Enhanced Sea Horse Optimization with Deep Learning-based Multimodal Fusion Technique for Rice Plant Disease Segmentation and Classification

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Received: 25 August 2023 | Revised: 6 September 2023 | Accepted: 11 September 2023

 DOI: https://doi.org/10.48084/etasr.6324

ABSTRACT

The detection of diseases in rice plants is an essential step in ensuring healthy crop growth and maximizing yields. A real-time and accurate plant disease detection technique can assist in the development of mitigation strategies to ensure food security on a large scale and economical rice crop protection. An accurate classification of rice plant diseases using DL and computer vision could create a foundation to achieve a site-specific application of agrochemicals. Image investigation tools are efficient for the early diagnosis of plant diseases and the continuous monitoring of plant health status. This article presents an Enhanced Sea Horse Optimization with Deep Learning-based Multimodal Fusion for Rice Plant Disease Detection and Classification (ESHODL-MFRPDC) technique. The proposed technique employed a DL-based fusion process with a hyperparameter tuning strategy to achieve an improved rice plant disease detection performance. The ESHODL-MFRPDC approach used Bilateral Filtering (BF)-based noise removal and contrast enhancement as a preprocessing step. Furthermore, Mayfly Optimization (MFO) with a Multi-Level Thresholding (MLT) based segmentation process was used to recognize the diseased portions in the leaf image. A fusion of three DL models was used for feature extraction, namely Residual Network (ResNet50), Xception, and NASNet. The Quasi-Recurrent Neural Network (QRNN) was used for the recognition of rice plant diseases, and its hyperparameters were set using the ESHO method. The performance of the ESHODL-MFRPDC method was validated using the rice leaf disease dataset from the UCI database. An extensive comparison study demonstrated the promising performance of the proposed method over others.

Keywords-agriculture; plant disease detection; rice crops; computer vision; deep learning; sea horse optimizer

I. INTRODUCTION

Rice is an essential food in several nations around the world. Approximately half the world's population depends on rice-based food, while the world population will exceed nine billion in 2050. As rice plant diseases reduce production by 10-15%, it is a great challenge to ensure food protection for massive amounts of the population and the agricultural society [1]. Bacteria and fungi are the main causes of these diseases, which result in a decrease in rice production and an increase in the economic expenses of farmers [2]. Therefore, the detection of diseases in agricultural goods in their initial stages is crucial to prevent production loss and improve quality. Traditionally, the detection of diseases in rice plants can be performed by culturing pathogens in the laboratory or based on a visual assessment of symptoms. Visual evaluation is subjective and prone to inaccuracy [3]. Culturing pathogens in the lab is a time-consuming procedure and there is no guarantee of achieving results in time. These traditional techniques require specialists for the identification of diseases, and it is complicated for farmers to access them [4]. These problems have encouraged the research communities to examine different methods for developing automated classification and identification techniques for diseases of rice plants [5].

A computer vision approach can be used to identify plant diseases and can be a valuable tool to manage disease and breeding resistance [6]. Recently, pattern detection approaches and image processing have been used for the diagnosis of plant diseases. The quality of agriculture and its products could also be evaluated using images and various methods based on Artificial Intelligence (AI) [7]. The application of computer vision and AI to automatically detect and identify rice plant diseases is currently being widely studied, as manual supervision of plant diseases is uninteresting, time-consuming, and laborious [8]. Today, Deep Learning (DL) methods are very often applied in the diagnosis of diseases. However, due to the need for higher hardware resources to train Convolutional Neural Networks (CNNs) in many large databases, it takes a long time and is not favorable to its advancement and usage [9]. Authors in [10] suggest a Transfer Learning (TL) method to identify the combination of pre-trained processes using databases of diseased rice plant leaves to train the system.

This paper presents an Enhanced Sea Horse Optimization with Deep Learning-based Multimodal Fusion technique for Rice Plant Disease Detection and Classification (ESHODL-MFRPDC). This approach uses a DL-based fusion process with hyperparameter tuning to improve rice plant disease detection performance. The ESHODL-MFRPDC approach uses Bilateral Filtering (BF)-based noise removal and contrast enhancement as a preprocessing step. Then, Mayfly Optimization (MFO) with a Multi-Level Thresholding (MLT)-based segmentation process is used to recognize the diseased portions in the leaf image. A fusion of three DL models is used for feature extraction, namely Residual Network (ResNet50), Xception, and NASNet. The Quasi-Recurrent Neural Network (QRNN) model is used for the recognition of rice plant disease, and its hyperparameters can be altered using the ESHO method. The performance of the ESHODL-MFRPDC method was validated in the UCI rice leaf disease dataset and compared with other methods.

