IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 5, October 2025, pp. 4050~4060
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i5.pp4050-4060

Laurent series intelligent multidimensional object optimization classification for crop disease detection

Anandhan Karunanithi[1,2], Ajay Shanker Singh[2]
[1]Department of Computer Science and Engineering, GITAM Deemed to be University, Bengaluru, India
[2]School of Computing Science and Engineering, Galgotias University, Greater Noida, India

Article Info

Article history:

Received Jun 6, 2024
Revised Jun 28, 2025
Accepted Aug 6, 2025

Keywords:

Crop diseases
Generative adversarial networks
Intelligent multidimensional
Laurent series
LIMO classification
Multi-objective and cognitive learning routing

ABSTRACT

Rice crop disease detection and its diagnosis methods are vitally important for the agriculture field to be sustainable. Traditional methods suffer from paddy yield, complex issues, and crop diseases, leading to inefficiencies in the agriculture domain. Our research provides space for a novel approach, combining the Laurent series with an intelligent multidimensional object optimization (LIMO) classification framework based on generative adversarial networks (GANs) to recognize various types of crop diseases in agricultural fields. Through our proposed research work, IoT nodes sense the values of the field crop, and gathered information is shared with processing units through base station communication. Multi-objective and cognitive learning routing (MOCLEAR) protocol supports choosing the optimal path for data transmission improvement. Then, for image segmentation, GAN combined with cognitive residual convolution network (CRCNet) is modified to segment values from input images. After receiving segment input images, perform feature extraction and classification using significant attributes. The proposed Laurent series with IMO is newly formulated by integrating the Laurent series with Intelligent IMO algorithms. Through extensive experimentation and analysis, the proposed LIMO-based GAN network provides effective and improved performance metrics with overall accuracy, sensitivity, and specificity values at 91.5%, 92.6%, and 92.41%, respectively.

Corresponding Author:

Anandhan Karunanithi
Department of Computer Science and Engineering, GITAM Deemed to be University
Bengaluru, Karnataka, India
Email: anandhanpg13@gmail.com

1. INTRODUCTION

Rice is a staple food for a significant portion of the global population, and its cultivation is vital for food security, especially in countries like India, where agriculture forms the backbone of the economy. However, rice crops are highly susceptible to various diseases, which can lead to substantially less productivity, reduced food security, and economic difficulty for farmers. In earlier methods of disease detection are often manual, time-consuming, and prone to errors, leading to delayed interventions and further crop damage [1]. Rice plants are vulnerable to various leaf diseases, which can significantly impact crop yield and quality. These diseases, caused by fungi, bacteria, or viruses, often manifest as discoloration, lesions, or wilting, affecting the plant's ability to photosynthesize efficiently. Our primary focus is on the detection and diagnosis of rice crop diseases using advanced AI techniques, specifically a novel framework that combines the Laurent series with intelligent multidimensional object optimization (LIMO) and generative adversarial networks (GANs). This not only helps in reducing crop losses but also supports sustainable agricultural practices by minimizing the need for excessive pesticide use [2]. You only look once (YOLO) previous version did not have a constraint on location prediction, making it unstable on early iterations. The YOLOv2 predicts five parameters and applies the darknet function to a constraint if its value is between 0 and 1. The YOLOv2 method was implemented with a hidden layer for effective object retrieval in the smart agriculture field. YOLOv2 indicates information to farming people after the identification of rice crop diseases. Also, YOLOv2 improves productivity with needed information. This YOLOv2 model, through the sensor, receives plant leaf disease images and is refined with a median filter after the segmentation and classification process [3]. An advanced optimized algorithm supports the LIMO model to train the rice crop disease dataset to the machine. IoT has plenty of opportunities and has contributed a vital role in wireless networks, especially in the last fifteen years.

Various crop disease detection methods need more accuracy and dimensional corrections. Through this research work, planning to gear up the accuracy of the rice (paddy) crop disease detection system with the effect of a new-fangled image classification algorithm with cognitive learning [4]. Through this research work, rice crop disease detection and prevention with the help of GAN networks, which provide parallel significant speed-up samples (input images). Also, GANs are getting train data through LIMO's proposed framework, which integrates both the LIMO algorithm to improve the overall hit rate and accuracy of rice crop disease detection and prevention. For the texture classification approach, using a gray level co-occurrence matrix that considers overlap and edge pixel extract essential attributes is revised by the GAN network, which is trained by LIMO. The generator creates synthetic images of crop diseases based on the input data, while the discriminator evaluates the authenticity of these images. The two networks are trained simultaneously, with the generator improving its ability to create realistic images and the discriminator becoming better at distinguishing between real and synthetic images. GANs are particularly effective in scenarios where the available dataset is limited or imbalanced. By generating synthetic images, GANs help create a more diverse and representative dataset, which improves the performance of the classification model. The proposed system leverages IoT technology to collect real-time data from agricultural fields [5], which is then processed using a multi-objective and cognitive learning routing (MOCLEAR) protocol for optimal data transmission. The framework aims to improve the accuracy and efficiency of rice crop disease detection, which is critical for sustainable agriculture [6]. This paper is worth reading because it introduces a novel approach that combines the Laurent series with LIMO and GANs to create a more accurate and efficient system for rice crop disease detection. The proposed framework addresses the limitations of existing methods by integrating advanced AI techniques with IoT, enabling real-time monitoring and early detection of diseases [7].

