Maize Leaf Disease Detection using Manta-Ray Foraging Optimization with Deep Learning Model

Shanmugam Vimalkumar
Department of Computer Science & Applications, St. Peter's Institute of Higher Education and Research, Chennai, India
vimalcheyyar@gmail.com (corresponding author)

Ramavel Latha
Department of Computer Science & Applications, St. Peter's Institute of Higher Education and Research, Chennai, India
latharamavel@gmail.com

Received: 14 May 2024 | Revised: 25 May 2024 | Accepted: 27 May 2024

 DOI: https://doi.org/10.48084/etasr.7821

ABSTRACT

Maize (corn) is a major and high yield crop, cultivated worldwide although diseases may cause severe yield reductions. Monitoring and identifying maize diseases throughout the growth cycle are crucial tasks. Accurately detecting diseases is an issue for farmers who need expertise in plant pathology, while professional diagnosis can be time-consuming and expensive. Meanwhile, conventional Deep Learning (DL) and image recognition models are slowly entering the field of plant disease detection. This paper proposes the Intelligent Maize Leaf Disease Detection design using the Manta-Ray Foraging Optimization with a DL (IMLDD-MRFODL) model. The aim of the IMLDD-MRFODL method is to detect and categorize maize leaf diseases. The IMLDD-MRFODL method applies Median Filtering (MF) for image preprocessing, a densely connected network (DenseNet) for feature extraction, and the MRFO technique for hyperparameter tuning. The IMLDD-MRFODL technique exploits a Long Short-Term Memory (LSTM) network for maize leaf disease classification. Experimental evaluation was conducted to validate the IMLDD-MRFODL approach and the comparative analysis exhibited the superior accuracy of the proposed method.

Keywords-agriculture; maize leaf diseases; disease detection; computer vision; deep learning

I. INTRODUCTION

Maize leaf diseases drastically decrease crop production, thus, monitoring and detecting diseases during the developing seasons is essential [1]. Conventionally, plant pathologists, field experts, or cultivators analyze all diseases by physically examining the signs of the crop's diseases with the naked eye. This technique is not possible at a higher level due to limitations, such as physical accessibility, resource availability, cost, and time [2]. Often, the unobtainability of field experts can prevent the precise therapy of the ailments in the earlier phases. Hence, a cost-effective and fast technique for diagnosing crop diseases is needed [3]. In the existing conditions, automatic disease identification employing DL nearly exceeds the standard disease identification approach and offers nearly higher-level performances in challenging periods [3]. A digital image-assisted automated detection model in maize crops can be a sustainable option for reaching the stakeholders, namely maize cultivators and the country's massive population [4].

Artificial Intelligence (AI) and DL-based methodology are gradually employed in agricultural studies owing to their capacity to acquire deep features from image datasets automatically [5]. Convolutional Neural Networks (CNNs) were utilized and compared in [6, 7]. Fine-grained crop disease lesions' variability challenges CNNs, with enhanced network depth and method adjustments offering limited enhancement in classification effectiveness [8]. Moreover, visual disruptions like blur, dispersion, and reflection crucially impact fine-grained image classification [9]. Hence, fine-grained maize disease recognition needs increased computerized mechanisms and rational patterns in complex contextual field settings.

This paper presents the Intelligent Maize Leaf Disease Detection design using the Manta-Ray Foraging Optimization with a DL (IMLDD-MRFODL) model.

II. RELATED WORKS

Authors in [10] employed DL techniques for maize leaf detection. In [11], the authors examined the TL of deep-CNNs.

This work implements pre-trained Xception, InceptionV3, ResNet-50, and VGG16 frameworks for classification. Bayesian optimization was utilized to select optimum values for hyperparameters. Authors in [12] developed a multiscale convolution global pooling-NN method. Initially, a novel Inception framework and convolution layer were integrated to improve the capability of AlexNet feature extraction. Moreover, the TL method was implemented to solve the over-fitting issue. In [13], the Competitive Shuffled Shepherd Optimization (CSSO) approach was developed by incorporating the Shuffled Shepherd Optimizer Algorithm (SSOA) and Competitive Swarm Optimizer (CSO) models. The preprocessing was conducted by ROI extraction. Identification was performed by Deep Quantum-NN (Deep QNN). Authors in [14] developed a CNN technique-based model for classifying four types of images.