II. RELATED WORKS

In [11], an automated recognition system using CNN was proposed to detect rice leaf diseases, but its accuracy is highly questionable. In [12], a novel DL-based Automated Plant Disease Detection and Classification (DLAPDDC) approach was proposed, in which U2Net-based context elimination was used to extract leaf and fruit areas, SqueezeNet with Adam optimization was used for feature extraction, and finally, the XGBoost approach was used to classify plant diseases. In [13], preprocessed input images of various rice plant diseases were detected using GLCM and ANNs. This approach is extremely useful for farmers to detect rice diseases early and stop the use of pesticides that affect crop production. In [14], the ADSNN-BO approach was presented, based on MobileNet design and the augmented attention process, using the Bayesian Optimizer (BO) to tune its hyperparameters. This method was cross-validated on an open disease database with 4 types in total. To verify its interpretability, the system used an activation map and a filter visualization system. In [15], a system was proposed to present visual data to agriculturalists and allow them to decide on the necessary defensive processes. A lightweight DL system, based on the Vision Transformer (ViT) and a CNN, was presented for real-time automated plant disease classification. In [16], a real-time approach using DCNN was proposed to detect corn leaf diseases. DNN performance was improved by tuning the hyperparameters and modifying the pooling combination on a GPU system. Moreover, the parameter count of the established system was optimized to make it appropriate for real-time application. The pre-training DCNN approach can be used on a Raspberry Pi 3, using Intel Movidius Neural. In [17], an EfficientNet DL was proposed for the classification of plant leaf diseases. EfficientNet and other DL approaches were trained to use a Transfer Learning (TL) system. During the TL method, every layer of the method was fixed and trainable.

III. THE PROPOSED MODEL

This study presents an automatic rice plant disease recognition and classification technique using a DL-based fusion process with a hyperparameter tuning strategy to achieve improved rice plant disease detection performance. The proposed model consists of image preprocessing, MFO with MLT-based segmentation, QRNN and fusion-based classification and extraction, and ESHO-based hyperparameter tuning. Initially, the input plant leaf images are preprocessed to improve their quality. Then, the diseased portions are accurately segmented by the MFO with MLT. Afterward, the fusion process is carried out to generate a set of feature vectors. Lastly, the ESHO with QRNN is used for the disease detection and classification procedure. Figure 1 shows the complete workflow of the ESHODL-MFRPDC method.

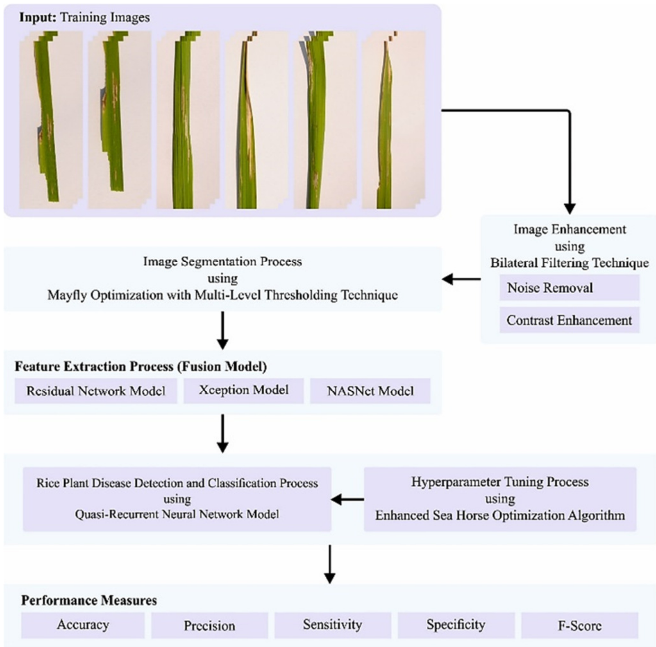

Fig. 1. The overall flow of the ESHODL-MFRPDC method.

A. Image Preprocessing

BF-based noise removal and contrast enhancement were used to preprocess the images. BF is a non-linear smoothing approach that aims to maintain edges and significant structural data of the image but decrease noise [18]. It assumes both spatial and intensity variances among neighboring pixels in the filter method. The BF system computes a weighted average of the pixel values in the well-defined neighborhood, but the weight can be resolved by the spatial distance and intensity similarity between the center pixel and its neighbors. Smoothing counts and edge preservation are controlled by altering the filter parameters, such as intensity and spatial kernels. Then, CLAHE was employed to enhance the local contrast of the image by redistributing the intensity values from its histogram. CLAHE splits the image at lesser areas, termed tiles, and executes Histogram Equalization (HE) individually to all tiles. The "contrast limited" feature of CLAHE avoids excessive noise amplification by clipping the histogram later to a certain limit. It confirms that the contrast enhancement was restricted, averting artifacts and maintaining the entire image's qualities.

