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Enhancing Rice Plant Disease Recognition and Classification Using Modified Sand Cat Swarm Optimization with Deep Learning

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Abstract—Rice plant diseases play a critical challenge to agricultural productivity and food safety. Timely and accurate recognition and classification of these ailments are vital for efficient management of the disease. Classifying and recognizing rice plant disease by implementing Deep Learning (DL) has emerged as a powerful approach to tackle the challenges associated with automated disease diagnosis in rice crops. DL, a subfield of artificial intelligence, concentrates to train neural networks with several layers for automated learning of the complex patterns and illustrations from data. In the context of rice plant diseases, DL methods can effectually extract meaningful features from images and accurately classify them into different disease categories. Therefore, this study introduces a new Modified Sand Cat Swarm Optimization with Deep Learning based Rice Plant Disease Detection and Classification (MSCSO-DLRPDC) technique. The main objective of the MSCSO-DLRPDC technique focalize on the automated classification and recognition of rice plant ailments. To achieve this, the MSCSO-DLRPDC methodology involves two levels of pre-processing such as median filter-based noise removal and CLAHE-based contrast enhancement. Besides, Multi-Layer ShuffleNet with Depthwise Separable Convolution (MLS-DSC) methodology is utilized for feature extraction purposes. Moreover, the Multi-Head Attention-based Long Short-Term Memory (MHA-LSTM) methodology is utilized for the process of rice plant disease detection. At last, the MSCSO method is utilized for the tuning process of the MHA-LSTM approach. The MSCSO approach inspired by the collective behaviour of sand cats and the mutation operator, is implemented for optimizing the parameters of the MHA-LSTM network. To demonstrate the enhanced accomplishment of the MSCSO-DLRPDC method, a broad set of simulations were carried out. The extensive outputs show the greater accomplishment of the MSCSO-DLRPDC method over other methods. The proposed approach has the capability in assisting farmers and agricultural stakeholders in effectively managing rice plant diseases, contributing to improved crop yield and sustainable agricultural practices.

Keywords- Rice plant diseases; Deep learning; Computer vision; Sand cat swarm optimization; Machine learning.

I. INTRODUCTION

Farming is considered a major income source for the economy. Plants are also infected with diseases that affect the growth of plants [1]. Diseases can be in fruit, leaf, root, and flower that is in any part of the plant. Owing to the vast variety of crops and complexity and cultivated plants, the number of diseases is large. Hence, pathologists do not detect a disease precisely [2]. The timely and precise detection of plant disease protects crops from qualitative and quantitative loss. Many agriculturalists lack knowledge regarding the potential diagnosis of plant disease [3]. The detection of plant disease by the bare eye is time-consuming, necessitates continuous observing and is less precise. The automatic diagnosis of diseases diminishes human efforts and presents precise outcomes [4]. Automatic plant disease recognition is helpful to farmers, as they know less about plant diseases.

Rice and wheat are among the world's major crop. For underdeveloped countries and agriculturalists, rice was an essential food, and the farmers and economy are more reliant on the yield of rice [5]. Any crop yield can be affected by negative impacts (i.e., hereditarily clutter, mechanical harm, weather condition, wholesome lack, and so on.). As an alternative, the main problem is ailment made by microorganisms and microbes. Sicknesses are the main reason for return misfortune and lesser advantages in paddy crops [6]. Different attacks and diseases by pest insects cut crop production by 8 to 10% per annum. Rice was an essential food source after maize and wheat all over the world. To fulfil the increasing food demands of the country, a massive rice quantity should be produced [7]. The growth in rice productivity should be obtained through the irrigation executive's advancements, developed cultivars and coordinated harvest. The limitation of the acknowledgement of superior

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outcomes of rice is its susceptibility to creepy crawly bugs, abiotic stresses, and sicknesses [8].

The automatic diagnoses of disease in plants were largely studied nowadays. The diagnosis of diseases in plants necessitates precise and precise data in terms of the quantitative measurement of disease [9]. For classifying diseases with the use of handcrafted features, there exists a necessity for the extraction, pre-processing, and segmentation of features from the images which can be time-consuming and laborious. With the technical advances, Machine Learning (ML) related Artificial Intelligence (AI) has grabbed much attention in the expansion of novel approaches and methods in Computer Vision (CV) [10]. DL methods were utilized in domains namely image recognition, voice recognition and other complicated applications. The implementation of DL in agriculture and specifically in the plant disease recognition domain is much new and limited.

This study introduces a new Modified Sand Cat Swarm Optimization with Deep Learning based Rice Plant Disease Detection and Classification (MSCSO-DLRPDC) technique. The main objective of the MSCSO-DLRPDC technique focalize on the automated classification and recognition of rice plant ailments. To achieve this, the MSCSO-DLRPDC methodology involves two levels of pre-processing such as median filter-based noise removal and CLAHE-based contrast enhancement. Besides, Multi-Layer ShuffleNet with Depthwise Separable Convolution (MLS-DSC) methodology is utilized for feature extraction purposes. Moreover, the Multi-Head Attention-based Long Short-Term Memory (MHA-LSTM) methodology is utilized for the process of rice plant disease detection. At last, the MSCSO method is utilized for the tuning process of the MHA-LSTM approach. The MSCSO approach inspired by the collective behaviour of sand cats and the mutation operator, is implemented for optimizing the parameters of the MHA-LSTM network. To demonstrate the enhanced accomplishment of the MSCSO-DLRPDC method, a broad set of simulations were carried out.

