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Automated Rice Disease Diagnosis using Deep Learning: A Wavelet-Enhanced VGG-16 Model with Manta Ray Optimization

Sachin Vasant Chaudhari[1], Jayesh Anil Khaire[2], Harshad Atul Desai[3], Prathamesh Shankar Pathak[4].

Department of Electronics & Computer Engineering, Sanjivani College of Engineering, Kopargaon, Ahemadnagar, Maharashtra, India

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Abstract

Plant diseases significantly impact crop yields and financial stability, especially in Asia where rice is a staple crop. This study introduces the Automated Deep Learning with Wavelet Neural Network (ADLWNN) model to effectively identify and classify rice plant diseases. The ADLWNN model integrates the VGG-16 Convolutional Neural Network (CNN) for feature extraction from rice plant images. VGG-16, with its deep architecture of thirteen convolutional layers and two fully connected layers, is fine-tuned for binary classification by reinitializing the final SoftMax layers. Hyperparameter tuning is achieved through the Manta Ray Foraging Optimization (MRFO) algorithm, which mimics the foraging behavior of manta rays using techniques like somersault foraging and cyclone foraging to optimize the model parameters.For robust recognition, the Wavelet Neural Network (WNN) is employed, which decomposes input signals into simpler wavelet components for precise pattern identification. The WNN's wavelet analysis, combined with the optimized features extracted by VGG-16, enhances the model's classification capability. Simulation results on a rice plant image dataset show that the ADLWNN model achieves a remarkable 98.18% accuracy, outperforming existing methods in sensitivity, specificity, precision, and F-score. This comprehensive approach demonstrates the ADLWNN model's effectiveness in automated rice disease diagnosis, offering a valuable tool for safeguarding crop yields.

Keywords — Convolution neural network, Image classification, Disease diagnosis, Manta Ray optimization, Machine learning, Rice plant images

Introduction

THE Significance of Rice as a Staple Food and the Need for Automated Plant Disease Detection Rice is a staple food in India and around the globe, with approximately 50% of the global population depending on it.1 Unfortunately, rice plant diseases have caused reduction of ten to fifteen percent in rice production, posing a significant challenge to ensuring food security for these significant populations. Fungi and bacteria are believed to be the primary culprits behind these diseases ,2 leading to decreased rice production and substantial economic losses for farmers annually. Early diagnosis of diseases in agricultural products is essential in preventing productivity losses and improving quality, 3 making it a crucial factor in a country's economic growth. Traditionally, rice plant disease recognition relied on subjective visual evaluation of indications or experimental outcomes by culturing pathogens in labs.4 However, both methods have their limitations, such as the subjectivity and error-proneness of visual evaluation and the time-consuming nature of culturing pathogens in labs with no guarantee of timely results.

Furthermore, both methods require expert knowledge for disease identification, which can be difficult for agriculturalists to access, especially in remote areas. 5 Researchers have examined a range of approaches for creating automated algorithms for rice plant disease detection and classification to solve such problems. Conventional farming tactics have always struggled to accurately detect diseases and evaluate their spread across large areas, leading to difficulty in aiding farming areas.6 Timely detection of pests and diseases is essential for successful agricultural outcomes. Given this need for innovation, several automation techniques have been developed in agronomics to address these challenges.7 Recent research has focused on the use of AI (Artificial Intelligence) methods to provide valuable data on soil quality, ideal planting times, and optimal herbicide application to minimize pest infestations. AI has been implemented worldwide to enhance the efficiency of crop health monitoring and disease management for almost every crop, leading to increased accuracy in crop management .8-9 AI has been shown to outperform humans in this regard, making it a promising avenue for improving agricultural productivity. Advanced Deep Learning Techniques for Rapid and Precise Rice Disease RecognitionRice disease diagnosis could be a time-consuming and laborious process, but with the advent of advanced DL methods, it is now possible to achieve rapid and precise disease recognition. In,10-11 the ADSNN-BO ("Attention-Related Depthwise Separable NN with Bayesian Optimization") was developed to identify and categorize rice illness from rice leaf images. This novel method achieves AI-based illness identification by combining an enhanced attention system with a MobileNet framework. Bayesian optimization is also used to fine-tune the hyper-parameters of the method, further enhancing its effectiveness. Other studies have also explored the use of DL methods for rice disease classification. For instance, in,12 existing DL techniques were applied to categorize different disease indicators in photos of rice plants. The effectiveness of top GoogleNet CNN as well as pre-trained VGG-16 approaches was evaluated on the held-out data using a threefold cross-validation method. In,13-14 A CNN approachconnected to DL is established to prepare the process of diagnosis for first recognition. The developed prototype is demonstrated by combining the Keras Inception ResNet V2 structure with the XGBOOST ensemble learning algorithm to address many tasks, including object segmentation, image feature extraction, and input image categorization. The Adam optimizer was used to greatly enhance the developed method by improving the efficiency of the training and learning procedures. In , a novel approach utilizing CNN and image processing is developed to categorize paddy plants into disease-type class data obtained from sources of agricultural image data.