The research's main aim is to implement a four-phase framework for rice crop disease detection: IoT communication phase: sensors collect data from the field, which is transmitted to a processing unit using the MOCLEAR protocol for optimal routing. Pre-processing phase: The collected data undergoes data reduction and feature engineering to improve the quality of input values for segmentation and classification. Image processing phase: the cognitive residual convolution network (CRCNet) is used for image segmentation, followed by feature extraction and classification using the LIMO framework. Disease detection phase: the LIMO framework, combined with GANs, classifies the disease and provides insights into the severity of the infection. The paper also includes a comparative analysis of the proposed framework with existing models, demonstrating its superior performance in terms of accuracy, sensitivity, and specificity. The structure of the sections is as follows: section 2 provides a review of related work in the field of crop disease detection, highlighting the limitations of existing methods. Section 3 describes the materials and techniques used in the proposed framework, including the dataset, IoT communication, and the LIMO classification framework. Section 4 details the experimental results, comparing the performance of the proposed framework with existing models. Section 5 concludes the paper, summarizing the key findings and suggesting future directions for research.

2. RELATED WORK

Earlier investigations in the domain of rice disease classification using deep learning methods have been directed extensively by experts globally. This study investigated the effects of IoT, an important technology that needs to connect communication devices to the internet. It makes an immense smart application. The IoT has grown rapidly, and that is the reason many researchers are showing interest in this platform. An agro-weather station installed in an agriculture field, through this platform, can collect versatile information with various sensors for the application's sustainability. Various dimensional features are extracts and detecting crop diseases in an effective manner. With this computational intelligence, we can able to perform numerous sensors and communication (network) devices for smart agricultural processes, which improve extreme productivity. Cloud models, machine learning, and IoT materialization technologies play a vital role in field information collection for smart farming [8].

The author examined how crop disease detection methods effectively control farming factors by using various sensors with those values, creating a convolutional neural network model-trained dataset. This model amended the overall framework and is an effective monitoring system based on thermal camera images to find whether crop leaves are infected or not. Invented a new framework for the agricultural industry that performs edge computing for data transmission from IoT sensors to cloud storage. The main objective of this model is field monitoring, evaluating, and transmitting values to the cloud. Optimization also plays a vital role in this model, which means continuous monitoring and evaluating values communicates the cloud in assorted dairy circumstances. The author validated this in five crops, 17 diseases, and a 121,955 images dataset over field conditions. The author implemented a deep learning model and achieved a multi-crop convolution neural network (CNN) accuracy of 98%. However, this model is absent in training dynamically the learning algorithms for miscellaneous crop diseases and symptoms [8], [9]. This study investigated crop disease detection with enough weighty literature review and various activities to tolerate the new IoT model for farming. One more thing is the IoT platform provides user-friendly models for crop disease detection and prevention. The IoT model directly connects farmers with computation (intelligence computation). In this study, the author achieved an accuracy of 82.41%, and the F1-score of 67% was the lowest among all the classifiers. The smart agriculture system works fast and accurately on crop disease identification with summarised different train sets for meticulousness in the agriculture field [10]. From the above literature survey, different solutions for plant disease detection methods are not up to expectations.

3. METHOD

3.1. Experimental setup

The experiment was conducted using MATLAB R2023b, leveraging its robust image processing, deep learning toolboxes for segmentation and classification tasks. The system was configured with a Windows 11 operating environment, a 64-bit architecture, and 16 GB RAM. Both the training and testing process of LIMO with GAN is facilitated with TensorFlow 2.15 as well as Keras 2.x. The Laurent series is a mathematical tool used in complex analysis to represent functions with singularities. In our framework, we integrate the LIMO to enhance the accuracy of crop disease detection.

3.2. Data acquisition

Nowadays, we are equipped with different types of sensors in farming using the sensed data used for our research work. The Table 1 listed overview of diseases with a number of images and resolutions. The rice crop disease dataset contains various rice crop disease images, around 2,400 various crop disease images (various range of resolution jpeg format images) datasets used for this experiment. The dimensionality of each dataset was various quantities, various sizes of images, and the characteristic of the attribute (like HSV, gradient, and RGB). This dataset is used in three stages: first pre-processing, second image enhancement, and segmentation, and last one is classification methodology.

Table 1. Dataset description [11]–[13]

Disease type	Number of images	Image resolution
Bacterial blight	300	1920×1080
Bacterial leaf streak	250	1920×1080
Blast (leaf and collar)	400	1920×1080
False smut	200	1920×1080
Rice grassy stunt	150	1920×1080
Brown spot	300	1920×1080
Total images	2,400	NA