II. LITERATURE SURVEY

Latif et al. [11] present a Deep CNN (DCNN) Transfer Learning (TL)-based process for the precisely classifying and identifying diseases of paddy leaves. An improved presented method contains an enhanced VGG19-based TL technique. Akshitha et al. [12] projected effort a semi-supervised and DCN approaches can be trained to differentiate crop species and the state of illness in leaf. This approach for recognizing rice illness comprises 2 important stages: a primary is a trained method, and the secondary is recognizing the disease in the given image. The presented effort utilized the CNN, VGG19, and DenseNet approaches for classifying the Rice Crop Disease.

Sowmyalakshmi et al. [13] presented a novel CNNIR-OWELM CNN-related inception with ResNset v2 method and Optimal Weighted ELM depends on classifying and recognizing the rice plant disease in a smart agriculture atmosphere. The presented approach utilizes the histogram segmenting model for determining the infected region in the images of rice plants. As well, DL-based initiation with the ResNetv2 approach is involved in extracting the features. In addition, in OWELM, the Weighted ELM (WELM), maximized by Flower Pollination Algorithm (FPA) can be utilized for classifying process. Jhatial et al. [14] try to make the best and simple method for identifying rice leaf disease with the use of the DL method Yolov5. The method was updated to v5 that is the newest YOLO version. The accuracy and performance of object recognition utilizing YOLOV5 are superior to YOLO4 and YOLO3 approaches. This method can distinguish and successfully find the diseases in the rice leaves.

In [15], presented a DL-related CNN method for equipping the detection for earlier identification. The presented prototype was introduced by incorporating the XGBOOST ensemble learning approach with the Keras Inception ResNetV2 technique to resolve different jobs like classification of image feature extracting process, object segmentation, and input images. The Adam optimizer can be exploited to optimize the presented structure by making the training and learning better. In [16], the author suggested a potential rice plant disease identifying algorithm that depends on the CNN approach. This study concentrated on three familiar paddy diseases, like leaf smut and brown spotting produced by bacteria and fungus. This research devises a potential approach for the identification of ailments in rice plants depending on the shape, colour of lesions, and size in the leaf images. The presented porch method implements Otsu's universal thresholding method to achieve image binarization for removing the background image noise.

III. THE PROPOSED MODEL

In the current article, focus is given on the development of the MSCSO-DLRPDC methodology for accurate and automated recognition of rice plant diseases. The main intention of the MSCSO-DLRPDC methodology focuses on the automated classification and recognition of ailments in the rice plant leaves. To achieve this, the MSCSO-DLRPDC method comprises different processes like data pre-processing, MLS-DSC-based feature extraction, MHA-LSTM-based disease identification, and MSCSO-based tuning process. Fig. 1 portrays the working flow of the MSCSO-DLRPDC method.

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A. Image Pre-processing

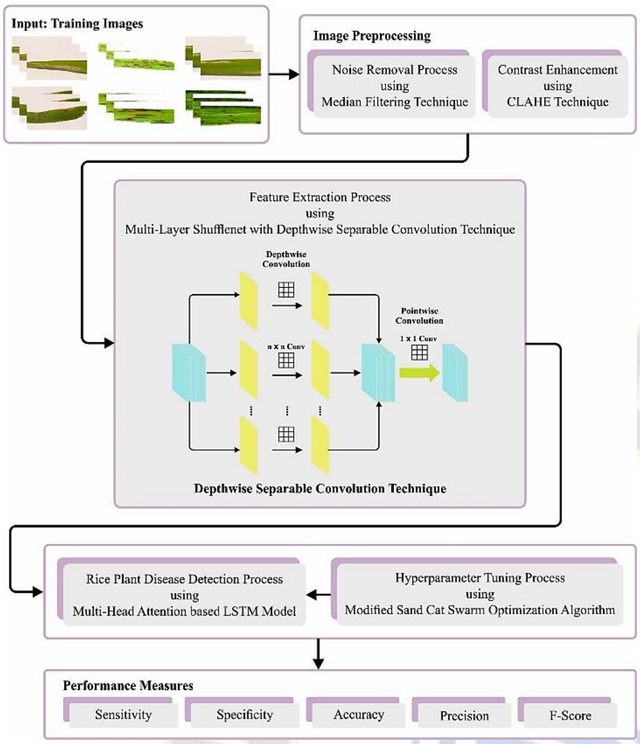

Figure 1. Complete workflow of the MSCSO-DLRPDC method

To pre-process the input rice plant images, the median filtering and CLAHE technique are used. Median Filtering (MF) is a nonlinear filtering technique widely applied for noise reduction in images [17]. All the image pixels are substituted with the median value of the adjacent pixel. The MF is efficient to remove salt-and-pepper noise while preserving edges and fine details. CLAHE is a variant of histogram equalization that adapts the equalization process to a small region of an image rather than using it globally. This method assists in enhancing the local details and the contrast in an image.