It seemed a natural choice as CNN is a DL approach associated with rapid convergence and accuracy in classifications using small training sets. Finally, in,15 a method for classifying rice illnesses from leaf photos that are connected to segmentation and use DNN was modeled. Using a local segmentation technique, disease-affected rice leaf areas were identified, and the CNN was trained using those pictures. The method shown in ,16-17 uses three CNN structures that are already in existence: DenseNet, VGG, and ResNet. These structures were trained using three datasets, one of which is created using photos of rice leaves that were gathered from the BRRI ("Bangladesh Rice Research Institute"). The classification was carried out with an ensemble of linear classifiers that applied the RSM ("Random Subspace Method").

This research proposes the ADLWNN model, an automated DL model based on wavelet NNs for rice plant classification. The efficient identification and classification of photos of rice plants is the main goal of the suggested ADLWNN model. CNNs are the main tool used by the suggested ADLWNN model to extract characteristics from the input images of rice plants. Furthermore, the MRFO method is employed as a hyperparameter optimizer. Additionally, photos of rice plants are reliably recognized and classified using the WNN model. The simulation study of the ADLWNN approach was examined with a series of images of rice plants, and findings exhibited that the ADLWNN model performed better than other methods.

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proposed model

The ADLWNN model is designed to effectively categorize rice plant images by incorporating the MRFO algorithm with the VGG-16 model for feature extraction. Additionally, the WNN model is utilized for robust recognition of these images. This approach results in improved accuracy and efficiency in recognizing and categorizing rice plants.

Feature Extractor VGG-16:

CNN is an algorithm composed of two important building blocks: the pooling and convolutional layers. The convolutional layer uses local filters to compute a feature map from input feature maps. This feature map is passed via a linear function, typically ReLU, to approximate complex tasks and decrease the need for extensive processing. The pooling layer performs downsampling by averaging sub-regions of the feature map. The FCL ("Fully Connected Layers") utilizes multiple stacked convolution and pooling layers to generate a SoftMax layer, which produces scores and predictions for different classes. The overall structure of CNN is depicted in Figure 1.

