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ORIGINAL ARTICLE

ERROA: Enhanced remora rider optimization algorithm-based AlexNet for rice leaf disease classification

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Abstract

Rice is a major food in India, playing an important role in the agricultural sector. However, various leaf diseases adversely affect rice production by reducing both quality and yield, leading to financial losses for farmers. Detecting these diseases at an early stage through automated methods can facilitate timely intervention and minimize crop damage. To classify diseases of rice, a novel method called ERROA-AlexNet was introduced. This model was designed to identify four categories of diseases such as bacterial leaf blight, rice leaf blast, brown spot, and tungro. The classification process utilized AlexNet, with its weights optimized using the Enhanced Remora Rider Optimization Algorithm (ERROA), a hybrid approach that integrated the Enhanced Remora Optimization Algorithm (EROA) and Rider Optimization Algorithm (ROA). Experimental results, assessed by utilizing a k-fold cross-validation technique, demonstrated that the proposed technique achieved an accuracy of 95.4%, a sensitivity of 94.3%, and a specificity of 98.1%. These results indicate that the ERROA-AlexNet approach outperformed conventional deep learning models such as RSW-Deep RNN, hybrid CNN-SVM and Deep CNN, as cited in the literature. This study focused on the promising features of DL in precision agriculture, providing an efficient and reliable solution for automatic detection of rice leaf diseases.

Keywords: AlexNet, classification, Enhanced Remora Optimization Algorithm (EROA), rice leaf diseases, Rider Optimization Algorithm (ROA)

Introduction

Rice is one of the most important foods in most of India, providing sustenance to millions of people (Chaudhari and Karunakaran 2024a). However, various diseases affecting rice plants can lead to substantial reductions in both crop production and value (Ramesh and Vydeki 2019). Early detection (Gong and Zhang 2023) and effective management is essential to prevent significant agricultural losses. Farmers often rely on traditional methods to identify and manage plant diseases, but manual detection is protracted and leads to errors. Recent advancements in technology have introduced automated solutions for disease detection (Prajapati *et al.* 2017), which provide accurate and efficient disease classification, allowing for timely intervention. Several rice leaf diseases (Haridasan *et al.* 2023), including bacterial leaf blight (BLB) (*Xanthomonas oryzae* pv. *oryzae*), tungro (*Rice tungro bacilliform virus* and *Rice tungro spherical virus*), leaf blast (LB) (*Magnaporthe oryzae*), brown spot (BS) (*Bipolaris oryzae*), and leaf smut (LS) (*Entyloma oryzae*) (Chaudhari and Karunakaran 2024b), can severely impact crop productivity if not identified early. DL models, particularly CNN (Abasi *et al.* 2023), have substantially enhanced the accuracy of disease classification by automatically removing the features. Unlike traditional methods that require extensive manual preprocessing, CNN-based approaches (Yakkundimath *et al.* 2022) streamline the identification process, enhancing precision and speed.

This study introduced a novel approach called, ERROA-AlexNet (Chowdhury *et al.* 2020) for rice leaf disease classification. The method began with pre-processing, employing a bilateral filtering (Zhou *et al.* 2019) process to enhance quality of image. Image augmentation techniques, including random erasing and rotation, were applied to expand the dataset. Feature extraction incorporated CNN-based and statistical features, followed by classification using the AlexNet model (Lwin and Htwe 2023) trained with the proposed ERROA algorithm. ERROA integrates the Enhanced Remora Optimization Algorithm (EROA) (Wang *et al.* 2022) with the Rider Optimization Algorithm (ROA) (Binu and Kariyappa 2018) to optimize the classification process. By leveraging this approach, the study aimed to enhance the accuracy and efficiency of rice leaf disease detection, aiding farmers in increasing production of healthy crops and secure sustainable agricultural practices. The major contributions of the study were:

- Development of ERROA-AlexNet for Rice Leaf Disease Classification: A novel classifier, ERROA-AlexNet, was introduced for effective classification.
- Implementation of GrabCut Algorithm for Segmentation: The segmentation of diseased regions was performed using the GrabCut algorithm, improving the accuracy of disease identification.
- Optimized Training of AlexNet with ERROA: The AlexNet model was optimized using ERROA, a hybrid algorithm combining EROA and ROA, to achieve optimal weight adjustments for better classification performance.
- Introduction of the Rider Optimization Algorithm (ROA): ROA is a newly proposed technique motivated by the behavior of a category of riders moving towards a target.
- Enhancement of ROA through EROA: The Enhanced Remora Optimization Algorithm (EROA) integrated a Restart Strategy (RS) with ROA to improve optimization efficiency and enhance classification accuracy.

Identifying research gaps in the field of rice leaf disease classification encourages scholars to develop novel classification techniques. This section reviews previous studies on rice leaf disease classification and highlights their limitations.

Chaudhari and Malathi (2024a) presented the Fractional Remora Reptile Search Algorithm-based LeNet (FRRSA-LeNet) for classifying rice leaf diseases. This method integrates Fractional Calculus (FC), Remora Optimization Algorithm (ROA), and Reptile Search Algorithm (RSA). FRRSA-LeNet achieved a maximum testing accuracy of 90.3%, a TPR (True positive rate) of 88.3%, a TNR (True negative rate) of 90.4%, and a mean squared error (MSE) of 0.800. However, the primary limitation of this approach is its classification accuracy, which could be improved through parameter optimization.

