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Optimizing rice plant disease detection with crossover boosted artificial hummingbird algorithm based AX-RetinaNet

Senthil Pandi Sankareshwaran · Gitanjali Jayaraman · Pounambal Muthukumar · ArivuSelvan Krishnan

Abstract Rice is the most important cereal food crop in the world, and half of the world's population uses rice as a staple food for its energy source. The yield production qualities and quantities are affected by biotic and abiotic factors namely viruses, soil fertility, bacteria, pests, and temperature. Rice plant disease is the most crucial factor behind communal, economic, and agricultural losses in the agricultural field. Farmers detect and identify diseases through the naked eye, which takes more time and resources, leading to crop loss and unhealthy farming. To overcome these issues, this paper presents a novel rice plant disease detection approach named the crossover boosted artificial hummingbird algorithm based AX-RetinaNet (CAHA-AXRNet) approach. This current research paper mainly concentrates on the effectiveness of rice plant disease detection and classification.

The hyperparameters of the AX-RetinaNet model are optimized through the CAHA optimization model. In this paper, three types of disease detection datasets namely rice plant dataset, rice leaf dataset, and rice disease dataset are included to classify rice plants as healthy or unhealthy. The most essential performance metrics are precision, F1-score, accuracy, specificity, and recall, employed to validate the effectiveness of disease detection. The proposed CAHA-AXRNet approach demonstrates its effectiveness compared to other existing rice plant disease detection methods and achieved an accuracy rate of 98.1%.

Keywords Rice plant disease detection · Crossover boosted · Artificial hummingbird · Food source · Classification

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Introduction

The agricultural sector plays a significant role in the Indian gross domestic product (GDP), and rice is the most widely used food source for Indian people. The well-being of plants is crucial for achieving food sustainability and security in the agricultural sector. Rice plant diseases are one of the causes of crop loss or decreased crop production (Anandhan & Singh, 2021). Around 30 types of plant diseases affect rice plants, reducing the quantity and quality of the product. Bacteria and fungi are the major causes of plant diseases, and biological factors such as climate

change, unbalanced soil nutrients, moisture stress, and temperature variation also reduce crop production (Archana et al., 2022). The most commonly occurring rice plant diseases are leaf smut, brown spot, rice blast, and bacterial blight. Early detection of plant diseases is crucial for reducing crop production loss. Visual evaluation and laboratory testing are the major diagnosis methods for rice plant diseases, but they sometimes cause errors. These methods also require more execution time and are difficult for large areas of the crop field (Singh et al., 2022; Senthil Pandi et al., 2022a; Dhiravidachelvi et al., 2023).

The automatic testing model for plant disease detection is responsible to ensure plant quality and high crop production. Advancements in deep learning networks and image processing techniques provide a chance to increase crop protection (Patil & Kumar, 2022a, b). In image processing, paddy plant images are captured from paddy fields, preprocessed, and segmented into healthy and unhealthy plants. Then, features in the segmented images are extracted and the rice plant diseases are classified by using deep learning techniques (Jiang et al., 2021). By using these techniques, the diagnosis of plant disease is more efficient, accurate, and requires less time. The advancement of technologies helps farmers to choose the right pesticides at the correct time. The accuracy of the plant disease diagnosis system mainly relies on feature descriptors, feature extraction, and feature selection. The technique of feature descriptors is implemented to extract features from the rice plant images because the features of images play a significant role in image processing (Islam et al., 2021). The main objective of this image processing technique is to increase the production of crops by examining plant fields (Senthil Pandi et al., 2022b; Kalpana et al., 2023; Sankareswaran & Krishnan, 2022).

In the examination phase, a classifier is used to diagnose plant disease by testing images and categorizing them into healthy or unhealthy plants. The quality of plant images captured for training relies on cameras because real-time images include background, shadow, and noise. Consequently, careful examination is required to remove the background and noise of selected images (Vishnoi et al., 2021). Specific devices are required to capture images such as hyperspectral, thermal, and fluorescent. Hyperspectral imaging techniques are now used to detect changes in crops, mainly for detecting rice smut diseases (Zhang et al., 2021). Additionally, some artificial intelligence (AI) technologies like Pestoz and Plantix are used to detect plant diseases (Temniranrat et al., 2021). In the agricultural sector, these technologies are used as plant disease detection tools by farmers and officers for the timely prevention and management of plant diseases (Shrivastava & Pradhan, 2021).

This paper focuses on a new automated rice plant disease detection system to help farmers increase the quality and yield of rice. The novel rice plant disease detection model is implemented in this paper to avoid unhealthy farming and crop loss. Our research article provides several new contributions and advances in the field of rice plant disease detection and classification. These contributions can be summarized as follows:

- Development of the CAHA-AXRNet model: We propose a novel and efficient detection and classification system, the CAHA-AXRNet model, specifically designed for rice plant disease analysis. This model addresses key challenges such as misclassification, misdetection, overfitting issues, and limited disease detection that are prevalent in previous research. By integrating the AXRNet architecture with the channel attention module and utilizing the CAHA optimization model, we enhance the performance of disease detection and classification.
- Overcoming scale changes and extracting multiscale feature information: The CAHA-AXRNet model incorporates the X-module to tackle the problem of scale changes in rice plant images. This module enables the extraction of multiscale feature information, ensuring that the model can effectively analyze images with varying scales, thereby improving accuracy in disease detection and classification.
- Optimization of parameters and hyperparameter prediction: We optimize the parameters of the AXRNet model using the CAHA optimization model. By attaining optimal parameter values, we enhance the overall performance of the model and reduce the loss function. Additionally, the CAHA-AXRNet model predicts optimal hyperparameters, resulting in an accurate and efficient detection model.
- Comparative performance analysis: We conduct a comparative analysis of the CAHA-AXRNet model with other state-of-the-art models, including DCNN, Faster RCNN, DNN-CSA, and ADSNN-BO. The results demonstrate that our proposed model achieves higher performance in terms of accuracy, precision, recall, specificity, and *F*1-

score, highlighting its superiority in rice plant disease detection and classification.

- Comprehensive evaluation and dataset analysis: We employ multiple datasets, including the rice plant dataset, rice leaf dataset, and rice disease dataset, for evaluation purposes. Performance measures such as accuracy, precision, recall, specificity, and F1-score are calculated, providing a comprehensive understanding of the CAHA-AXRNet model's capabilities in detecting and classifying rice plant diseases.

Overall, our research contributes to the field by presenting a novel model, addressing key limitations in existing approaches, and achieving improved performance in rice plant disease detection and classification. The combination of techniques used in our model, including the AXRNet architecture, multiscale feature extraction, parameter optimization, and comparative analysis, enhances the understanding and effectiveness of rice plant disease analysis methodologies.

The remaining sections of this rice plant disease detection paper are arranged as follows: "Literature survey" provides a detailed description of many existing research works related to rice plant disease detection. In "Materials and methods," the proposed methodology is presented for detecting rice plant diseases with the help of deep learning and optimization methods. "Experimental results and discussions" presents the experimental results to find the effectiveness of the proposed deep learning model. At last, this paper is concluded with future directions in "Conclusion".

Literature survey

The different research papers related to rice plant disease detection and classification were selected for designing an improved model. Table 1 described the literature survey of various existing research works, including their advantages and drawbacks.

Latif et al. (2022) established a deep convolutional neural network (DCNN) model for the detection and classification of rice plant diseases. This DCNN model has a modified VGG19 framework–based transfer learning model, and six types of disease classes were detected and classified. To validate the performance, the rice leaf image dataset was included, and an accuracy of 96.08% was attained through this

dataset. However, real-time rice disease detection was not possible, and only limited diseases were detected in this paper.

Bari et al. (2021) illustrated the faster region-based convolutional neural network (faster RCNN) model for real-time detection of rice leaf disease. The rice leaf infected images were classified into four types using a publically available dataset named as Kaggle dataset. Real-field images and laboratory-based images were taken to classify the disease types and detection criteria were used to locate and identify the rice leaf diseases. Some misclassification and overfitting issues occurred in this detection.

Krishnamoorthy et al. (2021) elaborated a convolutional neural network (CNN) model to recognize rice leaf disease. This deep learning model was implemented for resolving computer vision problems such as image analysis, object segmentation, and image classification. The InceptionResNetV2 model was used to identify the diseases in the rice leaf images. The data were proportioned into 70:30 for performance validation. However, limited diseases were detected in this paper, and the optimal parameters were not accurately selected.

Wang et al. (2021) developed an attention-based depthwise separable neural network with Bayesian optimization (ADSNN-BO) approach to detect and classify rice leaf disease. The optimization approach was used to achieve optimal parameter values for performance enhancement. The rice disease dataset classified the image into different classes, and the filter visualization and activation mapping approaches were employed to analyze the features. The classification accuracy of 94.65% was captured from the dataset. However, it has low computational time, and weather conditions of the field affect the rice disease image.

Goluguri et al. (2021) demonstrated a deep convolutional neural network–based long short-term memory (DCNN-LSTM) method to identify rice diseases. The efficient artificial fish swarm optimization (EAFSO) algorithm was included to optimize the parameters, identify optimal weights, and enhance performance. The publically available dataset classified the image into different types of diseases, and the EAFSO with DCNN-LSTM model displayed better accuracy compared to other methods. However, other types of artificial intelligence models were required to enhance performance.