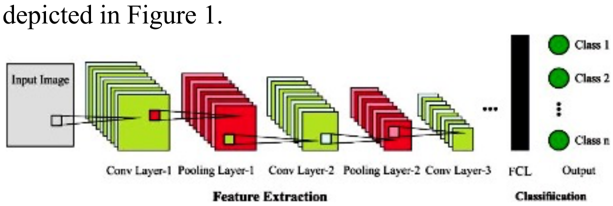

Fig. 1. CNN Structure

Understanding the VGG Depth Group: Trainable Variables and Max Pool Layers. The VGG depth group is focused on exploring the impact of deep convolution networks on image classification and recognition. Some of the layers in this group include trainable variables, while others, such as the Max pool layer, do not have any trainable parameters. [17]. The VGG architecture comprises multiple convolution layers and FCL. It contains fifteen layers with two FCLs and thirteen convolution layers. The "non-linear activation function" and hidden layers are represented by 13 blue rectangles, while the max-pooling layers are denoted by five red rectangles. Additionally, there are 2 FCLs, indicated by two green rectangles. To adapt this architecture for the dataset, the last two layers, i.e. the SoftMax layers, were finetuned. This involved re-initializing the SoftMax function to suit the binary classification task of differentiating between non-Rumex and Rumex plants. Starting with a small channel capacity of 64, the VGG-16 model was trained using a scale factor, which increased the capacity at each block. The architecture consisted of five blocks, with the first two blocks having max-pooling and paired convolution layers, and the last three blocks having three convolutional layers followed by max-pooling. For the final classification, 3 dense layers, or FCLs, were used. The first two FCLs were flattened, with a depth of 512, while the last FCL had a depth of 128. The channel size was reduced by half after each max-pooling layer, leading to a more compact overall model.

Hyperparameter Tuning based on MRFO

The MRFO approach is applied in this study as the VGG16 model is a hyperparameter optimizer. The intriguing actions of MR (Manta Rays) can serve as an inspiration for the MRFO technique [18]. Three distinct machine learning processes—somersault foraging, chain, and cyclone—were taken into account while creating a prospective optimum approach to find answers for various optimized challenges. The optimal position of the prey, which includes many planktons, is used in the MRFO technique to update the agent's location at each round.

$$x_t^d(t+1) = \{\begin{matrix} x_i^d + r\,x\,((x_{best}^d(t) - x^d i(t)) \\ a\,x\,x_{best}^d(t) x_t^d - x_i^d(t))i = 1 \\ \frac{x_i d(t) + r\,x\,((x_{i-1}^d - x_i^d(t) - x_i^d(t))}{a\,x\,x_{best}^d(t) - x_i^d,(t)), i = 2.....N} \end{matrix}\} \quad (1)$$

Where x_best^d (t) denotes specific plankton density, aimplies "weight coefficient, r signifies an arbitrary number in [0,1}x_best^d (t) indicates the position of and, the (i-1)*th representatives at iteration t in the dth dimension, and" a is found via Equation (2):

$$a=2r \times \log |r|^{\frac{1}{2}} \quad (2)$$

In the case that the plankton is fixed, the animals swim closer to the bait and build lengthy bait chains. The following is a quick explanation of the storm process:

$$x_t^d(t+1) = \{\begin{matrix} x_i^d + r\,x\,((x_{best}^d(t) - x^d i(t)) \\ a\,x\,x_{best}^d(t) - x_i^d(t))i = 1 \\ \frac{x_i d(t) + r\,x\,((x_{i-1}^d - x_i^d(t) - x_i^d(t))}{a\,x\,x_{best}^d(t) - x_i^d,(t)), i = 2.....N} \end{matrix}\} \quad (3)$$

$$\beta = 2exp(r \times (\frac{T-t+1}{T})) \times \sin(2\pi) \quad (4)$$

The storm process is a way of attempting to discover the best possible solution to a given problem by exploring various arbitrary points. The process makes use of a reference, referred to as Bait, that is utilized to guide the exploration for suitable solutions. A parameter, denoted by r, is a value between 0 & 1 and is used to denote the optimal locations, whereas T stands for the maximum iterations. A weight coefficient, denoted by B, is used to capture progress and direct the process accordingly. The process involves varying the initial parameters to find the ideal solutions for the given problems.

