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Optimized decision science approach for accurate detection of rice plant diseases

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Abstract

Rice cultivation is an integral part of India's changing landscape of agriculture. It offers an ALO-based Random Forest Classifier for accurate disease diagnosis and sorting in rice plants, including brown spot, bacterial leaf blight, and leaf smut. It begins with gathering the dataset from Kaggle and then continues the step of image pre-processing to upgrade its quality. Feature extraction extracts statistical features based on GLCM, whereas the segmentation applies the Otsu threshold approach. The optimized RFC is done using ALO for better precision. High accuracy rates and lower computation times are ensured and validated compared with alternatives, affirming that such a framework in rice plant disease detection and classification works well.

Subject Classification: *92C80, 68T07.*

Keywords: *Adaptive filter method, Ant lion optimization, Gray level co-occurrence metrics, Otsu threshold approach, Random forest classifier.*

1. Introduction

Paddy cultivation is an important crop in the Indian agricultural landscape, including both population and economy. The prompt detection of crop diseases lags behind the cultivation of crops, leading to a very

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unsatisfactory cultivation practice [1-4]. Traditional manual monitoring methods are impractical for large-scale implementation, necessitating cost-effective and reliable predictive approaches like machine learning. Despite the utility of machine learning, variability in input data accuracy poses challenges in disease prediction. Recognizing the significance of automated disease detection systems, efforts to enhance productivity and standards are imperative [5-8]. Image processing emerges as a pivotal tool, aiding in accurate disease detection and reducing human efforts [9-11]. Employing computational imaging and machine learning approaches, this study attempts to upsurge the accuracy of rice plant disease identification. A review of the relevant literature, an explanation of the suggested methodology, a presentation of the findings and conclusions, and closing remarks make up the remaining portions of the work [12-15].

II. Proposed methodology

This section discusses artificial ant lion optimization-based random forest for accurately detecting RICE plant disease. Figure 1 shows the block structure of the suggested system for identifying rice plant diseases. The procedure is divided into four stages: image capture, feature extraction, pre-processing, segmentation, and rice plant disease classification. Thus, a full description of each step is specified below,

- **Image Acquisition**
- **Pre-processing using the adaptive filter method**

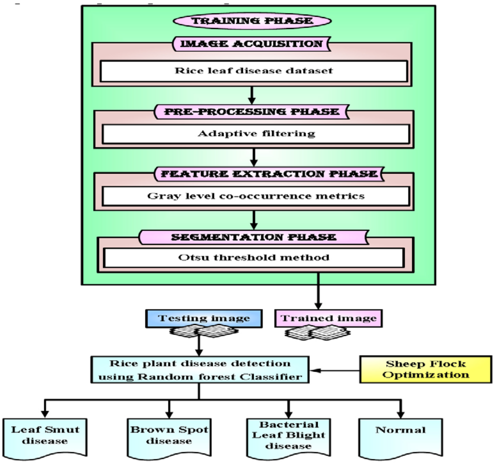

Figure 1

Block structure of the suggested system for identifying rice plant diseases

- **Feature extraction using grey-level co-occurrence metrics (GLCM)**
  - Homogeneity
  - Contrast
  - Energy
  - Kurtosis
  - Correlation
  - Mean
  - Entropy
  - Skewness
- **Segmentation using Otsu's threshold method**
- **Random Forest classifier classification**
- **Optimization using ant lion optimization**

Steps:

1. **Starting over:** To improve classification efficiency, initialise the ant lions' beginning population and optimise the C and Fc weight parameters of the RF classifier technique (Figure 2).