B. MLS-DSC-based Feature Extraction

To derive a useful set of features, the MLS-DSC model is exploited. ShuffleNetV1 exploits group convolution on a 1x1 convolutional layer (pointwise convolution) instead of a 3x3 convolutional layer, which is conducive to improving the representation ability and decreasing computation cost [18]. Furthermore, it applies the channel shuffle process to resolve problems of blocking data flow between channel groups. We have adopted the ShuffleNet unit as a backbone unit of the network. Based on ShuffleNet, it is a residual block that exploits channel shuffle operation, pointwise group convolution, and 3x3 depthwise convolution in its residual block. The ShuffleNet unit decreases the computational cost and the channel numbers using channel shuffle operation and pointwise group convolution. Then, 3 x 3 depth-wise convolution helps the interchange of data among channels and the second pointwise group convolution restores the original channel width. For enhancing the representation ability of the model, add 4 layers of depthwise convolutions. The difference between the 4 layers of depthwise convolutions is mostly in input and output sizes, and SE block was utilized. In comparison to typical convolution, depthwise convolution is mainly split into depthwise and pointwise convolution layers, making the operation cost and the number of parameters comparatively low. Instinctively, this comprises breaking the standard convolution into 2 convolutions. Initially, the convolution of (w, h, input channel) and (w, h, output channel) reduces the parameters of the method and increases the channel depth of the method.

C. MHA-LSTM-based Classification

The MHA-LSTM method was used for rice plant disease recognition. The LSTM method is a new version of the RNN that overcomes the constraint of RNN to handle long-term dependency [19]. Furthermore, this model captures long-and short-term temporal dependency along with enhancing the predictive accuracy by leveraging missing patterns.

The LSTM model comprises four key elements: forget gate, output gate, input gate, and cell state.

The input gate i_t upgrade the cell state by sending the prior layer of the Hidden Layer (HLs) data with existing input data to the subsequent layer to define the prominence of the upgraded dataset using the subsequent formula:

$$i_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \quad (1)$$

The forget gate f_t chooses to retain or discard data from prior HLs, and the existing input data was sent to the subsequent layer afterwards the sigmoid activation function with the subsequent formula:

$$f_t = \sigma\left(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}\right) \quad (2)$$

The cell state g_t gets past the prior layer with existing input data to *the tanh* function for creating a candidate vector g that is given below:

$$g_t = \tanh\left(W_{ig}\mathrm{x_t} + b_{ig} + W_{hg}h_{t-1} + b_{hg}\right) \quad (3)$$

The output gate o_t define the next HL value by sending prior input data into the sigmoid activation function for obtaining output value that can be shown below:

$$\mathrm{o}_t = \sigma(W_{io}\mathrm{x_t} + b_{io} + W_{ho}h_{t-1} + b_{ho}) \quad (4)$$

The LSTM method has h_0 and c_0 two custom parameters that are the first HL and first cell state, correspondingly. $h(t)$ and $c(t)$ of the following state were attained by computation. $h(t)$ has additional memory of novel data and change faster as t change,· $c(t)$ record further and prior data and slowly changes than t as follows:

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$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \quad (5)$$

$$h_t = o_t \odot \tanh(c_t)$$

From the expression, $\odot$ denotes the Hadamard product, representing a multiplication of the respective element of the matrix.

The study reports that it is valuable to utilize multi-head attention for values, queries, and keys by considering the attention layer as a function that will be mapping the queries and a series of key-value pair to the output [20]. The multi-head attention model calculated a hidden dataset that demonstrates the best effectiveness when related to single-head attention by straightly projecting the context vector into dissimilar subspaces. We compute output by the weight value that is evaluated by the respective query and key. The time dimension computing for attention weight is represented as follows:

$$s_t = softmax(o_{last} \times (o_{all} \times W_t)^H), o_{last} \in R^{B,1,Z} \quad (6)$$

$$o_t = s_t \times o_{all}, o_{all} \in R^{B,T,Z}, s_t \in R^{B,1,T} \quad (7)$$

Where B indicates the batch size, 0_{last}, s_t, o_{all}, T, and Z denotes the last time output, the time dimension's attention score, the all-time output, the time step numbers and a feature dimension. 0_t, H, and W_t depicts the time-dimension attention layer's output, the transpose operator, and the parameter matrix.

We apply two kinds of LSTM result for the attention module. The aim to select the last time step outcome is that it involves the unwanted data amongst each time step:

$$K_i = W_{i,k} \times o_{all} + b_{i,k}, K_i \in R^{B,T,\frac{Z}{n}}, W_{i,k} \in R^{Z,\frac{Z}{n}}, b_{i,k} \in R^{\frac{Z}{n}} \quad (8)$$

$$V_i = W_{i,v} \times o_{all} + b_{i,v}, V_i \in R^{B,T,\frac{Z}{n}}, W_{i,v} \in R^{Z,\frac{Z}{n}}, b_{i,v} \in R^{\frac{Z}{n}} \quad (9)$$

$$Q_i = W_{i,q} \times o_{last} + b_{i,q}, Q_j \in R^{B,1\frac{Z}{n}}, W_{i,q} \in R^{Z,\frac{Z}{n}}, b_{i,q} \in R^{\frac{Z}{n}} \quad (10)$$

Where b means bias, $K, V, and\ Q$ specify a value, key, and query and n represents the attention head number.