Chaudhari and Malathi (2024b) proposed a Remora-CNN model for identifying and classifying four types of rice leaf diseases such as bacterial blight, leaf blast, brown spot, and tungro. The CNN model was trained using the Remora Optimization Algorithm (ROA), and classification was enhanced through segmentation via the K-means method with a Fractional Tangential-Spherical Kernel (FTSK) algorithm. Although the Remora-CNN method achieved an Accuracy of 92.5%, Sensitivity of 93.1%, and Specificity of 94.1%, it does not classify all known rice leaf diseases.

Daniya and Vigneshwari (2023) developed the RWW-based NN for rice leaf disease detection. The network training utilized Rider Optimization Algorithm (ROA) combined with Water Wave Optimization (WWO). However, the approach was not tested on diverse databases, limiting its generalizability. Future research should explore standard optimization techniques to assess their effectiveness.

Jiang *et al.* (2020) utilized an integration of DL and support vector machines (DL-SVM) to classify and predict rice plant diseases. While this approach effectively identified diseases and offered practical guidance for crop management, it did not significantly improve classification accuracy.

Upadhyay and Kumar (2022) proposed an efficient rice disease detection technique using CNN for disease classification. The integration of feature extraction and classification simplified the model, reducing processing time and complexity. However, the method did not significantly improve classification effectiveness.

Devi and Neelamegam (2019) applied techniques of image processing to automate rice leaf disease identification. Their approach involved back propagation neural networks, KNN, multiclass SVM, and Naïve Bayes classifier. Despite its effectiveness, the technique did not reduce the complexity of the detection process.

The confronted challenges of traditional methods are given below.

- Existing methods struggle to extract distinct and relevant features from diseased areas.
- Poor classifier selection and inefficient feature extraction reduce detection accuracy.
- The complexity of visual disease patterns makes identification challenging.
- Accurate diagnosis is complicated by multiple factors, including nutrient levels, pathogens, and environmental conditions.

- The effectiveness of rice leaf disease classification models is hindered by the limited availability of large-scale, diverse datasets.

Materials and Methods

This section introduces a novel model for the detection and classification of rice plant diseases. A schematic diagram of the developed system is provided in Figure 1. Initially, input images of the rice plants underwent a pre-processing phase to prepare them for further analysis. Then they were exposed to a segmentation process, where the GrabCut algorithm (Chaudhari and Malathi 2023, 2024a) was used to separate the relevant portions of the image. This step helped remove unwanted distortions, refining the image before it moves forward to the feature extraction process. After segmentation, the system moved to the feature extraction steps, where both CNN features (Zhang *et al.* 2016) and statistical features (Chaudhari and Malathi 2024a) were extracted from each segment. Once the segments were isolated, the CNN and statistical features were collected and compiled into a feature vector for classification. For the classification task, the AlexNet architecture was employed, with a novel optimization method called the Enhanced Remora-Rider Optimization Algorithm (ERROA) used to train the model. ERROA is a hybrid optimization (Goluguri *et al.* 2021) approach that combined the advantages of the traditional Enhanced Remora Optimization

