Optimal Training Ensemble of Classifiers for Classification of Rice Leaf Disease

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***Abstract*—Rice is one of the most extensively cultivated crops in India. Leaf diseases can have a significant impact on the productivity and quality of a rice crop. Since it has a direct impact on the economy and food security, the detection of rice leaf diseases is the most important factor. The most prevalent diseases affecting rice leaves are leaf blast, brown spots, and hispa. To address this issue, this research builds a new classification model for rice leaf diseases. The model begins with a preprocessing step that employs the Median Filter (MF) process. Improved BIRCH is then utilized for picture segmentation. Features such as LBP, GLCM, color, shape, and modified Median Binary Pattern (MBP) are retrieved from segmented images. Then, an ensemble of three classification models, including Bi-GRU, Convolutional Neural Network (CNN), and Deep Maxout (DMN) is utilized. By adjusting the model weights, the suggested Opposition Learning Integrated Hybrid Feedback Artificial and Butterfly algorithm (OLIHFA-BA) will train the model to improve the performance of the proposed work.**

Keywords—Rice leaf; modified MBP; Bi-GRU; improved BIRCH; OLIHFA-BA Algorithm

I. Introduction

Agriculture is more important to the Indian economy than other industries. Rice production is a significant aspect of agriculture [1] [2] [3] [4]. 20% of India's GDP is contributed by rice agriculture [5] [6] [7] [8]. Rice is cultivated in most Indian states (Odessa, Uttar Pradesh, Punjab, West Bengal, Assam, Tamil Nadu, Bihar, etc.) [9] [10] [11] [12]. Due to the several diseases that can impact rice plants, rice productivity is currently falling. Farmers have only a limited comprehension of the disease. This crisis diminishes the efficiency of rice production, hence reducing the agricultural income [13] [14] [15].

Not only are rice leaf diseases prevalent in India, but they are also prevalent in other countries. There are several types of leaf diseases, such as brown spot, tungro, bacterial blight, blast, etc. Farmers have no control over these infections. Consequently, visual examination or laboratory tests are used to detect illnesses on leaves [16] [17] [18]. Visual analysis of this issue is time-consuming for a specialist. In addition, when chemical reagents are necessary, the experimental procedure becomes more difficult.

Certain strategies are employed to simplify these matters. The Deep Learning (DL) algorithm is applicable to agricultural problems such as root segment, fruit count, seed selection, disease classification, etc. [19] [20] [21]. DL algorithms are sophisticated versions of ML for detecting crop infections. With this method, the inputs were automatically learned, and the output was generated based on the decision criteria. CNN technology was utilized during the development of the visual image. In addition, "Rice Doctor" and "Rice Xpert" smart phone applications for farmers were introduced using the internet and mobile technology. The "Rice Doctor" app serves as a questionnaire for farmers [22] [23] [24] [25].

This study considered the most prevalent rice leaf diseases, including brown spot, leaf blast, and bacterial blight. The CNN model was calibrated to improve its accuracy. It is exceptionally accurate. Only the disorders were treated with the tuned model. We have to implement advanced DL algorithms [26] [27] [28] [29] due to the need to identify different forms of rice leaf disease and raise the degree of accuracy.

The contributions are detailed as follows:

- Proposed a new classification model for rice diseases with enhanced BIRCH-based segmentation.
- Utilizes an ensemble model based on OLIHFA-BA with a defined feature set consisting of enhanced MBP features, Local Binary Pattern (LBP), Gray Scale Co-Occurrence Matrix (GLCM), color, and shape features.

The structure of the paper is as follows: Section II describes standard works. Section III describes the adopted phases of the suggested classification strategy, whereas Section IV describes characteristics. Section V displays optimised ensemble classifiers, while Section VI depicts an assisted OLIHFA-BA optimization algorithm. Results and conclusions are provided in Sections VII and VIII.

II. Literature Review

A. Related Works

In 2021, Krishnamoorthy N et al. [1] conducted study on rice leaf disease classification. Moreover, fifty percent of the world's population consumes rice. Therefore, rice is the world's principal source of energy. Rice plant diseases, which are caused by viruses, bacteria, fertile soil, pests, temperature fluctuations, and so on, are the most significant obstacles in rice cultivation. Finding and treating rice plant illnesses is a challenging undertaking for farmers. In this investigation, sickness identification was performed using a DL approach. CNNs were used for object segmentation, image classification, and image analysis in Deep Learning. The

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recommended model achieved the highest accuracy, 95.67 percent.

Kumar Sethy et al. [2] looked at how to find diseases on rice leaves in 2020. This study talks about the four diseases that can hurt rice leaves: bacteria blight, blast, tungro, and brown spot. DL technology is used to find out if someone is sick. In this study, TL with CNN models, deep features, and SVM were used to figure out how to group things. Two conclusions were similar, but the deeper features of SVM performed much better.

Chen et al. [3] conducted rice plant disease detection research in 2021. Using CNN models constructed with the DL approach presented various technical challenges, such as picture identification and classification. In this work, however, MobileNet-V2 was employed, and numerous techniques were employed to assess the significance of spatial sites for input characteristics and inter-channel interaction. Using DL-based CNN approaches, most of the technical challenges associated with picture recognition and classification have been resolved. Transfer learning and the enhanced loss function were repeated on two separate occasions. The public dataset [48] utilized for this investigation was 99.67% accurate. In difficult research environments, the accuracy of rice plant disease diagnosis was determined to be 98.48%. Therefore, the suggested method was more efficient at identifying rice plant diseases.

Madhavi and M.A. Saleem [4] studied the identification of rice leaf diseases in 2021. To preserve the growth of the agricultural sector, the first step of plant disease identification was taken. The comparison between automatic and manual plant monitoring is required and beneficial. CNN is frequently used for this kind of categorization. It does a good job of classifying and diagnosing plant diseases by utilizing highly accurate data collected from a range of sources.

Jjang et al. [5] studied the leaf diseases of wheat and rice plants in 2021. To reduce plant growth loss, this issue would be diagnosed quickly and precisely. In this study, the Image NET pre-training model, alternating learning, and the VGG16 implementation were used to facilitate multitask learning, TL, and recognition. This model's accuracy for rice plants was 98% and for wheat plants it was 99%. This model has proved the excellent performance of the VGG16 model and the multi-task TL, which is accurate in recognizing plant diseases.

Jiang et al. [6] conducted a study on image-based disease diagnosis in rice leaf images using Support Vector Machine (SVM) and DL in 2020. Combining these two approaches has helped to effectively address the issue while also improving precision. The authors of this study have utilized CNN to derive the images of the relevant leaf. During the last round of the evaluation, the classic Back Propagation Neural Network (BPNN) models were compared to the more accurate SVM models.

Zhang et al. [7] conducted study in 2020 utilizing spectral image technology to identify leaf illnesses in rice crops. This method was utilized to determine the severity of rice leaf explosions. In this work, a hyperspectral imaging method was used to distinguish between images of afflicted and healthy leaves. The data was then reconstructed using the SRR method. This model's precision was approximately 98%.

In 2021, Bakade et al. [8] conducted a study on preventing bacterial illness in rice leaves. Xoo is the primary cause of this problem. This investigation revealed the interconnected actions of genes and plant immune pathways, which could be leveraged to develop resistant rice cultivars.

B. *Review*

Once, the only means for diagnosing a disease was a manual analysis of the leaf. This was accomplished manually by examining plant leaves or consulting a book to identify the disease [5]. This method has three major drawbacks: it is imprecise, it cannot study every leaf, and it is time-consuming. Several approaches for effectively identifying these ailments have been created because of the advancement of science and technology. Image processing and deep learning are methodologies. Image processing includes a range of techniques, including filtering, clustering, histogram analysis, and image processing algorithms, to discover damaged areas and diagnose diseases. In contrast, DLNN are used to identify diseases. There are two principal causes of plant diseases. The first is a bacterial or fungal attack, and the second is an unanticipated shift in the weather [6].

