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Detection of paddy plant diseases using SVM-RFE, AROA with MBi-LSTM model

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The prime objective of this manuscript is to identify diseases affecting paddy plants, which are an important cause of crop loss. The proposed work have been carried out into four stages: stages first deals with data gathering and pre-processing where data have been gathered from kaggle and in pre-processing quality have been improved. To clean up the green section of the image, a median filter has been applied on an RGB image. Stage second deals with extraction of features where texture and colour features have been extracted from each cleaned image. Stage third deals with selection of features where the most important features have been selected using SVM-RFE, AROA, and both the intersection of SVM-RFE and AROA methods. Last stage fourth deals with the MBi-LSTM classification on the selected features to detect the diseases in the image. The proposed method namely intersection of both SVM-RFE and AROA with MBi-LSTM has shown the ability to detect paddy crop diseases as well.

Keywords: Classification, Feature extraction, Feature selection, Leaf diseases, Median filter

1 Introduction

Agriculture is the primary means of producing food in the modern world to feed the growing population. The GDP is mostly derived from the agricultural, fishing, and forestry sectors. Nonetheless, agricultural goods' share of India's GDP is progressively declining year[1].The paddy plant is among the most significant in the entire planet. Rice is a basic meal for billions of people worldwide, thus increasing its production in both quality and quantity is essential[2]. This massive loss in agricultural productivity is mostly the result of plant diseases. The conventional methods for assessing the severity of an illness include visually assessing the symptoms caused by the pathogen and identifying the characteristics of the disease symptoms. Only by thorough examination and research will a qualified individual be able to observe and assess the severity of the illness. More time is needed for this procedure and more experts in plant disease diagnosis are needed. Plant growth and development are influenced by several environmental factors, including temperature, rainfall, sunshine, and climate change[3]. Plant growth requires the right conditions of the soil, including pH, nutrients, and moisture[4]. The amount and quality of the ultimate crop might be greatly decreased by the presence of plant diseases. Pests and diseases account for 25% of crop losses overall, according to estimates from the Food and Agriculture Organisation (FAO)[5].

It is crucial to regulate this parameter as a result. If not, it may negatively impact agricultural output by negatively affecting plant growth. Plant diseases impose a significant financial burden on farmers worldwide every year. These losses between planting and harvesting agricultural goods are realistic to expect[6]. Plant diseases pose a serious risk to human health as well since they may cause liver illness, skin allergies, stomach issues, and strokes. Common plant diseases in agriculture include leaf spots, ergot, rust, nematodes, bacterial wilt, root rot, and powdery mildew[7]. Plant diseases must be identified, prevented, and managed with the use of efficient approaches. It is critical to create timely and suitable technologies in order to assess various plant diseases quickly and efficiently.

The leaf of a plant is often considered to be the most crucial component. The deterioration and eventual loss of leaf is caused by a number of variables, including illnesses, pests, inadequate nutrition, lack of sunshine, and floods. One of the main factors influencing a plant's ability to develop is disease-related damage to its leaf. Plant functions such as transpiration, photosynthesis, germination,

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pollination, and others are significantly reduced by diseases. Consequently, it is thought that detecting leaf diseases early is essential to increasing agricultural productivity. The three main pathogens responsible for illness are fungi, viruses, and bacteria so crop output has decreased[8]. Fungi have been shown to be the pathogen that most significantly affects crop development out of all of them. Common foliar diseases that affect plants include Downy mildew, Anthracnose, Bacterial spots, early and late blight, apple scab, Common rust, leaf spot[9, 10].

To face the difficulties of growing output and to keep up with future agricultural trends, innovative solutions are required. Therefore, effective identification and management of plant leaf diseases depend on accurate diagnosis. A farmer may expend money, effort, and time trying to identify a problem with an unidentified cause until a disease is identified. In order to replace the visual assessment method with an efficient automated plant disease diagnosis system, both new method development and enhancements to current techniques are needed. With more precision and less expense, image processing algorithms[11,12] identify every factor connected to plant leaf diseases. These (image processing) methods can access the more precise characteristics of visual complaints. The current plant leaf disease classification techniques have low performance criteria, including specificity, sensitivity, and accuracy.