Table 1 Literature survey of different research works

Author's name	Techniques	Dataset	Metrics	Pros	Cons
Latif et al. (2022)	DCNN model	Rice leaf image dataset	Precision, $F1$-score, accuracy, recall, and specificity	Better performance	Limited disease detection
Bari et al. (2021)	Faster RCNN model	Kaggle dataset	Loss and accuracy	Locate and identify the rice leaf disease	Misclassification and overfitting problem
Krishnamoorthy et al. (2021)	CNN model	Kaggle dataset	Classification accuracy, precision, recall, and $F1$-score	Resolve computer vision problems	Limited disease detection and optimal parameter were not accurately selected
Wang et al. (2021)	ADSNN-BO approach	Rice disease dataset	Classification accuracy, $F1$-score, recall, and precision	Reduce crop losses	Low computational time
Goluguri et al. (2021)	EAFSO with DCNN-LSTM model	Publically available dataset	Convergence, accuracy, sensitivity, specificity, RMSE, and Matthews correlation coefficient	Optimal weigh identified	Required optimal parameters
Chen et al. (2021)	DL-CNN approach	PlantVillage dataset	Sensitivity, precision, specificity, accuracy, and $F1$-score	Applicable for diverse plant disease identification	Real-time applications were not suited
Ramesh and Vydeki (2020)	DNN-JOA approach	Rice leaf image dataset	Cross entropy loss, accuracy, precision, and $F1$-score	High stability	High false classification
Nalini et al. (2021)	DNN-CSA approach	Open-source database	Recall, precision and accuracy	High efficiency	Lack of real-time analysis
Sharma et al. (2022)	InceptionResNetV2 model	Rice disease dataset	Validation accuracy and validation loss	High rice plant disease diagnosis rate	Need large dataset to identify more diseases
Upadhyay and Kumar (2021)	Fully connected CNN framework	Rice leaf dataset	Accuracy and loss	Low complexity and computational time	Severity level detection was not considered
Narmadha et al. (2022)	DenseNet169-MLP	Rice plant image dataset	Accuracy, precision, $F1$-score, sensitivity, specificity, and negative predicted value	High image quality	Need some performance enhancement
Daniya and Vigneshwari (2022)	RSW-Deep RNN method	Rice disease dataset	Specificity, sensitivity, and accuracy	High efficiency	Limited disease detection
Patil and Kumar (2022a, b)	Improved CNN model	Rice plant dataset	Accuracy, true positive rate, and mean average precision	Better performance	Proper maintenance of natural crop quality was required

Table 1 (continued)

Author's name	Techniques	Dataset	Metrics	Pros	Cons
Dogra et al. (2023)	CNN-VGG19 model	Rice leaf disease dataset	Accuracy, precision, sensitivity, $F1$-score, and specificity	Higher performance	Overfitting issue
Nayak et al. (2023)	CNN framework	Rice leaf image dataset	Specificity, sensitivity, false positive rate, accuracy, F-beta score, and Matthew's correlation coefficient	Has the capability to handle large image dataset	Lack of micronutrient deficiency identification
Daniya and Vigneshwari (2023)	RWW-NN model	Rice disease dataset	Computational time, training accuracy, sensitivity, specificity, and F-measure	Less computational time	Required more datasets for better performance

Chen et al. (2021) portrayed a deep learning–based convolutional neural network (DL-CNN) approach to identify and classify rice plant diseases. The learning capability of MobileNet-V2 was improved for lesion features, and the attention mechanism was included with MobileNet-V2 for input features. The transfer learning model was used to optimize the loss function, and the classification was performed using the PlantVillage dataset. The result of this paper showed better validity and feasibility in diverse plant disease identification. However, real-world applications were not suitable for this model.

Ramesh and Vydeki (2020) established a deep neural network–based Jaya optimization algorithm (DNN-JOA) approach to recognize and classify paddy leaf disease. In preprocessing, the RGB images were converted into HSV images according to the saturation part of the binary image. The rice leaf image dataset was chosen to classify the images into various types of diseases, but it has a high false classification rate.

Nalini et al. (2021) developed a paddy leaf disease detection approach using the deep neural network–based crow search algorithm (DNN-CSA). The paddy leaf disease was identified using the DNN model from plant image data, and the classification errors were reduced with the help of the CSA model by optimizing weights. The feature extraction was performed from the isolated disease regions to ensure better classification accuracy. The open-source database was selected for performance validation, but real-time analysis and remote devices were required to attain the detection performance.

Sharma et al. (2022) elaborated a transfer learning method for the early detection of rice plant detection. The rice disease dataset was employed in this paper to train and test different rice diseases such as rice blast, rice bacterial leaf blight, and rice brown spot. The image was resized into a suitable size at the preprocessing stage and the dataset extension was performed by using the data augmentation method. The InceptionResNetV2 model provided a greater performance related to other deep learning models. A large dataset was needed to detect a number of rice plant diseases.

Upadhyay and Kumar (2021) illustrated a fully connected CNN model for attaining efficient rice plant disease detection. The rice leaf dataset was taken from the Kaggle to identify the healthy and unhealthy cases by using three types of diseases such

as bacterial leaf blight, brown spot, and leaf smut. The preprocessing phase was implemented to ensure the image quality by removing background noise, resizing, and cropping. The image features were automatically learned in the feature extraction phase and this model reduced the complexities and computational time. The severity level analysis was more important to find accurate detection.

Narmadha et al. (2022) designed a densely CNN and multilayer perceptron (DenseNet169-MLP) to diagnose rice plant diseases. The preprocessing phase was used to perform noise removal, grayscale conversion, and channel separation. The diseased portion of rice plant image was identified by applying fuzzy c-means (FCM)-based segmentation process. In the classification stage, the rice plant image dataset was categorized into three classes namely brown spot, bacterial leaf blight, and leaf smut. The hyperparameter tuning process was necessary to enhance detection performance.

Daniya and Vigneshwari (2022) established a RideSpider water wave–based deep recurrent neural network (RSW-Deep RNN) to find the diseased spot of the rice plant. The artifacts and noises present in the image were removed by preprocessing the images and the segmentation network was used to extract texture features, CNN features, and statistical features. The rice disease dataset was employed in this paper for detecting three types of rice diseases such as bacterial leaf blight, blast, and brown spot. This paper revealed higher efficiency but it covered limited number of rice plant diseases.

Patil and Kumar (2022a, b) demonstrated an improved CNN model for addressing limitations during rice plant disease detection. The images of rice plant dataset were collected from the real-time rice farms and the deep features were extracted by using multi stream framework. The cross attention model was applied to learn the correlation and variance that integrates the extracted attention map for gaining related features. The management system was essential to handle the quality of natural crops.

Dogra et al. (2023) represented a CNN-based visual geometry group (CNN-VGG19) model for the detection and classification of brown spot disease. The images were selected from rice leaf disease dataset and the data was preprocessed by enhancing image features. The parameters and spatial sizes were compressed for minimizing the dimensionality of the image. The higher spatial dimension leads to an overfitting problem.

Nayak et al. (2023) developed a different CNN framework to detect rice plant diseases and nutrient deficiency. In this paper, the different rice diseases such as rice blast, bacterial blight, brown spot, stem rot, leaf burn, leaf smut, and rice tungro virus as well as deficiency symptoms, namely nitrogen deficiency, potassium deficiency, and phosphorus deficiency were identified. The micronutrient deficiency symptoms were not able to identified by using this research.

Daniya and Vigneshwari (2023) presented a rider water wave–based neural network (RWW-NN) model to find rice plant diseases. The image preprocessing was performed by using histogram equalization and segmentation which enhanced gray level images and cropped the important regions respectively. The rice disease dataset was utilized to classify the diseases like blast, bacterial leaf blight, and brown spot. More number of datasets were necessary to accurately identify the diseases.

Research gap:

Based on the literature review, it was found that several research works have been conducted to detect and classify rice plant diseases using deep learning techniques. However, most of the previous studies were limited to the detection of a few specific types of rice plant diseases, and the detection accuracy was not satisfactory. Moreover, some studies had issues such as misclassification, overfitting, and lack of real-time analysis and large datasets.

Therefore, there is a research gap in the development of efficient rice plant disease detection and classification system that detects various types of diseases and provides accurate detection by using a number of datasets. This paper proposes a novel approach that addresses these issues by using a crossover boosted artificial hummingbird algorithm based AX-RetinaNet model, which is optimized through the CAHA optimization model.

The AX-RetinaNet is applied to provide disease detection, eliminate overfitting issues that appeared in the augmented images and remove inadequate training data problems. The misdetection and misclassification issues are eliminated by providing effective feature layers using multiscale feature fusion model. The resource weights are optimized during training process by using the AX-RetinaNet model and the channel attention model changes the

network into more efficient to predict valuable features and reduce the redundant information.

The large database uses data from three types of datasets such as rice plant dataset, rice leaf dataset, and rice disease dataset. The collected data is resized into 600×600 for image augmentation then the proposed detection model removes an overfitting issue from the augmented image. The optimal parameter values are selected from the predicted valuable features by applying AHA algorithm for improving efficiency.

The crossover operation is implemented to integrate with the AHA algorithm that improves the diversity and exploration ability of the searching process. The proposed detection and classification model classified the extracted features into healthy and unhealthy classes. The proposed approach is evaluated using multiple datasets and essential performance metrics, demonstrating its effectiveness related to other rice plant disease detection and classification models.

Materials and methods

This section demonstrates the materials and methods used to build the hybrid model for performing efficient detection and classification of rice plant disease. The AX-RetinaNet model is implemented for ensuring rice plant disease detection and eliminating overfitting issues in the augmented images. The AHA algorithm solves the optimization problems by using exploration and exploitation phases. The exploitation capability and local search capability are balanced through a crossover strategy. In the crossover boosted algorithm, the vertical and horizontal crossover strategies are included in this paper to solve the local optimum problem and to improve global search capability respectively.

Background information

The proposed AX-RetinaNet–based CAHA model is designed by using the combined concept of CNN and convolutional auto encoder (CAE). The rice plant disease detection models involved in this paper are explained in the upcoming sections.