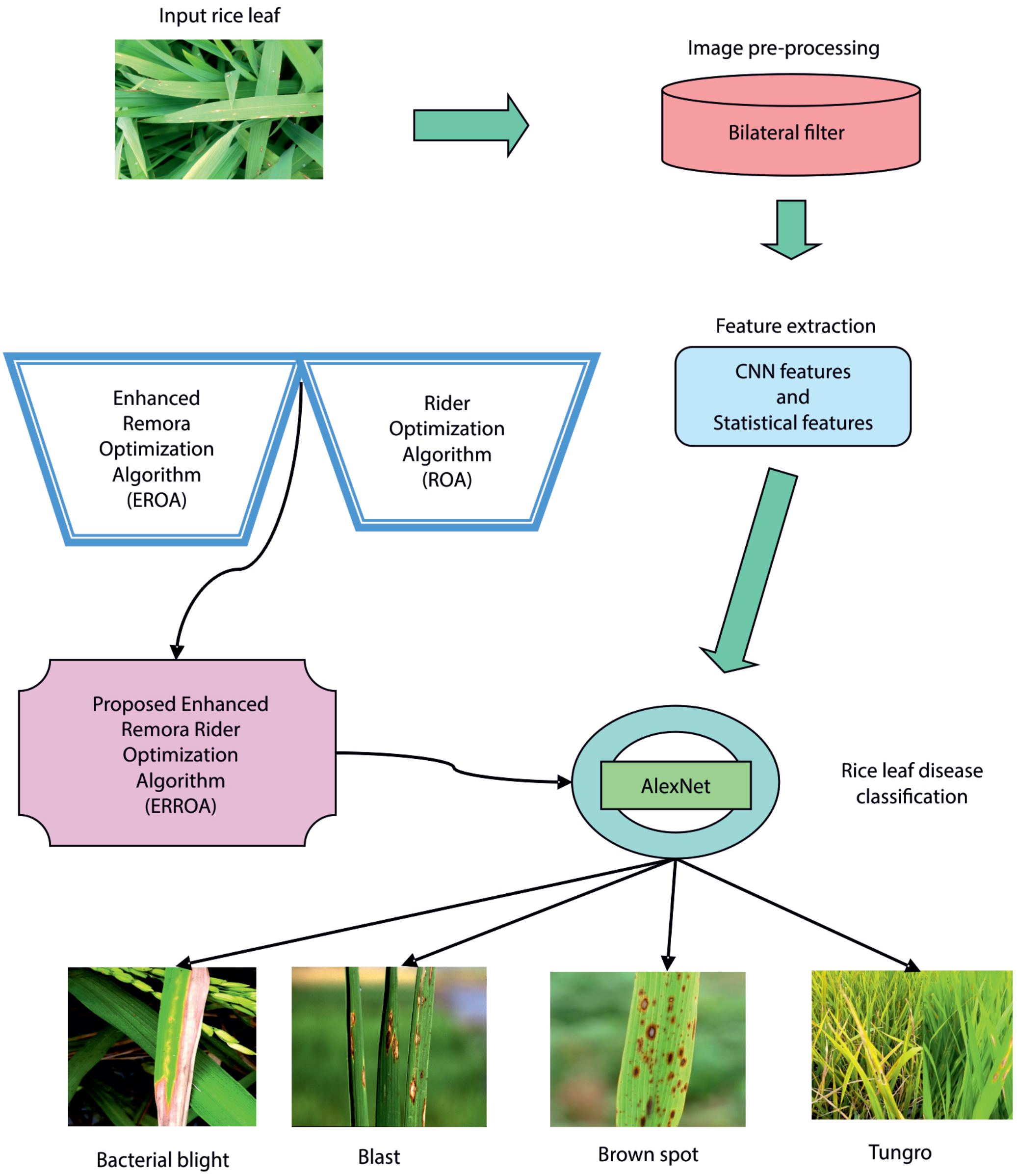


Fig. 1. Schematic view of the proposed ERROA-AlexNet for classification of rice leaf images

Algorithm (EROA) (Wang *et al.* 2022) and Rider Optimization Algorithm (ROA) (Binu and Kariyappa 2018; Daniya and Vigneshwari 2023) to effectively train the classifier and improve its performance.

Disease detection was then performed using the ERROA-AlexNet model, which benefited from the enhanced capabilities of both optimization algorithms (Mirjalili and Lewis 2016; Shadravan *et al.* 2019).

Dataset D should consist of n images, represented as:

$$D = \{K_n\};\ (1 \leq v \leq n) \tag{1}$$

where: n – all the images and K_n – the n^{th} image.

Pre-processing

In this section, pre-processing was performed using a bilateral filter (Chaudhari and Malathi 2024a; Anoop and Bipin 2019) for noise removal. Bilateral filter is a non-iterative and non-linear filter that helped to maintain edges while eliminating noise. Each pixel in the neighborhood contributed to the output based on a weighted average, where the weights were determined by both the spatial and intensity distances of the pixels.

Segmentation

Segmentation (Chen *et al.* 2021) was primarily applied to remove unnecessary portions of an image. This helped reduce computational complexity and minimized incorrect predictions. In the designed model, the GrabCut algorithm (Chaudhari and Malathi 2024a) was employed for segmentation. Following image preprocessing, segmentation was performed on an input, where the disease-affected region was extracted using the GrabCut method.

Data augmentation

Once segmentation was completed, the output underwent image augmentation (Prottasha and Reza 2022) to expand the dataset. This process helped improve model performance by increasing data diversity. In this case, rotation (Sethy *et al.* 2020) was applied to modify the image while preserving its essential features.

Feature extraction

In this study, both CNN features (Liang *et al.* 2019) and statistical features such as mean, variance, standard deviation, kurtosis, skewness, and entropy were extracted (Azim *et al.* 2021).

Thus, the extracted feature vector was represented as:

$$F_{vector} = \{F_{CNN}, F_m, F_v, F_{sd}, F_k, F_s, F_e\}, \tag{2}$$

where: F_{vector} – feature vector, F_{CNN} – CNN features, F_m – feature mean, F_v – feature variance, F_{sd} – feature standard deviation, F_k – feature kurtosis, F_s – feature skewness and F_e – feature entropy.

Proposed ERROA-AlexNet algorithm

The extracted features from the previous stages were fed into AlexNet for classification, where the training process was optimized using the proposed ERROA, a hybrid approach combining the Enhanced Remora Optimization Algorithm (EROA) and Rider Optimization Algorithm (ROA). The proposed ERROA method leveraged the strengths of both techniques, leading to improved convergence speed, and enhanced solution diversity. The structure of AlexNet, coupled with ERROA-based optimization approach, is outlined below.

Architecture of AlexNet

The selected features F_{vector} from the CNN and statistical features were used as input for the AlexNet classifier. The architecture of AlexNet contained the following different components.

Convolutional layer

This operation involved convolving a two-dimensional array of weights (filters) with an input data array. After applying each filter to the input image, feature maps were generated.

In this architecture, the ReLU activation function was employed. ReLU is a non-linear function that activated multiple neuron layers while efficiently handling back-propagation errors.

Pooling layer

The primary role of the pooling layer was to progressively reduce the spatial dimensions of feature representations. By minimizing the number of parameters and computational complexity, it helped to prevent overfitting. In this implementation, a 2 × 2 max-pooling filter with a stride of 2 was used, ensuring efficient feature extraction while preserving key spatial information.

Fully connected layer

The fully connected layer was accountable for classification and detection after the pooling layer has processed the data. To enhance performance and mitigate overfitting, a dropout layer was incorporated. This regularization technique improved generalization and ensured a more robust model. The architecture of AlexNet (Hemmer *et al.* 2018) is delineated in Figure 2.