Authors in [15] proposed the SKPSNet50-CNN technique, which changes the 3×3 convolutional kernel from the backbone network ResNet50 with the Select Kernel-Point-Swish-B (SKPS) model. Authors in [16] introduced a DL model named MaizeNet in which a ResNet50 technique with spatial-channel attention was incorporated into an enhanced Faster-RCNN model. Authors in [17] proposed a model that incorporates CNN for visual detection. Authors in [18] implemented three optimization approaches. The Modified Wiener Filter (MWF) model was utilized for preprocessing, and the Improved Ant Colony Optimization (IACO) method was employed for feature extraction. The Hybrid Grasshopper Optimization with a modified Artificial Bee Colony Algorithm (HyGmABC) was employed for classification.

III. THE PROPOSED MODEL

This paper uses the novel IMLDD-MRFODL approach to detect and categorize maize leaf diseases. For this to be accomplished, it encompasses MF-based pre-processing, DenseNet feature extraction, LSTM classification, and MRFO-based hyperparameter tuning. Figure 1 exemplifies the structure of the proposed IMLDD-MRFODL method.

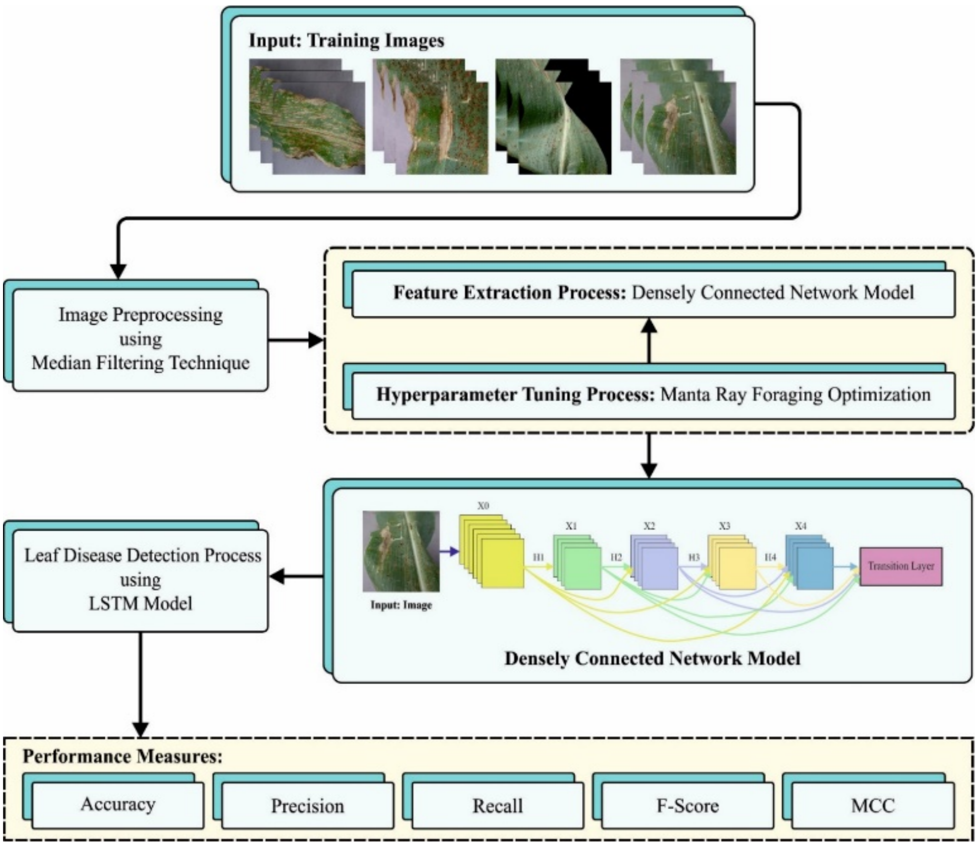

Fig. 1. Structure of the proposed IMLDD-MRFODL approach.

A. *Image Preprocessing*

Primarily, the IMLDD-MRFODL approach applies the MF technique to remove noise [19]. MF eliminates the "salt and pepper" noise that appears as an image's random bright and dark pixels. Due to such impulsive noise, this method is particularly relevant when the linear filter may not work well. Substituting the pixel value with the median efficiently eliminates the outlier value caused by noise while maintaining the fine details and edges in an image, in contrast to other smoothing filters, such as the mean filter, which can blur structures and edges.