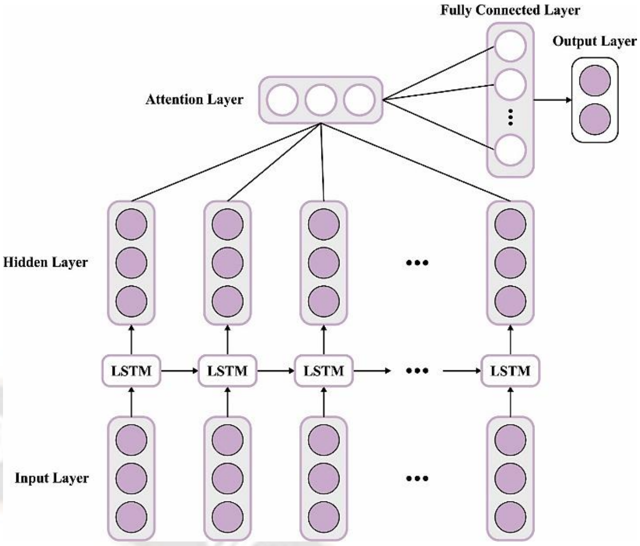

Figure 2. Structure of ALSTM

The context vector and multi-head attention score are evaluated by Eq. (11):

$$s_i = softmax(Q_i \times K_i^H), s_i \in R^{B,1,T} \quad (11)$$

$$context_i = s_i \times V_i, context_i \in R^{B,1,\frac{Z}{n}} \quad (12)$$

$$CV = Concat([context_1, \dots, context_n]), CV \in R^{B,1,Z} \quad (13)$$

Where $context_i$ signifies reduced dimension context vector from all the subspaces and s_i shows the multi-head time dimension attention score. Then, the context vector is fed into the FC layer. Then, the outputs are given to the $softmax$ layer for the last prediction. Fig. 2 displays the architecture of ALSTM.

D. Hyperparameter Tuning using MSCSO Approach

Finally, the MSCSO is utilized for the hyperparameter tuning of the MHA-LSTM method. In this SCSO approach, every SC shows the solution and the 1D array represents the solution of d-dimension problems [21]. Thus, all the variable values $(x_1, x_2, \dots, x_d)$ have the floating-point value added to them. Initially, based on the problem size, the model constructs a candidate matrix having the amount of SC populaces needed to resolve the problems. Also, the FF for all the SCs is estimated. An FF was a mathematical function that determines variables for resolving issues and defines how they are set for a solution. Therefore, all the SCs are allocated a value depending on the Fitness Function (FF). Depending on the maximization or minimization problem, the better searching agent in all the iterations has the optimal cost value. Thus, the searching agent tries to update the position relies upon the better searching agent location in the upcoming iteration. In this way, the better solution in all the iterations is used to signify the SC neighbouring to the prey. The prior result is not saved in memory needlessly letting memory to be effectively utilized because of improved solution.

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Using the SCSO approach, SC is capable of finding prey by identifying lower-frequency noise emissions. The SCSO method exploits the SC's hearing ability for detecting lower frequencies. Here, the sensitivity ranges of all the cats are compared. The SC senses lower frequencies under 2 kHz. It is forecasted that the parameter value $\overrightarrow{r_G}$ might linearly decline from 2 to 0 as the iteration progresses, as the algorithm search for hunting and not to pass or lose it. As a result, the SM value is set to 2, meanwhile, SCs have a range of hearing from $[2-0]$ kHz (Eq. (14)). Hence, the SC is predictable to have a range of sensitivity from $[2-0]$ kHz (Eq. (14)). There exist several issues that could affect the speed where searching agents react. The value would be greater and lesser than 1 in the iteration's first and other half, if you have a maximal amount of iterations of 100, to control the shift between exploitation and exploration stages, R denotes the final and main parameters. Eq. (15) gives an adaptive approach that reduces imbalance among the opportunities and transitions.

During the search step, the search agent position was randomly updated. The search space can be initialized randomly between determined boundaries, which allows the searching agents for exploring the newest areas. Thus, the sensitivity range linearly declined from 2 to 0, as all the SCs have a dissimilar sensitivity range, thereby avoiding the local optimal trap. Furthermore, $iter_c$ shows the existing iteration and $iter_{\text{Max}}$ denotes the maximal iteration, even demonstrating the sensitivity range of all the cats.

$$\overrightarrow{r_G} = s_M - \left(\frac{s_M - iter_c}{iter_{\text{Max}}}\right) \tag{14}$$

$$\vec{R} = 2 \times \overrightarrow{r_G} \times rand\ (0,1) - \overrightarrow{r_G} \tag{15}$$

$$\vec{r} = \overrightarrow{r_G} \times rand(0,1) \tag{16}$$

Based on the optimum candidate location of the searching agent ($\overrightarrow{Pos_{bc}}$), along with the existing location ($\overrightarrow{Pos_c}$) of the searching agent and sensitivity range ($\vec{r}$), all the SCs upgrade to their location. Thus, the SCs are capable of determining another potential best-prey location (Eq. (17)). Thus, the model has one more opportunity to find a novel local optimum within the searching region, which leads to a location in-between the existing location of prey and the existing location of cat. Another advantage is that it was lower in operational price and moderate in difficulty since it depends randomly instead of precise techniques. By providing search agents with the random advantage, the model is higher in efficacy and lower in operational cost.

$$\overrightarrow{Pos}(t+1) = \vec{r}.\left(\overrightarrow{Pos_{bc}}(t) - rand(0,1) \cdot \overrightarrow{Pos_c}(t)\right) \tag{17}$$

Afterwards exploration (finding prey), the SCSO move towards exploitation of prey that was discovered. The distance between the fittest location of all the searching agents and its existing locations is calculated by applying Eq. (18). The SCSO provides a random angle for hunting the prey, hence the SC define the location to move depending on the roulette wheel in SCSO. This allows the searching agent to move circularly using Eq. (18), the position is defined by the optimum solution ($\overrightarrow{Pos_b}$) and random position ($\overrightarrow{Pos_{rnd}}$).

$$\overrightarrow{Pos}(t+1) = \overrightarrow{Pos_b}(t) - \vec{r} \cdot \overrightarrow{Pos_{rnd}} \cdot \cos(\theta) \tag{18}$$

Even though the model is based on the key concept of the SCSO technique, it is adapted to utilize the location-updating stage to accomplish optimum outcomes. Therefore, the SCSO method is capable of achieving optimum outcomes by applying the Genetic Algorithm's (GA) mutation concept. The mutation was used for increasing diversity and the chance to discover the worst solution. Thus, a specific region of the worst solution is used for improving the system's performance. Therefore, a controlled mutation technique is integrated into the MSCSO technique. But the mutation is utilized in discrete systems, the MSCSO method can utilize discrete search space.