This advanced framework provides markable improved performance on crop disease detection systems, but the main drawback of this system is its struggle with including various types of disease training data. Streaming image inputs-based crop disease detection system to detect the crop diseases and their level was formulated with real-time crop disease detection [14], [15]. At the initial level, the streaming image was converted into static-margined multiple images. In the second step streamed multiple images were diagnosed with object identification. Here, this process also takes gradient values and provides mapping, which is called image segmentation. At the last, images are prepared for disease detection results. Figure 1 shows the overall architecture of crop disease detection. This model encompasses a few levels only there are raw images collected from the agricultural field using various sensors, pre-processing (252×252 size of images, data transformation, data reduction, and feature engineering), segmentation using CRCNet, feature learning, feature's extraction, classification using proposed LIMO with GAN, and evaluation metrics. The plant disease process has to find the depth of diseases attacking a particular crop [16]–[18]. This severity identification is also divided into three phases like networks (authentic, malicious, and attacker). The Laurent series allows us to model complex patterns in the data, particularly in the presence of noise or irregularities in the images. By incorporating the Laurent series, we can better capture the understated variations in crop disease symptoms, which are often missed by traditional methods. LIMO is an optimization algorithm inspired by the hunting behavior of grey wolves. It is used to optimize the feature selection and classification processes in our framework. LIMO combines the strengths of IMO with cognitive learning techniques to improve the accuracy and efficiency of disease detection. GANs are a class of deep learning models that consist of two neural networks: a generator and a discriminator [19]. In our framework, GANs are used to generate synthetic images of crop diseases, which are then used to augment the training dataset. This helps in improving the robustness and generalization of the model. CRCNet is a modified version of the traditional CNN that incorporates cognitive learning and residual connections. It is used for image segmentation and feature extraction in our framework. MOCLEAR is a routing protocol used in the IoT communication phase of our framework. It is designed to optimize the transmission of data from the sensors to the processing unit, ensuring minimal loss and maximum efficiency. Before the images are processed by the CRCNet and LIMO frameworks, they undergo a series of preprocessing steps, including feature engineering and data reduction.

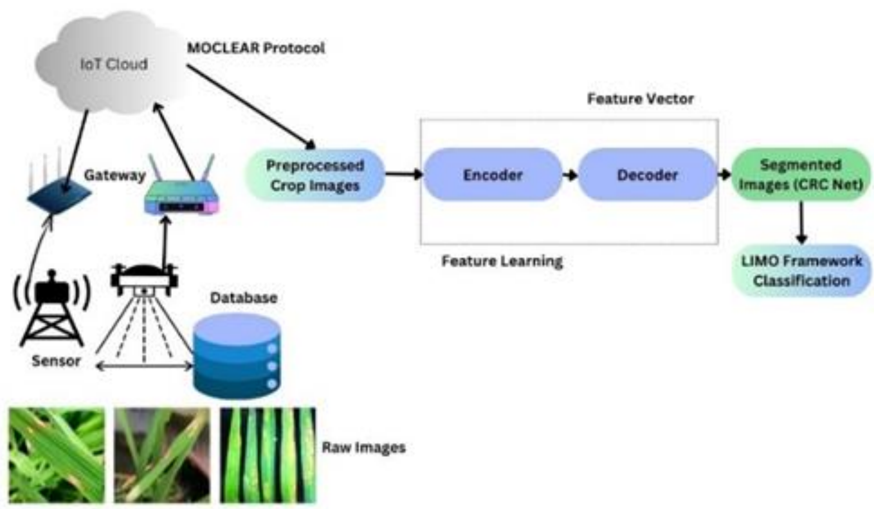


Figure 1. Architecture of crop disease detection using LIMO with GAN approach model

These steps are designed to improve the quality of the input data and reduce the computational complexity of the model. In the IoT communication phase, sensors and other devices are subjected to network routing protocols. In this network communication phase, path selection and decision-making are carried out by multi-objective and cognitive learning-based routing algorithms [20]. Once communication started with MOCLEAR routing on board the unit got information about crop (images). After receiving images of the rice plant, regular image processing is performed. Feature engineering (pre-processing) starts the process of expert knowledge fed to the machine. Segmentation and feature extraction methods are used to attain input images through sensors and IoT devices. Feature engineering to improve the image quality and transformation for comfortability. After that, image segmentation is carried out based on the expected object, design, and color, which are segmented with CRCNet support. Feature extraction is achieved using pattern, texture, and gradient to inhale the required features to detect crop diseases [21], [22]. Finally, received features are classified and optimized, whereas rice plant disease detection is done using the LIMO framework. The proposed LIMO framework model is a combination of LIMO. LIMO framework combined with CRCNet network for rice crop disease detection for smart agriculture with IoT network. We will discuss more clearly the process of path selection (routing algorithm) and crop disease detection with cognitive learning. Assume rice crop disease dataset Rpd and x count of input values. The equation is written as in (1).

$$Rpd = \{I_1, I_2, I_3 \ldots\ldots, I_x\} \quad (1)$$

Where, I_x indicates x^{th} plant images (input). Assume that i^{th} node or device holds the values pertaining to subject field plants or crop to IoT communication phase. Rice plant data is transmitted to an onboard unit (BS), and the MOCLEAR algorithm helps to find the best route for data communication.