AX-RetinaNet model

The RetinaNet model provides a better outcome compared to other existing network models which has some difficulties during the detection of rice plant disease. These difficulties are occurred in the natural environment due to presenting dense leaves, large-scale changes, and complex background of rice plants (Bao et al., 2022). The improved version of RetinaNet is named as AX-RetinaNet used in this paper. The AX-RetinaNet comprises a channel attention module and an improved multiscale feature fusion X-module. By using the ResNet-50 framework, the X-module fuses extracted multiscale features that make a feature layer as layer with high semantic information. In the down-sampling process, this high semantic information carrying feature layer solves the gradient disappearance problem of small targets. Due to solving this gradient disappearance problem, the effective feature layers are attained by using a multiscale feature fusion X-module that minimizes network misdetection rate. The attention module is added to the last feature layer by AX-RetinaNet and the features are extracted with the help of ResNet-50 which makes the feature layer as layer with high spatial information.

Each feature map channel is assigned to the weight optimized network via attention module so this network provides more concentration to error detection, interference reduction of redundant features, and valuable feature layer. The ResNet-50 model extracts the lower layer features using down and upsampling processes for making the feature layer into a layer with high semantic information. The targets are accurately identified and detected through regression and classification networks from the high semantic information. The extraction of high semantic information features is performed using ResNet-50, and it is processed through the channel attention module. Then, the processed features were given to the input of X-module for feature layers. Finally, the output of the X-module attained a target's multiscale feature information that resolves the scale changes problem in the target. Based on the importance of the resources, the original allocated resources are redistributed through an attention mechanism. The unimportant resource has a smaller weight and the important resources have a greater weight.

Then, the weights are optimized based on the sample distribution and structure of network. The channel attention module is integrated with AX-RetinaNet for allocating different weights to extract high-level feature layer channels using ResNet-50. The module's input is assumed as a feature maps and is processed with the help of ReLU activation function, fully connected layer, and global pooling layer for attaining different channel's weight values. In this module, the input of the feature maps are multiplied via weight values then the output of the module improves high spatial information features. While performing training process, the network optimizes the weights and the channel attention model makes the network more efficient for minimizing the interference in the redundant information and predicting valuable features.

Steps involved in the algorithm:

At first, each type of rice plant disease from the rice plant image is split into testing set and training set based on the proportion of 1:4. To provide the manual annotation about the disease types and disease location, the annotation tool is used which is named as LabImg. In the training set, the diseased rice plant images were augmented using an image augmentation model that eliminates the network overfitting problem and solves the inadequate training data problem. The augmented auxiliary images are shown in the form of gray bars and square as well as the size of the images are adjusted to 600×600. Secondly, the AX-RetinaNet parameters are initialized and VOC pre-training model's weight is loaded to speed up the network coverage. The input of the AX-RetinaNet is training images then the parameters are properly trained and saved. At last, the attained test images are given as an input to the trained network to make the rice plant disease detection model as more accurate. The algorithm of the AX-RetinaNet is explained in the below mentioned steps,

Step 1: The disease types of the rice plant image are split into testing and training sets with a proportion of 1:4.

Step 2: The annotations of disease types and locations are provided by LabImg.

Step 3: The image augmentation method is implemented to augment the diseased rice plant images in the training set.

Step 4: The augmented auxiliary images are shown in the form of gray bars and square as well as the size of the images are adjusted to 600×600.

Step 5: The AX-RetinaNet parameters are initialized and VOC pre-training model's weight is loaded.

Step 6: The parameters of the training images in the AX-RetinaNet are properly trained and saved.

Step 7: Attained test images are given as an input to the trained network to make the rice plant disease detection model as more accurate.

Artificial hummingbird algorithm (AHA)

The recently used bio-inspired optimization method is AHA which describes the intelligent behavior of hummingbirds. The comparison generates the exploitation and exploration stages as well as three components like visit table, hummingbirds, and food sources are involved in this optimization to solve optimization problems (Ramadan et al., 2023). The hummingbirds remember and pass the information about pace and location of nectar replenishment to their community. The hummingbird visit table has the record of how many hummingbirds visited a single food source. The visit table is gradually updated after completing each loop and three foraging methods are included to determine the development there are migrating foraging, territorial foraging, and directed foraging. The mathematical formation of each foraging method is described below:

Initialization process:

The food source position is assumed as a solution of the specific problem and is expressed as follows:

$$P_j = L + \text{Random} * (U - L), j = 1, ..., m \qquad (1)$$

From the above equation, U, L, m, and Random are represented as upper limit, lower limit, number of hummingbirds, and random vector between (0, 1) respectively. The visit table initialization of food source is formulated as follows:

$$I_{j,i} = \begin{cases} 0 \ if \ j \neq i \\ \text{null if} \ j = i \end{cases}, j = 1, ..., m; i = 1, ..., m \qquad (2)$$

If the condition $j = i$ is satisfied, the visit table initialization is null which means the hummingbird consumes food from the particular food source.

Guided foraging:

The flying positions of hummingbirds are named as omnidirectional flight, diagonal flight, and axial flight. The definitions of axial, diagonal, and omnidirectional flights are given in below mentioned equations (3 to 5):

$$E^{(j)} = \begin{cases} 1 \text{ if } j = \text{random } j([1,c]) \\ 0 \text{ else} \end{cases}, j = 1, ..., c \qquad (3)$$

$$E^{(j)} = \begin{cases} 1 \text{ if } j = Q(i), i \in [1,l], Q = \text{Rand}_{\text{perm}}(l), \\ l \in \left[2, \lceil \text{Random}_1 * (c-2) \rceil + 1 \right], j = 1, ..., c \\ 0 \text{ else} \end{cases}$$
$$(4)$$

$$E^j = 1, \ j = 1, ..., c \qquad (5)$$

Here, Random_1, $\text{random}j([1,c])$, and $\text{Rand}_{\text{perm}}(l)$ are depicts the random number between 0 and 1, number of random numbers generated and number of permutations respectively. The direct foraging behavior with their corresponding food source is given by the following:

$$a_j(q+1) = P_{j,t}(q) + G * E * \left(P_j(q) - P_{j,t}(q)\right) \qquad (6)$$

$$GN_d(0,1) \qquad (7)$$

$P_{j,t}(q)$ is the hummingbird position intended food source and the normal distribution with mean 0 and deviation 1 is known as $N_d(0,1)$. From the above equations, the guided factor and food source location at time are denoted as G and $P_j(q)$. The new position of the food source is updated based on Eq. (8) and is expressed as follows:

$$P_j(q+1) = \begin{cases} P_j(q) F_s\left(P_j(q)\right) \le F_s\left(a_j(q+1)\right) \\ a_j(q+1) F_s\left(P_j(q)\right) > F_s\left(a_j(q+1)\right) \end{cases}$$
$$(8)$$

where $F_s\left(a_j(q+1)\right)$ and $F_s\left(P_j(q)\right)$ are the candidate food source and current food source respectively. If the nectar refilling rate of candidate food source is greater than the current food source, the hummingbird feeds at the candidate food source.

Territorial foraging:

In territorial foraging, the hummingbird is able to locate a new food source and easily move to the nearby location. The local foraging and territorial foraging strategies of the hummingbird are explained in below equations:

$$a_j(q+1) = P_j(q) + T * E * P_j(q) \qquad (9)$$

$$TN_d(0,1) \qquad (10)$$

From the above equations, the territorial factor and the normal distributions are denoted by T and N_d.

Migration foraging:

The hummingbird migration from the lowest nectar refilling source to the new nectar refilling source is formulated as follows:

$$P_{\text{low}}(q+1) = L + \text{Random} * (U - L) \qquad (11)$$

The hummingbird uses territorial foraging and directed foraging techniques to visit each food source based on the visit table. The foraging methods such as territorial foraging and guided foraging has 50% of chance for successfully meeting their food source. So, this study required the migratory foraging method to expand the search area and mitigate stasis. For the coefficient mitigation, the population size specification is implemented as follows:

$$N = 2m \qquad (12)$$

Crossover boosted algorithm

In the artificial hummingbird optimization algorithm (AHA), the horizontal and vertical crossover strategies are utilized for balancing local search capability and global exploitation capability. The horizontal crossover strategy is used to improve global search capability by using population while searching space edges. The vertical crossover strategy performs the crossover operations between different dimensions using population that helps to escape from the local optimum problem. The optimal solutions are attained at the final stage for achieving better results related to its parent individuals (Ma & Yue, 2022).

Horizontal crossover strategy:

In this horizontal crossover strategy, the crossover operation is performed for different hummingbirds at the same dimension. At first, the hummingbirds in the population are grouped into non-repeating two-by-two groups, then the offspring are generated based on the pairs while performing horizontal crossover operation. The offspring of each group are derived as follows:

$$F_{r,a}^H = x_1.O_{r,a} + (1 - x_1).O_{s,a} + y_1.(O_{r,a} - O_{s,a}) \qquad (13)$$

$$F_{s,a}^H = x_2.O_{s,a} + (1 - x_2).O_{r,a} + y_2.(O_{s,a} - O_{r,a}) \qquad (14)$$

Here, x_1, x_2, and y_1, y_2 are represented as memory coefficients and diffusion coefficients within the range of [0,1] and [−1,1] respectively. $O_{r,a}$, $O_{s,a}$ and $F_{r,a}^H$, $F_{s,a}^H$ represents a dimensional vectors and the offspring created from the crossover of O_r and O_s respectively. Due to integrating parent and nonparent hummingbirds in the population, the parent's location memory is conserved by using this horizontal crossover strategy which enhances the search space. After performing the horizontal operation, the hummingbirds attained a higher probability of generated offspring. Then, the generated offspring is compared with parents for selecting hummingbirds with higher fitness value and the global exploitation capability is enhanced without changing the optimization accuracy.