B. *Feature Extraction using DenseNet*

The IMLDD-MRFODL technique applies the DenseNet model to derive feature vectors. Prior studies faced a common issue with CNN: the gradient update becomes irrelevant once the method is too deep, and the derivation value evaluated for BP converts lower [20]. This problem is widely known as the gradient disappearing issue. To overcome this issue, the concept of connecting each layer to increase the data flow was discovered. DenseNet comprises seven dense blocks, each having four convolution sublayers. The outputs from the sublayers are concatenated into the input and transmitted by the following sublayers. Each symmetrical sublayer comprises the ReLU activation function, Batch Normalization, Convolution, and Dropout. In all the cases, the dropout likelihood is 0.5, and the size is 5. This is stimulated by the skip connection of ResNet in which the layer only gets feature mapping from the final layer. This dense connection helps make differentiated features since all layers receive the feature mapping of the prior layer as input. The dense connection amid the sublayers follows the sequential flow. A sublayer completes the forward pass as long as each prior sublayer has completed its computation. The dense connection allows the best gradient flow with fewer parameters.

C. Hyperparameter Tuning with the MRFO Approach

In this phase, the IMLDD-MRFODL methodology uses the MRFO technique. The steps and concept of the MRFO methodology are presented and discussed in [21]. They are the chain, cyclone, and somersault food search tactics.

1) Chain Food - Searching Approach

In this phase, every MR updates the location of the MR situated in front of it and its existing position using the optimal solution so far achieved, excluding the first one, which updates its position based on the best solution obtained. The mathematical expression of the chain food searching approach is:

$$p_k^{itr+1} = \begin{cases} p_k^{itr} + rn * \left(Gbest^{itr} - p_k^{itr}\right) + 2 * rn \\ * \sqrt{|log(r)|} * \left(Gbest^{itr} - p_k^{itr}\right)\ k = 1 \\ p_k^{itr} + rn * \left(p_{k-1}^{itr} - p_k^{itr}\right) + 2 * rn \\ * \sqrt{|\log(r)|} * \left(Gbest^{itr} - p_k^{itr}\right)\ k = 2, \dots, N \end{cases} \tag{1}$$

where rn means a number in [0,1], N denotes the overall amount of MRs (viz., population size), p_k^{itr} shows the position of the k^{th} manta ray at itr iteration, $Gbest$ demonstrates the global best solution attained, and p_k^{itr+1} indicates the new position in the subsequent iteration.

2) Cyclone Food Searching Approach

The MR walks in the search space cyclically. The mathematical modeling of the cyclone food searching process is:

$$p_k^{itr+1} = \begin{cases} Gbest + rn * \left(Gbest^{itr} - p_k^{itr}\right) + 2 * e^{rn * \frac{\mathrm{Max}Itr - itr + 1}{\mathrm{Max}Itr}} * \sin(2 * \pi * rn) * \left(Gbest^{itr} - p_k^{itr}\right), \\ k = 1 \\ Gbest + rn * \left(p_{k-1}^{itr} - p_k^{itr}\right) + 2 * e^{rn * \frac{\mathrm{Max}Itr - itr + 1}{\mathrm{Max}Itr}} * \sin(2 * \pi * rn) * \left(Gbest^{itr} - p_k^{itr}\right), \\ k = 2, \dots, N \end{cases} \tag{2}$$

$MaxItr$ and rn denote the iteration count and a random integer within [0,1]. Based on random position, each MR makes a random walk by updating the location to improve diversification, as follows:

$$p_k^{itr+1} = \begin{cases} p_{rn} + rn * \left(p_{rn}^{itr} - p_{rn}\right) + 2 * e^{rn * \frac{\mathrm{Max}Itr - itr + 1}{\mathrm{Max}Itr}} * \\ sin(2 * \pi * rn) * \left(p_{rn}^{itr} - p_k^{itr}\right), \\ k = 1 \\ p_{rn} + rn * \left(p_{k-1}^{itr} - p_k^{itr}\right) + 2 * e^{rn * \frac{\mathrm{Max}Itr - itr + 1}{\mathrm{Max}Itr}} * \\ sin(2 * \pi * rn) * \left(p_{rn}^{itr} - p_k^{itr}\right), \\ k = 2, \dots, N \end{cases} \tag{3}$$

where p_{rn} is a reference point in the searching space:

$$p_m = LowerBound + rn * (UpperBound - LowerBound) \tag{4}$$

$LowerBound$ and $UpperBound$ are defined as the lower and upper limitations of the searching space.