When addressing rice infections, we must consider a few critical elements. Collecting samples from a damaged rice plant is one of the crucial and critical duties. To do this, multimedia sensors may be deployed across the farm. This permits routine monitoring of rice plants. Additionally, the effects of climate change on rice plants can be monitored and studied. This approach has several disadvantages, including the necessity for frequent system maintenance and low precision due to shadows in the gathered photos. It is crucial to accurately identify rice infections in order to avert the disease's devastating effects on crop productivity. However, the present methods for diagnosing illnesses in rice are neither exact nor effective, necessitating the need of supplementary equipment.

III. Adopted Phases in Proposed Classification Approach

The following are the adopted phases of the proposed rice leaf disease classification:

- In the very first phase, the input image is submitted to MF for the aim of pre-processing. Then, Improved BIRCH is implemented to segment the images.
- The LBP, GLCM, colour, and improved MBP-based feature set is derived from segmented images. Then, ensemble model-based classification is performed with three classifiers, including Bi-GRU, CNN, and DMN as shown in Fig. 1.
- The final classification results are determined by the combined averaged outcome.

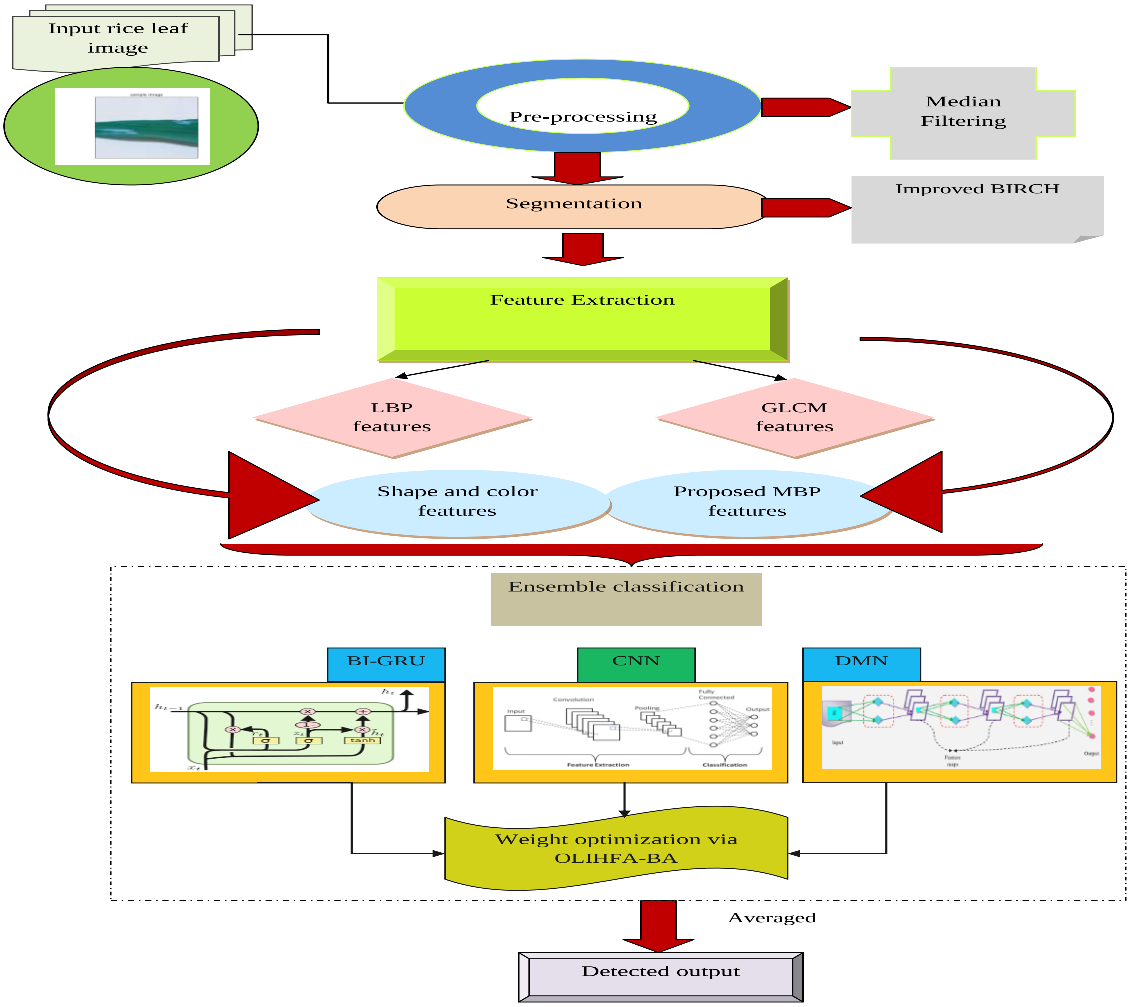


Fig. 1. A diagram of the rice disease classification model that was used.

A. Pre-processing

In this research, median filtering is utilised to pre-process the image input.

MF [30]: The median filter is a common non-linear digital filtering technique used to remove noise from a picture or signal. This type of noise reduction is a typical pre-processing technique used to improve the results of future processing (edge recognition in image). MF is widely utilised in the processing of digital photos, and in certain instances it preserves edges while lowering noise.

The MF oriented pre-processed image is designated as $\left(ig^{mf}\right)$.

Following image processing, improved BIRCH is utilized for image segmentation.

B. Modified BIRCH Model

Clustered features [31] store the information necessary for data grouping and provide a concise description of a set of points in feature space. Consider the set of points in the dimension [31].

Conservatively, the size, of a set is described as the average distance between two points, as shown in Eq. (1).

$$Di = \sqrt{\frac{\sum_{i=1}^{M}\left\|s_i - t_i\right\|_2^2}{M(M-1)}} \tag{1}$$

As per improved BIRCH, Di is modeled as shown in Eq. (2).

$$Di(s_i, t_i) = \sqrt{\frac{\sum_{i=1}^{M}(s_i - t_i)^2}{\sum_{i=1}^{M}(s_i)^2 + \sum_{i=1}^{M}(t_j)^2 - \sum_{i=1}^{M}s_i t_j}} \tag{2}$$

The representation of clustering feature, cf, of set X is specified in Eq. (3).

$$cf = (M, L, x) \tag{3}$$

Here, M points out points in X, $L = \sum_{i=1}^{M} s_i$ refers to summation of every points in X and the scalar $x = \sum_{i=1}^{M}\left\|s_i\right\|_2^2$ refers to summation of square of every element of every points in X. Thus, an individual point is indicated by a cluster feature. A cluster feature represented the set X, and retained data to calculate the centroid, s_c, of X, the size Di of set, and the distance, $d(X_1, X_2)$, among 2 sets. Conservatively, these can be expressed as in Eq. (4).

$$s_c = \frac{L}{M} \tag{4}$$

As per enhanced BIRCH, s_c is computed as exposed in Eq. (5), in which, $corr$ points out correlation that is modeled as in Eq. (6).

$$s_c = \frac{L}{M} * corr \tag{5}$$

$$corr = 1 - \left(\frac{\sum_{i=1}^{M}(s_i - \bar{s})(t_i - \bar{t})}{\sqrt{\sum_{i=1}^{M}(s_i - \bar{s})^2}\sqrt{\sum_{i=1}^{M}(t_i - \bar{t})^2}} \right)^2 \tag{6}$$

The improved BIRCH image is denoted as ig^{IBIRCH}.

IV. Extracting LBP, GLCM, Color, Shape and Improved MBP Features

From ig^{IBIRCH}, the feature set including LBP, GLCM, color, shape and improved MBP are extracted.