The literature has classified paddy illnesses according to their characteristics and images using a variety of methods and investigations. Senan *et al.*[13] have used a strong CNN to create a model for identifying plant leaf diseases and pests. CNN model have been used successfully by the researchers. Improving the speed and accuracy of paddy disease and pest detection has been the primary objective. A total of 4855 images has been acquired and grouped into four categories: leaf blast, Hispa, Tungro, and photos of healthy rice. The images have been sorted using the CNN technique, which has had five layers. The DNN has been boosted by the Jaya method[14] to detect and classify rice leaf diseases. All five of the image categories that have been examined are sheath rot, blast diseases, bacterial blight, tungro, and normal. The RGB images have been converted into HSV format in advance so that the background does not appear. Following that, photographs processed from hue and saturation has been transformed into binary images to analyze the affected and unaffected parts. Clustering has been performed to identify the diseased area and distinguish it from the healthy parts of the image. Disease classification has been carried out using Optimized DNN and JOA (DNN-JOA)[14]. A feedback process has been implemented during the post-processing step to precisely measure the technique's stability. The experimental findings of the above stated work bythe researchers have been compared and assessed with the results obtained from DAE, DNN, and ANN.

Therefore, the work automates the prediction of leaf diseases with the help of a deep learning system.

Here is how the research's main contribution of the authors can be described:

The model for predicting leaf diseases covers four steps: pre-processing, extracting features, selecting features, and classifying them.

- After the images have been divided into red, green, and blue colour bands, a Median filter eliminates Noise is initially isolated from the green spectral band, after which feature extraction is performed on the same band.
- Next, using machine learning techniques and an optimisation approach, the suitable attributes are chosen.

The SVM-RFE, AROA, and the Intersection of both SVM Recursive Feature Elimination (SVM-RFE) and Adaptive Rain Optimization Algorithms (AROA) are used in this instance to choose the features. The shared attributes are then selected.

- By providing the Modified Bi Long Short Term Memory (MBi-LSTM) classifier with the required attributes, the picture is classed as a normal image, a blast sickness, a bacterial leaf blight disease, or Tungro.

2 Materials and Methods

The proposed work have been carried out into four stages: stages first deals with Data gathering and pre-processing where data have been gathered from kaggle and in pre-processing quality have been improved. Stages second deals with extraction of features where texture and colour features have been extracted from each cleaned image. Stages third deals with selection of features where the most important features have been selected using the SVM-RFE, AROA and both the intersection of SVM-RFE and AROA methods. Last stages fourth deals with the MBi-LSTM Classification on the selected features to detect the diseases in the image. Figure 1 shows the process of the approach.

2.1 Data gathering and pre-processing

We use Rice Leaf Images Dataset, which is the merges of Rice Disease[15] attribute name Healthy and Dataset Rice Leaf Disease Images[16]attribute name Blast, Bacterial Blight, and Tungro. This dataset encompasses four distinct types of paddy leaf: Healthy, Blast, Bacterial Blight, and Tungro, as detailed in Table 1.

At first, a Median filter is used as the main technique for pre-processing. Doing pre-processing before classification helps improve the technique's accuracy and makes it operate more smoothly. The image that was captured has some noise and images of various sizes. Thus in the initial step, A Median filter is used to decrease the noise in the images at the start of pre-processing.

After that, the signal is changed to RGB format and the green channel is chosen for further steps. Equation (1) describes the mathematical formula for the Median filter.

$$M(p,q) = \underset{(f,m)\in S_{i,j}}{Median}\{f,m\} \quad \dots (1)$$

Where $M(p,q)$ indicates the median filter output.

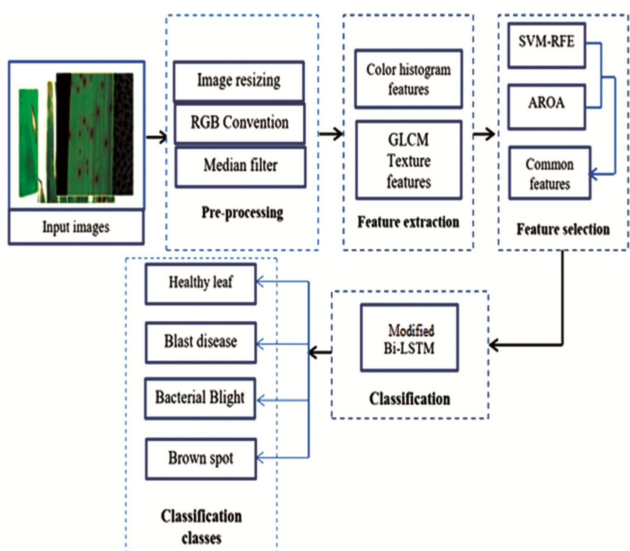

Fig. 1 — Process for classifying leaf diseases that is being proposed.

