity and are hesitant to use such applications. These models face a challenge from needing to be able to predict new variant threats to crops and their adaption. Sharing the image datasets for other purposes can raise privacy concerns. The inaccuracy and error in the results can be due to inappropriate processing of AI models. There is potential for such applications to help improve management, increase yield and reduce the environment stress in the paddy crop fields. Using the IoT (Joshi et al., 2022) and AI together can produce an application which accurately and quickly helps in identification, categorization, and analysis of biotic stress in rice crops. Thus, AI helps in the prediction of paddy crop diseases much faster and more accurately, increasing rice crop production.

4. Conclusions

Rice is the most common food grain produced and consumed all over the world by a large section of the population. The protection of paddy fields from attack by various pathogens and insects is of major concern. Such crops are prone to diseases from these causative agents which significantly reduce crop growth, development, and production potential. There is a need for an appropriate application for the farmers, and AI is one possible solution. In the past, detection of diseases in a paddy crop was mainly based on observations and monitoring of the symptoms, which was an inaccurate and time-consuming process. Deep learning, CNN, k-clustering, ANN, and SVM are various sub-fields of AI which can be used to identify and classify different paddy crop diseases. Deep learning is the most popular AI sub-class. It optimizes multi-layered structure processing of the image. Biotic stress in paddy crops can be detected, identified, and categorized using different CNN models such as VGG-16, VGG-19, DenseNet, and AlexNet. Different image classifiers, such as SVM, k- nearest neighbor (k-NN) and BPNN, all work with the CNN models. DenseNet was shown to have an accuracy of 99.75 %, (highest among all CNN models), when identified and classified paddy crop diseases. CNNs and the IoT can be used for a disease detection and classification system, where images captured by cameras, and drones can be manipulated and analyzed by a deep learning application that extracts features of the image and identifies diseased paddy crops. By optimizing a multi-layered network at input, hidden and output layer stages, the input images obtained can be processed by a multi-structured CNN. Training, validation, and testing sets use data from the input image. Machine learning involves using data from such images to improve the various CNN model, and improve their efficiency and accuracy. Thus, using AI has made the process of identification and classification of paddy crop diseases much faster, easier, user-friendly, and highly efficient.

CRediT authorship contribution statement

Shubhika Shubhika: Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Pradeep Patel:** Writing – review & editing, Data curation. **Rickwinder Singh:** Writing – review & editing, Formal analysis. **Ashish Tripathi:** Writing – review & editing. **Sandeep Prajapati:** Writing – review & editing. **Manish Singh Rajput:** Writing – review & editing. **Gaurav Verma:** Writing – review & editing. **Ravish Singh Rajput:** Writing – review & editing. **Nidhi Pareek:** Writing – review & editing. **Ganesh Dattatraya Saratale:** Writing – review & editing. **Aakash Chawade:** Writing – review & editing. **Kamlesh Choure:** Writing – review & editing. **Vivekanand Vivekanand:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

There's no financial/personal interest or no competing interests exist.

Data availability

Data will be made available on request.

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