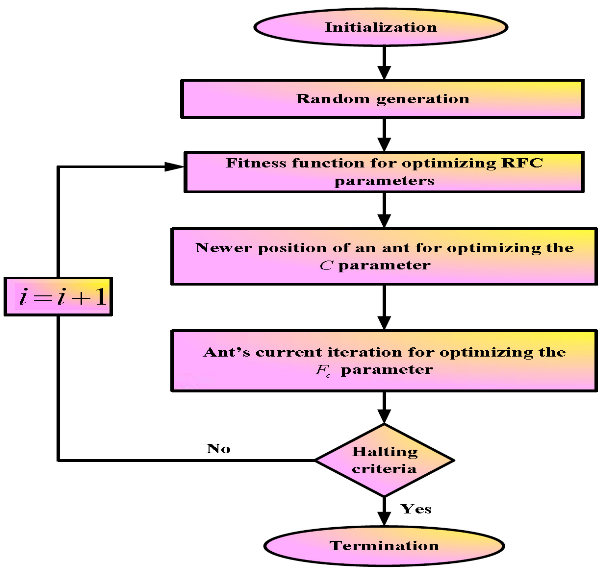

Figure 2

Flow chart for the ALO for optimizing the RF classifier parameters

2. **Random Generation**
3. **Fitness function for optimizing RFC parameters**
4. **Newer position of an ant for optimizing the *C* parameter**
5. **Ant's current iteration for optimizing**
6. **Dismissal:** The altered behaviour of ALO is used to enhance the random forest classifier's parameters. The objective function that is produced reduces computing time and increases accuracy by tolerating errors.

III. Result with discussion

This section discusses the experimental findings related to the optional approach. Numerous performance parameters like precision, sensitivity, accuracy, F1-score, error rate, specificity, and computing time, are simulated using Python for the proposed technique. Figure 3, 4, 5, 6, 7, and 8 shows the result of proposed method.

- **Dataset description**

The effectiveness of the recommended approach is evaluated using the Rice Plant Disease dataset. This collection has 120 photos of rice leaves that are sick. Depending on the kind of illness, the pictures are characterized into three groups. There are forty pictures in each class. 30% is the testing dataset, and 70% is the training dataset. Each class's sample photographs are included in Table 1.

Table 1

Sample images in each class

Dataset	Class Name	Sample image	Total Number of images
Rice Leaf	Smut of Leaf		40
	Spots of Brown colour		40
	Blight on Bacteria in Leaf		40