B. MFO with MLT-based Segmentation

Once the input images are preprocessed, the segmentation process is performed by the MFO using the MLT approach. MFO is a population-based method consisting of the following succeeding functions: (i) initializes an equivalent amount of male and female agents, (ii) allows male Mayflies (MFs) to identify the best location as *loc* for the preferred task, (iii) allows the female MF to search and fuse with a male MF placed at *loc*, (iv) generate an offspring, and (v) end the search and display the concluding output. In [19], a threshold-based technique was presented to calculate the optimal threshold for the segmentation and increasing entropy. An objective function was obtained for the computation of the bi-level threshold:

$$FUN_{kap}(t) = k_1 + k_2 \tag{1}$$

where k_1 and k_2 are calculated as:

$$k_1 = \sum_{s=1}^{t} \frac{p_s}{\omega_0} \ln\left(\frac{p_s}{\omega_0}\right) \tag{2}$$

$$k_2 = \sum_{s=(t+1)}^{L} \frac{p_s}{\omega_1} \ln\left(\frac{p_s}{\omega_1}\right) \tag{3}$$

where p_s denotes the probability distribution of the intensity level of the grayscales, and ω_0 and ω_1 indicate the probability distribution for k_1 and k_2 class labels. This entropy-based method is as flexible as possible for MLT. Therefore, there is a need to divide the images into *n*-class labels using the (*n*-1) threshold number.

$$FUN_{kap}(T) = \sum_{s=1}^{n} k_s \tag{4}$$

$T = [t_1, t_2, t(n-1)]$ represents a vector consisting of a threshold number. The entropy is defined separately with the corresponding threshold *t* value and the following equation was adapted for *n* entropy:

$$k_n^c = \sum_{i=t_{(n+1)}}^{L} \frac{p_i}{\omega_{(n-1)}} \ln\left(\frac{p_i}{\omega_{(n-1)}}\right) \tag{5}$$

where (ω_0, ω_1, …, $\omega_{(n-1)}$) represents the probability of occurrence for *n* classes, and the MFO technique is used for the optimal threshold number. Similarly, the MFO method was projected for the mating process and the fighting feature of MFs [20]. The MFs in swarms can be identified as male and female individuals. The MFO method changes the location based on the velocity $velocity_i(t)$ and location $loc_i(t)$ at the existing iteration:

$$loc_i(time+1) = loc_i(time) + velocity_i(time+1) \tag{6}$$

Each male and female MF changes location using (6) about time, but it can be applied to velocity-adapting features. The half-male and female MFs pass over mating and produce children. The offspring were produced in the parent as follows:

$$offspr_1 = PxMale + (1-P)x\ Female \tag{7}$$

$$offspr_2 = PxFemale + (1-P)xMale \tag{8}$$

where *P* denotes a Gauss distribution random number.

C. Fusion-based Feature Extraction

In this phase, fusion-based feature extraction was carried out using three DL models, namely ResNet50 [21], Xception [22], and NASNet [23]. The resultant features were fused by the entropy approach. Entropy-based feature fusion uses the concept of entropy to combine features from multiple sources. Entropy measures the amount of information or uncertainty in a set of data. In the context of feature fusion, entropy can be used as a criterion to determine the importance or relevance of individual features.

D. Image Classification using the QRNN Model

In the final stage, the QRNN model receives the features to classify them. QRNN is an NN fusion of CNNs and LSTMs, integrating the merits of both [24]. QRNNs are extremely parallelizable like CNNs. All QRNN layers integrate 2 seed mechanisms related to the convolution and pooling layers in CNNs. The formulas for the QRNN unit are as follows:

$$\begin{aligned}
\hat{x}_t &= tanh(W \times X_t) \\
f_t &= \sigma(W_f \times X_t) \\
o_t &= \sigma(W_o \times X_t) \\
c_t &= f_t \odot c_{t-1} + (1-f_t) \odot \hat{x}_t \\
h_t &= o_t \odot tanh(c_t)
\end{aligned} \tag{9}$$