2.2 Extraction of features

After pre-processing, we take the key elements out of each of the green bands in the picture. This article extracts characteristics from two feature sets: texture attributes and colour histogram features.

2.2.1 RGB histogram attributes

Images are analyzed and their visual information extracted using the RGB histogram. In this approach, both the mean and standard deviation of a rice plant leaf image's color are used as features.

❖ Mean: The mean is the procedure for finding the average lightness of every pixel in an image. When an image is brighter in average, its mean will be higher than when it is dimmer. The mean value is determined with Equation (2).

$$M_j = \frac{1}{A}\sum_{i=1}^{A} P_{xy} \quad \dots (2)$$

Here, P_{xy} shown as j^{th} a channel in color at the i^{th} picture pixel

❖ Normal Deviation: The square root of variance is called standard deviation and is used to measure how spread out are the pixel intensity values in an image. Low contrast images have less variance and a smaller standard deviation, yet images with a lot of contrast have higher values. This can be realized by studying the following:

$$\sigma_j = \sqrt{\frac{1}{A}\sum_{i=1}^{A}(U_{xy} - V_y)^2} \quad \dots (3)$$

σ_j Means the standard deviation of the feature., A represents the entire number of elements (pixels, samples, and so on).

$\sum$ indicates to add up the results for all the A's., the difference between a score and the mean is squared.

2.2.2 Texture attribute

The textures are taken out of every image using the GLCM features. Twenty-two GLCM characteristics are taken out of every picture in this research. To extract GLCM features, utilise the following expressions in Table 2.

Table 1 — Details of rice leaf images dataset[15,16].

Name of attributes	Description of attributes	No. of images
Healthy	Images of rice leaf with Healthy	523
Blast	Images of rice leaf infected with Blast	1440
Bacterial blight	Images of rice leaf infected with Bacterial blight	1584
Tungro	Images of rice leaf infected with Tungro	1308

Table 2 — Features of the extracted GLCM.

Characteristic description	Features name	Formulas
F_1	Angular second moment	$F_1 = \sum_{f=0}^{G^L-1} \sum_{m=0}^{G^L-1} \{p(f,m)\}^2$
F_2	Contrast	$F_2 = \sum_{n=0}^{G^L-1} n^2 \left\{ \sum_{u=1}^{G^L} \sum_{v=1} p(f,m) \right\}, \lvert f-m \rvert = n$
F_3	Inverse difference moment	$F_3 = \sum_{u=0}^{G^L-1} \sum_{v=0}^{G^L-1} \frac{1}{1+(f-m)^2} p(f,m)$
F_4	Entropy	$F_4 - \sum_{u=0}^{G^L-1} \sum_{v=0}^{G^L-1} p(f,m) \times \log(p(f,m))$
F_5	Correlation	$F_5 = \sum_{u=0}^{G^L-1} \sum_{v=0}^{G^L-1} \frac{\{f,m\}\, p(f,m) - \{f_i \times m_v\}}{\sigma_i \times \sigma_v}$
F_6	Variance	$F_6 = \sum_{f=0}^{G^L-1} \sum_{m=0}^{G^L-1} (f-\mu)^2 p(f,m)$
F_7	Sum average	$F_7 = \sum_{u=0}^{2G^L-1} u\ p_{i+j}(u)$
F_8	Total deviation	$F_8 = \sum_{u=0}^{2G^L-1} (u - Aver)^2 p_{i+j}(u)$
F_9	Total entropy	$F_9 = -\sum_{u=0}^{2G^L-2} P_{i+j}(f) \log(p_{i+j}(f))$
F_{10}	Difference entropy	$F_{10} - \sum_{f=0}^{G^L-1} P_{i+j}(f) \log(p_{i+j}(f))$
F_{11}	Inertia	$F_{11} = \sum_{u=0}^{G^L-1} \sum_{v=0}^{G^L-1} (f-m) \times p(f,m)$
F_{12}	Cluster shade	$F_{12} = \sum_{f=0}^{G^L-1} \sum_{m=0}^{G^L-1} \{f+m-\mu_i-\mu_j\}^3 \times p(f,m)$
F_{13}	Cluster prominence	$F_{13} = \sum_{x=0}^{G^L-1} \sum_{y=0}^{G^L-1} \{x+y-\mu_i-\mu_j\}^4 \times p(x,y)$
F_{14}	Dissimilarity	$F_{14} = \sum_{f,m} \lvert f-m \rvert\, p(f,m)$
F_{15}	Homogeneity	$F_{15} = \sum_{f,m} \frac{1}{1-(f-m)^2} p(f,m)$
F_{16}	Energy	$F_{16} = \sum_{f,m} p(f,m)^2$