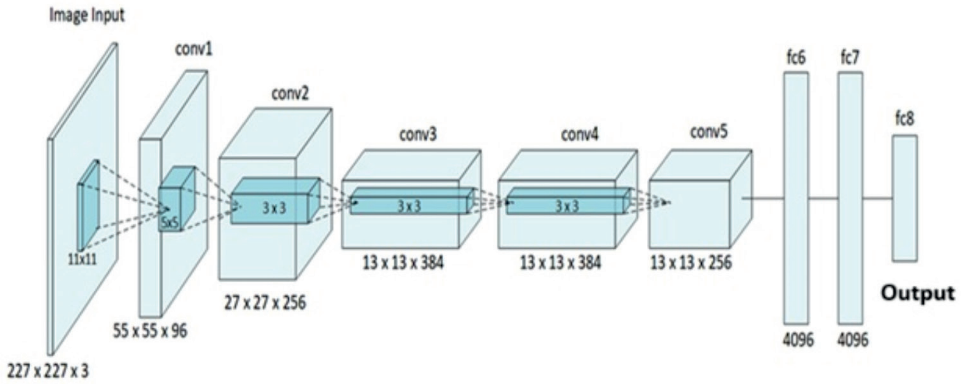


Fig. 2. Architecture of AlexNet (Hemmer *et al.* 2018)

Enhanced remora optimization algorithm

The fundamental framework of Enhanced Remora Optimization Algorithm (EROA) (Zheng *et al.* 2022) remained similar to Remora Optimization Algorithm (ROA), with the key enhancement being the addition of the restart strategy (Wang *et al.* 2022; Zhang *et al.* 2021) at the final stage of the optimization process. Restart strategies were employed in EROA to help poorly performing individuals escape local optima and prevent population stagnation.

Rider optimization algorithm

The Rider Optimization Algorithm (ROA) (Binu and Kariyappa 2018) followed the fictional computing concept to identify optimal solutions with enhanced convergence speed. The positions of the four distinct groups of riders were initialized randomly. The initialization of groups (Wang *et al.* 2019) was defined as follows:

$$M_t = \{M_t(i,k)\};\ 1 \le i \le R;\ 1 \le k \le Z \qquad [3]$$

where: R – the total number of riders, Z – the dimension or the number of dimensions in problem space, $\{M_t(i, k)\}$ – the location of the i^{th} rider.

To determine the final rider and ultimately the winner, the positions of all riders in the system must be updated continuously. The process of updating riders position in each group is described below. The equation governing this update is:

$$M^P_{t+1}(i,k) = \lambda[M_t(\eta,k) * \beta(k) + \\ + M_t(\vartheta,k) * [1-\beta(k)]] \qquad [4]$$

where: λ, η and ϑ – random values, and β – a random variable ranging between 0 and 1 with dimensions of $1 \times Z$.

From the Remora method (Jia *et al.* 2021), the position update was as follows:

$$M^P_{t+1}(i,k) = M_t(\eta,k) + V \qquad [5]$$

where:

$$V = K * (M^P_{t+1}(i,k) - W * M_t(\eta,k) \qquad [6]$$

Substituting equation [6] in equation [5], we get:

$$M^P_{t+1}(i,k) = M_t(\eta,k) + \\ + K * (M^P_{t+1}(i,k) - W * M_t(\eta,k)) \qquad [7]$$

$$M^P_{t+1}(i,k)(1-K) = M_t(\eta,k)(1-KW) \qquad [8]$$

$$M_t\ (\eta,k) = \frac{M^P_{t+1}(i,k)(1-K)}{(1-KW)} \qquad [9]$$

Substitute equation [9] in equation [4]:

$$M^P_{t+1}(i,k) = \lambda[\beta(k) * \frac{M^P_{t+1}(i,k)(1-K)}{(1-KW)} + \\ + M_t(\vartheta,k) * [1-\beta(k)]] \qquad [10]$$

$$M^P_{t+1}(i,k)[1 - KW - \text{ʎ}\beta(k) + \text{ʎ}\beta(k) * K)] = \\ = \lambda M_t(\vartheta,k) * [1-\beta(k)] * (1-KW) \qquad [11]$$

Thus, the final equation for updating the bypass rider's position was:

$$M^P_{t+1}(i,k) = \frac{1}{[(1-KW) - \text{ʎ}\beta(k)(1-k)]} \times \\ \times \lambda M_t(\vartheta,k) * [1-\beta(k)] * (1-KW) \qquad [12]$$

where: $M^P_{t+1}(i,k)$ – the new location of the bypass rider, W – the remora factor, and K – random host volume fluctuations.

Once the update process was finalized, the success rate was recalculated. All the parameters of the rider were updated accordingly in the final iteration. The process continued iteratively until the predefined ride-off time was reached, determining the leading rider. These steps were repeated until an optimal solution was achieved.

Classification using the ERROA-based AlexNet classifier

The test input provided to the classifier should be denoted as x^t, with dimensions $1 \times w$. Utilizing the optimal weights determined through ERROA, the classification outcomes (Binu and Kariyappa 2018) were calculated as follows:

$$O^t = \varphi\left(\sum_{i=1}^{w}\left(x_i^t * D_i^O\right) + W_{io}\right), \qquad [13]$$

where: ϕ – the activation function, and D^O – the optimal weights obtained through the proposed ERROA algorithm.

The corresponding rice leaf disease classes are listed below:

$$\left.\begin{array}{ll} x^t \in \text{bacterial blight}; & \text{if } o^t = 0 \\ x^t \in \text{rice blast}; & \text{if } o^t = 1 \\ x^t \in \text{brown spot}; & \text{if } o^t = 2 \\ x^t \in \text{tungro}; & \text{if } o^t = 3 \end{array}\right\} \qquad [14]$$

Results and Discussion

This section describes the results obtained using the developed ERROA-AlexNet model and evaluated using standard performance metrics. It also outlines the experimental setup, explains the dataset utilized, and highlights the effectiveness of the new method by comparing it with conventional techniques.