3.3. Cognitive learning-based MOCLEAR algorithm for data communication

In the data communication phase, received data is transmitted to an onboard unit by selecting the optimal path using a cognitive learning-based MOCLEAR algorithm. Effective and lossless data communication is archived with the help of the MOCLEAR algorithm, which is a combination of IMO and optimal cluster head node iteratively in the IoT cloud network model. IMO, the algorithm implements grey wolf hunting behaviour concepts. It has three stages: approach, hunt, and attack stages. A cognitive expert position is created, and after positioning, every legitimate move gets updated. Intelligent multi-objective optimization has four set solutions, alpha, beta, omega, and delta, with the expert position. Expert positions are also updated with a gravitational search algorithm. The MOCLEAR algorithm is the model that decides the best route for data communication to the board unit. This hybrid model is the most advantageous for finding a number of routes for data communication using convergence. The updating process archived the way that terms are included in the IMO optimization technique with the help of the IoT cloud network algorithm. Modified MOCLEAR expression as in (2).

$$GW(t+1) = \frac{GW_1+GW_2+GW_3+GW_4}{4} \tag{2}$$

Where GW_1, GW_2, and GW3 indicate the initial and continued positions of grey images. Also, GW_4 denotes, at the time, grey images end position with MOCLEAR. Further grey images representation as in (3)-(5).

$$\mathrm{GW_1} = \mathrm{GW_\alpha} - \mathrm{I_1}(\mathrm{D_\alpha}) \tag{3}$$

$$GW_2 = GW_\beta - I_2(D_\beta) \tag{4}$$

$$GW_3 = GW_\delta - I_1(D_\delta) \tag{5}$$

Where GW_α, $GW_\beta$and GW_δ denotes the optimal solution. Indicates the gap between the position and the evaluated expert position. D_β represents the reverse of D_α, i.e., the gap between the evaluated position and the expert position is β, which indicates the distance between cognitive expert δ and the prediction-based position. GW_4 indicates the position of Fractional Grey Search algorithm with a time of t, estimation equation as in (6).

$$GW_4 = \gamma C_j^i(t) + T^i(t+1) + \frac{1}{2}\gamma C_j^i(t-1) \tag{6}$$

Where $C_j^i(t)$denotes the position of expert I at the j^{th} factor at a time, whereas the expert's evaluated front position at $the\ j^{th}$ dimension in the $\mathrm{t}-1^{th}$ time is indicated by $C_j^i(t-1)$, here, $T^i(t+1)$ denotes velocity with$(t+1)^{th}$ location while γrepresents probability values from 0 to 1. Thus, rice plant data gained through sensors or cameras and other communication devices are given to an onboard unit, where rice plant disease detection and prevention is implemented.

3.4. Identification/detection of rice crop diseases

The rice crop disease detection and prevention with sensed rice crop information through IoT. After receiving values or images followed by the processes are image transformation, denoising, data reduction, image segmentation, features extraction, enhancement, image classification with optimization, and performance calculation for future machine training purposes. Image segmentation is achieved with CRCNet architecture for image localization. It is attained with segments that support significant and efficient object detection of feature extraction. Finally, LIMO proposed a framework that was performed with the GAN network MOCLEAR and trained the model with the LIMO algorithm. A detailed design of LIMO and MOCLEAR for rice crop disease detection will be discussed in the impending position of this research work. Consider the intellectual segments created from input crop images, where it denotes overall segments surviving on input rice plant image, $and\ IS_e$ represents $the\ e^{th}$ segment of the input.

$$IS = \{IS_1, IS_2, \ldots, IS_e, \ldots, IS_f\} \tag{7}$$

3.4.1. Laurent series expression

The Laurent series with complex coefficients can be used to study the behavior of functions near individualities, especially in complex analysis. A laurent polynomial is a laurent series in which only a finite number of coefficients are non-zero. The Laurent polynomial differs from normal polynomials in that it can have negative degree terms. Where f(x) is Laurent series complex function, and y is constant with a_n defined by a contour integral.

$$f(x) = \sum_{n=-\infty}^{\infty} a_n (x - y)^n \tag{8}$$

3.5. LIMO with GAN network for rice crop disease prevention and detection

This proposed LIMO framework aims to identify the disease of rice crops with intellectual multi-object optimization and MOCLEAR. Laurent series implements the methods of complex variables with the addition of infinite terms and extensions. For image processing and object detection, this LIMO framework is an effective and powerful detection method because of computational integration and infinite sum creation. Moreover, this LIMO series is a one-step process of monitoring with high-dimensional terms. This Laurent series supports the deriving of imaginary upper error and convergence. The IMO model maintains stability between manipulation and investigation. IMO, Laurent seriously increases the optimal way for conjunction processes, the most favorable ground solutions, and the symmetry between trained and test data. Here, integrated IMO optimization and the Laurent series are used to raise the overall throughput significantly. Figure 2 shows the following GAN with LIMO network and its architecture used in this rice plant disease detection system. GAN networks involve two types of neural network models: generators and discriminators. Generators make predictions or approximate samples on an original or expected outcome basis. Discriminator finds the variation from regular activities. This process between generator and discriminator models leads up to the levels of perfection. Various optimum values are received through different algorithms that support the training of crop disease images and the compilation of the framework.