The MSCSO technique has derived a FF to accomplish higher efficiency of classification. It describes a positive integer that characterized the better efficiency of the candidate solution. The decline in classifier error rate is a FF.

$$fitness(x_i) = ClassifierErrorRate(x_i)$$
$$= \frac{No.of\ misclassified\ samples}{Overall\ samples} * 100 \tag{19}$$

IV. RESULTS AND DISCUSSION

The rice plant disease detection results of the MSCSO-DLRPDC method are tested on the plant disease dataset [22], encompassing 115 instances with three categories as depicted in Table 1.

TABLE I. DATASET DEPICTION

Class	Sample Numbers
Bacterial Leaf Blight (BLB)	40
Brown Spot (BS)	37
Leaf Smut (LS)	38
Overall Sample Number	115

Fig. 3 portrays the classification output of the MSCSO-DLRPDC approach under testing data. Figs. 3a-3b portrayed the confusion matrix presented by the MSCSO-DLRPDC approach at 70:30 of TRP/TSP. The figure identified that the MSCSO-DLRPDC approach has identified and classified all 3 class labels exactly. Similarly, Fig. 3c reveals the PR assessment of the MSCSO-DLRPDC approach. The figures identified that the MSCSO-DLRPDC method has gained greater PR

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accomplishment under 3 classes. Finally, Fig. 3d reveals the ROC evaluation of the MSCSO-DLRPDC method. The figure described that the MSCSO-DLRPDC method has productive outputs with greater values of ROC under 3 class labels.

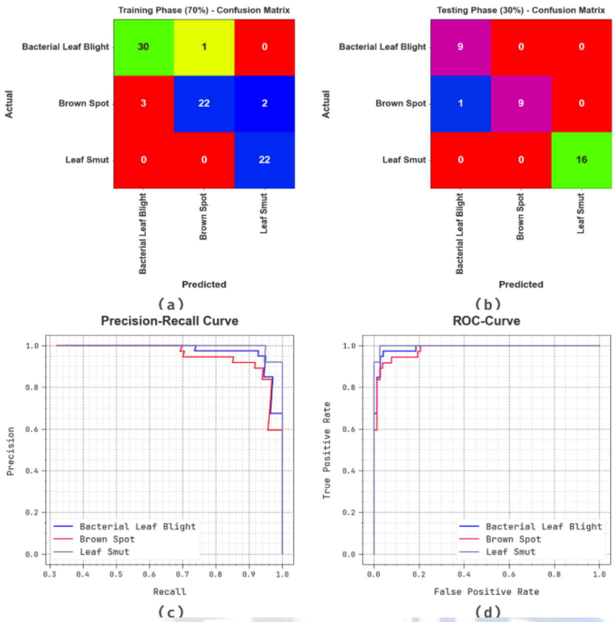

Figure 3. Classifier output of (a-b) Confusion matrices, (c-d) Curves of PR and ROC

TABLE II. DISEASE RECOGNITION OUTPUT OF MCSCO-DLRPDC METHOD ON 70:30 OF TRP/TSP

Class	$Accu_y$	$Prec_n$	$Sens_y$	$Spec_y$	F_{score}
Training Phase (70%)					
BLB	95.00	90.91	96.77	93.88	93.75
BS	92.50	95.65	81.48	98.11	88.00
LS	97.50	91.67	100.00	96.55	95.65
Average	**95.00**	**92.74**	**92.75**	**96.18**	**92.47**
Testing Phase (30%)					
BLB	97.14	90.00	100.00	96.15	94.74
BS	97.14	100.00	90.00	100.00	94.74
LS	100.00	100.00	100.00	100.00	100.00
Average	**98.10**	**96.67**	**96.67**	**98.72**	**96.49**

In Table 2, the comprehensive disease recognition outputs of the MSCSO-DLRPDC approach are portrayed under 70:30 of TRP/TSP. Fig. 4 depicts the disease classification outcomes of the MSCSO-DLRPDC approach with 70% of TRP. The outputs inferred that the MSCSO-DLRPDC method recognizes three types of diseases. For instance, on BLB, the MSCSO-DLRPDC method offers $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{score} of 95%, 90.91%, 96.77%, 93.88%, and 93.75% respectively. Moreover, on the brown spot, the MSCSO-DLRPDC method offers $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{score} of 92.50%, 95.65%, 81.48%, 98.11%, and 88% correspondingly. Furthermore, on LS, the MSCSO-DLRPDC method offers $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{score} of 97.50%, 91.67%, 100%, 96.55%, and 95.65% correspondingly.