Vertical crossover strategy:

Due to the lack of mutation operation, the vertical crossover strategy is included after performing horizontal crossover operation for developing spatial edge region. When the dimensions in the hummingbird fall into the local optimum the hummingbirds in the population also fall into the local optimum, this strategy uses different dimensions of two vectors for learning escaped hummingbird's dimensions from the local optimum. The offspring of the hummingbird during vertical crossover operation is expressed as follows:

$$O_{r,a_1}^{wz} = c.O_{r,a_1} + (1 - c).O_{r,a_2} \tag{15}$$

Here, O_{r,a_1}^{wz} and c are offspring and random numbers respectively and a_1 and a_2 are denoted as a dimension of the hummingbird. Sometimes, the AHA falls into a local optimum problem because a few dimensions of the hummingbird in the population become stagnant. The vertical crossover is used to escape the hummingbirds from the current local optimum problem by using valid information in the dimension of the hummingbird. The optimal solution is attained at the search mode while improving population diversity and providing the capacity to escape from the local optimum problem.

Proposed model to detect rice plant diseases

The overall architectural diagram of this paper is presented in Fig. 1. The database has three types of datasets namely rice plant dataset, rice leaf dataset and rice disease dataset. Each dataset collects different image samples so the image resizing process is involved in this architecture. Because all images were taken from different types of cameras and different agricultural fields, this image resizing process changes the sizes of all images to 600×600, then the resized image is passed to the augmentation block. The resized images are expanded in the image augmentation block then the proposed CAHA-AXRNet model is included for rice plant disease classification. The AHA model uses crossover operation to improve the diversity and exploration ability of the food source searching process. The proposed CAHA-AXRNet model is implemented for optimal parameter prediction and classification. The classification phase removes all overfitting issues in the image augmentation phase and also classifies the rice plant images into healthy and unhealthy. Finally, the performance of the paper is evaluated for attaining the effectiveness of detection and classification.

Hyerparameter initialization and fitness function evaluation

The functional relationship between hyperparameters and loss function is expressed in the below equation as follows:

$$A^* = \text{ArgMin}_{A \in a} L(A) \tag{16}$$

From the abovementioned equation, the set of parameters, optimum parameters, and objective function are denoted by A, A^* and $L(A)$ respectively. The loss function of this paper is derived by the following:

$$L(A_i) = \sqrt{\frac{\sum_{j=1}^{M} (\hat{x}_j(A_i) - x_j)^2}{M}} \tag{17}$$

$$x_j = L(A_j) \tag{18}$$

These equations show that A, $x(A)$, x_j, and A_i are the true value, result of output model, respective error output, and hyperparameters respectively.

Proposed CAHA-AXRNet model

The improved version of RetinaNet is named as AX-RetinaNet which prevents distortions in the
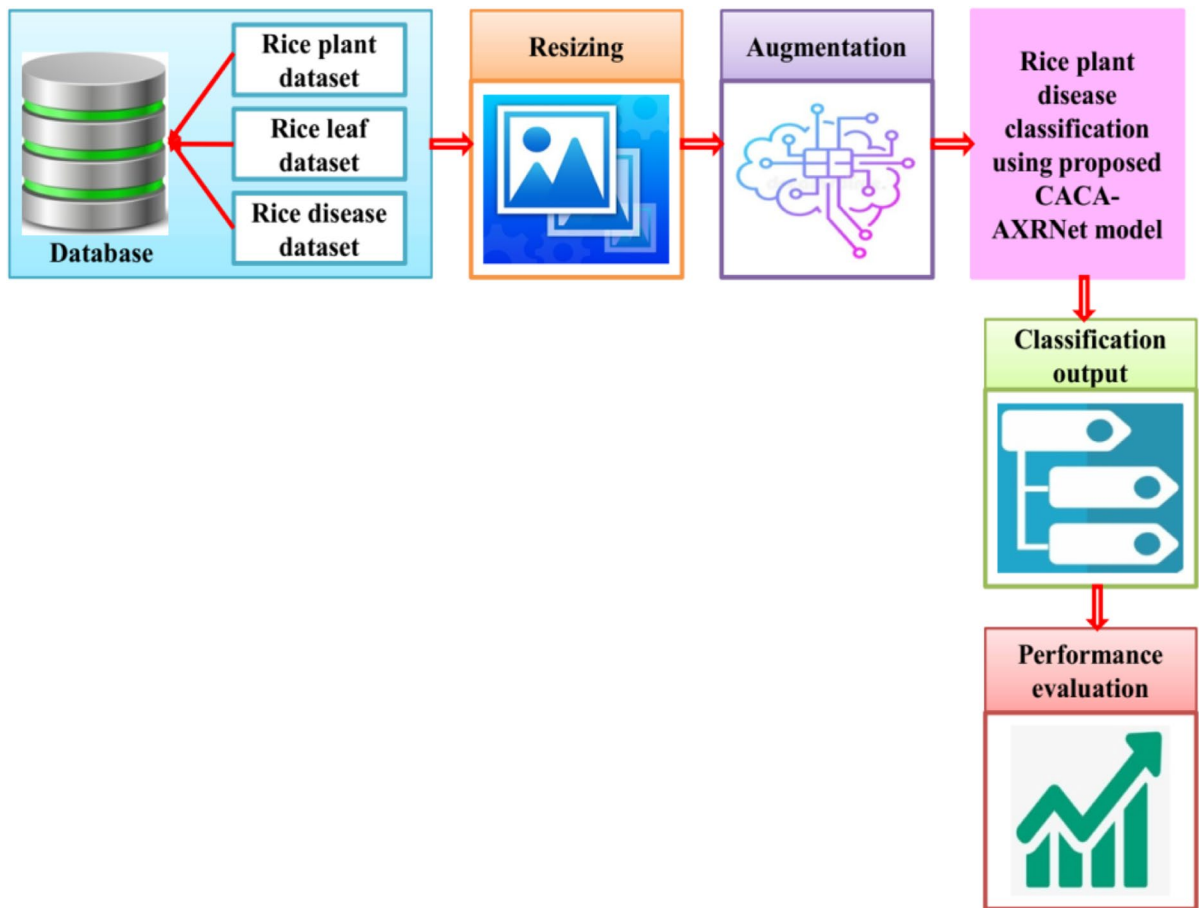
Fig. 1 Overall flow diagram

complex and deeper network. The bottleneck block is added to this enhanced model to speed up the training process of the AX-RetinaNet. So, the chosen AX-RetinaNet is optimized for achieving accurate rice plant disease detection related to other existing research works. The AX-RetinaNet comprises a channel attention module and an improved multiscale feature fusion X-module. The multiscale feature fusion module provides effective feature layers to minimize network misdetection and the features are extracted using ResNet-50 network. This weight optimized network has more concentration on the error detection, interference reduction of redundant features, and valuable feature layer. During the training process, the network optimizes the weights and the channel attention model for detecting rice plant disease by minimizing the interference of redundant information and

predicting valuable features. The predicted optimal parameter values improve the efficiency of the proposed model. Therefore, the AHA optimization model is implemented to predict the optimal parameter values. The hybrid evolutionary algorithm based on AHA is the crossover boosted AHA (CAHA) model that uses crossover operations for improving the exploration ability and diversity of the food source searching process. The main aim of the CAHA model is to combine the identified best solutions and also produce new populations in the best solutions. For optimal hyperparameter prediction as well as accurate rice plant disease detection, the CAHA-AXRNet model is implemented. The proposed CAHA-AXRNet model effectively extracts and classifies the features into healthy and unhealthy classes. The overall flowchart of the proposed CAHA-AXRNet model is shown in Fig. 2.

Experimental results and discussions

In this section, the experimental details of the CAHA-AXRNet model are explained. The experimental validation uses various evaluation metrics such as precision, F1-score, accuracy, specificity, and recall. The rice plant disease detection datasets namely rice plant dataset, rice leaf dataset, and rice disease dataset are employed to detect and classify the images into healthy and unhealthy. Here, the training and testing data are split into the proportion of 80:20. Further details about comparison work, implementation platform, and optimal parameters are provided in the next subsections.

Experimental setup

The experiments for the rice plant disease detection are conducted on the MATLAB 2019b platform with 3.2 GHz CPU, 16 GB RAM, and Intel Core i7 processor.

Hyperparameter configuration

The hyperparameters are optimized by using the CAHA optimization model to attain optimal values. These optimal hyperparameter values improve the detection performance of the proposed CAHA-AXRNet model. The predicted optimal parameters and their optimal values are tabulated in Table 2.