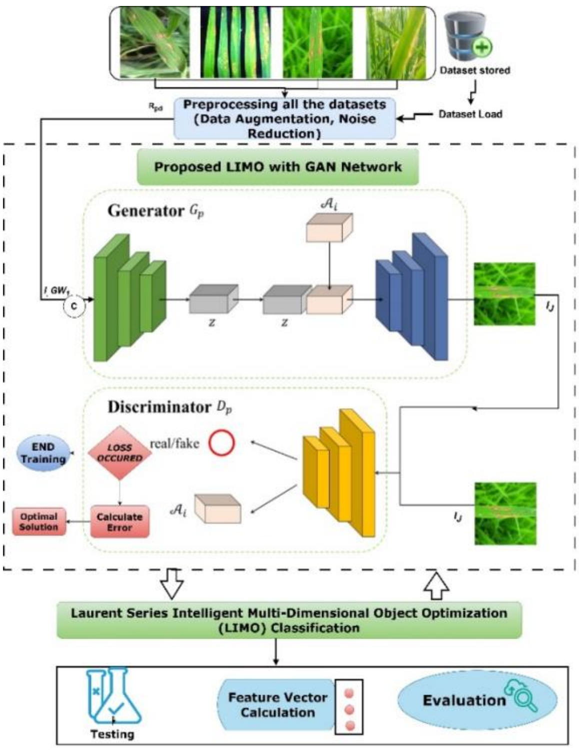


Figure 2. Rice plant disease detection using LIMO with GAN framework

4. RESULTS AND DISCUSSION

Our research work investigated the effects of LIMO classification and MOCLEAR segmentation on rice crop disease detection. While earlier studies have explored the impact of deep learning-based classification methods and IoT-based disease monitoring, they have not explicitly addressed its influence on the integration of the Laurent series with IMO for enhanced disease detection accuracy. We found that the integration of LIMO classification with MOCLEAR segmentation correlates with enhanced accuracy in rice crop disease detection. Our proposed method in this study provides a tremendously advanced proportion of correctly classified disease instances compared to misclassified cases. Figure 3 shows experimental analysis using LIMO with GAN network, Figure 3(a) explains the various rice crop disease images obtained from the rice crop disease dataset. Figure 3(b) shows an image pre-processing with data reduction and feature engineering contained from input values. Figure 3(c) describes the ground truth values of input images segmented input obtained boundary values by CRCNet is represented in Figure 3(d) final segmentation process. This performance analysis focused on calculating highly accurate prediction and recall with the proposed LIMO in the GAN network to express its efficacy in standings of accuracy, recall, precision, sensitivity, and specificity metrics. This performance analysis process has diverse dimensionalities, such as various epoch values, such as 2,500 to 3,400, and different batch sizes (ranging from 80 to 220). The proposed method could potentially enhance the accuracy of crop disease classification without negatively affecting the model's ability to distinguish between different disease types. Figure 4 shows the experimental rice plant disease results conquered with the LIMO framework (Laurent series-IMO) based GAN network using the rice crop disease dataset. The experimental analysis of LIMO with the generative network to calculate the percentage accuracy rate, sensitivity values, and specificity values using various epoch values. This study examined a comprehensive LIMO-based classification framework for rice crop disease detection with GAN-enhanced segmentation techniques. However, more thorough research may be required to validate its generalizability across different crop types, particularly in relation to variations in environmental conditions and image quality.

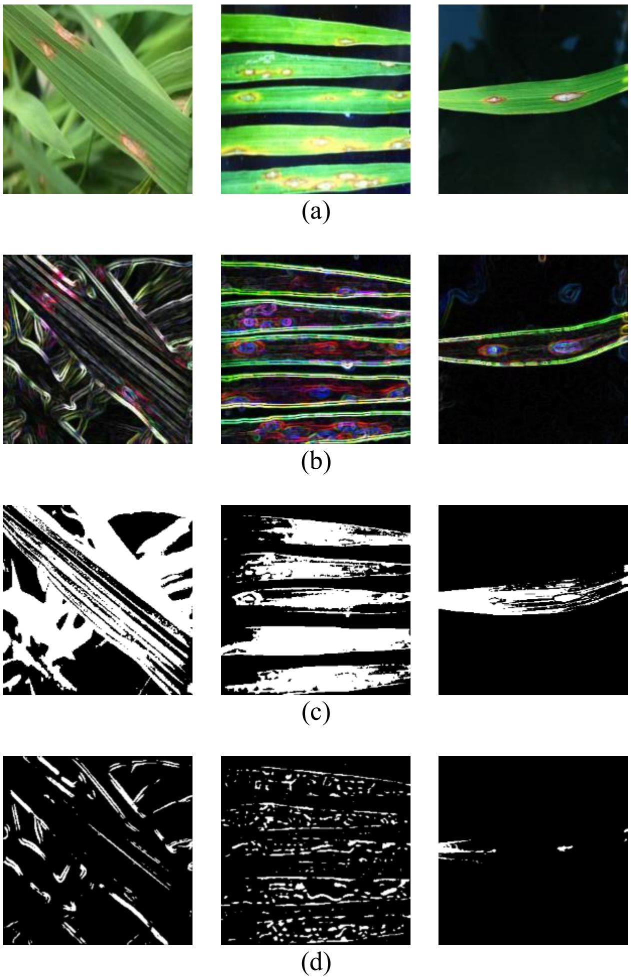
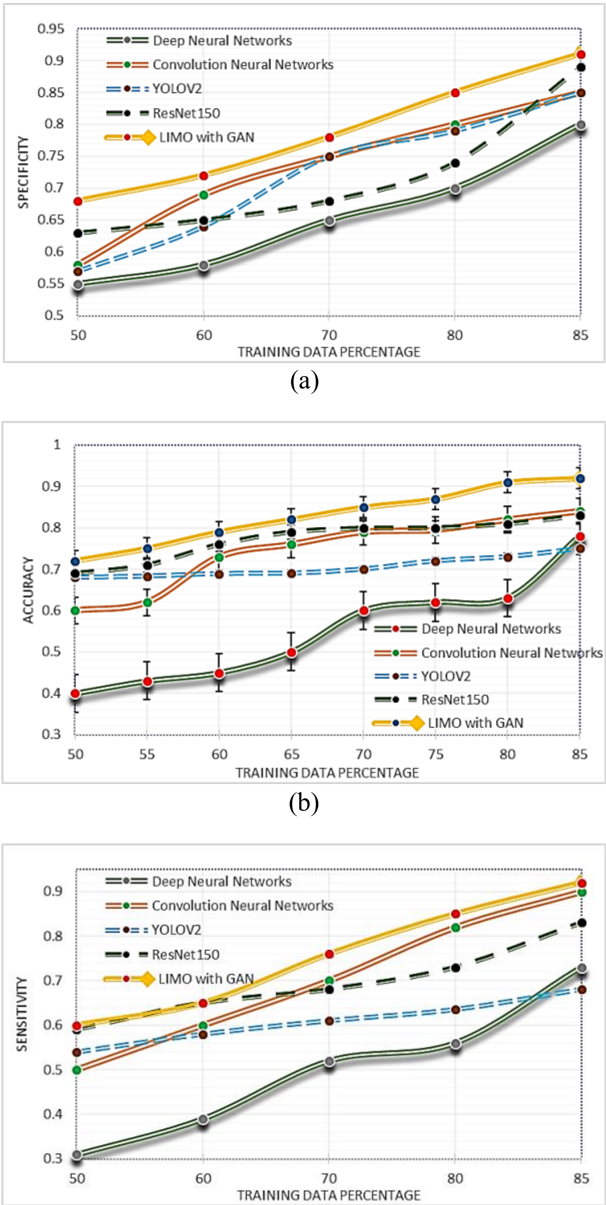