A. Shape Features

The primary source of information used for object identification is shape [32]. Without shape, a visual item cannot be effectively recognised. Without understanding shape, an image is incomplete. Although the two items cannot have the exact same shape, we may identify comparable shapes by utilising a variety of techniques. Triangle, Circle, Rectangle, Square, Oval, and Diamond are some of the available shapes. The features of the extracted shapes are indicated by fs^{Sh}.

B. Colour Features

Colour space characterizes colour in the type of intensity value [32]. By employing the colour space approach, we can define, see, and produce colour. The colour histogram shows the image from various angles. The colour histogram used to describe the frequency distribution of colours in the image counts and stores related pixels. Every statistical colour frequency in an image is examined using the colour histogram. The colour histogram not only focuses on specific areas of an image, but also solves difficulties with translation, rotation, and angle of view changes. The local colour histogram is simple to calculate and robust to minute image fluctuations, making it crucial for the retrieval and indexing of image databases.

C. GLCM Features

GLCM is employed to evaluate the spatial association among the pixel [33]. The constraints in GLCM are given in Table I.

TABLE I. GLCM Features

S. No.	Features	Arithmetical term
1.	Energy	$E = \sum_{\omega}\sum_{\xi} \upsilon_{\omega\xi}^2$ here $\upsilon_{\omega\xi}$ is the $(\omega,\xi)^{th}$ entry in GLCM
2.	Entropy	$Et = -\sum_{\omega}\sum_{\xi} \upsilon_{\omega\xi} \log_2 \upsilon_{\omega\xi}$
3.	Variance	$Var = \sum_{\omega}\sum_{\xi} (\omega - \mu)^2 \upsilon_{\omega\xi}$, where μ specifies the mean of $\upsilon_{\omega\xi}$
4.	Contrast	$Con = \sum_{\omega}\sum_{\xi} (\omega - \xi)^2 \upsilon_{\omega\xi}$
5.	Correlation	$Cor = \frac{\sum_{\omega}\sum_{\xi}(\omega\xi)\upsilon_{\omega\xi} - \mu_x\mu_y}{\sigma_x\sigma_y}$, where σ_x, σ_y, μ_x, μ_y are the std deviations and mean of υ_x, υ_y
6.	Sum Average	$SA = \sum_{\omega=2}^{2N_\upsilon} \omega.\upsilon_{x+y}(\omega)$, where N_υ indicates the varied gray levels in image.
7.	Homogeneity	$Hom = \sum_{\omega}\sum_{\omega} \frac{1}{1+(\omega-\xi)^2} \upsilon_{\omega\xi}$
8.	Sum Variance	$SV = \sum_{\omega=2}^{2N_\upsilon} (\omega - SE)^2 s_{x+y}(\omega)$
9.	Sum Entropy	$SE = \sum_{\omega=2}^{2N_\upsilon} \upsilon_{x+y}(\omega) \log\{\upsilon_{x+y}(\omega)\}$
10.	Difference Variance	$DV =$ variance of $\upsilon_{\omega x-y}$
11.	MCC	$MCC = \sum_{k} \frac{g(\omega,k)g(b,k)}{g_x(\omega)g_y(k)}$
12.	Difference Entropy	$DE = \sum_{\omega=0}^{N_\upsilon - 1} \upsilon_{x-y}(\omega) \log\{\upsilon_{x-y}(\omega)\}$
13.	IMC 1	$IMC1 = \frac{hxy - hxy1}{\max\{hx, hy\}}$
14.	IMC 2	$IMC2 = \sqrt{(1 - \exp[-2.0[hxy1 - hxy]])}$, where $hxy = -\sum_{\omega}\sum_{\xi} \upsilon_{\omega\xi} \log_2 \upsilon_{\omega\xi}$, $hxy1 = -\sum_{\omega}\sum_{\xi} \upsilon_{\omega\xi} \log_2 \{\upsilon_x(\omega)\upsilon_y(\xi)\}$,,

D. Modified MBP Features

The MBP [34] attempts to determine the LBP by thresholding pixels with a median value above the threshold. In this level of filtering, the centre pixel is evaluated, providing 29 potential structures. MBP is conventionally represented using Eq. (7).

$$MBP = \sum_{i=1}^{J} f(b_i) \times 2^i \tag{7}$$

As per modified MBP, it is modelled as in Eq. (8). Here, we point out weight function that is evaluated by means of cubic chaotic map.

$$MBP = \sum_{i=1}^{J} f(b_i) \times 2^i * we \tag{8}$$

Conventionally, $f(b_i)$ is modeled based upon median as in Eq. (9).

$$f(b_i) = \begin{cases} 1; & if\ b_i \geq med \\ 0; & otherwise \end{cases} \tag{9}$$

As per modified MBP, $f(b_i)$ is modeled based upon median absolute deviation (MAD) as in Eq. (10) and Eq. (11).

$$f(b_i) = \begin{cases} 1; & if\ b_i \geq MAD \\ 0; & otherwise \end{cases} \tag{10}$$

$$MAD = Median\left| b_i - \bar{b} \right| \tag{11}$$

E. LBP Features

In a variety of comparison analyses, the patterns of LBP [35] are provided with a high level of discrimination and simplicity. The fundamental LBP is used to derive the differential features between a certain reference pixel and its neighbours with radius. The resultant LBP for a pixel is given by Eq. (12), where is the geometric mean of nearby pixels and represents the grey values of the middle pixel and surrounding pixels with radius.

$$LBP_{P,R}(q_e, r_e) = \sum_{P=0}^{P-1} s * 2^P \tag{12}$$

The derived LBP, GLCM, color, shape and modified MBP are totally implied by fs, i.e., $fs^{Sh} + fs^{Cl} + fs^{glcm} + fs^{IMBP} + fs^{LBP} = fs$.

V. Optimized Bi-GRU, CNN and DMN Models

The derived fs is then given as input to three classifiers such as Bi-GRU, CNN and DMN.

A. Bi-GRU

It [36] is a sort of Recurrent Neural Network (RNN) that facilitates the handling of data from successive and previous time steps in order to provide output predictions based on the present state. Eq. (13) to (16) expose the BI-GRU calculation by displaying the sigmoid function, hidden, and input vectors as, and respectively. The reset data is represented as, weight, time interval, and the condition of the cell at the previous time stamp.

$$F_t = \left(WG_i * \left[v_t, hi_{t-1}, \right] \right) \sigma \tag{13}$$

$$r_t = \left(WG_i * \left[v_t, hi_{t-1} \right] \right) \sigma \tag{14}$$

$$hi_t = \left(WG_c * \left[r_t . v_t, hi_{t-1} \right] \right) \tanh \tag{15}$$

$$hi_t = .C_{t-1}(1 - F_t) + hi_t F_t \tag{16}$$

B. CNN

The features of CNN [37] are depicted in Eq. (17).

$$D^l_{r,t,w} = \varpi^{l\,T}_w PA^l_{r,t} + B^l_w \tag{17}$$

In Eq. (17), ϖ^l_w → weight tuned optimally by means of OLIHFA-BA model, B^l_w →bias. At core location (r,t) of l^{th} layer, the input patch is signified as $PA^l_{r,t}$, $D^l_{r,t,w}$ → convolution features and $\left(act^l_{r,t,w} \right)$ → activation value.

$$act^l_{r,t,w} = act\left(D^l_{r,t,w} \right) \tag{18}$$

Pooling layer: CNN loss PL is given in Eq. (20), here, θ → term linked with W^l_w and B^l_w. The output, the labels and h^{th} input feature is termed as $F^{(h)}$, $H^{(h)}$ and $PA^{(h)}$ and $nn_{r,t}$ signifies (r,t) near neighbor position.

$$H^l_{r,t,w} = pool\left(act^l_{m,h,w} \right), \forall (m.h) \in nn_{r,t} \tag{19}$$

$$PL = \frac{1}{wn} \sum_{h=1}^{wn} l\left(\theta; H^{(h)}, F^{(h)} \right) \tag{20}$$

C. DMN Classifier

DMN [38], a form of NN, is utilized well in a few applications. A NN contains candidate components in each neuron. It is intended to use an extendable maximum value component for neuron activation [39]. Mark as the node of the hiding layer and each of its components. Eq. (21) and Eq. (22) demonstrate their relationship to one another:

$$J^i_m = \max_{j \in 1,2,\ldots,u} O^{ij}_m \tag{21}$$

By forwarded propagation, O^{ij}_m is modeled as in Eq. (22).

$$O_m = W^{*G}_{m-1} J_{m-1} + f_m \tag{22}$$

Here, $O_1 \in L^O$ refers to l^{th} layer vector

$J_{m-1} \in L^H$ and $W^*{}_{m-1} \in L^{H \times O}$ refers to max out activation vector and weight matrix of $m-1$ layer.