$$x_{rand}^d = L^d + r \times (U^d - L^d) \quad (5)$$

$$x_t^d(t+1) = \{\begin{matrix} x_i^d + r\,x\,((x_{best}^d(t) - x^d i(t)) \\ a\,x\,x_{best}^d(t) - x_i^d(t))i = 1 \\ \frac{x_i d(t) + r\,x\,((x_{i-1}^d - x_i^d(t) - x_i^d(t))}{a\,x\,x_{best}^d(t) - x_i^d,(t)), i = 2.....N} \end{matrix}\} \quad (6)$$

whereas Ld indicates the lower constraint of the dth dimension and Ud denotes the higher constraint of the dth dimension, Xrand denotes the arbitrary location solution. Somersault foraging pivoting establishes the feeding location. Agents attempt somersaults and pivots to reach alternative locations. As a result, the locations were considered to have achieved the most advantageous positions. Consequently, it is denoted by Equation (7):

$$x_i^d(t+1) = x_i^d(t) + S \times \left(r_2 \times x_{best}^d - r_3 \times x_{best}^d - x_i^d(t)\right) \quad (7)$$

whereas S describes somersault bait and comes to 2 and r, and r2 displays arbitrary numbers. The confusion would be reduced by reducing the distance between individual planktons. As the number of repetitions increased, the somersault forage ranges decreased. The MRFO methodology has built an "objective function", implying a positive integration to indicate the maximal outcome, to select the optimal variable of the CNN technique. The solution with the least amount of error is regarded as optimum in this instance, and the error rate may be deemed as the fitness function. It is explained as follows:

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{number\ of\ misclassified\ samples}{Total\ number\ of\ Samples} \times 100 \quad (8)$$

Integration of MRFO with VGG-16 for Hyperparameter Tuning

In this study, the Manta Ray Foraging Optimization (MRFO) approach is utilized to optimize the hyperparameters of the VGG-16 model. Inspired by the intriguing foraging behaviors of manta rays, MRFO employs three distinct machine learning processes—somersault foraging, chain foraging, and cyclone foraging. These processes are designed to explore and exploit the search space effectively, helping to identify the optimal hyperparameters for VGG-16, which enhances the model's performance in classifying rice plant diseases.

Somersault Foraging: This process simulates the somersault movements of manta rays, allowing them to explore new areas in the search space. The position of each agent (representing a potential solution) is updated based on the best-known position in the swarm:

$$x_i^d(t+1) = x_i^d(t) + S \times \left(r_2 \times x_{best}^d - r_3 \times x_{best}^d - x_i^d(t)\right).$$

Chain Foraging: Agents move closer to each other, forming chains to exploit the search space efficiently.

Cyclone Foraging: This method models the spiral movements of manta rays, allowing them to explore the search space more thoroughly.

The MRFO algorithm dynamically adapts to the search landscape, improving the likelihood of finding optimal hyperparameters. By integrating MRFO with VGG-16, the hyperparameters are fine-tuned effectively, leading to improved performance in classifying rice plant diseases. The combination of advanced feature extraction from VGG-16 and the intelligent optimization capabilities of MRFO results in a powerful and accurate classification model.

$$\Psi_j(x) = \left|d_j\right|^{-\frac{1}{2}} \Psi\left(\frac{x-t_j}{d_i}\right),\ d \neq 0\ j = 1,2,..,k \quad (9)$$

Wavelet analysis is a technique used to understand signals by decomposing them into simple parts that correspond to different frequencies or times. Wavelet analysis is commonly used in areas such as signal detection, the study of computer graphics, computer vision, control, and dynamical systems. [19] The corresponding wavelet family for offering (x) is acquired by

$$\Psi_j(x) = \left|d_j\right|^{-\frac{1}{2}} \Psi\left(\frac{x-t_j}{d_i}\right),\ d \neq 0\ j = 1,2,..,k \quad (9)$$

From the equation x={x_1+x_2+....x_n}, and is achieved from psi(x) through scaling them via factord_j={d_1j,d_2j,....d_nj} and transform them through
t_j={t,t_2j,....t_nj}

WNN (Wavelet Neural Network) is a method of estimating the relationship between a given input and its corresponding output by using wavelets, scaling, and translation. By applying this technique, the input-output mapping can be determined for the given data.

$$y=\sum_{j=1}^{k} \omega_j \Psi_j(x) = \sum_{j=1}^{k} \omega_j \lfloor d_j \rfloor^{-1/2} \Psi\left(\frac{x-t_j}{d_j}\right) \quad (10)$$

Equation (10), denotes the synaptic weight, x presents the input unit, and signifies the parameter that is considered the wavelet.