(*Contd.*)

Table 2 — Features of the extracted GLCM. (*Contd.*)

Characteristic description	Features name	Formulas
F_{17}	Autocorrelation	$F_{17}=\sum_{f=0}^{G^L-1}\sum_{m=0}^{G^L-1}\left(p_i-\mu_u\right)/\sigma_u\sigma_v$
F_{18}	Maximum probability	$F_{18}=\max\left(f,m\right)p\left(f,m\right)$
F_{19}	Inverse difference normalized (INN)	$F_{19}=\sum_{u=0}^{G^L-1}\sum_{v=0}^{G^L-1}\frac{\lvert p(u,v)\rvert}{1+(u-v)}$
F_{20}	Inverse difference moment normalize	$F_{20}=\sum_{u=0}^{G^L-1}\sum_{v=0}^{G^L-1}\frac{p\left(f,m\right)}{1+\left(f-m\right)^2}$
F_{21}	Correlation 1 of information measure	$F_{21}=\frac{MUV-MUV1}{\max\left\{MU,MV\right\}}$
F_{22}	Correlation 2 information measure	$F_{22}=\sqrt{(1-\exp)}$

2.3 Selection of features

The selection of features has been done in three ways: (a) SVM-RFE (b) AROA (c) Intersections of both SVM-RFE and AROA.

2.3.1 SVM-RFE feature selection

After identifying the features, SVM-RFE is applied to get the most important ones. The method joins the abilities of support vector machines with the successive removal of features done in recursive feature elimination. By deleting the least significant attribute that the SVM represents, the classifier is retrained using the current attribute to choose features using SVM-RFE [14].

The hyper plane, or decision function, in the suggested SVM is created.

$$H(\vec{y})=(\vec{w}.\vec{x})+b \quad \text{... (4)}$$

It is possible to ignore the feature with the lowest weight since it makes the least contribution to the final hyper plane. A considerable amount of features are eliminated each time this RFE method is used. This method is repeated iteratively with the goal of eliminating many traits while leaving the most important ones intact.

Initially, this approach eliminates a significant number of features; but, as the algorithm progresses, the fraction of features deleted at each step lowers. In iteration, for instance, SVM is used to train the n^{th} presentation features, and $1/(1+n)$ least significant features are eliminated. This process is carried out until the user-defined variable, m, is the sole feature remaining. S1 displays the chosen feature subsets. Feature selection approach based on SVM-RFE shown in Table 3.

Feature selection based on the ARO algorithm is shown in Table 4.

2.3.2 Process for selecting features by using intersections of both SVM-RFE and AROA

In this section, the feature is first selected using the SVM RFE approach; this algorithm only selects feature associated to categories.The AROA method is then used to choose the features. Further, we have selected the feature by using the intersections of both SVM-RFE and AROA. The procedure of feature selection is shown in Fig. 2.

2.4. Classification by using MBi-LSTM

LSTM units work on the sequence in contrasting directions and their results are merged. The last task of classification is handled by a Softmax layer. An LSTM unit has the forget gate, input gate, output gate, and memory cell. The entire structure of the LSTM model is demonstrated in Fig. 3.