Figure 3. Experimental analysis of the LIMO combined with GAN network: (a) real input image, (b) multi-objective based pre-processing input image, (c) ground truth input image, and (d) LIMO segmentation portion

In this experimental analysis, Figure 4(a) shows the specificity factors evaluation of the proposed classification model with other existing models. At the time 85% of the training process was completed, the specificity percentage of the LIMO model was attained at only 92.4%. also, other models are Deep Neural Network (DNN) was 80.4, CNN was 85.3, YOLOv2 was 84.3, and ResNet was 88.6% [23]–[25]. Figure 4(b) explains the comparison of the sensitivity factors of LIMO with other existing models. At the time of the 85% training set completed, the sensitivity rate was LIMO=92.6, DNN=73.1, CNN=90.2, YOLOv2=68.8, and ResNet=83.4%. Figure 4(c) portrays 50 to 85% of training data attained accuracy levels with the LIMO framework and other existing models. At the end of the analysis, when the 85% training set is completed, the accuracy percentage is LIMO with GAN=91.5, DNN=70.2, CNN=80.4, YOLOv2=69.7, and ResNet150=80.3%. Through this proposed research work, LIMO supports identifying crop diseases and their levels very effectively, which helps to make advanced smart agriculture for better productivity. According to our study, a higher sensitivity in disease detection does not necessarily indicate poor specificity performance. The proposed method could potentially enhance the accuracy of crop disease classification without negatively affecting the model's ability to distinguish between different disease types.



(a)

(b)

(c)

Figure 4. Experimental analysis of 50% to 85% training set of detection (a) specificity, (b) sensitivity, and (c) accuracy by LIMO with GAN model compared with various existing models

Table 2 data provide our proposed LIMO model, with the GAN network getting the highest accuracy rate is 91.5%, whereas the accuracy rate compared with existing classification models obtained by DNN, CNN, YOLOv2, and ResNet were 70.2%, 80.4%, 69.7%, and 80.3% [19], [26], [27]. A comparison of these accuracy values reveals our proposed LIMO framework provides 34.7% better than the deep neural networks model. Experimental results show that LIMO with a GAN network can enlarge the classification accuracy rate and control overfitting issues. The accuracy and prediction rate have significantly improved since our research work provides totally different suggestions from existing GAN-only models.

These GAN networks are used to improve image resolution values controlled with cognitive learning methods. Table 2 compares the act of our proposed LIMO framework with existing models such as DNN, CNN, YOLOv2, and ResNet in terms of accuracy, sensitivity, and specificity [28]. Our study demonstrates that the LIMO classification framework combined with GAN-based segmentation is more resilient than traditional deep learning models in detecting rice crop diseases [29], [30]. Our study suggests that the proposed framework can transform agricultural disease management by enhancing detection accuracy, ensuring real-time monitoring, and enabling more efficient decision-making. These advancements not only improve crop yield and quality but also contribute to the broader goal of sustainable and technology-driven agriculture and real-time disease prediction and monitoring.