where $X_t \in \mathbb{R}^{kxn}$ implies the input series of k *n*-dimensional vectors $x_{t-(\kappa+1)}$, …, x_t and mask convolutional beside the timestep size. W, W_f and W_o are all convolution filter banks in $\mathbb{R}^{dxnxk}$, and k denotes the filter width. The three primary terms are QRNN convolution segments that can create *m*-dimension series $\hat{x}_t$, f_t, and o_t. The symbol $\odot$ signifies element-wise multiplication. The final 2 terms are pooling parts of QRNN, while the familiar element-wise gates perform in the LSTM unit. As shown in (9), a single QRNN performs three multivector functions that depend on the input sequence *X*, without dependency on prior outcomes as $h_{(t-1)}$. With known input, these multiply-vector functions $W \times X_t$ are pre-calculated in several time steps. Thus, weighted matrices with a huge count of memory do not require to be loaded at every time step. Therefore, these functions are correlated in a single matrix to matrix multiplication, as shown in (10):

$$u^T = \begin{pmatrix} W \\ W_f \\ W_o \end{pmatrix} \left[X_{(k-1)}, X_k, \dots, X_{L+(k-1)}\right] \tag{10}$$

where $U \in R^{Lx3d}$, d, and $L = T - (k+1)$ refer to the combined outcome matrix, hidden state neuron count, and the length of the input sequence.

E. Hyperparameter Tuning using the ESHO Algorithm

The Enhanced Sea Horse Optimization (ESHO) technique was used to improve the accuracy of the QRNN approach. Sea Horse Optimization (SHO) is motivated by the breeding, natural displacement, and predation strategies of Sea Horses (SHs) [25]. This technique has three major elements: mobility predation, and breeding. Global and local search models were introduced for the social behavior of predation and mobility, similarly to equalizing the exploration and exploitation of the method. The SHO can be split into four stages: initialization, mobility, predation, and breeding behaviors of SHs. SHO, like other metaheuristics, begins with the initial population. Once a SH signifies a feasible solution to the issue from the searching space, the entire populace of SHs is represented as:

$$S = \begin{bmatrix} x_1^1 & \cdots & x_1^D \\ \vdots & \ddots & \vdots \\ x_P^1 & \cdots & x_P^D \end{bmatrix} \quad (11)$$

where P, s, D, and UB and LB indicate the population size, seahorses, variable's dimension, and the Upper and Lower Bounds of the problems, respectively, that are used as starting points for the randomly generated solution. In the search space, for the i^{th} individual's X_i:

$$X_i = [x_i^1, \ldots, x_i^D] \quad (12)$$

$$x_i^j = rand \times (UB^j - LB^j) + LB^j \quad (13)$$

where $rand$ denotes a random value in the interval [0,1], x_i^j signifies the j^{th} variable in the i^{th} individual, i refers to the integer with a positive value in the interval [1, P], and j represents an integer with positive values within [1, D]. The optimized upper and lower boundaries of the j^{th} parameter of the optimized problems is indicated as LB^j and UB^j. The fittest individual is designated by X_{best} using the maximal or minimal optimization tasks and is considered the lowest or highest fitness level.

$$X_{best} = arg_{\min\ or\ \max}\left(f(X)\right) \quad (14)$$

In (14), $f(X_i)$ shows the objective function value for certain tasks. During movement, the movement pattern of SHs corresponds to the uniformly distributed random value within $[0, 1]$. Now, set $r_1 = 0$ as a cut-off point to tradeoff between the performance of exploration and exploitation, with half going to the global search and the rest to local mining. The ESHO method grows a Fitness Function (FF) to obtain an optimal classifier solution. This gives a positive integer to signify the optimum solution of candidate performances. In such cases, the reduction of the classifier error rate can be assumed to be as follows:

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{no.of\ misclassified\ instances}{Total\ no.of\ instances} \times 100 \quad (15)$$

IV. RESULTS AND DISCUSSION

The effectiveness of the ESHODL-MFRPDC technique was investigated in a plant disease dataset [27-28], consisting of 215 instances with 5 classes. Table I shows the experimental leaf disease recognition results of the ESHODL-MFRPDC approach, using a 70:30 for TRP/TSP, offering $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{score} of 98%, 94.74%, 97.30%, 98.23%, and 96%, respectively. The simulation was performed using Python 3.6.5 on an i5-8600K, 250GB SSD, GeForce 1050Ti 4GB, 16GB RAM, and 1TB HDD PC. The parameter settings were learning rate: 0.01, activation: ReLU, epoch count: 50, dropout: 0.5, and batch size: 5. Figure 2 shows a comparison of ESHODL-MFRPDC with other DL methods [29]. The results show that the DAE and ANN methods performed worse, DNN, SIFT-SVM, and SIFT-KNN performed better, and DNN-JOA and CNN provided even better results. The ESHODL-MFRPDC method achieved maximum performance with $accu_y$ of 98.77%, $prec_n$ of 97.21%, $sens_y$ of 97.65%, $spec_y$ of 99.22%, and F_{score} of 97.30%.