The MBi-LSTM classifier checks the data to determine if it is regular or not using the features that it studied. According to Fig. 4, the data is examined using two types of LSTM and dense layers plus a final prediction model. With this approach, both Bi-LSTM and LSTM are used to help avoid the problems caused by gradient vanishing and explosion. Figure 4 illustrates the general structure of the MBi-LSTM model.

As a result, the proposed MBi-LSTM model effectively classifies input data into normal and abnormal categories.

Table 3 — Feature selection approach based on SVM-RFE.

Inputs:

Extracted features $F_0 = [f_1, f_2, ..., f_k, ..., f_l]^T$

Class labels : $c = [Cl_1, Cl_2, ..., Cl_k, ...Cl_l]^T$

Output:

Ranked features

Set:

Consider the subset of present attributes

$a = [1, 2, ..., n]$

Set ranked list of attributes $R = [\ ]$

Repeat until $a = [\ ]$

Limit training to get a good feature

$F = F_0(:, s)$

Then, the classifier is trained

$\beta = SVM - train\ (F, c)$

Find out the weight vector (W)

$W = \sum_k \beta_k \gamma_k F_k$

Calculate the ranking

$d_i = (w_i)^2$, for all i

Repeat $length(s) \times \frac{1}{n+1} times$

Choose the attribute with a small rank

$f = \arg\min(c)$

Update ranked list of features

$R = [S(f), R]$

Remove smallest rank features

$s = s(1 : f - 1, f + 1 : length(s))$

end

end

Output

Ranked feature list R

Table 4 — Feature selection based on the ARO algorithm.

Input: Population size, the maximum number of iterations, and a random weight value

Output: The ideal weight

1	Set the droplets or solutions to a random initialization.
2	Come up with the opposing answer.
3	Determine each solution's fitness.
4	Move the drop to a different spot if there is a dominating neighbouring point.
5	Set the droplet's position to inactive after the explosion if it does not have a dominating neighbour point.
6	If additional points close to a higher rank are dropped, or if there is a lower rank, Make a list of merits and take the drops out.
7	Let T= T+1
8	Proceed to step 3 if there is a drop there and It is not possible to reach the maximum number of iterations.
9	Put an end to the algorithm.

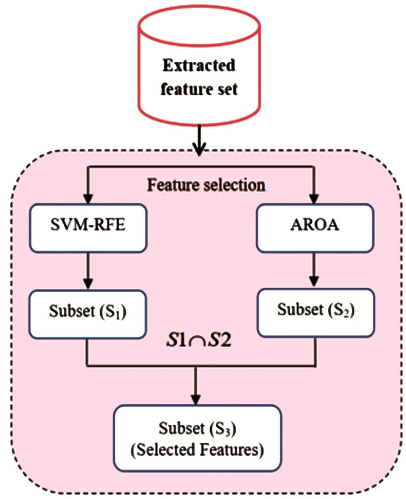

Fig. 2 — Feature selection process.

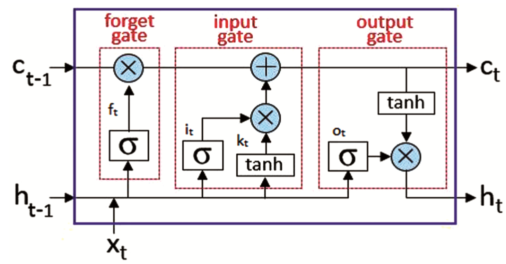

Fig. 3 — Structural diagram of LSTM.

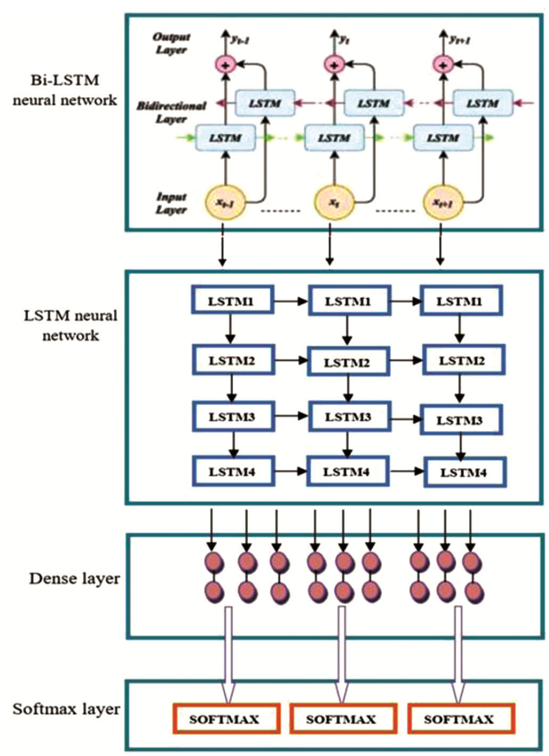

Fig. 4 — General structure diagram of MBi-LSTM.