3) Somersault Food Searching Approach

In this phase, the MR changes its position by performing a somersault and walking towards the optimal position obtained. This can be mathematically modeled and simulated by (5):

$$p_k^{itr+1} = p_k^{itr} + Somersault\ factor * \left(rn1 * Gbest - rn_2 * p_k^{itr}\right) \tag{5}$$

where $i = 1, \dots, N$, the $Somersault\ factor$ is assumed to be 2, and rn_1 and rn_2 signify the arbitrary value within [0,1]. The MRFO method uses a Fitness Function (FF) to enhance classifier efficiency by assigning higher values to more significant candidate outputs The error rate reduction of the classification is regarded as an FF.

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{No.of\ misclassified\ instances}{Total\ No.of\ instances} \times 100 \tag{6}$$

D. Image Classification Utilizing the LSTM Approach

The LSTM model is used for classification, utilizing its inherent recursive nature [22]. With its input, forget, and output gates, the LSTM network effectually administers long-term dependencies in sequential data like vibration signals, addressing gradient exploding and vanishing issues. This method is appropriate for examining time series data, namely the changing trends reflected in the vibration signal dataset employed in this study. The LSTM method is used for state detection in time sequences, where each unit contains a memory cell withing the LSTM structure. The memory unit is managed by three gates, typically operated by tanh or sigmoid functions. Specifically, the LSTM unit integrates external data from previous hidden and current states at regular intervals to process data. Also, the internal input, having the memory units' layer, is dispersed across all gates to compute data from several sources, influencing the activation status. The input gate cooperates with the memory unit, guided by the forget gate, to generate a new memory unit. This unit endures processing via a non-linear function and dynamic control by the output gate before becoming the LSTM unit's output. These networks efficiently manage long-term dependencies by selectively retaining valuable data, discarding unnecessary data, and transmitting relevant data to subsequent stages via the resultant gate. The data transmission within LTSM is shown below:

Input gate:

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \quad (7)$$

Forget gate:

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right) \quad (8)$$

Output gate:

$$0_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \quad (9)$$

Cell memory state

$$c_t = f_t c_{t-1} + i_t \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (10)$$

Cell output:

$$h_t = \mathrm{o}_t \tanh(c_t) \quad (11)$$

where σ refers to the sigmoid activation function; $W_{xc}, W_{xi}, W_{xf}, W_{xo}$ denote the weight matrix related to the input signal x_t; $W_{hc}, W_{hi}, W_{hf}, W_{ho}$ indicate the weighted matrix linked to the outcome signal h_t of the hidden state; W_{ci}, W_{cf}, W_{co} show the diagonal matrix connected to the output vector of neuron activation and gate functions, and b_i, b_c, b_f, b_o represent the bias vector.

IV. RESULTS AND DISCUSSION

The maize leaf ailment recognition of the IMLDD-MRFODL method is examined using the plant disease dataset in [23]. The dataset includes four classes with 7316 instances, as evidenced in Table I. Figure 2 displays some sample images. The simulation uses the Python 3.6.5 tool on PC i5-8600k, 250GB SSD, GeForce 1050Ti 4GB, 16GB RAM, and 1TB HDD. The parameter settings are: learning rate: 0.01, activation: ReLU, epoch count: 50, dropout: 0.5, and batch size: 5.

TABLE I. DATASET SPECIFICATION

Class	Instance count
Gray_leaf_spot	1642
Common_Rust	1907
Leaf_Blight	1908
Healthy	1859
Overall	7316

Figure 3 illustrates the classifier evaluation of the IMLDD-MRFODL method on 80:20 training/testing rate of the TR/TS set. Figures 3(a)-(b) depict the confusion matrices presented. The output portrayed that the IMLDD-MRFODL approach precisely detected and classified all four classes. Figure 3(c) depicts the PR study of the IMLDD-MRFODL approach. The output illustrated that the IMLDD-MRFODL approach has attained superior PR accomplishment in all four classes. Figure 3(d) specifies the ROC of the IMLDD-MRFODL method. It can be seen that the IMLDD-MRFODL methodology attained efficient experimental results with great ROC on all four classes.

Fig. 2. Sample images.

The Maize leaf disease recognition evaluation of the IMLDD-MRFODL approach with 80:20 of TR/TS set analysis is exhibited in Table II. The experimental data identified the productive accomplishment of the IMLDD-MRFODL approach on diverse disease classes. On the 80% TR set, the IMLDD-MRFODL model provides average $accu_y$, $prec_n$, $reca_l$, F_{score}, and MCC of 98.14%, 96.27%, 96.27%, 96.26%, and 95.03%, respectively. On the 20% TS set, the IMLDD-MRFODL model offers average $accu_y$, $prec_n$, $reca_l$, F_{score}, and MCC of 98.57%, 97.13%, 97.12%, 97.12%, and 96.17%, respectively.