TABLE I. LEAF DISEASE RECOGNITION RESULTS OF ESHODL-MFRPDC ON 70:30 OF TRP/TSP

Class	$Accu_y$	$Prec_n$	$Sens_y$	$Spec_y$	F_{Score}
Training Phase (70%)					
Bacterial Leaf Blight	99.33	100.00	95.65	100.00	97.78
Brown Spot	99.33	100.00	96.00	100.00	97.96
Leaf Smut	98.67	100.00	93.33	100.00	96.55
Leaf Scaled	98.00	92.11	100.00	97.39	95.89
Rice Blast	98.00	94.74	97.30	98.23	96.00
Average	**98.67**	**97.37**	**96.46**	**99.12**	**96.84**
Testing Phase (30%)					
Bacterial Leaf Blight	96.92	100.00	88.24	100.00	93.75
Brown Spot	98.46	92.31	100.00	98.11	96.00
Leaf Smut	100.00	100.00	100.00	100.00	100.00
Leaf Scaled	98.46	93.75	100.00	98.00	96.77
Rice Blast	100.00	100.00	100.00	100.00	100.00
Average	**98.77**	**97.21**	**97.65**	**99.22**	**97.30**

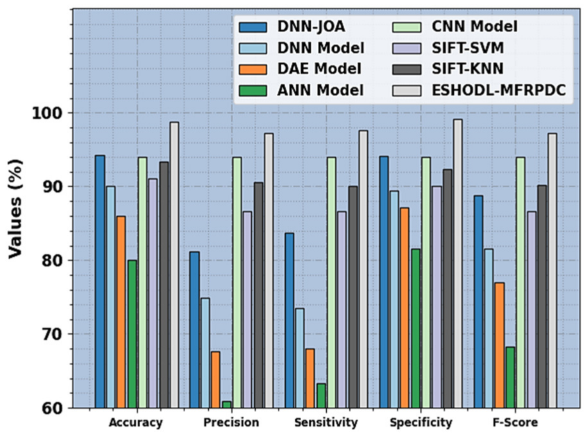

Fig. 2. Comparison of ESHODL-MFRPDC results with other DL algorithms.

Figure 3 shows a Computation Time (CT) test of the ESHODL-MFRPDC. The results identify the effectual efficiency of the ESHODL-MFRPDC model with a minimal CT of 0.12s. In contrast, the DNN-JOA, DNN, DAE, ANN, CNN, SIFT-SVM, and SIFT-KNN models reached at maximum CT of 0.29 s, 0.26 s, 0.27 s, 0.25 s, 0.25 s, 0.29 s and 0.27 s, respectively. These results highlight the greater efficiency of ESHODL-MFRPDC over the other models.

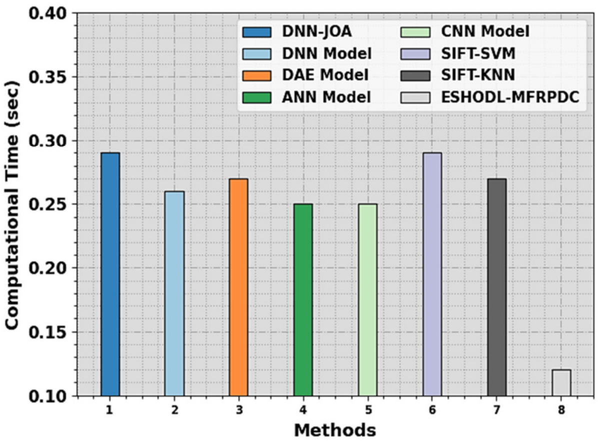

Fig. 3. CT results of ESHODL-MFRPDC approach with other DL methods.

V. CONCLUSION

This study presented an automatic rice plant disease recognition and classification technique. The proposed ESHODL-MFRPDC method uses a DL-based fusion process with a hyperparameter tuning strategy to improve rice plant disease detection performance. This method consists of image preprocessing, MFO with MLT-based segmentation, QRNN and fusion-based classification and extraction, and ESHO-based hyperparameter tuning. The ESHO model aids in the optimal choice of the hyperparameters of the QRNN model, resulting in improved classification performance. The effectiveness of the ESHODL-MFRPDC technique was validated on a rice leaf disease dataset from the UCI database. An extensive comparison of the results with other methods demonstrated the effectiveness of the proposed ESHODL-MFRPDC technique in both performance and computation time.

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