Experimentation setup

The developed ERROA-AlexNet model for rice leaf disease categorization was implemented using Python. Its functionality and performance were evaluated using a rice leaf disease dataset. The experiments were implemented on a system with an Intel(R), Core(TM) i7-1235U processor (2.50 GHz), 32 GB of RAM, a 512 GB SSD alongside a 1 TB HDD, 64-bit windows-11 OS (operating system). (2.50 GHz), 32 GB of RAM, a 512 GB SSD alongside a 1 TB HDD, 64-bit windows-11 OS (operating system). The experiments were implemented on a system with an Intel(R), Core(TM) i7-1235U processor (2.50 GHz), 32 GB of RAM, a 512 GB SSD alongside a 1 TB HDD, 64-bit windows-11 OS (operating system). Table 1 describes the experimental parameters used in the proposed work.

Table 1. Experimental parameters

Parameters	Value
Number of data items	5932
Batch size	16
Epochs	10
Activation function	Relu
Learning rate	0.0001
Loss	categorical_crossentropy

Description of dataset

The dataset utilized in this study was obtained from mendeley (data.mendeley.com 2024) and was comprised of a total of 5,932 images categorized into four groups of rice leaf diseases: bacterial leaf blight, leaf blast, brown spot and tungro. Each of these diseases is caused by a specific pathogen. Bacterial leaf blight is caused by *Xanthomonas oryzae* pv. *oryzae*, a bacterial species. Leaf blast is a fungal disease caused by *Magnaporthe oryzae* (also known as *Pyricularia oryzae*). Brown spot is induced by the fungus *Bipolaris oryzae*, and tungro disease results from a viral complex involving *Rice tungro bacilliform virus* (RTBV) and *Rice tungro spherical virus* (RTSV), transmitted by the green leafhopper *Nephotettix virescens*. In the presented research the dataset was divided into training and testing sets using different distribution ratios: 90–10%, 80–20%, 70–30% and 60–40% for training and testing, respectively.

Experimental outcome

This section presents the experimental results obtained from the developed model. Figure 3 illustrates sample outcomes of image pre-processing, data augmentation, and segmentation techniques. Specifically, Figure 3A displays the input image, Figure 3B shows the pre-processed image, Figure 3C presents the segmented image and Figure 3D represents the rotated image.

Performance metrics

The concert of the proposed ERROA-AlexNet technique was assessing, using testing accuracy, testing sensitivity, and testing specificity.

Comparative techniques

The proposed ERROA-AlexNet technique was compared with a few existing methods, including RSW-Deep RNN (Daniya and Vigneshwari 2021), hybrid

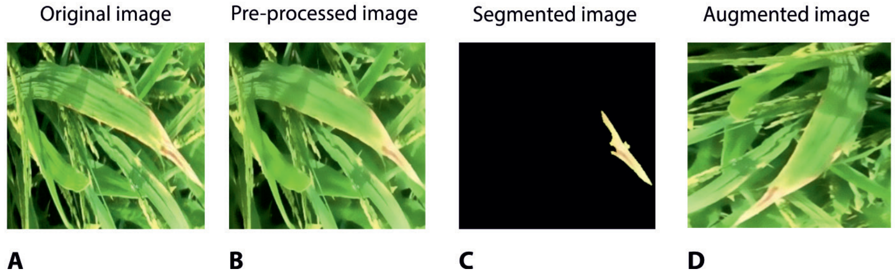


Fig. 3. Sample results: (A) input image, (B) pre-processed image, (C) segmented image, (D) rotated image

CNN-SVM (Chaudhari and Malathi 2023), and Deep CNN (Krishnamoorthy *et al.* 2021) to validate the effectiveness of the proposed approach. Specifically, the ERROA-AlexNet classifier, trained using optimization techniques, was evaluated against these models, demonstrating its superiority over conventional deep learning approaches. The selected baseline methods were chosen based on their relevance and reported effectiveness in image-based plant disease detection and classification task. Daniya and Vigneshwari (2021) introduced a Deep RNN classifier for rice plant disease detection, in which the Deep RNN is trained using a proposed RSW algorithm. Chaudhari and Malathi (2023) proposed a hybrid CNN-SVM model to detect rice leaf diseases. Krishnamoorthy *et al.* (2021) employed a pre-trained deep convolutional neural network (Deep CNN) with a transfer learning approach for detecting rice leaf diseases.

Comparative analysis

This section presents a comparative analysis, evaluating the performance of all techniques based on the percentage of training data used and the selected *k*-values.

Analysis based on training data percentage

The evaluation of the proposed ERROA-AlexNet method in terms of testing accuracy, testing sensitivity, and testing specificity, based on the percentage of training data used, is illustrated in Figure 4. Figure 4A shows the investigation of the devised scheme using testing accuracy. Examination of the devised ERROA-AlexNet scheme with testing sensitivity is described in Figure 4B, and an evaluation of the ERROA-AlexNet method with testing specificity is shown in Figure 4C. For 60% training data, the accuracy of RSW-Deep RNN, hybrid CNN-SVM, Deep CNN and proposed ERROA-AlexNet were 0.670, 0.725, 0.741 and 0.785, respectively. The sensitivity of RSW-Deep RNN, hybrid CNN-SVM, Deep CNN and proposed ERROA-AlexNet were 0.665, 0.710, 0.740 and 0.775, respectively. The specificity of RSW-Deep RNN, hybrid CNN-SVM, Deep CNN and proposed ERROA-AlexNet were 0.681, 0.690, 0.740 and 0.765, respectively. Likewise, for 70% training data, the accuracy of RSW-Deep RNN, hybrid CNN-SVM, Deep CNN and proposed ERROA-AlexNet were 0.750, 0.790, 0.812 and 0.851, respectively. The sensitivity of RSW-Deep RNN, hybrid CNN-SVM, Deep CNN and proposed ERROA-AlexNet were 0.748, 0.780, 0.810 and 0.855, respectively. The specificity of RSW-Deep RNN, hybrid CNN-SVM, Deep CNN and proposed ERROA-AlexNet were 0.740, 0.770, 0.814 and 0.843, respectively.