Dataset description

This paper uses three types of datasets namely rice plant dataset, rice leaf dataset, and rice disease dataset for detecting and classifying the different diseases appeared in the rice plants. The data was collected

Fig. 2 Flowchart of proposed CAHA-AXRNet model
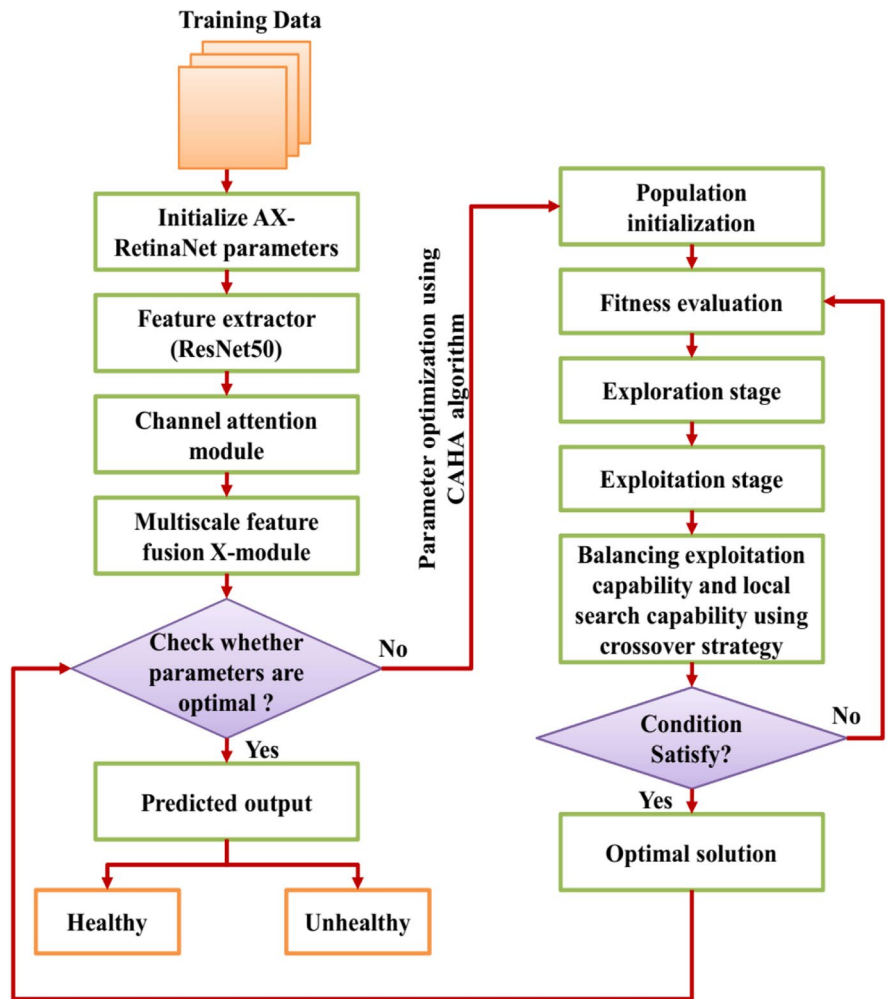
from https://www.kaggle.com/datasets/bahribahri/riceleaf. This dataset has four types of rice leaf disease which are named as healthy, bacterial leaf blight, leaf smut, and brown spot. Here, 120 images are chosen for the classification attained from this rice leaf dataset. This dataset contains 619 images and grouped into three types of rice diseases such as rice blast, brown spot, and bacterial leaf blight. The data of rice disease dataset were collected from the Indira Gandhi Agricultural University, Raipur, Chhattisgarh, India. The images were captured during the daytime through Gionee, Canon Powershot SX530HS digital camera and LYF mobile set. This image background can reduce the computational cost as well as background complexity and this rice disease data are chosen from https://github.com/aldrin233/RiceDiseases-DataSet. In the rice plant dataset, there are 5932 images are used to find the unhealthy and healthy plants from the agricultural field. The most dangerous disease in the rice plant is rice blast fungal generated from the seed of the plant which affects the entire plant of the field. This data was collected by https://www.kaggle.com/datasets/rajkumar898/rice-plant-dataset. The sample images for each dataset are delineated in Table 3.

Evaluation measures

The evaluation measures namely precision ($RP_{precision}$), F1-score ($RP_{F1-score}$), accuracy ($RP_{accuracy}$), recall (RP_{recall}), specificity ($RP_{specificity}$), AUC/ROC and loss are analyzed by using true positive values (RP_{TP}), false

positive values (RP_{FP}), true negative values (RP_{TN}), and false negative values (RP_{FN}). These evaluation measures predict the effectiveness of the proposed CAHA-AXRNet model. True positive is referred to as the correct prediction of unhealthy cases and the correct predictions of healthy cases are true negative. The healthy cases are sometimes labeled as unhealthy cases known as false positives and sometimes the unhealthy cases are labeled as healthy cases are named as false negatives. Detailed explanations about these entire measures are given in the below subsections.

Precision ($RP_{precision}$):

Precision measures the number of correctly predicted unhealthy cases in the rice plant among all the correct and incorrect predictions of unhealthy cases in the rice plant. The precision rate is measured by using this equation:

$$RP_{precision} = \frac{RP_{TP}}{RP_{TP} + RP_{FP}} \qquad (19)$$

F1-score ($RP_{F1-score}$):

The ratio of doubling the product of precision and recall to the sum of precision and recall is known as F1-score. The mathematical format of the F1-score is derived by the following:

$$RP_{F1-score} = \frac{2 \times \left(RP_{precision} \times RP_{recall}\right)}{RP_{precision} + RP_{recall}} \qquad (20)$$

Accuracy ($RP_{accuracy}$):

The accuracy values represent the classification model superiority that evaluates correctly predicted healthy and unhealthy cases in the rice plant from all correctly and incorrectly predicted healthy and unhealthy cases. The accuracy is formulated as follows:

$$RP_{accuracy} = \frac{RP_{TP} + RP_{TN}}{RP_{TP} + RP_{TN} + RP_{FP} + RP_{FN}} \qquad (21)$$

Recall (RP_{recall}):

The proportion of correctly predicted unhealthy cases to the correctly and incorrectly predicted unhealthy cases of the rice plant is known as recall. The recall of this rice plant disease detection model is computed using the below mentioned equation:

$$RP_{recall} = \frac{RP_{TP}}{RP_{TP} + RP_{FN}} \qquad (22)$$

Specificity ($RP_{specificity}$):

Table 2 Hyperparameter configuration

Different approaches	Optimal parameters	Optimal parameter values
AHA	Total number of iterations	100
	Population size	25
	Number of epochs	50
AX-RetinaNet	Learning rate	0.0001
	Weight decay	0.0005
	Momentum	0.9
	Batch size	4
	Optimizer type	Adam
	Activation function	ReLU

Table 3 Sample images of different datasets.

Different datasets	Healthy	Unhealthy
Rice plant dataset		
Rice leaf dataset		
Rice disease dataset		

Specificity is used to find the healthy cases means that the number of correctly identified healthy cases from the total number of correctly and incorrectly predicted healthy cases of the rice plant. This is evaluated based on the below equation as follows:

$$RP_{specificity} = \frac{RP_{TN}}{RP_{TN} + RP_{FP}} \tag{23}$$

The AUC is used to summarize the overall accuracy of rice plant disease which varies from 0 to 1. This measures the classification model performance at the different threshold ranges.

Performance results

The performance results of this paper are explained in Table 4 and this table is created in terms of precision, F1-score, accuracy, recall, specificity, AUC/ROC, and loss. This table contains information on the development and strength of this proposed CAHA-AXRNet model.

A confusion matrix is a tabular format to visualize the classification performance of the model. This confusion matrix is generated based on the actual values as well as the predicted values and each value has two classes such as healthy and unhealthy. This 2×2 matrix only classifies the sample into correct prediction and wrong prediction to find the success rate. The confusion matrix is presented in Fig. 3.

Figure 4 shows the AUC/ROC evaluation by using true positive values and false positive values that achieved the AUC rate of 0.98. The ROC is the metric to identify the binary classification problems and the probability curve separates the classification performance from the noise. The highest AUC values distinguish the better detection ability of rice plant disease.

The performance evaluation for rice plant dataset is performed by using different evaluation measures like accuracy, F1-score, specificity, recall, and precision as portrayed in Fig. 5. The proposed CAHA-AXRNet model provides an accuracy rate of 97.8%, precision rate of 98.2%, recall rate of 95.5%, specificity rate of 97.3%, and F1-score rate of 96.7% by using a rice plant dataset. The rice plant diseases are classified into healthy and unhealthy classes.

Table 4 Performance evaluation results

Evaluation measures	Performance rates
Precision	98.4%
F1-score	97.8%
Accuracy	98.1%
Recall	96.9%
Specificity	97.5%
AUC/ROC	0.98
Training accuracy	0.981
Training loss	0.15
Testing accuracy	0.954
Testing loss	0.22

The performance evaluation of proposed CAHA-AXRNet model for the rice leaf dataset is depicted in Fig. 6. The performance rate of 96.1%, 97.4%, 95.8%, 96.5%, and 95.3% are attained from the various evaluation measures namely accuracy, precision, recall, specificity, and F1-score respectively. This rice leaf dataset split the rice leaf diseases into four types there are leaf smut, healthy, bacterial leaf blight, and brown spot.

Figure 7 represents the performance validation with the help of proposed CAHA-AXRNet model for the rice disease dataset. This graph is plotted between the different metrics and performance rates. In this rice disease dataset, the rice diseases are grouped into three types such as rice blast, bacterial leaf, and blight brown spot. The accuracy

Fig. 3 Confusion matrix

of 95.9%, precision of 97.1%, recall of 96.2%, F1-score of 95.6%, and specificity of 96.7% are achieved from the proposed CAHA-AXRNet model.

The accuracy analysis of the proposed CAHA-AXRNet model is conducted based on the different epochs that are explained in Fig. 8. The accuracy analysis comprises a training process and a testing process to validate the performance. From this analysis, the training accuracy has a higher rate compared to the testing accuracy rate because the training process has a maximum amount of data. The proposed CAHA-AXRNet model has a training accuracy and testing accuracy of 0.981 and 0.954 respectively.

The loss analysis is conducted based on the number of epochs and the loss analysis has training loss and testing loss validation that is delineated in Fig. 9. When the training process reaches the lowest loss point, the proposed rice plant disease detection system provides better detection performance. The training and testing loss of 0.15 and 0.22 are attained from the proposed CAHA-AXRNet model.

Comparison study

In this comparison study, a few existing methods like DCNN, faster RCNN, DNN-CSA, and ADSNN-BO are compared with the proposed CAHA-AXRNet model to validate the performance and find the superiority.

The accuracy of the different rice plant disease detection approaches such as DCNN, faster RCNN, DNN-CSA, ADSNN-BO, and proposed CAHA-AXRNet model is evaluated in Fig. 10. This graphical representation depicts the accuracy rates of 98.1%, 83.5%, 87%, 93%, and 88% from proposed CAHA-AXRNet model, DCNN, faster RCNN, DNN-CSA, and ADSNN-BO. This proposed CAHA-AXRNet model achieved a higher accuracy rate compared to other existing methods which indicates better rice plant disease detection performance.