Implementation in ADLWNN

Within the ADLWNN framework, WNN is integral to the classification process. The detailed steps are as follows:

Feature Extraction: Initially, the VGG-16 CNN extracts high-level features from rice plant images. These features capture essential details that distinguish healthy plants from diseased ones.

Wavelet Transformation: The extracted features are then subjected to wavelet transformation. This step involves decomposing the feature vectors using wavelet functions ψ\psiψ. The transformation scales and translates the features to various levels, emphasizing different aspects of the data.

Wavelet Neural Network: The transformed features are input into the WNN. Here, the wavelet functions are combined with synaptic weights to model the complex relationship between the input features and the output classes (healthy or diseased).

Optimization: The synaptic weights and wavelet parameters are optimized during training. The MRFO algorithm aids this process by fine-tuning the hyperparameters to minimize the classification error.

Classification: The final step involves using the optimized WNN to classify the input images. The network outputs the probability of each class, and the image is categorized based on the highest probability.

Novelty in ADLWNN

The novelty of the ADLWNN model lies in its hybrid approach, combining the strengths of VGG-16 for feature extraction and WNN for classification, with MRFO for hyperparameter optimization. This integration offers several advantages:

Enhanced Feature Extraction: VGG-16's deep architecture effectively captures intricate features from the images, providing a solid foundation for classification.

Robust Classification: WNN's ability to decompose features into wavelet components allows for precise pattern recognition, improving classification accuracy.

Effective Optimization: MRFO's intelligent foraging behavior optimizes the model parameters, ensuring the best possible performance.

Superior Performance: The combination of these techniques results in higher accuracy, sensitivity, specificity, precision, and F-score compared to existing methods.

TABLE I
COMPARISON OF THE ADLWNN METHOD WITH PRESENT ALGORITHMS

Method	Sensitivity	Specificity	Pre	Acc	F-Score
ADLWNN	99.97	99.78	98.15	98.18	99.13
DesenNet-MLP	96.93	98.65	96.32	97.47	96.82
DNN JOA	83.07	93.66	81.30	93.59	89.33
DNN	73.75	88.75	74.88	89.31	80.76
DAE	68.71	87.58	66.80	86.23	77.05
ANN	63.42	81.93	61.11	79.97	67.57
CNN	94.55	93.52	94.34	94.06	93.27
KNN	65.68	77.90	72.62	70.37	65.74

Result & Discussion

A collection of 1550 images of rice plants is used to investigate the ADLWNN model’s simulated analysis. Table 1 presents a thorough comparative analysis that aims to illustrate the improved outcomes of the ADLWNN model. Fig. 2 shows the results of a sensitivity evaluation of the ADLWNN model compared to other recent models. The KNN, ANN, and DAE models had Sensitivity values of 68.71%, 63.42 %, and 65.68%, respectively, which were significantly lower than the other models. The DNN and DNN-JOA models had sensitivity values of 83.07% and 73.75%, respectively, providing reasonable results. The CNN and DenseNet-MLP models reported closer Sensitivity values of 96.93% and

94.55%. Finally, the ADLWNN model had the highest Sensitivity of 99.97%.

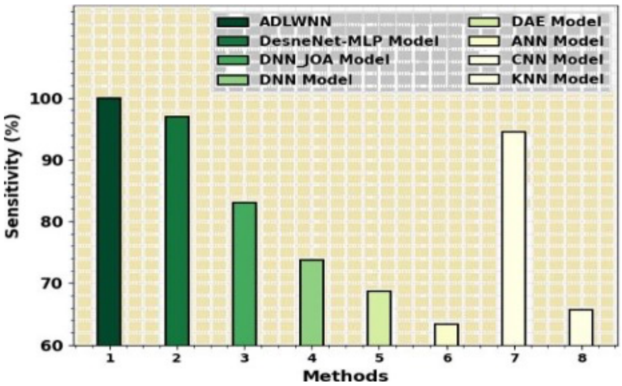

Fig. 2. ADLWNN Method Analysis with Other Recent Algorithms

The results demonstrate that the ADLWNN approach provides the highest Specificity value of 99.78%, followed by DensNet MLPD and CNN with 98.64% and 93.51%, respectively. DNN-JOA and DNN have achieved better results compared to DAE, ANN, and KNN, with Specificity values of 93.66% and 88.75%, respectively. However, minimal Specificity scores were provided by KNN (77.90%), ANN (81.93%), and DAE (87.58%) models.