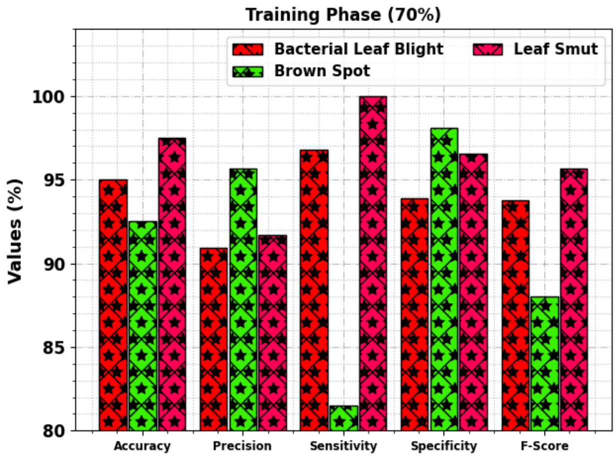

Figure 4. Disease recognition output of MSCSO-DLRPDC method on 70% of TRP

Fig. 5 represents the disease classification outcomes of the MSCSO-DLRPDC technique with 30% of TSP. The figure inferred that the MSCSO-DLRPDC technique identifies three types of diseases. For example, on BLB, the MSCSO-DLRPDC method offers $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{score} of 97.14%, 90%, 100%, 96.15%, and 94.74% correspondingly. Likewise, on the brown spot, the MSCSO-DLRPDC method offers $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{score} of 97.14%, 100%, 90%, 100%, and 94.74% correspondingly. Still, on LS, the MSCSO-DLRPDC method offers $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{score} of 100%, 100%, 100%, 100%, and 100% correspondingly.

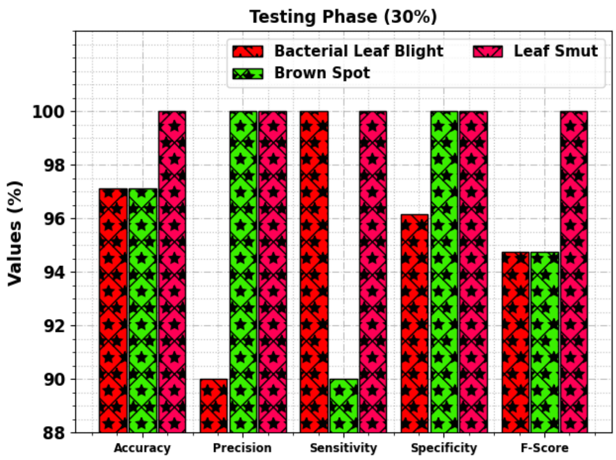

Figure 5. Disease recognition output of MSCSO-DLRPDC method on 30% of TSP

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Fig. 6 inspects the $accu_y$ of the MSCSO-DLRPDC methodology in the training and validation of the testing data. The figure pointed out that the MSCSO-DLRPDC methodology attains higher value of $accu_y$ over greater epochs. Also, the growing validation $accu_y$ over training $accu_y$ displays that the MSCSO-DLRPDC methodology learns productively on the testing dataset.

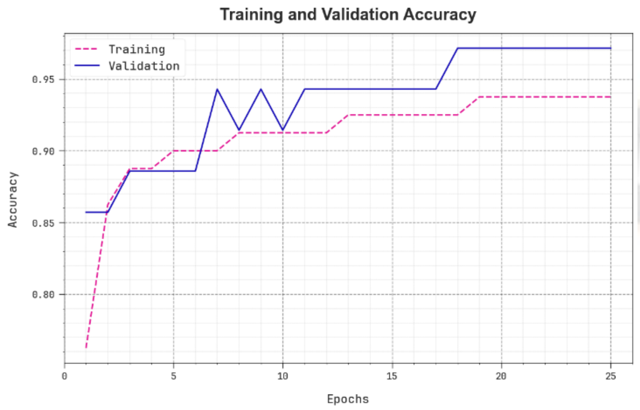

Figure 6. $Accu_y$ curve of the MSCSO-DLRPDC approach

The loss evaluation of the MSCSO-DLRPDC methodology in the training and validation is revealed on the testing data in Fig. 7. The figure specifies that the MSCSO-DLRPDC methodology revealed lesser loss values. The MSCSO-DLRPDC method learned productively on a testing dataset.

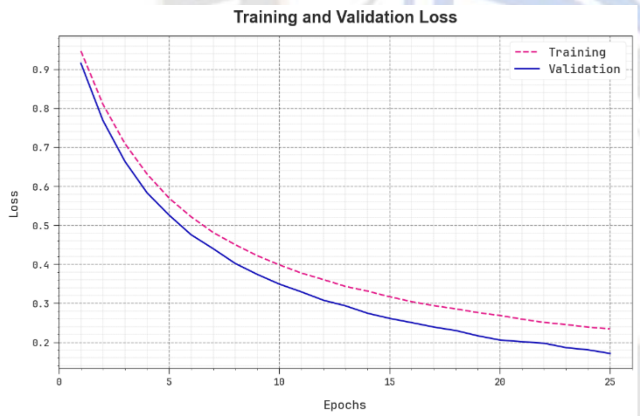

Figure 7. Loss curve of the MSCSO-DLRPDC method

TABLE III. RELATIVE ANALYSIS OF THE MSCSO-DLRPDC MODEL WITH OTHER RECENT METHODS

Models	$Accu_y$	$Prec_n$	$Sens_y$	$Spec_y$	F_{score}
DNN-JOA	94.25	81.24	83.70	94.04	88.74
DNN	90.00	74.91	73.46	89.42	81.51
DAE	86.04	67.58	68.02	87.18	77.03
ANN	80.01	60.87	63.30	81.58	68.31
CNN	94.00	94.00	94.00	94.00	94.00
SIFT-SVM	91.10	86.66	86.66	90.03	86.66
SIFT-KNN	93.33	90.60	90.00	92.34	90.14
MSCSO-DLRPDC	98.10	96.67	96.67	98.72	96.49

Table 3 and Fig. 8, a relative research of the MSCSO-DLRPDC approach with current models [23]. The figure indicates that the DNN, DAE, and ANN approaches have shown poor results whereas the SIFT-SVM, CNN, and SIFT-KNN methods have reached slightly enhanced performance. Although the DNN-JOA has near-optimal classification performance, the MSCSO-DLRPDC technique ensured its supremacy with maximum $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{score} of 98.10%, 96.67%, 96.67%, 98.72%, and 96.49% respectively.