Moreover, for 80% training data, the accuracy of RSW-Deep RNN, hybrid CNN-SVM, Deep CNN and proposed ERROA-AlexNet were 0.810, 0.833, 0.850 and 0.891, respectively. The sensitivity of RSW-Deep RNN, hybrid CNN-SVM, Deep CNN and proposed ERROA-AlexNet were 0.833, 0.845, 0.874 and 0.891, respectively. The specificity of RSW-Deep RNN, hybrid CNN-SVM, Deep CNN and proposed ERROA-AlexNet were 0.814, 0.831, 0.854 and 0.866, respectively, and lastly, for 90% training data, the accuracy of RSW-Deep RNN, hybrid CNN-SVM, Deep CNN and the proposed ERROA-AlexNet were 0.825, 0.846, 0.889 and 0.924, respectively. The sensitivity of RSW-Deep RNN, hybrid CNN-SVM, Deep CNN and proposed ERROA-AlexNet were 0.847, 0.870, 0.896 and 0.928, respectively. The specificity of RSW-Deep RNN, hybrid CNN-SVM, Deep CNN and proposed ERROA-AlexNet were 0.828, 0.841, 0.864 and 0.975, respectively.

In addition, Figure 5 illustrates the confusion matrix of the proposed ERROA-AlexNet method, evaluated using 90% of the data for training. The confusion matrix plays a crucial role in assessing the performance of classification models, particularly in multi-class classification tasks.

From the above analysis, it can be observed that the proposed ERROA-AlexNet method outperformed the RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN in terms of testing accuracy, testing sensitivity, and testing specificity across different percentage of training data.

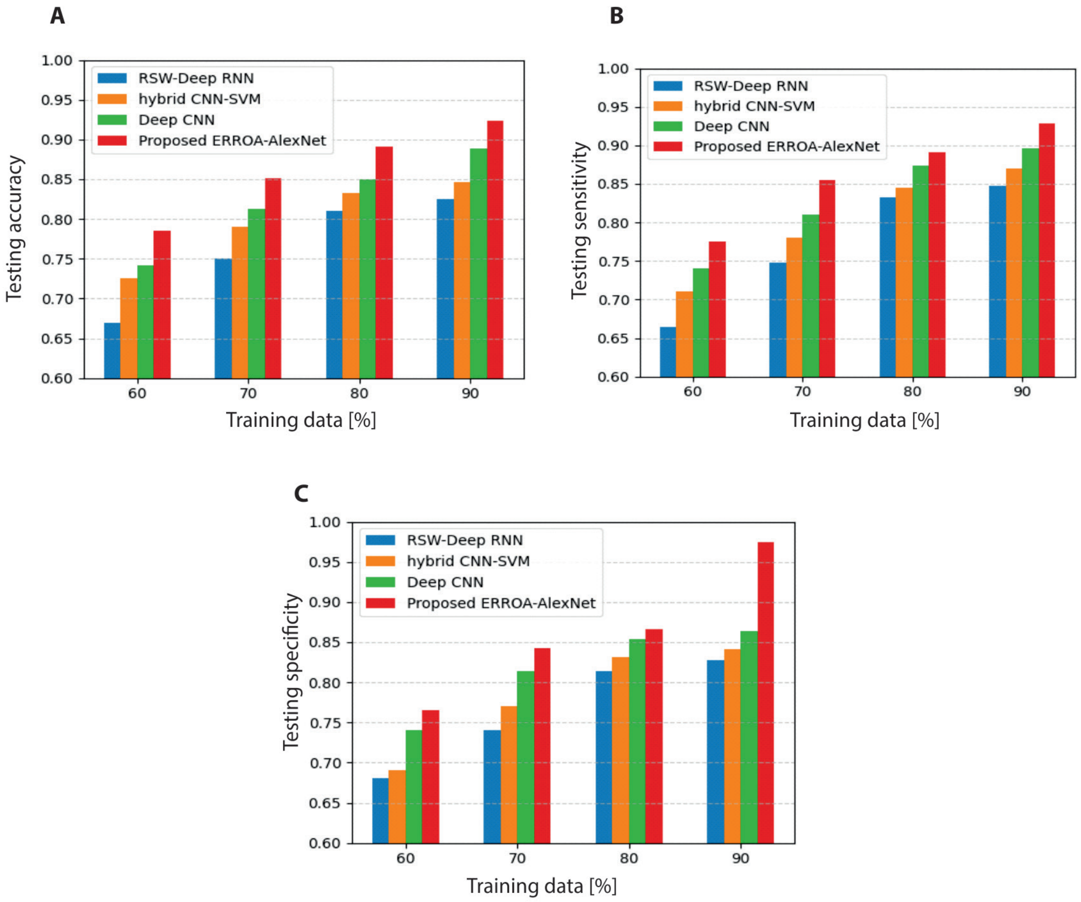
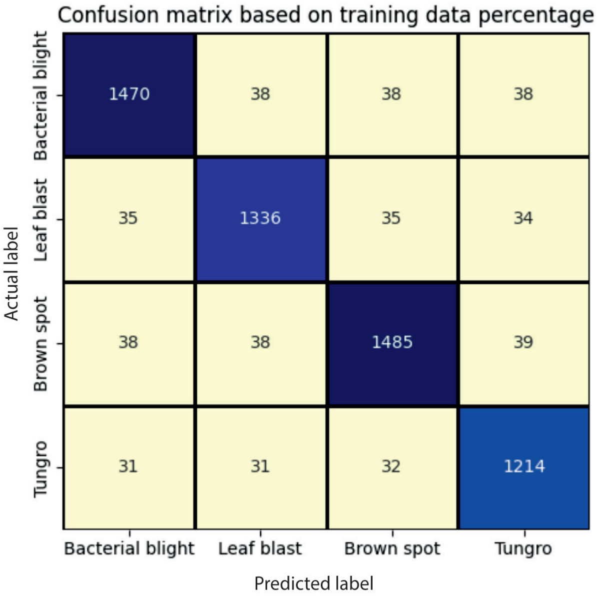