Using the MATLAB platform, the recommended rice leaf disease classification model is operated on a Windows 10 computer with an Intel Core i5 processor and 6GB of RAM. For this study, images of paddy leaf were sourced from[15,16] kaggle; this dataset contains images of several paddy leaf diseases. A range of evaluation criteria are used to assess the effectiveness of the suggested approach.

3 Results and Discussion

The suggested model for classifying rice leaf diseases is run on a Windows 10 PC equipped with an Intel Core i5 CPU, 6GB of RAM using the MATLAB platform. The images of paddy leaf have been obtained from[15,16] kaggle.

Figures (5-8) depict the screenshots of Healthy, Blast, Bacterial Blight, Tungro Paddy Leaf Plant.

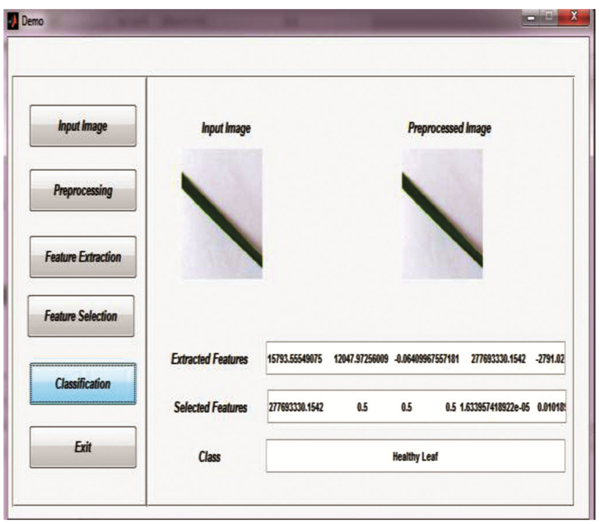

Fig. 5 — Screenshot for healthy leaf classification.

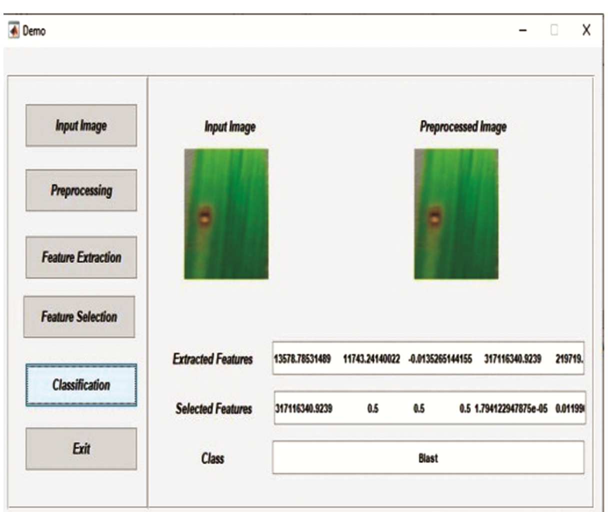

Fig. 6 — Screenshot for blast disease classification.

Figure 5 depicts the screenshot for healthy leaf classification. Figure 6 depicts the screenshot for blast disease classification. Figure 7 depicts the screenshot for bacterial blight disease classification. Figure 8 depicts the screenshot for Tungro disease classification

In this section we will see performance analysis based on the classification. Table 5 presents the performance of the proposed technique namely SVM-RFE, AROA, intersection of both SVM-RFE and AROA followed by MBi-LSTM in the context of precision, specificity, sensitivity, F1-score and accuracy.

Fig. 7 — Screenshot for bacterial blight disease classification.