Table 2. Overall performance analysis of accuracy, sensitivity, and specificity

Performance analysis percentage (%)	DNN	CNN	YOLOv2	ResNet	LIMO with GAN
Dataset count	5,000	3,500	2,650	1,550	2,400
Accuracy	70.2	80.4	69.7	80.3	91.5
Sensitivity	73.1	90.2	68.8	83.4	92.6
Specificity	80.4	85.3	84.3	88.6	92.4

5. CONCLUSION

Laurent series-IMO with GAN network for rice crop disease identification and prevention in the IoT platform. Through this framework, the IoT network nodes collect values from the rice crop leaves through the sensor, although the sensed values are communicated with the base station through MOCLEAR. This MOCLEAR method selected the optimal route between transmission nodes, which nodes participated in communication. The research framework was modified on pre-processing with data reduction and feature engineering to improve the quality of object detection. Then, the cognitive residual convolutional network was revised to segment the sensed values with appropriate feature selections to improve the efficiency of crop disease identification. LIMO classification was implemented using the Laurent series and intelligent multidimensional object-based optimization. Performance analysis of our LIMO model achieved better results such as accuracy: 91.5%, specificity: 92.41%, and sensitivity: 92.6%. Paddy leaf image classification will be enhanced by continued exploration in these directions, which will address real-world challenges in agriculture. Future studies investigate the adaptability of this approach to other crops species and explore feasible methods for producing real-time disease detection systems with minimal computational overhead.

FUNDING INFORMATION

The authors state no funding was involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Anandhan Karunanithi	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	
Ajay Shanker Singh	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [AK], upon reasonable request.

REFERENCES

[1] A. F. Jimenez, P. F. Cardenas, F. Jimenez, A. Canales, and A. López, "A cyber-physical intelligent agent for irrigation scheduling in horticultural crops," *Computers and Electronics in Agriculture*, vol. 178, 2020, doi: 10.1016/j.compag.2020.105777.

[2] A. Saini, N. S. Gill, P. Gulia, A. K. Tiwari, P. Maratha, and M. A. Shah, "Smart crop disease monitoring system in IoT using optimization enabled deep residual network," *Scientific Reports*, vol. 15, no. 1, 2025, doi: 10.1038/s41598-025-85486-1.

[3] A. F. Jimenez, P. F. Cardenas, A. Canales, F. Jimenez, and A. Portacio, "A survey on intelligent agents and multi-agents for irrigation scheduling," *Computers and Electronics in Agriculture*, vol. 176, 2020, doi: 10.1016/j.compag.2020.105474.

[4] Y. Zhao *et al.*, "An effective automatic system deployed in agricultural internet of things using multi-context fusion network towards crop disease recognition in the wild," *Applied Soft Computing Journal*, vol. 89, 2020, doi: 10.1016/j.asoc.2020.106128.

[5] R. Sharma, S. S. Kamble, A. Gunasekaran, V. Kumar, and A. Kumar, "A systematic literature review on machine learning applications for sustainable agriculture supply chain performance," *Computers and Operations Research*, vol. 119, 2020, doi: 10.1016/j.cor.2020.104926.

[6] C. Zhou, Y. Zhong, S. Zhou, J. Song, and W. Xiang, "Rice leaf disease identification by residual-distilled transformer," *Engineering Applications of Artificial Intelligence*, vol. 121, 2023, doi: 10.1016/j.engappai.2023.106020.

[7] A. Subeesh and C. R. Mehta, "Automation and digitization of agriculture using artificial intelligence and internet of things," *Artificial Intelligence in Agriculture*, vol. 5, pp. 278–291, 2021, doi: 10.1016/j.aiia.2021.11.004.

[8] A. Khattab, S. E. D. Habib, H. Ismail, S. Zayan, Y. Fahmy, and M. M. Khairy, "An IoT-based cognitive monitoring system for early plant disease forecast," *Computers and Electronics in Agriculture*, vol. 166, 2019, doi: 10.1016/j.compag.2019.105028.

[9] M. M. Khalid and O. Karan, "Deep learning for plant disease detection," *International Journal of Mathematics, Statistics, and Computer Science*, vol. 2, pp. 75–84, 2023, doi: 10.59543/ijmscs.v2i.8343.

[10] L. Zhong, L. Hu, and H. Zhou, "Deep learning based multi-temporal crop classification," *Remote Sensing of Environment*, vol. 221, pp. 430–443, 2019, doi: 10.1016/j.rse.2018.11.032.

[11] A. Karunanithi, "smut_diseases," *Figshare*. Accessed: Mar. 13, 2023. [Online.] Available: https://figshare.com/articles/figure/smut_diseases/21975236/1.

[12] A. Karunanithi, "Blast Disease_Dataset," *Figshare*. Accessed: Jan. 30, 2023. [Online.] Available: https://doi.org/10.6084/m9.figshare.21975287.v1.

[13] A. Karunanithi, "Bacterail blight_Dataset," *Figshare*. Accessed: Jan. 30, 2023). [Online.] Available: https://doi.org/10.6084/m9.figshare.21975239.v1.

[14] N. Bharanidharan, S. R. Sannasi Chakravarthy, H. Rajaguru, V. Vinoth Kumar, T. R. Mahesh, and S. Guluwadi, "Multiclass paddy disease detection using filter-based feature transformation technique," *IEEE Access*, vol. 11, pp. 109477–109487, 2023, doi: 10.1109/ACCESS.2023.3322587.