TABLE II. MAIZE LEAF DISEASE DETECTION ANALYSIS OF THE IMLDD-MRFODL APPROACH WITH 80:20 TRAINING/TESTING RATIO

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	MCC
TR set (80%)					
Gray_leaf_spot	98.27	95.83	96.62	96.22	95.11
Common_Rust	98.33	96.04	97.56	96.79	95.67
Leaf_Blight	98.26	96.15	97.16	96.65	95.48
Healthy	97.69	97.08	93.75	95.39	93.88
Average	98.14	96.27	96.27	96.26	95.03
TS set (20%)					
Gray_leaf_spot	98.91	97.12	97.74	97.43	96.73
Common_Rust	98.70	97.21	97.95	97.58	96.69
Leaf_Blight	98.77	96.99	98.47	97.73	96.89
Healthy	97.88	97.21	94.32	95.75	94.36
Average	98.57	97.13	97.12	97.12	96.17

Figure 4 showcases the classifier evaluation of the IMLDD-MRFODL method at 70:30 TR/TS set. Figure 4 signifies that the IMLDD-MRFODL model accurately identified and classified each of the four classes.

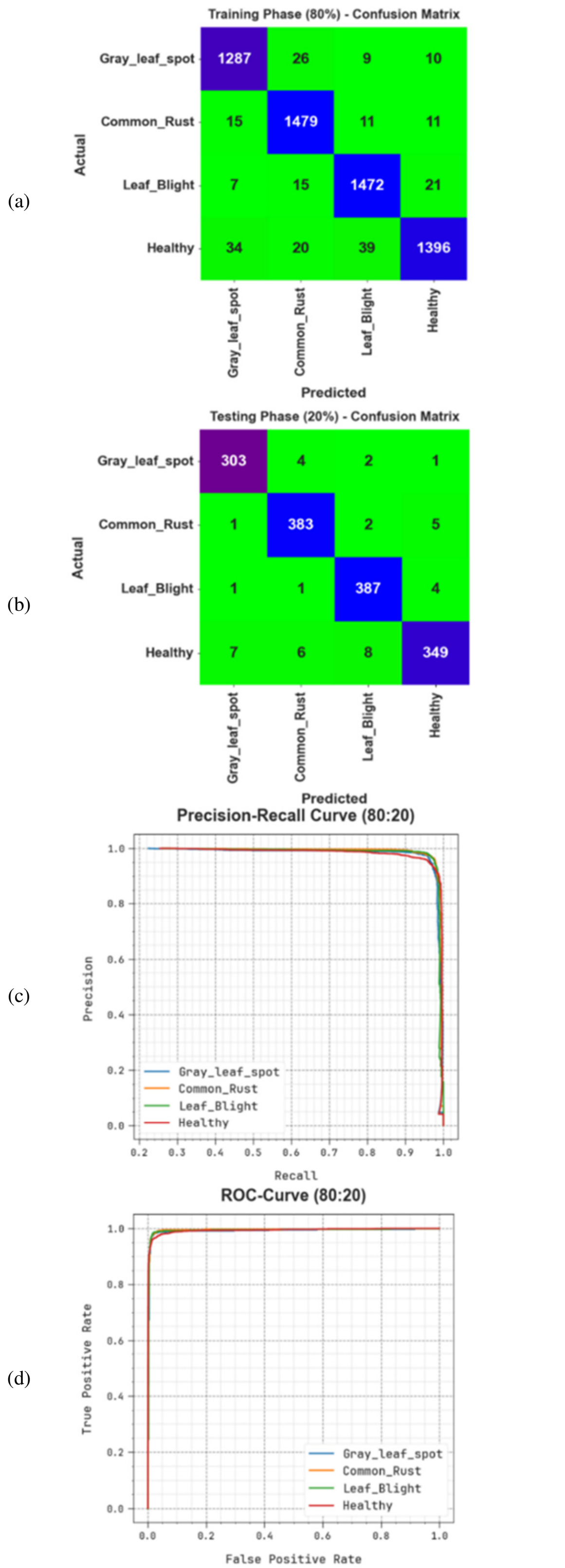

Fig. 3. 80:20 of TR/TS set: (a-b) Confusion matrices, (c-d) PR and ROC curves.