Performance measures

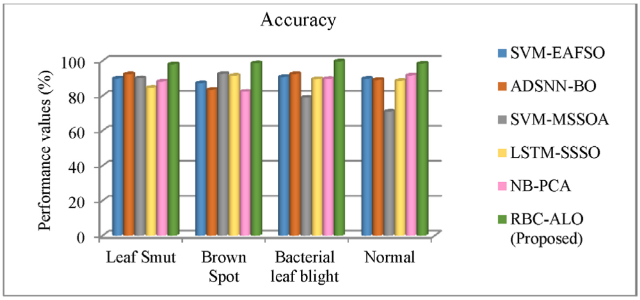

Figure 3

Comparison of the accuracy

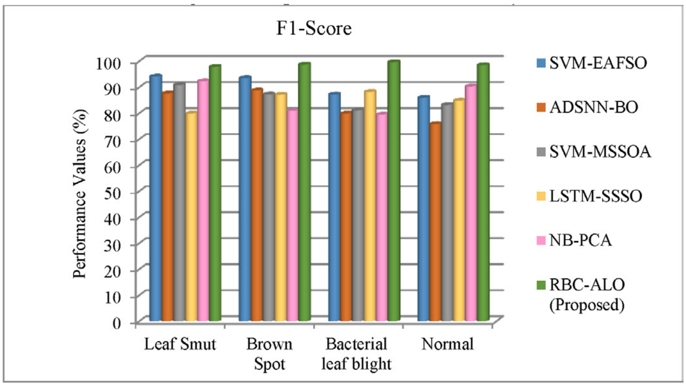

Figure 4

Comparison of the F1-Score

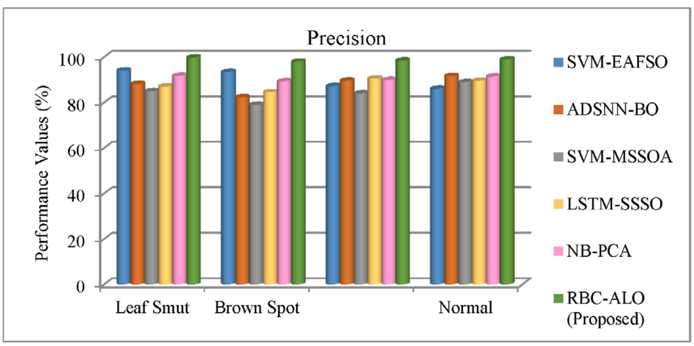

Figure 5

Comparison of the Precision

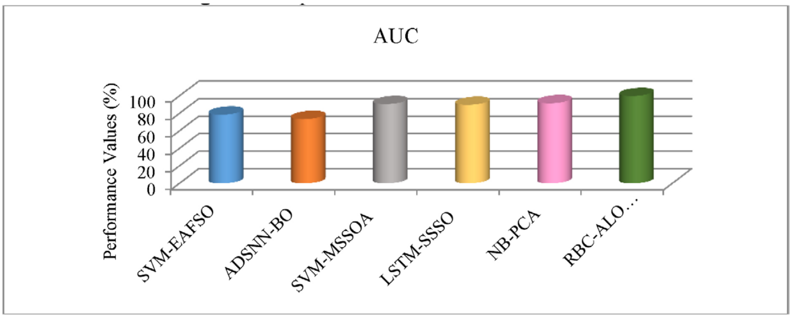

Figure 6

Performance Comparison of the AUC

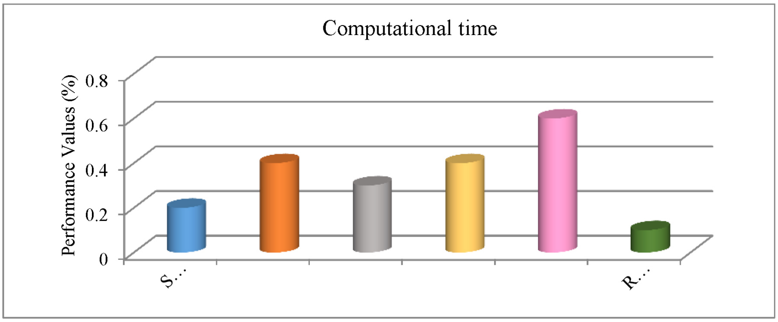

Figure 7

Computational time

In Figure 8 for their computational times.

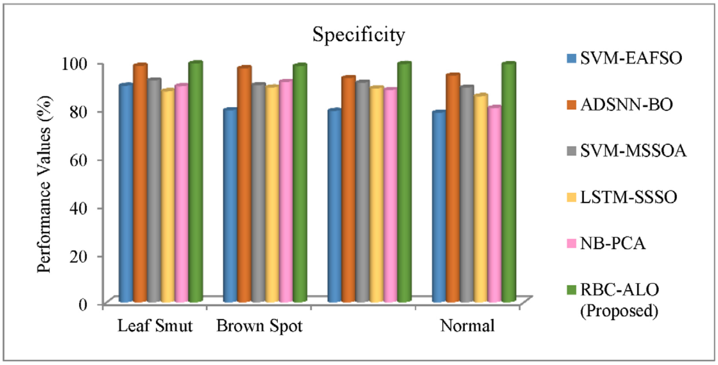

Figure 8

Comparison of the specificity

Table 2

Overall performance metrics

Methods	Performance assessment					
	Specificity	Precision	F1-Score	Accuracy	Recall	Computational time
SVM-EAFSO	98.99	99.8	97.89	98.04	97.89	0.2
ADSNN-BO	97.95	97.99	98.77	98.67	98.07	0.1
SVM-MSSOA	98.79	98.5	99.67	99.67	99.8	0.2
LSTM-SSSO	98.78	98.56	99.36	96.56	99.45	0.1
NB-PCA	99.08	98.78	97.69	98.56	99.34	0.2
RFC-ALO (Proposed)	98.67	99.09	99.08	99.68	98.89	0.1

The suggested RFC-ALO has produced the best results across all parameter validations, according to Table 2's computation of the overall performance metrics. Additionally, their results included 99.68 percent accuracy, 99.67 percent specificity, 99.08 percent F1-Score, 99.09 percent precision, and 99.63 percent recall. This confirms the robustness of the proposed RFC-ALO and its ability to identify rice leaf disease.

IV. Conclusion

In this study, the RFC is optimized using ALO for rice disease detection, achieving successful categorization of three rice leaf diseases. Simulation procedures are conducted in Python, showcasing notable specificity at 98.99%, surpassing comparative processes such as SVM-EAFSO, ADSNN-BO, SVM-MSSOA, LSTM-SSSO, and NB-PCA. Future research aims to enhance model accuracy by collecting additional images and incorporating cross-validation for result validation. The adaptable model also holds the potential for detecting other plant disease outbreaks threatening critical Indian crops.

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