The precision analysis is performed in Fig. 11 with the help of various detection models such as DNN-CSA, ADSNN-BO, proposed CAHA-AXRNet model, DCNN, and faster RCNN. The proposed CAHA-AXRNet model achieved a higher precision rate of 98.4% and the DNN-CSA model has a lower precision rate of 83%. Precision measures the positive predicted values that the actual diseased rice plants are diagnosed through the classification model.
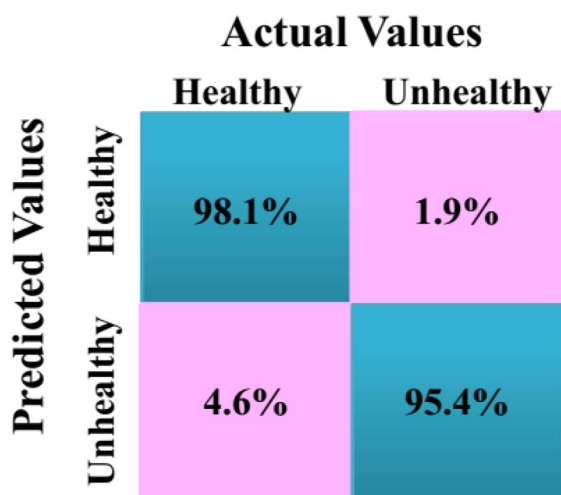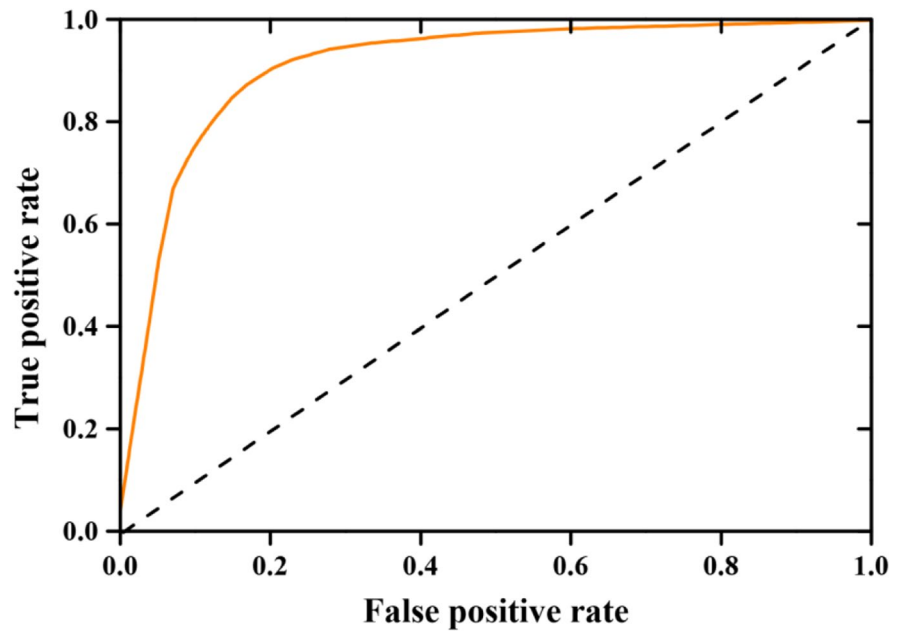
Fig. 4 Evaluation of AUC/
ROC

Figure 12 presents the recall analysis based on the various disease detection approaches namely DCNN, DNN-CSA, ADSNN-BO, faster RCNN, and proposed CAHA-AXRNet model. The recall analysis is used to detect all the unhealthy cases of rice plant disease detection. From this graph, the DCNN, DNN-CSA, ADSNN-BO, faster RCNN, and proposed

CAHA-AXRNet models offer the recall rate of 83%, 86.2%, 93%, 90%, and 96.9% respectively.

According to the analysis of different rice plant disease detection models, the specificity evaluation is portrayed in Fig. 13. The specificity has negative prediction values which denote the detection probability of healthy cases in the rice plant. This

Fig. 5 Performance analysis for rice plant dataset
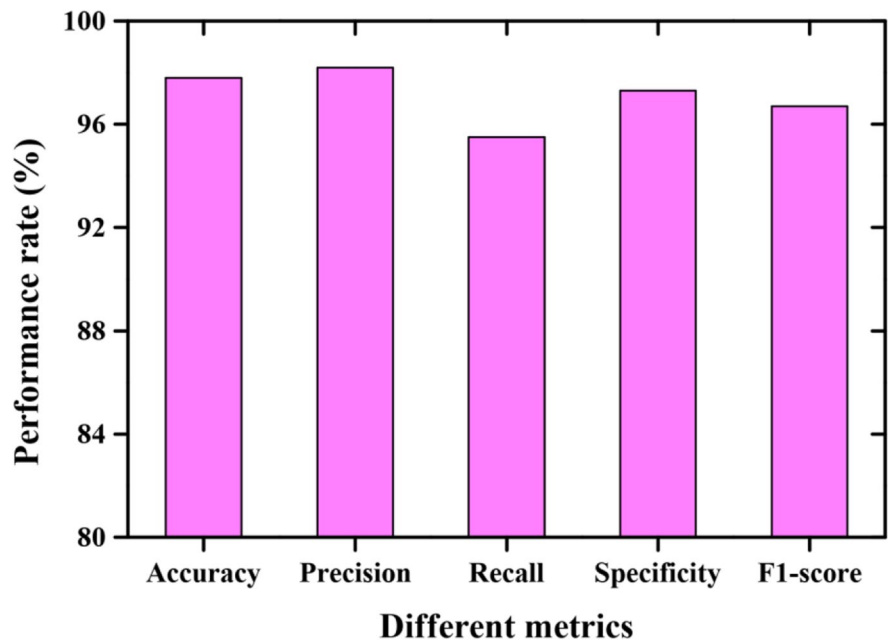
Fig. 6 Performance evaluation for rice leaf dataset
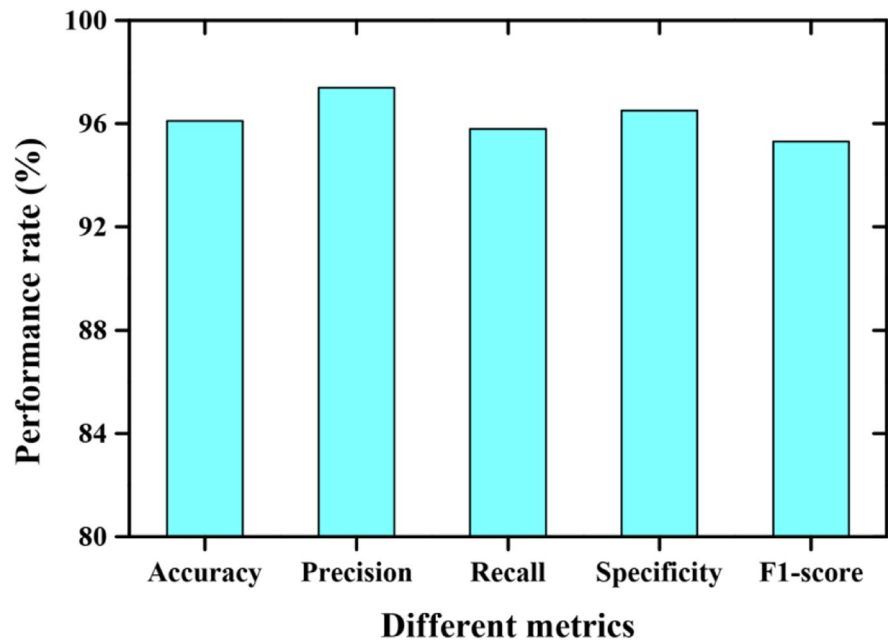
specificity analysis shows that the proposed CAHA-AXRNet model attained a higher specificity rate of 97.5% compared to other existing methods. The specificity measures the effectiveness of the rice plant diseases and is also used for quality control.

Figure 14 represents the *F*1-score evaluation based on various methods such as faster RCNN, DCNN,

DNN-CSA, proposed CAHA-AXRNet model, and ADSNN-BO. *F*1-score is the metric of machine learning evaluation for accuracy computation which is computed by using the combination of recall and precision. The proposed CAHA-AXRNet model achieved a better *F*1-score rate of 97.8% related to other rice plant disease detection approaches.