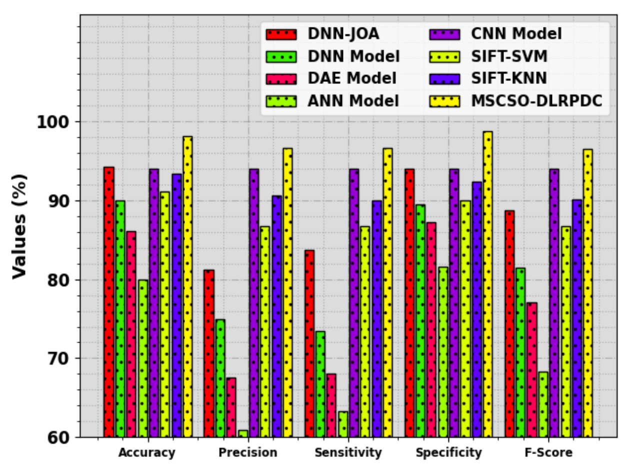

Figure 8. Comparative analysis of the MSCSO-DLRPDC method with other recent techniques

TABLE IV. CT ANALYSIS OF THE MSCSO-DLRPDC APPROACH WITH OTHER RECENT METHODS

Methods	Computational Time (sec)
DNN-JOA	0.29
DNN Model	0.26
DAE Model	0.27
ANN Model	0.25
CNN Model	0.25
SIFT-SVM	0.29
SIFT-KNN	0.27
MSCSO-DLRPDC	0.16

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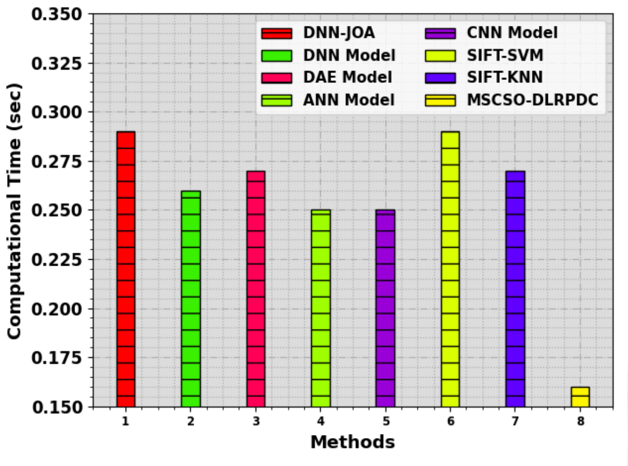

Figure 9. CT analysis of MSCSO-DLRPDC approach with other recent methods

To confirm the effectual computational complexity outcomes of the MSCSO-DLRPDC technique, a comparison study is shown in Table 4 and Fig. 9. The outputs inferred the improvements of the MSCSO-DLRPDC technique with the least CT of 0.16s.

On the other hand, the DNN-JOA, DNN, DAE, ANN, CNN, SIFT-SVM, and SIFT-KNN models have resulted in higher CT values of 0.29s, 0.26s, 0.27s, 0.25s, 0.25s, 0.29s, and 0.27s correspondingly. These results highlighted the better rice plant disease recognition efficacy of the MSCSO-DLRPDC technique.

V. CONCLUSION

In this study, we have focused on the development of the MSCSO-DLRPDC technique for accurate and automated rice plant disease recognition. The main objective of the MSCSO-DLRPDC technique concentrates on the automated classification and recognition of rice plant diseases. To achieve this, the MSCSO-DLRPDC approach comprises different processes like data pre-processing, MLS-DSC-based feature extraction, MHA-LSTM-based disease detection, and MSCSO-based hyperparameter tuning. In addition, the MLS-DSC approach is implemented for feature extraction purposes and the MHA-LSTM method is utilized for the rice plant disease recognition process. Finally, the MSCSO model is utilized for the hyperparameter tuning of the MHA-LSTM model. A comprehensive set of simulations were carried out to demonstrate the enhanced performance of the MSCSO-DLRPDC technique. The extensive results show the remarkable performance of the MSCSO-DLRPDC method over other approaches.

REFERENCES

[1] Upadhyay, S.K. and Kumar, A., 2022. A novel approach for rice plant diseases classification with deep convolutional neural network. International Journal of Information Technology, 14(1), pp.185-199.

[2] Kumar K, K. and E, K., 2022. Detection of rice plant disease using AdaBoostSVM classifier. Agronomy journal, 114(4), pp.2213-2229.

[3] Liang, W.J., Zhang, H., Zhang, G.F. and Cao, H.X., 2019. Rice blast disease recognition using a deep convolutional neural network. Scientific reports, 9(1), pp.1-10.

[4] Mr. Kankan Sarkar. (2016). Design and analysis of Low Power High Speed Pulse Triggered Flip Flop. International Journal of New Practices in Management and Engineering, 5(03), 01 - 06. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/45.