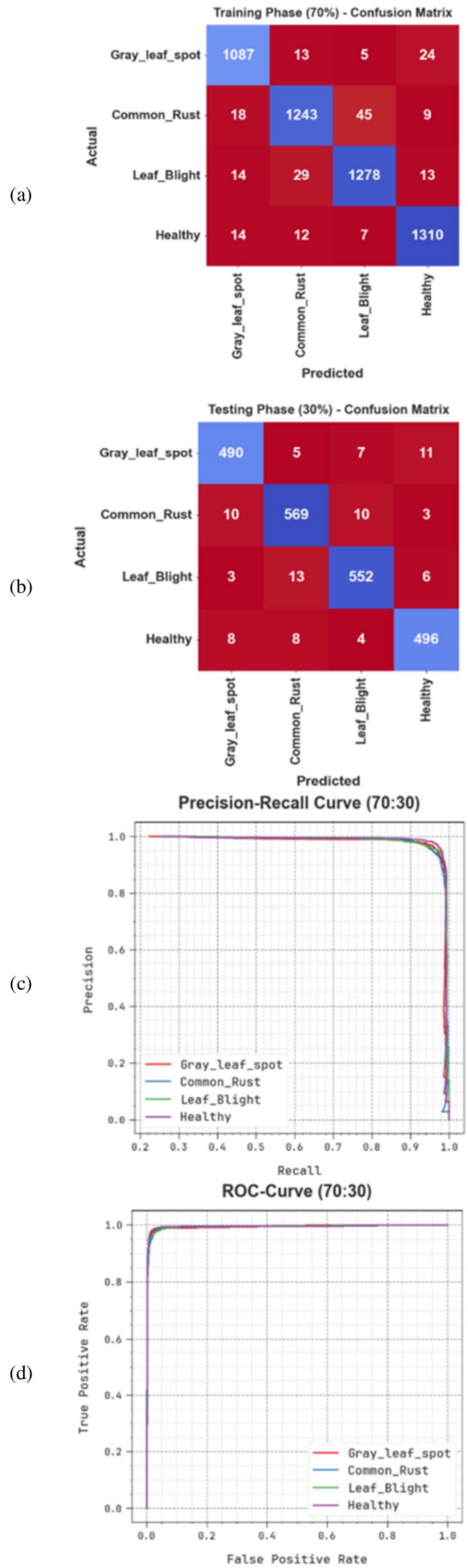

Fig. 4. 70:30 of TR/TS set: (a-b) Confusion matrices, (c-d) PR and ROC curves.

Figure 4(c) specifies the PR analysis of the IMLDD-MRFODL model. The IMLDD-MRFODL method had acquired excellent PR accomplishment in all four classes. The IMLDD-MRFODL methodology has attained practical investigational outputs with excellent ROC values under the four considered classes (Figure 4(d)).

The IMLDD-MRFODL model accuracy results with 70:30 of TR/TS are depicted in Table III. On the 70% TR set, the IMLDD-MRFODL model provided average $accu_y$, $prec_n$, $reca_l$, F_{score}, and MCC of 98.02%, 96.03%, 96.04%, 96.03%, and 94.71, respectively. On the 30% TS set, the IMLDD-MRFODL model provided average $accu_y$, $prec_n$, $reca_l$, F_{score}, and MCC of 98%, 95.99%, 95.98%, 95.99%, and 94.65%, respectively.

TABLE III. MAIZE LEAF DISEASE DETECTION ANALYSIS OF THE IMLDD-MRFODL APPROACH WITH 70:30 TRAINING/TESTING RATIO

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	MCC
TR set (70%)					
Gray_leaf_spot	98.28	95.94	96.28	96.11	95.01
Common_Rust	97.54	95.84	94.52	95.18	93.53
Leaf_Blight	97.79	95.73	95.80	95.77	94.27
Healthy	98.46	96.61	97.54	97.07	96.03
Average	98.02	96.03	96.04	96.03	94.71
TS set (30%)					
Gray_leaf_spot	98.00	95.89	95.52	95.70	94.40
Common_Rust	97.77	95.63	96.11	95.87	94.34
Leaf_Blight	98.04	96.34	96.17	96.25	94.93
Healthy	98.18	96.12	96.12	96.12	94.93
Average	98.00	95.99	95.98	95.99	94.65

Table IV outlines the comparative study results of the IMLDD-MRFODL and DCCNN, DENN, DCNN, and EO-3D-CNN [24]. The outputs show that the DCCNN approach attains poorer results, while the DENN and DCNN techniques achieve slightly closer performance. Meanwhile, the EO-3D-CNN technique achieves considerably enhanced performance. But, the IMLDD-MRFODL technique outperforms the others performance with better $accu_y$, $prec_n$, $reca_l$, and F_{score}.