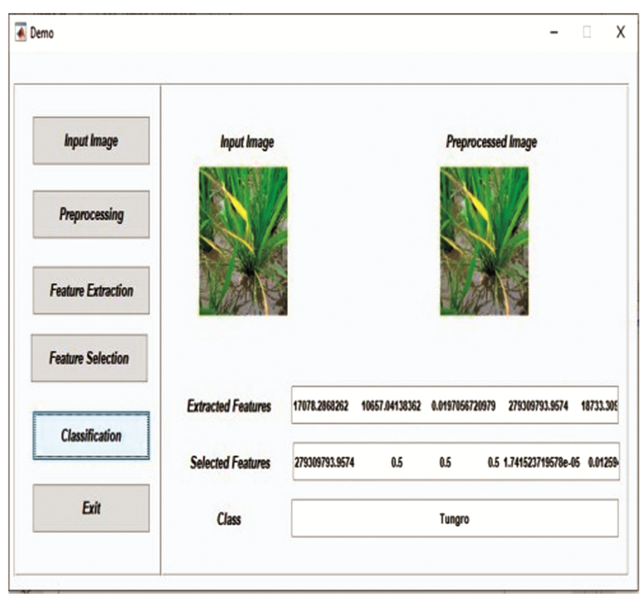

Fig. 8 — Screenshot for tungro disease classification.

Table 5 — Performance of feature selection followed by (->) MBi-LSTM techniques.

Technique	Precision	Specificity	Sensitivity	F1-score	Accuracy
SVM-RFE->MBi-LSTM	91.5%	96.3%	90.5%	91.0%	95.1%
AROA->MBi-LSTM	89%	94.8%	88.5%	88.7%	93.5%
SVM-RFE and AROA ->MBi-LSTM	97.03%	97.3%	96.23%	96.90%	98.06%

Table 6 — Performance of feature selection followed by(->) MBi-LSTM in terms of NPV and MCC.

Techniques	NPV	MCC
SVM-RFE->MBi-LSTM	96.12	89.45
AROA->MBi-LSTM	94.65	85.73
SVM-RFE and AROA ->MBi-LSTM	99.24	96.98

Table 7 — Performance of feature selection followed by(->) MBi-LSTM in terms of FPR and FNR.

Techniques	FPR	FNR
SVM-RFE->MBi-LSTM	0.034	0.099
AROA->MBi-LSTM	0.045	0.133
SVM-RFE and AROA ->MBi-LSTM	0.007545	0.026

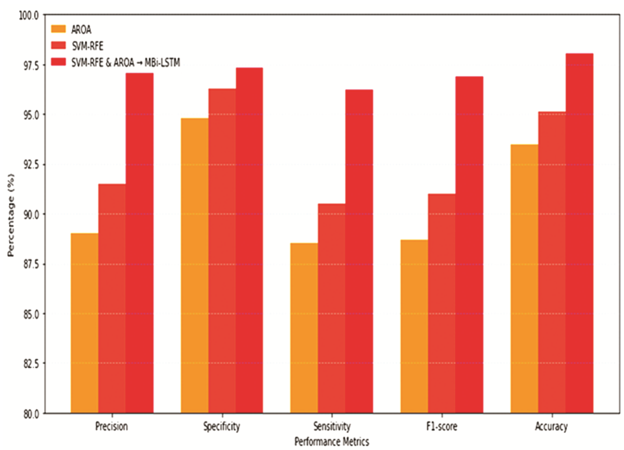

Fig. 9 — Comparison of feature selection followed by MBi-LSTM classification techniques.

Table 5 is represented in graphical form which is shown in Fig. 9. Table 6 present the performance of feature selection namely SVM-RFE, AROA and intersection of both SVM-RFE and AROA followed by MBi-LSTM in terms of NPV and MCC. The same Table 6 presented in graphical format shown in Fig. 10. The performance of feature selection in terms of NPV and MCC metrics is shown in Fig. 10. The same Table 7 are presented in graphical form as shown in Fig. 11.

The Table 8 has the confusion matrix for SVM-RFE followed by MBi-LSTM. Table 9 shows the confusion matrix for AROA followed by MBi-LSTM and Table 10 shows the confusion matrix for intersection of both SVM-RFE and AROA followed MBi-LSTM.

Table 8 — Confusion Matrix for SVM-RFE followed by MBi-LSTM.