[5] Senan, N., Aamir, M., Ibrahim, R., Taujuddin, N.M. and Muda, W.W., 2020. An efficient convolutional neural network for paddy leaf disease and pest classification. International Journal of Advanced Computer Science and Applications, 11(7).

[6] Gilanie, G., Nasir, N., Bajwa, U.I. and Ullah, H., 2021. RiceNet: convolutional neural networks-based model to classify Pakistani grown rice seed types. Multimedia Systems, 27(5), pp.867-875.

[7] Feng, S., Zhao, D., Guan, Q., Li, J., Liu, Z., Jin, Z., Li, G. and Xu, T., 2022. A deep convolutional neural network-based wavelength selection method for spectral characteristics of rice blast disease. Computers and Electronics in Agriculture, 199, p.107199.

[8] Goluguri, N.V., Devi, K.S. and Srinivasan, P., 2021. Rice-net: an efficient artificial fish swarm optimization applied deep convolutional neural network model for identifying the Oryza sativa diseases. Neural Computing and Applications, 33(11), pp.5869-5884.

[9] Rathore, N.P.S. and Prasad, L., 2020. Automatic rice plant disease recognition and identification using convolutional neural network. Journal of critical reviews, 7(15), pp.6076-6086.

[10] Koklu, M., Cinar, I. and Taspinar, Y.S., 2021. Classification of rice varieties with deep learning methods. Computers and electronics in agriculture, 187, p.106285.

[11] Renato Costa, Deep Reinforcement Learning for Autonomous Robotics , Machine Learning Applications Conference Proceedings, Vol 2 2022.

[12] Agrawal, M. and Agrawal, S., 2020. Rice plant diseases detection & classification using deep learning models: a systematic review. J Crit Rev, 7, pp.4376-90.

[13] Hmeed, A. R. ., A. Hammad, J. ., & J. Obaid, A. . (2023). Enhanced Quality of Service (QOS) for MANET Routing Protocol Using a Distance Routing Effect Algorithm for Mobility (DREAM). International Journal of Intelligent Systems and Applications in Engineering, 11(4s), 188–193. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2588.

[14] Latif, G., Abdelhamid, S.E., Mallouhy, R.E., Alghazo, J. and Kazimi, Z.A., 2022. Deep Learning Utilization in Agriculture: Detection of Rice Plant Diseases Using an Improved CNN Model. Plants, 11(17), p.2230.

[15] Akshitha, M., Siddesh, G.M., Sekhar, S.M. and Parameshachari, B.D., 2022, October. Paddy Crop Disease Detection using Deep Learning Techniques. In 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon) (pp. 1-6). IEEE.

[16] Sowmyalakshmi, R., Jayasankar, T., PiIllai, V.A., Subramaniyan, K., Pustokhina, I.V., Pustokhin, D.A. and Shankar, K., 2021. An optimal classification model for rice plant disease detection. Comput. Mater. Contin, 68, pp.1751-1767.
[17] Jhatial, M.J., Shaikh, R.A., Shaikh, N.A., Rajper, S., Arain, R.H., Chandio, G.H., Bhangwar, A.Q., Shaikh, H. and Shaikh, K.H., 2022. Deep Learning-Based Rice Leaf Diseases Detection Using Yolov5. Sukkur IBA Journal of Computing and Mathematical Sciences, 6(1), pp.49-61.
[18] Kannan, E., 2022. An Efficient Deep Neural Network for Disease Detection in Rice Plant Using XGBOOST Ensemble Learning Framework. International Journal of Intelligent Systems and Applications in Engineering, 10(3), pp.116-128.
[19] Upadhyay, S.K. and Kumar, A., 2021. A novel approach for rice plant diseases classification with deep convolutional neural network. International Journal of Information Technology, pp.1-15.
[20] Sadhukhan, T., Chatterjee, S., Das, R.K., Ghosh, S., Das, D. and Sanyal, J., 2019, October. Efficient Removal of Noise from an Image using HSV Filtering. In 2019 Global Conference for Advancement in Technology (GCAT) (pp. 1-4). IEEE.
[21] Qiao, L., Li, Z., Xiao, B., Shu, Y., Li, W. and Gao, X., 2023. Gesture-ProxylessNAS: A Lightweight Network for Mid-Air Gesture Recognition Based on UWB Radar. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing.
[22] Cheng, R., Qiao, Z., Li, J. and Huang, J., 2023. Traffic Signal Timing Optimization Model Based on Video Surveillance Data and Snake Optimization Algorithm. Sensors, 23(11), p.5157.
[23] Zhao, Y., Liang, Z., Du, J., Zhang, L., Liu, C. and Zhao, L., 2021. Multi-head attention-based long short-term memory for depression detection from speech. Frontiers in Neurorobotics, 15, p.684037.
[24] Arasteh, B., Seyyedabbasi, A., Rasheed, J. and M. Abu-Mahfouz, A., 2023. Program Source-Code Re-Modularization Using a Discretized and Modified Sand Cat Swarm Optimization Algorithm. Symmetry, 15(2), p.401.
[25] H. B. Prajapati, J. P. Shah and V. K. Dabhi, “Detection and classification of rice plant diseases,” Intelligent Decision Technologies, vol. 11, no. 3, pp. 357–373, 2017. [Online]. Available: https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases.
[26] Narmadha, R.P., Sengottaiyan, N. and Kavitha, R.J., 2022. Deep Transfer Learning Based Rice Plant Disease Detection Model. Intelligent Automation & Soft Computing, 31(2).