TABLE IV. COMPARATIVE OUTPUT OF IMLDD-MRFODL APPROACH WITH EXISTING MODELS

Method	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
DCCNN	97.20	95.35	95.48	95.52
DENN	97.50	95.63	95.33	95.91
DCNN	97.80	96.07	95.71	95.76
EO-3D-CNN	98.00	95.57	95.06	95.96
IMLDD-MRFODL	98.57	97.13	97.12	97.12

V. CONCLUSION

This paper focused on designing, developing, and validating the novel IMLDD-MRFODL technique. The IMLDD-MRFODL technique aims to detect and categorize maize leaf ailments. The IMLDD-MRFODL technique encompasses MF-based pre-processing, DenseNet feature extraction, LSTM classification, and MRFO-based hyperparameter tuning. The comparative study of the IMLDD-MRFODL approach exhibited superior performance under all considered measures.

The IMLDD-MRFODL approach may encounter restrictions in scalability to larger datasets. It could benefit from future studies concentrating on real-time implementation and integration with precision agriculture technologies for widespread adoption.

REFERENCES

[1] C. Ashwini and V. Sellam, "An optimal model for identification and classification of corn leaf disease using hybrid 3D-CNN and LSTM," *Biomedical Signal Processing and Control*, vol. 9, Jun. 2024, Art. no. 106089, https://doi.org/10.1016/j.bspc.2024.106089.

[2] Md. A. Haque, S. Marwaha, C. K. Deb, S. Nigam, and A. Arora, "Recognition of diseases of maize crop using deep learning models," *Neural Computing and Applications*, vol. 35, no. 10, pp. 7407–7421, Apr. 2023, https://doi.org/10.1007/s00521-022-08003-9.

[3] C. K. Rai and R. Pahuja, "Northern maize leaf blight disease detection and segmentation using deep convolution neural networks," *Multimedia Tools and Applications*, vol. 83, no. 7, pp. 19415–19432, Feb. 2024, https://doi.org/10.1007/s11042-023-16398-3.

[4] X. Qian, C. Zhang, L. Chen, and K. Li, "Deep Learning-Based Identification of Maize Leaf Diseases Is Improved by an Attention Mechanism: Self-Attention," *Frontiers in plant science*, vol. 13, Jan. 2022, Art. no. 864486, https://doi.org/10.3389/fpls.2022.864486.

[5] R. Rashid, W. Aslam, R. Aziz, and G. Aldehim, "An Early and Smart Detection of Corn Plant Leaf Diseases Using IoT and Deep Learning Multi-Models," *IEEE Access*, vol. 12, pp. 23149–23162, Jan. 2024, https://doi.org/10.1109/ACCESS.2024.3357099.

[6] L. Ma, Q. Yu, H. Yu, and J. Zhang, "Maize Leaf Disease Identification Based on YOLOv5n Algorithm Incorporating Attention Mechanism," *Agronomy*, vol. 13, no. 2, Feb. 2023, Art. no. 521, https://doi.org/ 10.3390/agronomy13020521.

[7] E. Iren, "Comparison of YOLOv5 and YOLOv6 Models for Plant Leaf Disease Detection," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13714–13719, Apr. 2024, https://doi.org/ 10.48084/etasr.7033.

[8] R. Rajamohanan and B. C. Latha, "An Optimized YOLO v5 Model for Tomato Leaf Disease Classification with Field Dataset," *Engineering, Technology & Applied Science Research*, vol. 13, no. 6, pp. 12033–12038, Dec. 2023, https://doi.org/10.48084/etasr.6377.

[9] A. Abbas, U. Maqsood, S. U. Rehman, K. Mahmood, T. AlSaedi, and M. Kundi, "An Artificial Intelligence Framework for Disease Detection in Potato Plants," *Engineering, Technology & Applied Science Research*, vol. 14, no. 1, pp. 12628–12635, Feb. 2024, https://doi.org/ 10.48084/etasr.6456.

[10] F. Khan, N. Zafar, M. N. Tahir, M. Aqib, H. Waheed, and Z. Haroon, "A mobile-based system for maize plant leaf disease detection and classification using deep learning," *Frontiers in Plant Science*, vol. 14, May 2023, Art. no. 1079366, https://doi.org/10.3389/fpls.2023.1079366.