True class	Predicted: Leaf blast	Predicted: Bacterial leaf blight	Predicted: Tungro	Predicted: Healthy
Leaf blast	299	8	6	2
Bacterial leaf blight	6	270	7	3
Tungro	5	6	244	5
Healthy	2	2	3	98

Table 9 — Confusion matrix for ARO followed by MBi-LSTM.

True class	Predicted: Leaf blast	Predicted: Bacterial leaf blight	Predicted: Tungro	Predicted: Healthy
Leaf blast	292	11	8	4
Bacterial leaf blight	5	260	12	9
Tungro	6	8	236	10
Healthy	3	4	5	93

Table 10 — Confusion matrix for SVM-RFE and AROA followed by MBi-LSTM.

True class	Predicted: Leaf blast	Predicted: Bacterial leaf blight	Predicted: Tungro	Predicted: Healthy
Leaf Blast	310	0	0	5
Bacterial Leaf Blight	2	284	0	0
Tungro	0	7	253	0
Healthy	0	0	8	97

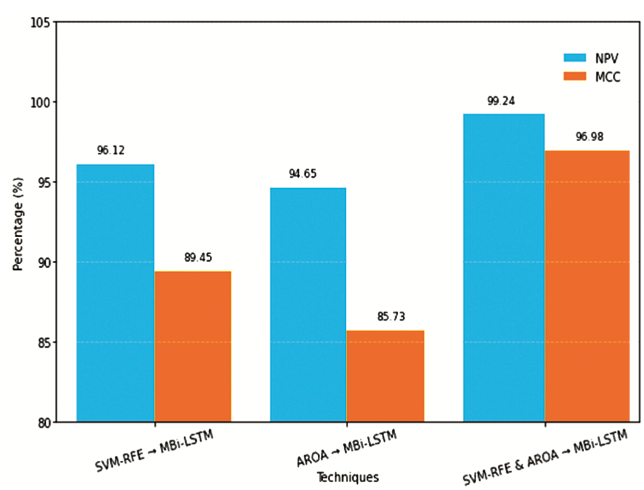

Fig. 10 — Comparison of feature selection followed by MBi-LSTM classification techniques in terms of NPV and MCC.

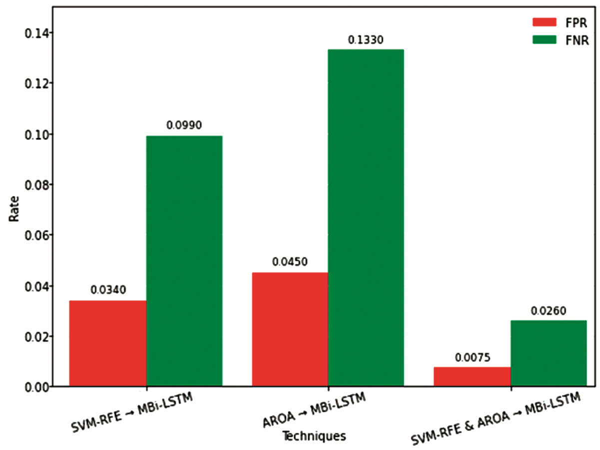

Fig. 11 — Comparison of feature selection followed by MBi-LSTM classification techniques in terms of FPR and FNR.

4 Conclusion

The experimental study explores the many diseases that harm rice plants and cause big losses in rice crops. The research highlights that it is possible to use deep learning together with a specific feature selection method to automatically identify leaf diseases in plants. Authors have blended the intersections of both SVM-RFE and AROA methods to make the feature selection more effective than the previous approaches.

We have implemented three methods: first SVM-RFE ->MBi-LSTM; AROA->MBi-LSTM; and finally the intersection of SVM-RFE and AROA followed by MBi-LSTM. As for all the evaluated techniques, the intersection of SVM-RFE and AROA followed by MBi-LSTM performance is highest, whereas AROA along with MBi-LSTM performance is lowest.

The performance has proved that the proposed method is effective in identifying leaf illnesses in growing crops. Besides, the approach works well for disease recognition in different crops.

Data Availability

The paddy leaf images have been obtained from kaggle[15,16]. This dataset includes different types of diseases of paddy leaf. The effectiveness of the planned method is analyzed based on different evaluation metrics.

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