$f_m \in L^O$ refers to bias vector of m^{th} layer.

The Bi-GRU, CNN and DMN outputs are averaged to get final result.

VI. OLIHFA-BA Assisted Algorithm for Optimization

Objective: The objective is to diminish error as in Eq. (23).

$$Objective = \min(Error) \tag{23}$$

Solution Encoding: The weights of BI-GRU (WG), CNN (ϖ) and DMN (k) are elected optimally by OLIHFA-BA scheme as given in Fig. 2.

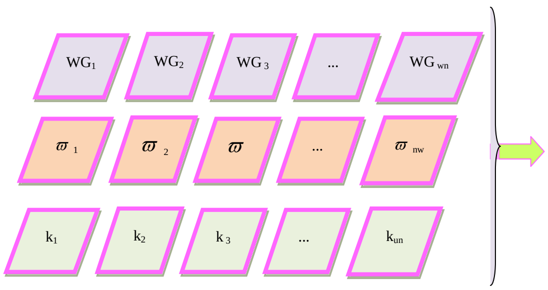


Fig. 2. Solution encoding.

Existing Butterfly Optimization Algorithm (BOA) [39] recognizes the best options, however it is not precise. FAT [40] is merged with BOA [39] to develop OLIHFA-BA, which addresses the shortcomings of original BOA [39] [41] [42] [43] [44]. The concepts of hybridization show considerable potential for advancing with improved outcomes [41] [42] [43] [44].

The butterfly mating and feeding behaviors inspired BOA. The distinctive characteristic of BOA represented by Eq. (24) is the fragrances with diverse aromas in butterflies, where the power exponent (between 0 and 1) relates to the index of sensor modality and indicates stimulus magnitude.

$$q = sl^{\theta} \tag{24}$$

Butterflies are capable of accurately locating scent sources and share this knowledge with one another. There were three stages of OLIHFA-BA, and they were as follows:

1) Initialization: The constraints and objectives would all be initialized. Additionally, chaotic-based OBL is produced according to the model in Eq. (25), which α refers to chaotic map function that uses a tent map.

$$\bar{y}_i = a + b - y_i * \alpha \tag{25}$$

2) Iteration: Both local and international searches were performed.

The traditional numerical depiction for butterfly global search movement is in Eq. (26), herein, t points out iteration, y_i^t points out i^{th} butterfly position at t, q_i points out scent of i^{th} butterfly and G_{best} points out finest position of global butterfly.

$$y_i^{t+1} = y_i^t + \left(ra^2 \times G_{best} - y_i^t\right) \times q_i \tag{26}$$

In OLIHFA-BA model, it is formulated depending upon FAT's branch update as in Eq. (27), in which, d points out smaller constant, (d = 0.382) and $rand(0,1)$ points out random numeral. Moreover, we use FAT based crossover operation to generate new branches.

$$y_i^{t+1} = y_i^t + \begin{pmatrix} rand(0,1) * y_{best} \\ - rand(0,1) * y_i \end{pmatrix} * d + levy(\beta) \tag{27}$$

Numerous typical events might hinder butterfly movement and fragrance dispersal. Local search is simulated by the butterfly positions according to Eq. (28).

$$y_i^{t+1} = y_i^t + \left(ra^2 \times y_j^t - y_k^t\right) \times q_i \tag{28}$$

3) Termination: OLIHFA-BA terminates once the utmost iterations were arrived. The OLIHFA-BA model is shown in Algorithm 1.

Algorithm 1: OLIHFA-BA model

```
Initializing populace
Intensity evaluation
While stop criterion wasn't met
  for every butterfly BF do
    Evaluating scent
  end for
  Find finest BF
  for each butterfly BF
  Assume ra
    if ra < pr
      Update positions based upon FAT update as in Eq. (27)
    else
      Update positions based upon Eq. (28)
    end if
  end for
  update θ
end while
```

VII. Results and Discussion

A. Simulation Set Up

Matlab was used to create the proposed Ensemble Classifiers (EC) (Bi-GRU, CNN, and DMN) + OLIHFA-BA focused classification for rice illness. On numerous measures, EC (Bi-GRU, CNN, and DMN) + OLIHFA-BA was compared against Improved Crossover Monarch Butterfly Optimization (ICRMBOS) [45], Transfer Learning based Deep CNN (TL-DCNN) [46], LMBWO [47], Deep Belief Network (DBN), Recurrent Neural Network (RNN), Quantum Neural Networks (QNN), SVM, RF, and Long Short Term Memory (LSTM), EC + DHO, EC + SMO (Spider Monkey Optimization), EC + CMBO (Cat and Mouse Optimization), EC + BMO (Blue Monkey Optimization), and EC + MFO (Mouth Flame Optimization). Fig. 3 displays the illustration of the sample image.

B. Performance Analysis

The performances of the proposed EC (Bi-GRU, CNN, and DMN) + OLIHFA-BA over existing met heuristic models are calculated and displayed in Fig. 4 to 6 for various measures. The EC (Bi-GRU, CNN, and DMN) + OLIHFA-BA model is compared to the EC + DHO, EC + SMO, EC + CMBO, EC + BMO, and EC + MFO models for several LPs. Table II compares EC (Bi-GRU, CNN, and DMN) + OLIHFA-BA with existing classifiers such as DBN, RNN, QNN, SVM, RF, LSTM, ICRMBOS [45], TL-DCNN [46], and LMBWO [47]. The proposed EC (Bi-GRU, CNN, and DMN) + OLIHFA-BA model has produced superior results compared to differentiated approaches for optimization and classification models. The improved prediction rate should result in slight negative results and bigger positive values. As seen in Fig. 4, the outputs of the EC model for all positive metrics grow, whilst the outputs for negative metrics decrease. Specifically for current and prospective schemes, the 50th LP yielded the best results. The proposed system at the 50th LP achieved the highest accuracy values (0.96), whereas other schemes achieved low precision levels. This improvement in classifier analysis and optimization analysis by EC (Bi-GRU, CNN, and DMN) + OLIHFA-BA is mostly due to the incorporation of enhancements in features, segmentation, and classifiers.