Fig. 7 Performance validation for rice disease dataset
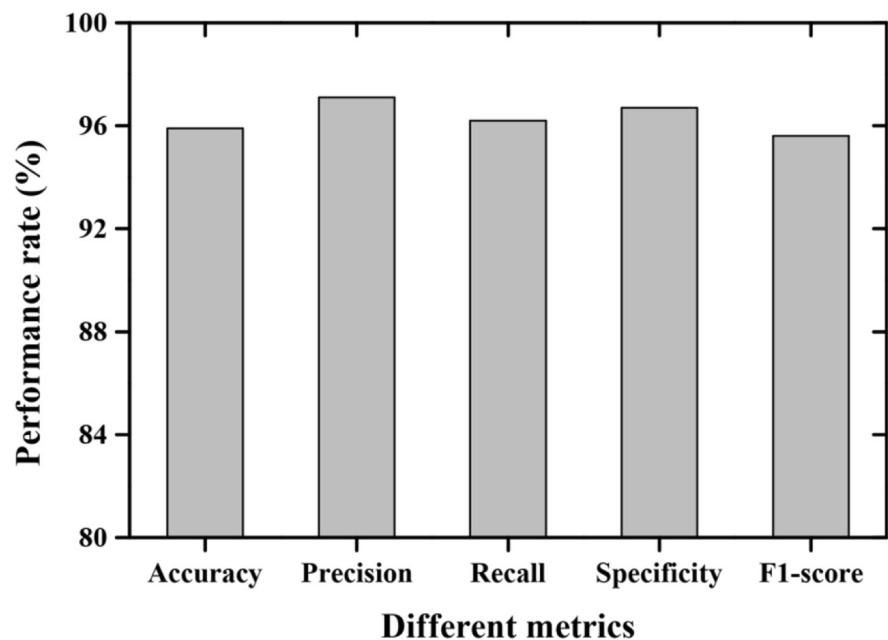
Fig. 8 Accuracy analysis
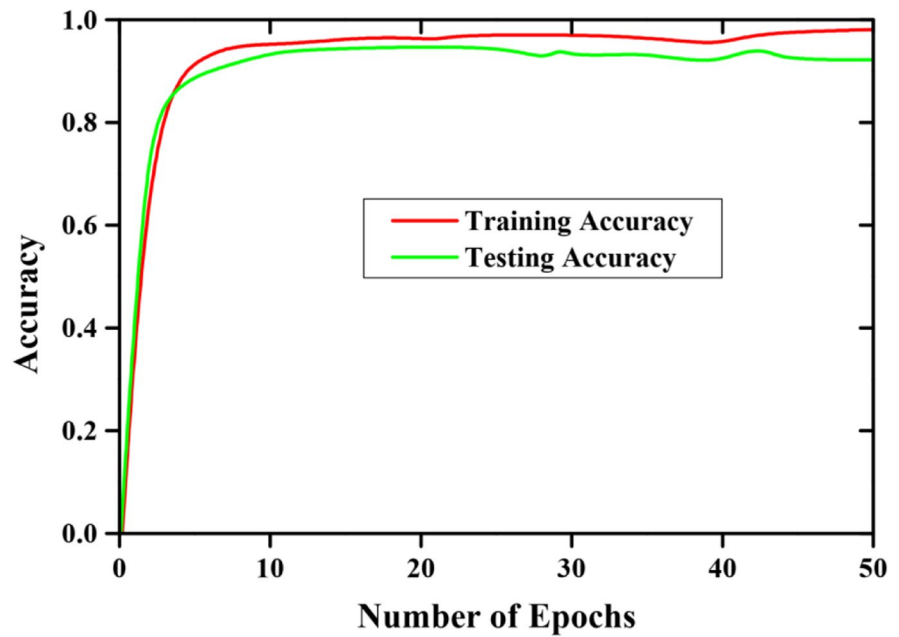
Discussions

Comparison with previous research

Previous research (Upadhyay and Kumar (2021), Daniya and Vigneshwari (2023), and Dogra et al. (2023)) efforts have aimed at detecting and classifying various rice plant diseases; however, they have been associated with limitations such as misclassification, misdetection, lack of real-time analysis, overfitting issues, and limited disease detection capabilities. In response to these challenges, we propose the CAHA-AXRNet model, an efficient system for rice plant disease detection and classification. This model

Fig. 9 Loss analysis
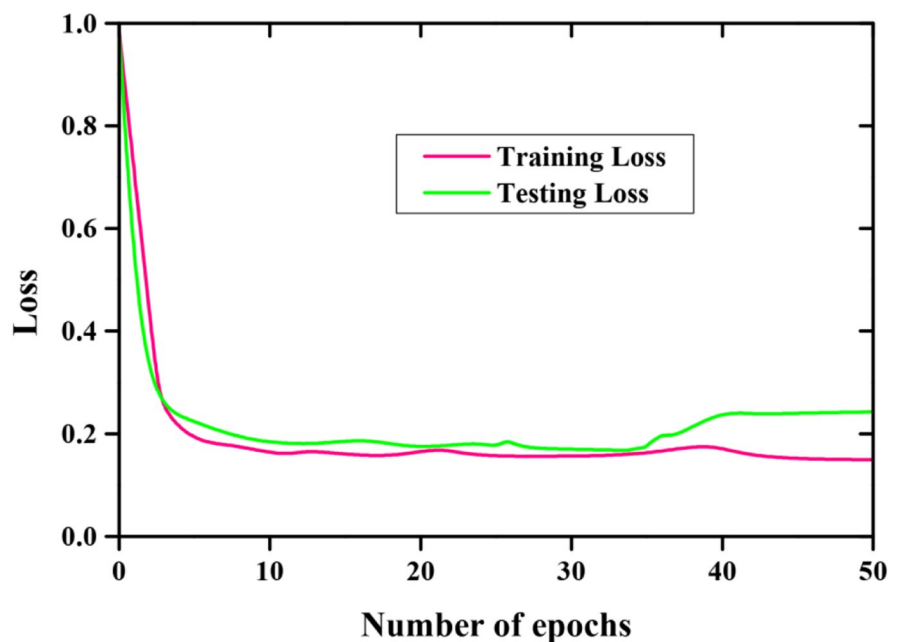
Fig. 10 Comparative
analysis of accuracy
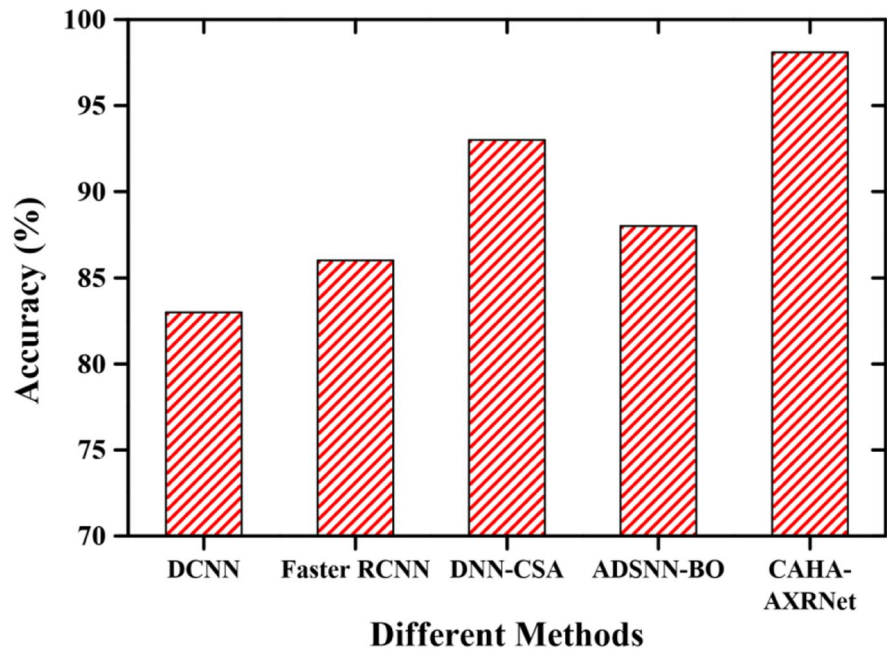
addresses the issue of overfitting in augmented images by utilizing the AXRNet architecture, and it tackles the problem of scale changes by extracting multiscale feature information through the X-module. By integrating the channel attention module and AXRNet model, we allocate various weights to extract high-level feature layer channels effectively.

Optimization and training

The training process of our model utilizes a dataset of tested images, resulting in a more efficient detection and classification model. To optimize the performance of the CAHA-AXRNet model, we employ the crossover operation in conjunction with

Fig. 11 Comparison study
of precision
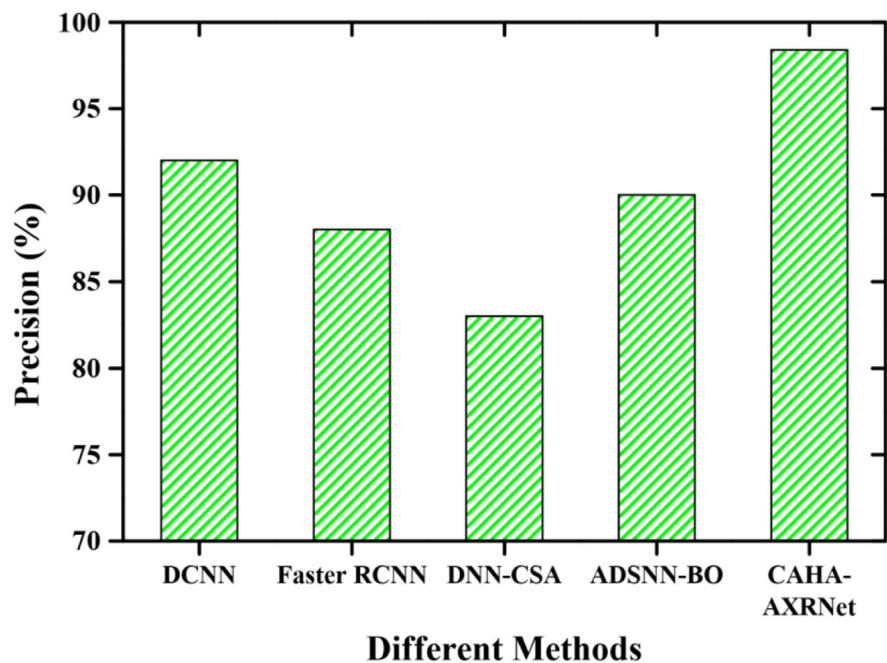
Fig. 12 Analysis of recall
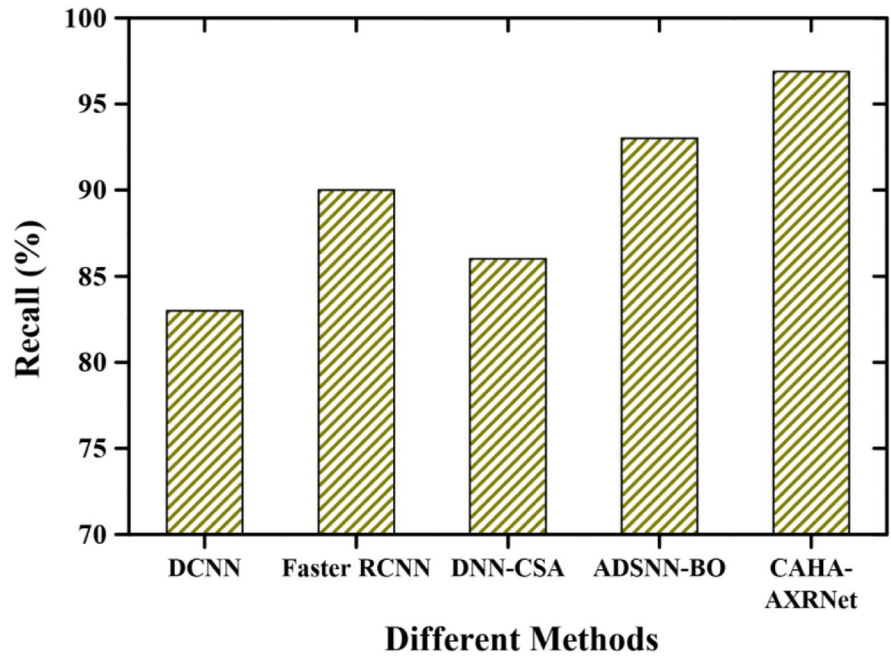
the AHA model. This approach balances the global exploitation capability and local search capability, with horizontal and vertical crossover strategies employed to enhance global search capabilities and overcome local optimum problems, respectively. The hybrid nature of our detection and classification model predicts optimal hyperparameters,