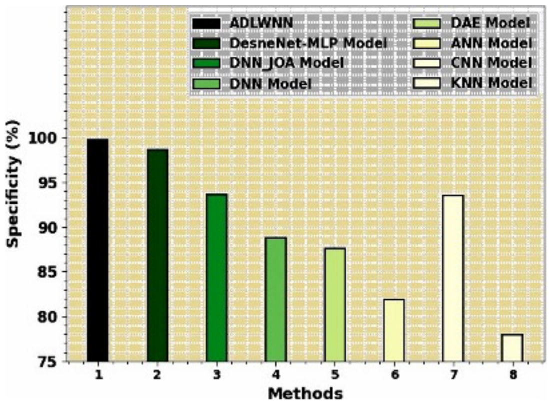

Fig.3.Comparison Analysis of ADLWNN method with Present Algorithms

The performance of the ADLWNN model has been assessed with recent methods, as revealed in Figure 4. The KNN, ANN, and DAE models have reported minimal Precision values of 66.80%, 61.11%, and 72.62%, respectively. The DNN as well as DNN-JOA approaches have provided better Precision values of 81.30% and 74.88%. The CNN and DenseNet-MLP models have had Precision values of 96.32% and 94.34%, respectively. However, the highest Precision values have been reported by the ADLWNN model, with a value of 98.15%.