[11] M. Subramanian, K. Shanmugavadivel, and P. S. Nandhini, "On fine-tuning deep learning models using transfer learning and hyper-parameters optimization for disease identification in maize leaves," *Neural Computing and Applications*, vol. 34, no. 16, pp. 13951–13968, Aug. 2022, https://doi.org/10.1007/s00521-022-07246-w.

[12] Y. Xu, B. Zhao, Y. Zhai, Q. Chen, and Y. Zhou, "Maize Diseases Identification Method Based on Multi-Scale Convolutional Global Pooling Neural Network," *IEEE Access*, vol. 9, pp. 27959–27970, Jan. 2021, https://doi.org/10.1109/ACCESS.2021.3058267.

[13] L. Gunisetti, S. B. Koduri, and V. Jagannathan, "Optimized deep learning system for smart maize leaf disease detection in IoT platform via routing algorithm," *Multimedia Tools and Applications*, vol. 82, no. 9, pp. 13533–13555, Apr. 2023, https://doi.org/10.1007/s11042-022-13775-2.

[14] K. Ullah, M. A. Jan, and A. Sayyed, "Automatic Diseases Detection and Classification in Maize Crop using Convolution Neural Network," *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 10, no. 2, pp. 675–679, Apr. 2021, https://doi.org/ 10.30534/ijatcse/2021/301022021.

[15] W. Zeng, H. Li, G. Hu, and D. Liang, "Identification of maize leaf diseases by using the SKPSNet-50 convolutional neural network model," *Sustainable Computing: Informatics and Systems*, vol. 35, Sep. 2022, Art. no. 100695, https://doi.org/10.1016/j.suscom.2022.100695.

[16] M. Masood *et al.*, "MaizeNet: A Deep Learning Approach for Effective Recognition of Maize Plant Leaf Diseases," *IEEE Access*, vol. 11, pp. 52862–52876, 2023, https://doi.org/10.1109/ACCESS.2023.3280260.

[17] P. B. Madhavi, T. Subaranjani, S. Sigtia, and V. Mehta, "A Hybrid Deep Learning Approach for Accurate and Transparent Maize Plant Disease Classification," in *11th International Conference on Computing for Sustainable Global Development*, New Delhi, India, Mar. 2024, pp. 229–234, https://doi.org/10.23919/INDIACom61295.2024.10498754.

[18] P. Pavithra and P. Aishwarya, "Plant leaf disease detection using hybrid grasshopper optimization with modified artificial bee colony algorithm," *Multimedia Tools and Applications*, vol. 83, no. 8, pp. 22521–22543, Mar. 2024, https://doi.org/10.1007/s11042-023-16148-5.

[19] N. Win, K. Kyaw, T. Win, and P. Aung, "Image Noise Reduction Using Linear and Nonlinear Filtering Techniques," *International Journal of Scientific and Research Publications*, vol. 9, no. 8, pp. 816–821, Aug. 2019, https://doi.org/10.29322/IJSRP.9.08.2019.p92113.

[20] R. Pramanik, B. Banerjee, G. Efimenko, D. Kaplun, and R. Sarkar, "Monkeypox detection from skin lesion images using an amalgamation of CNN models aided with Beta function-based normalization scheme," *PLOS ONE*, vol. 18, no. 4, Apr. 2023, Art. no. e0281815, https://doi.org/10.1371/journal.pone.0281815.

[21] M. Abdullahi, I. H. Hassan, M. D. Abdullahi, I. Aliyu, and J. Kim, "Manta Ray Foraging Optimization Algorithm: Modifications and Applications," *IEEE Access*, vol. 11, pp. 53315–53343, Jan. 2023, https://doi.org/10.1109/ACCESS.2023.3276264.

[22] D. Song and Y. Zhao, "A Data-Driven Approach Using Enhanced Bayesian-LSTM Deep Neural Networks for Picks Wear State Recognition," *Electronics*, vol. 12, no. 17, Jan. 2023, Art. no. 3593, https://doi.org/10.3390/electronics12173593.

[23] "PlantVillage Dataset." https://www.kaggle.com/datasets/emmarex/plantdisease.

[24] C. Ashwini and V. Sellam, "EOS-3D-DCNN: Ebola optimization search-based 3D-dense convolutional neural network for corn leaf disease prediction," *Neural Computing and Applications*, vol. 35, no. 15, pp. 11125–11139, May 2023, https://doi.org/10.1007/s00521-023-08289-3.