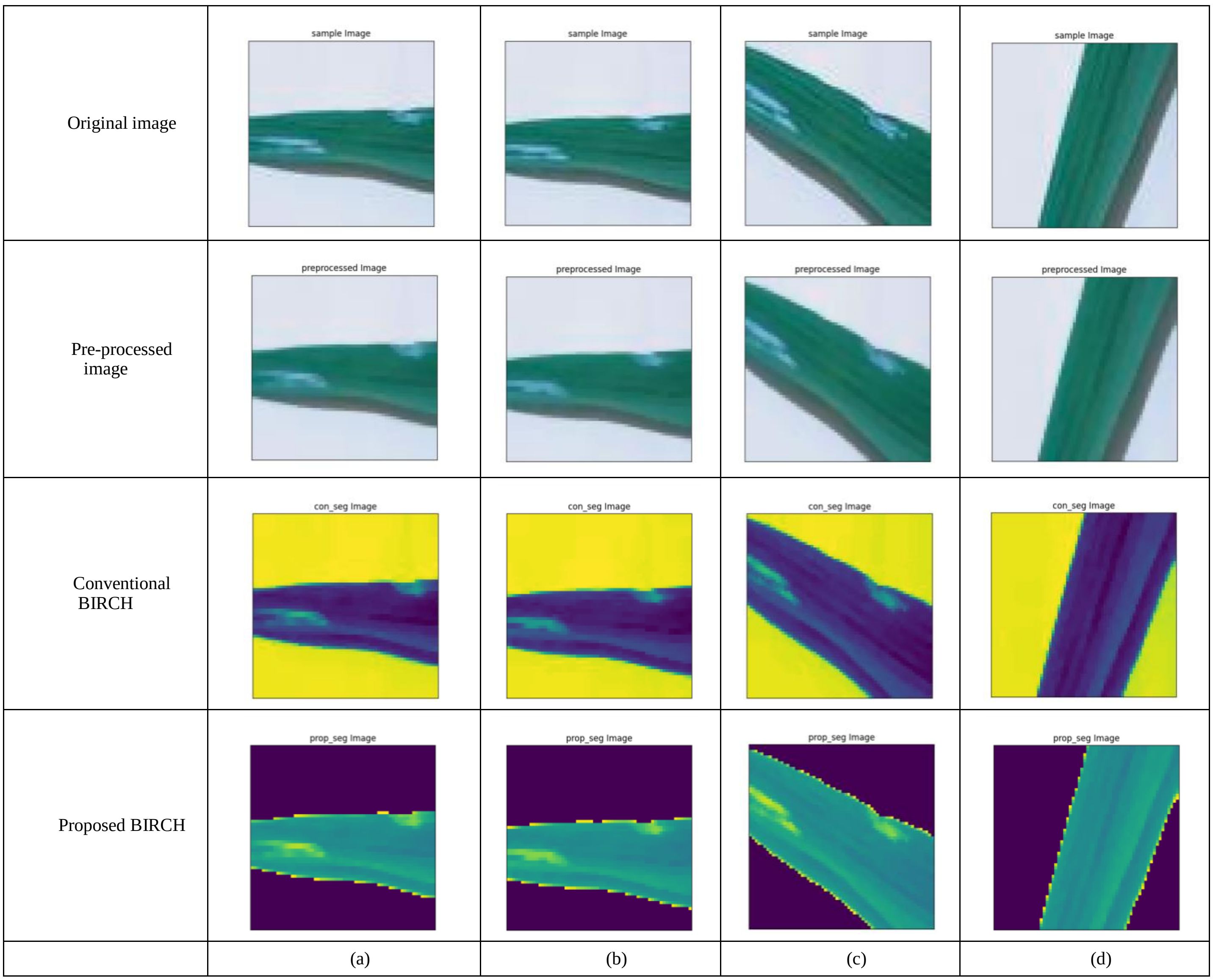
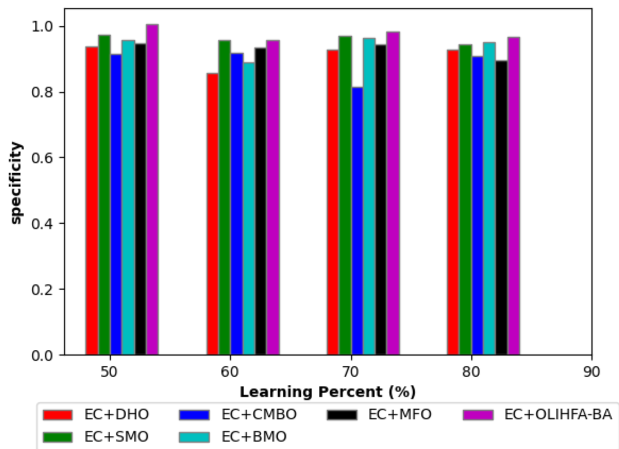
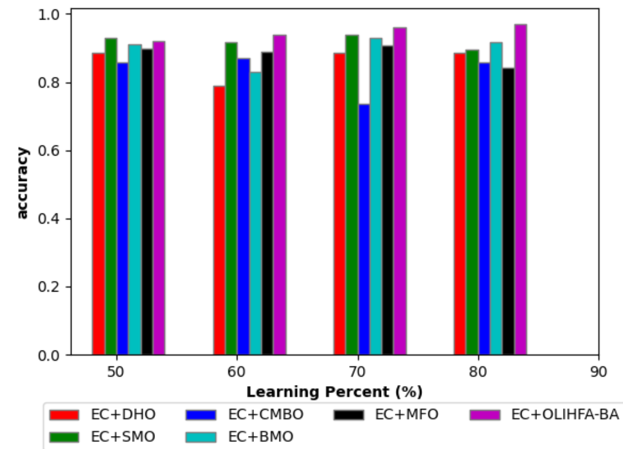


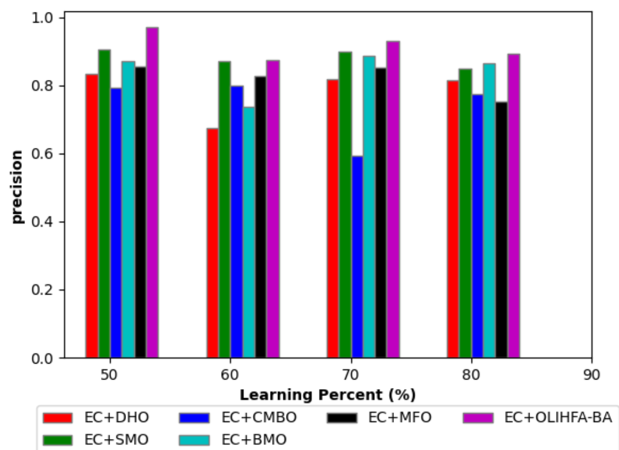
Fig. 3. Illustration sample of images for (a) 1 (b) 2 (c) 3 (d) 4.



(a)



(b)



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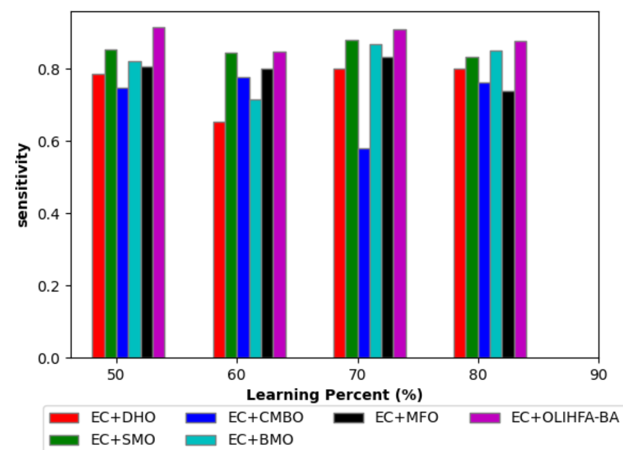
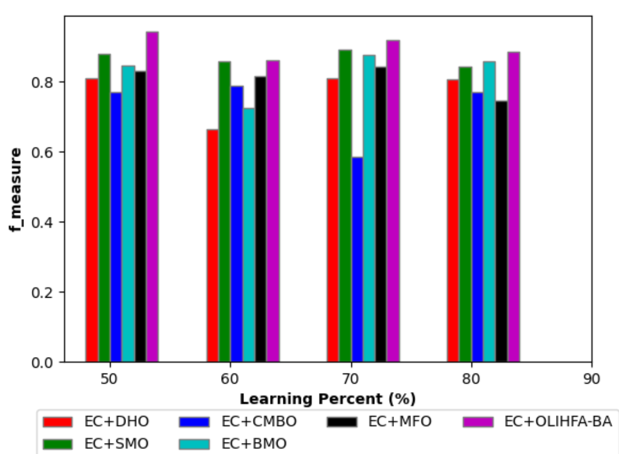
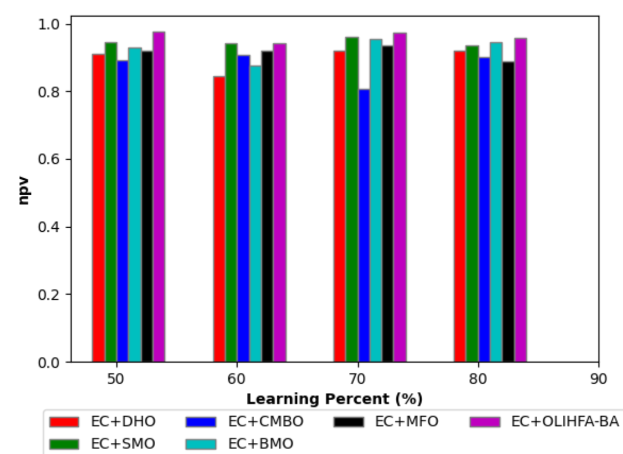