Fig. 4. Analysis based on training data percentage: (A) testing accuracy, (B) testing sensitivity, and (C) testing specificity



	Bacterial blight	Leaf blast	Brown spot	Tungro
Bacterial blight	1470	38	38	38
Leaf blast	35	1336	35	34
Brown spot	38	38	1485	39
Tungro	31	31	32	1214

Fig. 5. Confusion matrix using 90% training data

Analysis based on *k*-fold value

Figure 6 displays the evaluation of ERROA-AlexNet method using different *k*-fold value based on testing accuracy, testing sensitivity and testing specificity metrics. Figure 6A illustrates the testing accuracy of the ERROA-AlexNet method. The examination of the devised method using testing sensitivity is given in Figure 6B. The investigation of ERROA-AlexNet using testing specificity is illustrated in Figure 6C. For *k*-fold value 4, the accuracy of RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN were 0.680, 0.725 and 0.745, correspondingly, whereas the accuracy of the proposed ERROA-AlexNet was 0.772. The sensitivity of RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN were 0.721, 0.743 and 0.745, correspondingly, whereas the sensitivity of proposed ERROA-AlexNet was 0.770. The specificity of RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN were 0.682, 0.690 and 0.740, correspondingly, whereas the specificity of proposed ERROA-AlexNet was 0.762. Likewise, for *k*-fold value 5, the accuracy of RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN were 0.745, 0.775 and 0.800, correspondingly, whereas the accuracy of the proposed ERROA-AlexNet was 0.831. The sensitivity of RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN were 0.780, 0.810 and 0.825, correspondingly, whereas the sensitivity of the proposed ERROA-AlexNet was 0.856. The specificity of RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN were 0.753, 0.776

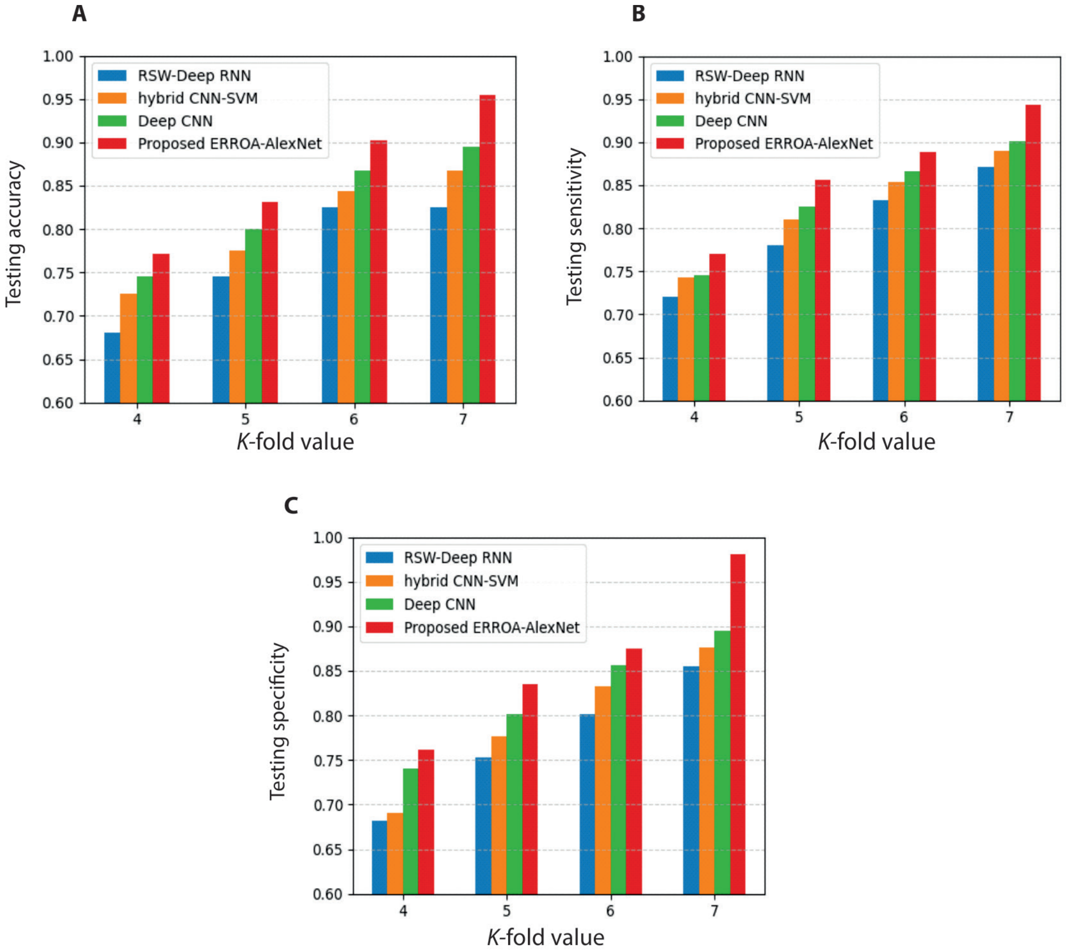


Fig. 6. Analysis based on *k*-fold value: (A) testing accuracy, (B) testing sensitivity, and (C) testing specificity

and 0.802, correspondingly, whereas the specificity of the proposed ERROA-AlexNet was 0.835.