enabling accurate feature extraction and classification of healthy and unhealthy plants. We optimize the parameters of the AXRNet model using the CAHA optimization model, which helps to attain optimal parameter values, enhancing overall performance and reducing the loss function.

Fig. 13 Specificity analysis
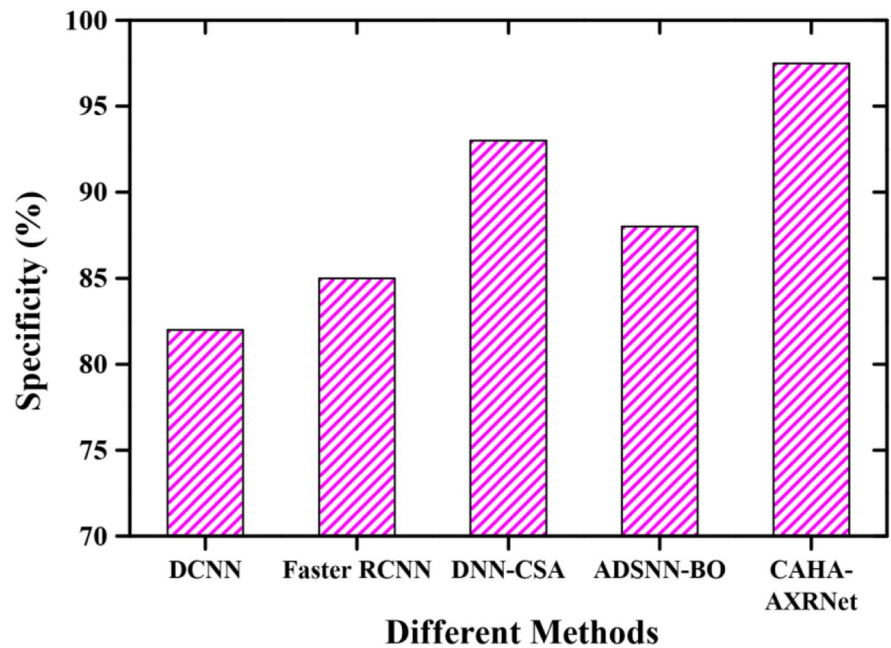
Fig. 14 Comparative analysis of *F*1-score
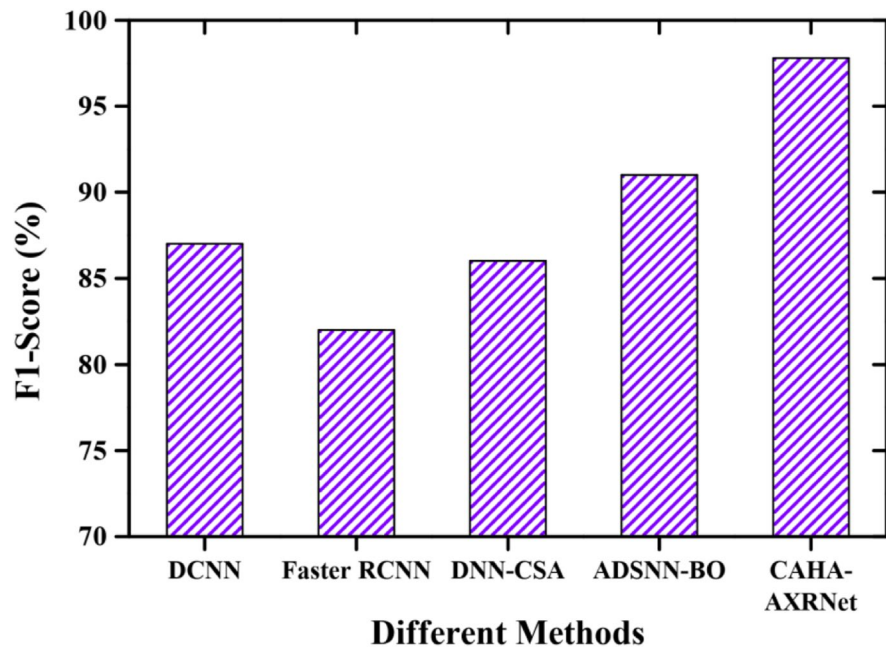
Performance evaluation

To evaluate the performance of the proposed CAHA-AXRNet model, we employ three datasets: the rice plant dataset, the rice leaf dataset, and the rice disease dataset. The classification results are represented using a confusion matrix. Additionally, we conduct AUC/ROC analysis to address the binary classification problem, identify noise, and evaluate the classification performance. From our analysis, the rice plant dataset achieved performance rates of 97.8%, 98.2%, 95.5%, 97.3%, and 96.7% for accuracy, precision, recall, specificity, and *F*1-score, respectively. Similarly, the rice leaf dataset showed performance rates of 96.1%, 97.4%, 95.8%, 96.5%, and 95.3%, while the rice disease dataset provided rates of 95.9%, 97.1%, 96.2%, 96.7%, and 95.6%, respectively.

Comparative analysis

To validate the performance of the proposed CAHA-AXRNet model, we compare it with other state-of-the-art models, including DCNN (Latif et al. (2022)), faster RCNN (Bari et al. (2021)), DNN-CSA (Nalini et al. (2021)), and ADSNN-BO (Wang et al. (2021)).

Accuracy measures the exact prediction related to the actual value. Our proposed model achieved an accuracy of 98.1%, outperforming the other models which obtained 83.5%, 87%, 93%, and 88%, respectively. Precision, representing the closeness of predicted measurements to the actual measurements, achieved rates of 98.4% for the proposed model, 83% for DNN-CSA, 92.1% for DCNN, 87.5% for faster RCNN, and 90% for ADSNN-BO. The recall rate, indicating the ability to detect positive cases, was 96.9% for the proposed model, higher than the other models' rates of 83%, 86.2%, 93%, and 90%, respectively. Moreover, specificity, which measures the detection probability of healthy cases, achieved rates of 97.5%, 82.2%, 85%, 92.5%, and 88% for the proposed model, DCNN, faster RCNN, DNN-CSA, and ADSNN-BO, respectively. Lastly, the *F*1-score, a measure similar to accuracy, demonstrated a performance rate of 97.8% for the proposed model, surpassing the rates of 87.2% for DCNN, 82% for faster RCNN, 86% for DNN-CSA, and 91% for ADSNN-BO.

Our performance analysis and comparative study clearly indicate that the proposed CAHA-AXRNet model outperforms other detection and classification models in terms of accuracy, precision, recall, specificity, and overall *F*1-score.

Conclusion

In this study, we have proposed the CAHA-AXRNet model for efficient rice plant disease detection and classification. Our research has addressed several limitations observed in previous approaches, such as misclassification, misdetection, lack of real-time analysis, overfitting issues, and limited disease detection. By introducing the CAHA-AXRNet model, we have achieved significant improvements in disease detection accuracy and performance. Our study contributes to the field of rice plant disease detection in several ways. First, we have successfully addressed the overfitting issues associated with augmented images by utilizing the AXRNet model. Through the integration of the channel attention module, we have effectively extracted high-level feature layer channels, enhancing the model's ability to detect diseases accurately. Moreover, we have tackled the challenge of scale changes in rice plant images by introducing the X-module in the CAHA-AXRNet model. This enables the extraction of multiscale feature information, allowing our model to adapt to varying scales and improving the overall accuracy of disease detection. Furthermore, the comparative analysis with state-of-the-art models, including DCNN, faster RCNN, DNN-CSA, and ADSNN-BO, has demonstrated the superior performance of the proposed CAHA-AXRNet model in terms of accuracy, precision, recall, specificity, and F1-score. These findings validate the effectiveness and advancements achieved through our research. Our study contributes new knowledge and understanding to the field of rice plant disease detection and classification. The CAHA-AXRNet model addresses existing limitations and achieves higher performance compared to previous approaches.

This research opens up new directions for future investigations. For instance, further exploration can be done to incorporate additional datasets, expand the application to other crops, and investigate the feasibility of real-time disease detection using the proposed model. By advancing the field of rice plant disease detection, our research has practical implications for the agricultural sector. It offers a valuable tool for farmers and researchers to accurately identify and classify diseases in rice plants, enabling timely interventions and effective disease management strategies. Overall, our work paves the way for future research endeavors aimed at enhancing disease detection and classification techniques in the agricultural domain, fostering sustainable crop production, and ensuring food security.

Declarations

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