(d)

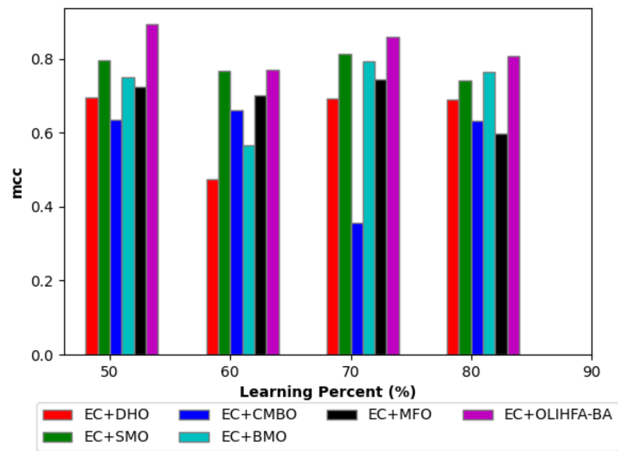
Fig. 4. Comparison of EC (Bi-GRU, CNN, and DMN) + OLIHFA-BA to optimization techniques for (a) Specificity (b) Accuracy (c) Precision and (d) Sensitivity.



(a)

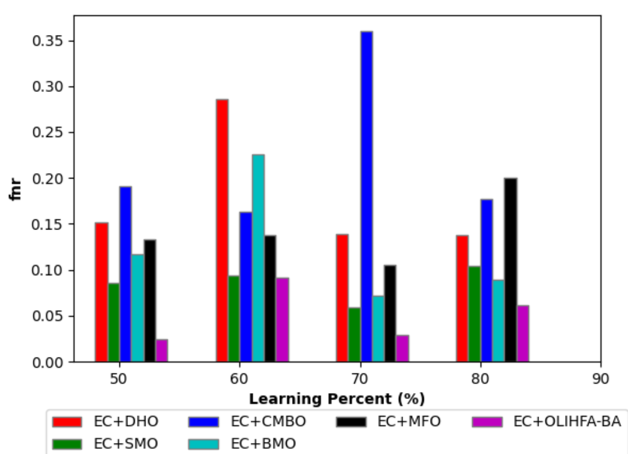


(b)

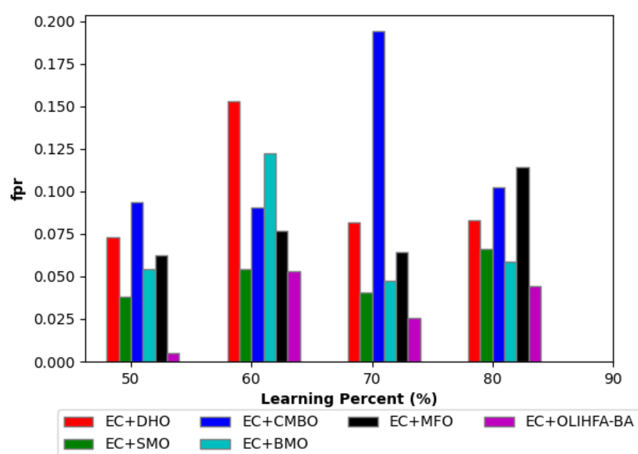


(c)

Fig. 5. Comparison of EC (Bi-GRU, CNN, and DMN) + OLIHFA-BA to optimization techniques for (a) F-measure, (b) NPV, and (c) MCC.



(a)



(b)

Fig. 6. Analysis of EC (Bi-GRU, CNN, and DMN) + OLIHFA-BA over optimization approaches on (a) FNR and (b) FPR

TABLE II. ANALYSIS ON PROPOSED AS WELL AS EXISTING VARIANTS

Metrics	DBN	RNN	QNN	SVM	RF	LSTM	ICRMBOS [45]	TL-DCNN [46]	LMBWO [47]	EC (Bi-GRU, CNN and DMN) + OLIHFA-BA
NPV	0.810489	0.863751	0.886403	0.848648	0.820849	0.864672	0.801257	0.854521	0.896886	0.958836
Sensitivity	0.869236	0.836111	0.811791	0.808681	0.881809	0.889946	0.79587	0.795495	0.795339	0.878906
FNR	0.260323	0.244131	0.291496	0.268448	0.289677	0.273445	0.23056	0.286253	0.204661	0.061094
Precision	0.823257	0.81249	0.896509	0.800818	0.872516	0.821655	0.80614	0.863017	0.807613	0.891852
FPR	0.465444	0.45827	0.410539	0.430812	0.421072	0.478837	0.458594	0.40966	0.096193	0.044074
MCC	0.800157	0.793013	0.866155	0.895368	0.872298	0.79213	0.866973	0.893905	0.701818	0.807754
Accuracy	0.835872	0.84927	0.805443	0.794296	0.865515	0.839268	0.844073	0.83556	0.856622	0.969837
F measure	0.806143	0.886593	0.824477	0.836322	0.898775	0.804303	0.854824	0.846638	0.801429	0.885329
Specificity	0.790013	0.865374	0.878082	0.886596	0.792012	0.822298	0.853153	0.848949	0.903807	0.965926

C. Convergence Study

Fig. 7 shows the completed cost analysis. EC (CNN, Bi-GRU, and DMN) is evaluated over EC + DHO, EC + SMO, EC + CMBO, EC + BMO, and EC + MFO. In view of Fig. 7, the cost of EC (Bi-GRU, CNN, and DMN) has increased little. From iterations 0 through 5, the CMBO model achieves a high cost of 1.095. In addition, between iterations 0 and 5, the cost of EC (Bi-GRU, CNN, and DMN) is approximately 1.084%. Thus, EC (Bi-GRU, CNN, and DMN) was able to obtain BIRCH at a reduced cost and with expanded features.

D. Conventional VS. Proposed Analysis

Table III compares the adopted EC (Bi-GRU, CNN, and DMN) + OLIHFA-BA scheme to EC without OLIHFA-BA, EC with traditional BIRCH, and EC with traditional MBP. Observing the Table, the recommended EC (Bi-GRU, CNN, and DMN) + OLIHFA-BA had superior values than the EC without OLIHFA-BA, the EC with conventional BIRCH, and the EC with conventional MBP. This demonstrates the effect of BIRCH enhancements and hybrid optimization.

E. Analysis on DICE and Jaccard Scores

Table IV provides a study of dice scores and Jaccard scores. The dice and Jaccard scores for suggested BIRCH are greater than those for FCM, K-mean, and conventional BIRCH.