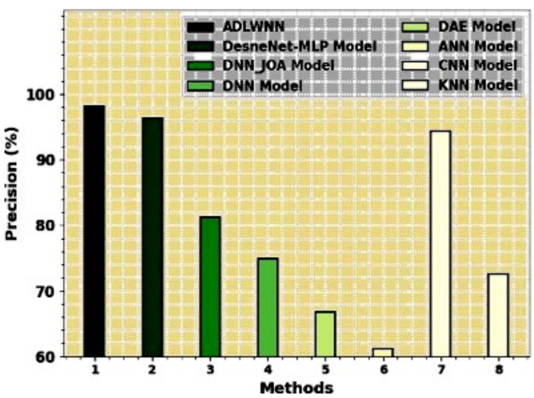

Fig. 4. Comparison Analysis of ADLWNN method with Present Algorithms

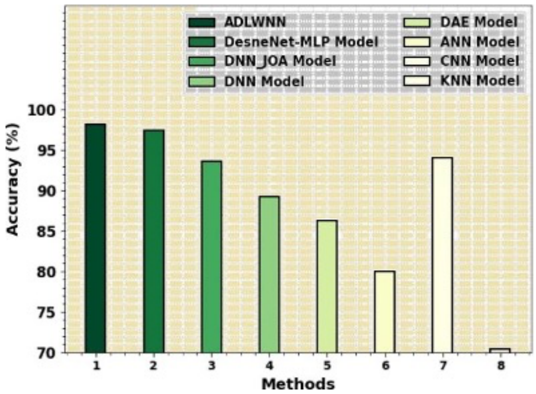

Fig. 5. Comparison Analysis of ADLWNN method with Present Algorithms

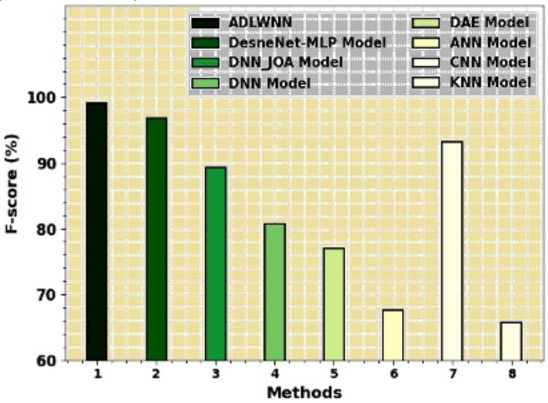

Fig. 6. Comparison Analysis of ADLWNN method with Present Algorithms

Fig. 5 and Fig. 6 show the accuracy and F-Score of the ADLWNN method compared to recent models. Results indicate that the KNN, ANN, and DAE models have low accuracy and F-Score values of 86.23%, 79.97%, 70.37%, 77.05%, 67.57%, and 65.74%, respectively. The DNN as well as DNN-JOA models have relatively better performance with accuracy and F-score values of 93.59%, 89.31%, 89.33%, and 80.76%, respectively. Furthermore, the CNN and Dense Net-MLP approaches have the highest accuracy and F-score values of 97.47% and 94.06%, 96.82% and 93.27%, respectively.

Fig. 7. ADLWNN approach VACC and TACC Analysis

Finally, the ADLWNN model achieved the best performance with an accuracy and F-score of 98.18% and 99.13%, respectively. The performance of the ADLWNN technique on rice plant classification has been investigated in terms of VACC, TACC, VLS, and TLS. As seen in Fig.7, the DLWNN model has enhanced performance in terms of VACC and TACC with increased values. The maximum TACC outcome has been reached by the ADLWNN method. On the other hand, Fig. 8 suggests that the ADLWNN model has emerged as a better performing method in terms of TLS and VLS with minimal values. Notably, the VLS outcome has seen a significant reduction due to the ADLWNN approach.

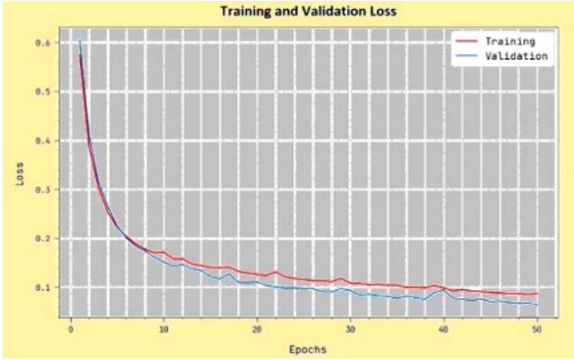

Fig. 8. VLS and TLS approach of ADLWNN

The findings of the experiment showed that the ADLWNN model showed superior performance compared to the other models.

The ADLWNN model demonstrates exceptional performance in identifying and classifying rice plant diseases, achieving a remarkable 98.18% accuracy. The integration of VGG-16 CNN for feature extraction and Wavelet Neural Network (WNN) for robust recognition proves to be a powerful combination. The Manta Ray Foraging Optimization (MRFO) algorithm's hyperparameter tuning further enhances the model's performance. Compared to existing methods, ADLWNN shows superior sensitivity, specificity, precision, and F-score, making it a valuable tool for automated rice disease diagnosis.

The ADLWNN model's effectiveness can be attributed to its ability to extract complex features from rice plant images and decompose them into simpler wavelet components for precise pattern identification. This comprehensive approach enables the model to detect subtle differences in disease symptoms, leading to accurate classification. The ADLWNN model's potential to increase crop yield by facilitating early disease detection and treatment makes it a significant contribution to the field of agricultural technology. Future research can focus on expanding the model's capabilities to detect multiple diseases and integrating it with real-time monitoring systems for practical applications.

Conclusion

This article outlines an ADLWNN model that can effectively recognize and classify images of rice plants. This model uses the WNN model to provide trustworthy recognition and classification, and the MRFO in conjunction with the VV16 model to extract features from the input photos. A collection of images of rice plants was utilized to assess the ADLWNN model’s competency. The analysis of the data revealed that the ADLWNN model performed better than most traditional methods. Thus, this model can not only detect rice plant diseases but also help increase crop yield.

CONFLICT OF INTEREST :

The authors declare that there is no conflict of interest

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