Moreover, for *k*-fold value 6, the accuracy of RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN were 0.825, 0.844 and 0.867, correspondingly, whereas the accuracy of the proposed ERROA-AlexNet was 0.902. The sensitivity of RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN were 0.833, 0.854 and 0.866, correspondingly, whereas the sensitivity of the proposed ERROA-AlexNet was 0.889. The specificity of RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN were 0.802, 0.832 and 0.856, correspondingly, whereas the specificity of the proposed ERROA-AlexNet was 0.875 and lastly, for *k*-fold value 7, the accuracy of RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN were 0.825, 0.867 and 0.895, correspondingly, whereas the accuracy of the proposed ERROA-AlexNet was 0.954. The sensitivity of RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN were 0.871, 0.890 and 0.901, correspondingly, whereas the sensitivity of the proposed ERROA-AlexNet was 0.943. The specificity of RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN were 0.855, 0.876 and 0.895, correspondingly, whereas the specificity of the proposed ERROA-AlexNet was 0.981.

In addition, Figure 7 illustrates the confusion matrix of the proposed ERROA-AlexNet method, evaluated with $k = 7$.

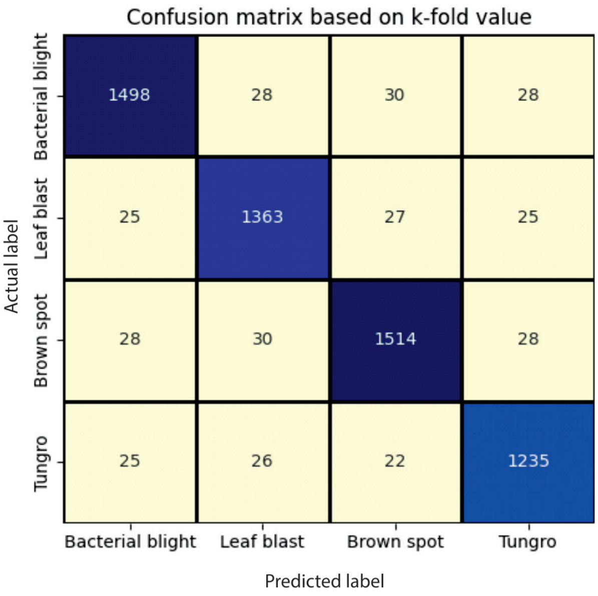


Fig. 7. Confusion matrix using *k*-fold value ($k = 7$)

Table 2. Comparative performance of proposed methods based on evaluation metrics

Analysis type	Metrics	Deep RNN	CNN-SVM	Deep CNN	Proposed ERROA AlexNet
Training data = 90%	testing accuracy	0.825	0.846	0.889	0.924
	sensitivity	0.847	0.870	0.896	0.928
	specificity	0.828	0.841	0.864	0.975
k-fold value (k = 7)	testing accuracy	0.825	0.867	0.895	0.954
	sensitivity	0.871	0.890	0.901	0.943
	specificity	0.855	0.876	0.895	0.981

Comparative discussion

Table 2 displays the comparative performance of the proposed ERROA-AlexNet method with conventional techniques with respect to evaluation metrics by modifying the percentage of training data and *k*-fold value. The table clearly revealed that the devised ERROA-AlexNet method achieved the maximum testing accuracy of 95.4%, testing sensitivity of 94.3%, and testing specificity of 98.1%, based on *k*-fold value. The experimental results indicated a significant performance improvement was achieved using the proposed model.

From the above analysis, it can be seen that the proposed ERROA-AlexNet method demonstrated superior performance compared to RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN in terms of testing accuracy, testing sensitivity, and testing specificity, based on different k-fold values.

Conclusions

In this paper, a novel ERROA-AlexNet was proposed for the detection and classification of four rice leaf diseases such as bacterial leaf blight, leaf blast, brown spot and tungro. The ERROA algorithm was invented by merging EROA and ROA optimization algorithm, which can be resorted to train the AlexNet classifier for finding the optimal weights. Once the classifier was trained on the rice leaf disease training dataset, it was evaluated for performance accuracy. After selecting optimal weights, the ERROA-AlexNet method gave classification results with testing accuracy of 0.954, testing sensitivity of 0.943, and testing specificity of 0.981. The investigational outcomes were analyzed and it was found that the ERROA-AlexNet method performed better than the traditional models such as RSW-Deep RNN, hybrid CNN-SVM, and Deep CNN.

In the future, additional features such as color, texture and shape descriptors, along with other deep learning models and larger dataset sizes, will be investigated to enhance the performance of the proposed model. Furthermore, this method can be integrated with smart technologies such as agriculture IoT and mobile devices to enable real-time monitoring and detection of diseases.

Data availability statement

The data used in this study is available in Rice Leaf -Disease Image Samples Dataset at https://data.mendeley.com/datasets/fwcj7stb8r/1.

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