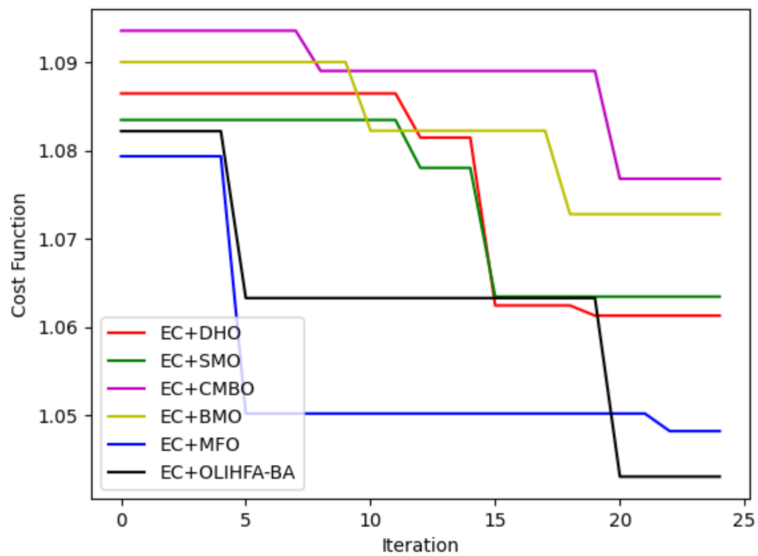


Fig. 7. Convergence study.

TABLE III. ANALYSIS ON PROPOSED AND EXISTING VARIANTS

Metrics	EC with no optimization	EC with conventional BIRCH	EC with conventional MBP	EC (Bi-GRU, CNN and DMN) + OLIHFA-BA
Precision	0.81814	0.812267	0.858096	0.891852
Specificity	0.800007	0.841113	0.848045	0.965926
MCC	0.80554	0.801643	0.841539	0.807754
FNR	0.304129	0.297652	0.316598	0.061094
F measure	0.808805	0.852687	0.818805	0.885329
FPR	0.393089	0.391654	0.382108	0.044074
NPV	0.811176	0.840228	0.852583	0.958836
Sensitivity	0.843219	0.825152	0.811886	0.878906
Accuracy	0.825021	0.832329	0.808423	0.969837

TABLE IV. ANALYSIS ON DICE AND JACCARD SCORES

	FCM	K-mean	Conventional BIRCH	Proposed BIRCH
Dice scores	0.525935	0.600694	0.506402	0.813585
Jaccard scores	0.494048	0.49131	0.501836	0.748445

VIII. Conclusion

We have developed a novel classification technique for rice leaf diseases in which the image was preprocessed using MF. The image was then segmented using BIRCH with enhancements. LBP, GLCM, colour, shape, and enhanced MBP-based features were recovered from segmented images. The data was then classified using three classifiers: Bi-GRU, CNN, and DMN. The results of the Bi-GRU, CNN, and DMN systems were averaged to determine the results. In addition, the Bi-GRU, CNN, and DMN schemes' weights were determined optimally using the OLIHFA-BA method. The 50th LP proposal produced the highest accuracy values (0.96), but other systems achieved low precision levels. This improvement in classifier analysis and optimization analysis employing EC (Bi-GRU, CNN, and DMN) + OLIHFA-BA is mostly attributable to the incorporation of enhanced features, segmentation, and classifiers. In the future, illness types should be analyzed.

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References

[1] Krishnamoorthy N a, L.V. Narasimha Prasad b, C.S. Pavan Kumar c, Bharat Subedi d, Haftom Baraki Abraha e, Sathishkumar V E a, "Rice leaf diseases prediction using deep neural networks with transfer learning", Environmental Research11 May 2021Volume 198 (Cover date: July 2021) Article 111275.

[2] Prabira Kumar Sethy , Nalini Kanta Barpanda , Amiya Kumar Rath , Santi Kumari Behera, "Deep feature-based rice leaf disease identification using support vector machine", Computers and Electronics in Agriculture, Volume 17517 , June 2020.

[3] Junde Chen, Defu Zhang, Adnan Zeb, Yaser A. Nanehkaran. "Identification of rice plant diseases using lightweight attention networks", Expert Systems with Applications, Volume 169, 5 January 2021.

[4] Rallapalli, S., Saleem Durai, M.A, "A contemporary approach for disease identification in rice leaf", Int J Syst Assur Eng Manag (2021).

[5] Zhencun Jiang, Zhengxin Dong , Wenping Jiang , Yuze Yang , "Recognition of rice leaf diseases and wheat leaf diseases based on multi-task deep transfer learning", Computers and Electronics in Agriculture 186 (2021) 106184 Available, Received 7 December 2020, Received in revised form 19 April 2021, Accepted 23 April 2021.

[6] Feng Jiang a, Yang Lu , Yu Chen , Di Cai , Gongfa Li, "Image recognition of four rice leaf diseases based on deep learning and support vector machine", Computers and Electronics in Agriculture 179 (2020) 105824 Available, Received 5 April 2020, Received in revised form 28 August 2020; Accepted 3 October 2020.

[7] GuoSheng Zhang, TongYu Xu, YouWen Tian, Han Xu, JiaYu Song, Yubin Lan, "Assessment of rice leaf blast severity using hyperspectral imaging during late vegetative growth", Australasian Plant Pathology: 9 August 2020. p.571–578.

[8] Rahul Bakade, Kishor D. Ingole, Sanjay Deshpande, Garima Pal, Swathi S. Patil, Saikat Bhattacharjee et.al, "Comparative Transcriptome Analysis of Rice Resistant and Susceptible Genotypes to Xanthomonas oryzae pv. oryzae Identifies Novel Genes to Control Bacterial Leaf Blight" , Molecular Biotechnology, https://doi.org/10.1007/s12033-021-00338-3 Received: 19 March 2021 / Accepted: 11 May 2021.

[9] Zarbafi, S.S., Rabiei, B., Ebadi, A.A. et al. "Association mapping of traits related to leaf blast disease in rice (Oryza sativa L.)", Australasian Plant Pathology, 49, 31–43 (2020).

[10] Lu, L., Yang, D., Tang, D. et al. "Transcriptome analysis of different rice cultivars provides novel insights into the rice response to bacterial leaf streak infection", Funct Integr Genomics 20, 681–693 (2020).

[11] Long Tian , Bowen Xue , Ziyi Wang , Dong Li , Xia Yao , Qiang Cao , Yan Zhu , Weixing Cao , Tao Cheng ," Spectroscopic detection of rice leaf blast infection from asymptomatic to mild stages with integrated machine learning and feature selection", Remote Sensing of Environment 257 (2021) 112350, Received 31 August 2020; Received in revised form 5 February 2021; Accepted 9 February 2021.

[12] Haniyam Badi B. Manoj Kumar, Chikka Balli A. Deepa K, Kodihally M, Harini Kumar, M. P. Rajanna, Belthur Chethan A, "Molecular profiling of blast resistance genes and evaluation of leaf and neck blast disease reaction in rice", Journal of Genetics, 2020.,

[13] Nan Jiang, Jun Fu, Qin Zeng , Yi Liang, Yanlong Shi, Zhouwei Li, Youlun Xiao, Zhizhou He, Yuntian Wu, Yu Long, Kai Wang, Yuanzhu Yang, Xionglun Liu, Junhua Peng. Genome-wide association mapping for resistance to bacterial blight and bacterial leaf streak in rice. Planta; 2021.

[14] Shrivastava, V.K., Pradhan, M.K. Rice plant disease classification using color features: a machine learning paradigm. J Plant Pathol 103, 17–26 (2021).

[15] Verma, T., Dubey, S, "Prediction of diseased rice plant using video processing and LSTM-simple recurrent neural network with comparative study", Multimed Tools Appl 80, 29267–29298 (2021).