[15] S. Lamba *et al.*, "A novel fine-tuned deep-learning-based multi-class classifier for severity of paddy leaf diseases," *Frontiers in Plant Science*, vol. 14, 2023, doi: 10.3389/fpls.2023.1234067.

[16] M. Mishra, P. Choudhury, and B. Pati, "Modified ride-NN optimizer for the IoT based plant disease detection," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 1, pp. 691–703, 2021, doi: 10.1007/s12652-020-02051-6.

[17] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018, doi: 10.1016/j.compag.2018.01.009.

[18] M. Brahimi, K. Boukhalfa, and A. Moussaoui, "Deep learning for tomato diseases: classification and symptoms visualization," *Applied Artificial Intelligence*, vol. 31, no. 4, pp. 299–315, 2017, doi: 10.1080/08839514.2017.1315516.

[19] J. Andrew, J. Eunice, D. E. Popescu, M. K. Chowdary, and J. Hemanth, "Deep learning-based leaf disease detection in crops using images for agricultural applications," *Agronomy*, vol. 12, no. 10, 2022, doi: 10.3390/agronomy12102395.

[20] R. M. J. Al-Akkam and M. S. M. Altaei, "Plants leaf diseases detection using deep learning," *Iraqi Journal of Science*, vol. 63, no. 2, pp. 801–816, 2022, doi: 10.24996/ijs.2022.63.2.34.

[21] N. Kumar, Nagarathna, and F. Flammini, "YOLO-based light-weight deep learning models for insect detection system with field adaption," *Agriculture (Switzerland)*, vol. 13, no. 3, 2023, doi: 10.3390/agriculture13030741.

[22] D. Mohan and M. Gopal Raj, "Quality analysis of rice grains using ANN and SVM," *Journal of Critical Reviews*, vol. 7, no. 1, pp. 395–402, 2020, doi: 10.31838/jcr.07.01.79.

[23] M. T. Ahad, Y. Li, B. Song, and T. Bhuiyan, "Comparison of CNN-based deep learning architectures for rice diseases classification," *Artificial Intelligence in Agriculture*, vol. 9, pp. 22–35, 2023, doi: 10.1016/j.aiia.2023.07.001.

[24] G. R. I. L. Jayasooriya and S. M. Arachchi, "Diagnosis of bacterial leaf blight, brown spots, and leaf smut rice plant diseases using light GBM," *International Journal of Computer Applications*, vol. 183, no. 48, pp. 53–58, 2022, doi: 10.5120/ijca2022921895.

[25] D. Elavarasan and P. M. D. Vincent, "Crop yield prediction using deep reinforcement learning model for sustainable agrarian applications," *IEEE Access*, vol. 8, pp. 86886–86901, 2020, doi: 10.1109/ACCESS.2020.2992480.

[26] V. Badrinarayanan, A. Kendall, and R. Cipolla, "SegNet: a deep convolutional encoder-decoder architecture for image segmentation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 12, pp. 2481–2495, 2017, doi: 10.1109/TPAMI.2016.2644615.

[27] W. J. Hu, J. Fan, Y. X. Du, B. S. Li, N. Xiong, and E. Bekkering, "MDFC-ResNet: an agricultural IoT system to accurately recognize crop diseases," *IEEE Access*, vol. 8, pp. 115287–115298, 2020, doi: 10.1109/ACCESS.2020.3001237.

[28] A. Stephen, A. Punitha, and A. Chandrasekar, "Optimal deep generative adversarial network and convolutional neural network for rice leaf disease prediction," *Visual Computer*, vol. 40, no. 2, pp. 919–936, 2024, doi: 10.1007/s00371-023-02823-z.

[29] Y. Dong, W. Huang, K. Lin, L. Han, G. Laneve, and J. Zhang, "Editorial: pests and diseases monitoring and forecasting algorithms, technologies, and applications," *Frontiers in Plant Science*, vol. 15, 2024, doi: 10.3389/fpls.2024.1518814.
[30] T. R. D. Fata, R. R. A. Siregar, and Indrianto, "Detection of brown spot and leaf blight in rice with the you only look once (YOLO) algorithm," *Petir*, vol. 16, no. 1, pp. 117–130, 2023, doi: 10.33322/petir.v16i1.2003.

BIOGRAPHIES OF AUTHORS

Anandhan Karunanithi has 12 years of teaching experience at a reputed university in India. He holds a B.Tech. in Information Technology and Master of Engineering in Embedded System Technologies from Anna University, Chennai, India, in 2011 and 2013. He is currently an assistant professor at Computer Science and Engineering, GITAM University, Bengaluru campus, India. His research includes deep learning, machine learning, and automotive embedded systems. He has published over 22 papers in international journals and conferences. He was a research scholar in Galgotias University, India. He can be contacted at email: anandhanpg13@gmail.com.

Ajay Shanker Singh has currently working as a senior professor at the School of Computing Science and Engineering at Galgotias University. He has a total experience of more than 26 years in industry, and teaching has been associated with Galgotias University since 2014. He was Program Head for B.Tech. CSE Specialized Programs in Cloud Computing. He worked with top University and institutes of India eg, UPES-Dehradun, GRIET-Hyderabad, JBIET Group-Hyderabad. His research includes cloud computing, deep learning, analytics, and programming. He can be contacted at email: drajaycse@gmail.com.