[16] Zhang, J., Lin, G., Yin, X. et al. "Application of artificial neural network (ANN) and response surface methodology (RSM) for modeling and optimization of the contact angle of rice leaf surfaces", Acta Physiol Plant 42, 51 (2020).

[17] Sethy, P.K., Barpanda, N.K., Rath, A.K. et al. "Nitrogen Deficiency Prediction of Rice Crop Based on Convolutional Neural Network", J Ambient Intell Human Comput 11, 5703–5711 (2020).

[18] Wani, J.A., Sharma, S., Muzamil, M. et al. "Machine Learning and Deep Learning Based Computational Techniques in Automatic Agricultural Diseases Detection: Methodologies, Applications, and Challenges", Arch Computat Methods Eng (2021).

[19] Shu, X., Wang, A., Jiang, B. et al. "Genome-wide association study and transcriptome analysis discover new genes for bacterial leaf blight resistance in rice (Oryza sativa L.)", BMC Plant Biol 21, 255 (2021).

[20] Rao, T.B., Chopperla, R., Methre, R. et al. "Pectin induced transcriptome of a Rhizoctonia solani strain causing sheath blight disease in rice reveals insights on key genes and RNAi machinery for development of pathogen derived resistance", Plant Mol Biol 100, 59–71 (2019).

[21] Goel, S., Goswami, K., Pandey, V.K. et al, "Identification of microRNA-target modules from rice variety Pusa Basmati-1 under high temperature and salt stress", Funct Integr Genomics 19, 867–888 (2019).

[22] Angel Prathyusha K., Mahitha Y., Prasanna Kumar Reddy N., Raja Rajeswari P, "A survey on prediction of suitable crop selection for agriculture development using data mining classification techniques", International Journal of Engineering and Technology(UAE); 2018. p. 107-109.

[23] Vishnu B.V., Srinivas C. (2018),'Metaheuristic Algorithms Based Crop Classification',Proceedings of the 3rd International Conference on Communication and Electronics Systems, ICCES 2018, (),PP. 1140-1144.

[24] Bhuyan H.K., Sirajul Huque M.D. (2018), "Sub-Feature Selection Based Classification", Proceedings of the 2nd International Conference on Trends in Electronics and Informatics, ICOEI 2018, (),PP. 210-216.

[25] Sridevi S., Bindu Prathyusha M., Krishna Teja P.V.S.J. User behavior analysis on agriculture mining system. International Journal of Engineering and Technology (UAE);7(2).2018. p. 37- 40.

[26] Balram G., Kiran Kumar K.(2018),"Smart farming: Disease detection in crops",,International Journal of Engineering and Technology(UAE),7(2),PP. 33- 36.

[27] Kalavala S.S., Sakhamuri S., Prasad B.B.V.S.V. (2019), "An efficient classification model for plant disease detection", International Journal of Innovative Technology and Exploring Engineering, 8(7), PP.126-129.

[28] Sakhamuri, S., Kumar, K.K, " DeepLearning and Metaheuristic Algorithm for Effective Classification and Recognition of Paddy Leaf Diseases", Journal of Theoretical and Applied Information Technology; 2022. p. 1127–1137.

[29] Sakhamuri, S., Kompalli, V.S, "An Overview on Prediction of Plant Leaves Disease using Image Processing Techniques", IOP Conference Series: Materials Science and Engineering; vol. 981(2); 2020. P.022-024.

[30] https://en.wikipedia.org/wiki/Median_filter.

[31] Siddharth Madan, Kristin J. Dana1, "Modified balanced iterative reducing and clustering using hierarchies (m-BIRCH) for visual clustering", THEORETICAL ADVANCES, Pattern Anal Applic, Received: 15 December 2013 / Accepted: 5 March 2015.

[32] Dhanashree S. Kalel , Pooja M. Pisal, Ramdas P. Bagawade, "Color, Shape and Texture feature extraction for Content Based Image Retrieval System: A Study", International Journal of Advanced Research in Computer and Communication Engineering, Vol. 5, Issue 4, April 2016.

[33] Punal M. Arabi, Gayatri Joshi, N. Vamsha Deepa,"Performance evaluation of GLCM and pixel intensity matrix for skin texture analysis",Perspectives in Science, vol.8,pp.203-206,September 2016.

[34] Adel Hafiane, Guna Seetharaman, and Bertrand Zavidovique, "Median Binary Pattern for Textures Classification", Springer-Verlag Berlin Heidelberg 2007, ICIAR 2007, LNCS 4633, pp. 387–398, 2007.

[35] Kuo-Chin Fan and Tsung-Yung Hung, "A Novel Local Pattern Descriptor—Local Vector Pattern in High-Order Derivative Space for Face Recognition", Ieee Transactions On Image Processing, vol. 23, no. 7, pp. 2877-89, July 2014.

[36] L. Tong, H. Ma, Q. Lin, J. He and L. Peng, "A Novel Deep Learning Bi-GRU-I Model for Real-Time Human Activity Recognition Using Inertial Sensors," IEEE Sensors Journal, doi: 10.1109/JSEN.2022.3148431.

[37] Jiuxiang Gu, Zhenhua Wang, Jason Kuen, Lianyang Ma, Amir Shahroudy, Bing Shuai, Ting Liu et.al, "Recent advances in convolutional neural networks", Pattern Recognition, vol. 77, pp354-377, 2018.

[38] M. Cai, Y. Shi and J. Liu, "Deep maxout neural networks for speech recognition," IEEE Workshop on Automatic Speech Recognition and Understanding, 2013, pp. 291-296.

[39] S, Arora & Singh, Satvir, "Butterfly optimization algorithm: a novel approach for global optimization", Soft Computing, 2018.

[40] Li, Q.Q., He, Z.C. & Li, E. "The feedback artificial tree (FAT) algorithm", Soft Comput 24, 13413–13440 (2020). https://doi.org/10.1007/s00500-020-04758-2.

[41] M. Marsaline Beno, Valarmathi I. R, Swamy S. M and B. R. Rajakumar, "Threshold prediction for segmenting tumour from brain MRI scans", International Journal of Imaging Systems and Technology, Vol. 24, No. 2, pages 129-137, 2014, DOI: https://doi.org/10.1002/ima.22087.

[42] Devagnanam J,Elango N M, "Optimal Resource Allocation of Cluster using Hybrid Grey Wolf and Cuckoo Search Algorithm in Cloud Computing", Journal of Networking and Communication Systems, Vol.3,No.1, pp.31-40,2020.

[43] Renjith Thomas and MJS. Rangachar, "Hybrid Optimization based DBN for Face Recognition using Low-Resolution Images", Multimedia Research, Vol.1,No.1, pp.33-43,2018.

[44] SK.Mahammad Shareef and Dr.R.Srinivasa Rao, "A Hybrid Learning Algorithm for Optimal Reactive Power Dispatch under Unbalanced Conditions", Journal of Computational Mechanics, Power System and Control, Vol.1,No.1, pp.26-33,2018.

[45] Nandhini, S., Ashokkumar, K.," Improved crossover based monarch butterfly optimization for tomato leaf disease classification using convolutional neural network", Multimed Tools Appl 80, 18583–18610 (2021).

[46] Raja sekaran Thangaraj, S. Ananda murugan, Vishnu Kumar Kaliappan, "Automated tomato leaf disease classification using transfer learning-based deep convolution neural network", Journal of Plant Diseases and Protection; 2020.

[47] Sridevi S,K Kiran Kumar,"A Novel Rice Leaf Disease Recognition and Classification Model: Neuro Fuzzy Model and Optimized DNN with Improved Kapur Segmentation", unpublished.

[48] https://www.kaggle.com/minhhuy2810/rice-diseases-image-dataset.