RESEARCH ARTICLE

INTERNATIONAL RESEARCH JOURNAL OF MULTIDISCIPLINARY TECHNOVATION

Asian Research Association

DOI: 10.54392/irjmt25516

Cognitive Attribute Selection and Laurent Series with Intelligent Multidimensional Object Optimization for Paddy Disease Detection

Anandhan Karunanithi [a, *], K.P. Arjun [a], R. Nagendra [b], D. Damodharan [c], S. Janarthanan [d], S. Sreeji [e]

[a] Department of Computer Science Engineering, GITAM Deemed to be University, Bengaluru, 561203, India
[b] Department of Electronics and Communication Engineering, New Horizon College of Engineering, Bengaluru, 560103, India
[c] Department of Computer Science Engineering, Dayananda Sagar University (DSU), South Bengaluru, 562112, India
[d] School of Computer Science and Engineering, JAIN (Deemed to be University), Bengaluru, 562112, India
[e] Department School of Computing, Sathyabama Institute of Science and Technology, Chennai, 600119, India
* Corresponding Author Email: anandhanpg13@gmail.com

DOI: https://doi.org/10.54392/irjmt25516
Received: 30-06-2025; Revised: 28-08-2025; Accepted: 16-09-2025; Published: 30-09-2025

Check for updates

Abstract: Sustainable agriculture depends on detecting diseases in rice crops and its diagnostic methods. Rice plant diseases must be minimized or avoided to achieve the best yield for farmers. Therefore, many researchers have been working to find the best solution. Disease has led to a more than 38% yearly drop in paddy production. Various crop disease detection methods require high accuracy and dimensionality corrections. Disease detection is indispensable for maintaining agriculture. In the meantime, automated rice plant disease detection systems also face various problems in detecting diseases in the current situation. The proposed research work provides solutions for the above-mentioned problems and requirements with a novel approach, which is the combination of the Laurent series with Intelligent Multidimensional object Optimization (LIMO classification framework) based on Generative Adversarial Network (GAN) and Swarm Intelligence Optimal Classification through Cognitive Attribute Selection (SIOC-CAS) to recognize various types of crop diseases in an agricultural field. A novel framework introduced to improve computational efficiency through optimized feature selection and scalable modeling, such as the SIOC+LIMO framework, a combination of SIOC and LIMO models. In the proposed approach, all preprocessing steps are controlled by the cognitive advisor, and for segmentation and better feature selection, the SIOC model is used. Also, the LIMO model is used for intelligent classification and optimal outcomes. The proposed SIOC+LIMO-based GAN network provides effective and improved performance metrics with overall precision, recall, F1 score, accuracy, sensitivity, and specificity values of 93.8%, 93.9%, 93.8%, 92.97%, 93.3%, and 92.97% respectively in evaluation with existing crop diseases detection.

Keywords: GAN, LIMO Framework, Diseases, Optimal Classification, Cognitive Attribute Selection

1. Introduction

The rice production increased almost five times in just 50 years, from 20.58 million tons in 1950-1951 to 104.86 million tons in 2014-2015 [1]. During the harvest time year of 2020–2021, China produced some 148 million tons of milled rice, the most of any nation. A year of growth, the total rice production in India for the agricultural year 2023-24 has reached an unprecedented milestone, estimated at 1378.25 Lakh Metric Tonnes (LMT), marking a significant increase of 20.70 LMT compared to the previous year's output of 1357.55 LMT [2]. The agricultural sector in India has experienced significant growth due to focused governmental reforms, climatic resilience, and advancements in farming technologies. This study presents a hybrid deep learning method for precise disease diagnosis using crop imagery in order to address the growing impact of rice diseases on crop quality and yield. A staple food that is essential worldwide, rice is still susceptible to a number of diseases, with blast disease posing serious risks to yield.

The usefulness of GAN in creating high-fidelity images for disease classification is investigated in our research work. Implementing multiple cycles, GAN which are made up of a generator and discriminator that work together improve image realism and training dataset robustness. Deep learning models exhibit superior adaptability across vision tasks by utilizing high-performance computational frameworks and large-scale annotated datasets. Furthermore, swarm intelligence and machine learning classifiers such as Particle Swarm Optimization (PSO) and Support Vector Machines (SVM) have been widely utilized for feature selection in plant pathology [3]. Wrapper based attribute selection, integrated with PSO and SVM models, refines predictive capability by optimizing feature subsets, thereby enhancing classification accuracy and generalizability.

Authors have also proposed variants in particle swarms to improve the efficiency in selecting highly predictive attributes [4]. The aim is to select an optimal attribute subset using PSO. This methodology requires the user to specify the size of the attribute subset for selection, which is rather difficult without prior knowledge about the attribute space and is problem specific. The PSO and SVM will build a wrapper-based attribute selection methodology for identifying keystroke dynamic systems in a designed attribute selection technique using a particle swarm optimizer and SVM with the one versus all method to classify multi-class problems. A wrapper based attribute selection methodology was developed using PSO and SVM [5]. The proposed methodology traverses the problem space to select an optimal attribute subset while simultaneously optimizing the parameters of SVM, unlike applied continuous valued PSO for optimizing parameters in SVM and PSO for optimizing attribute subset search.

In an adaptive selection strategy, select an attribute subset based on both its likelihood and its influence on other attributes already added to the subset. This strategy shows superior performance to search and scatter search algorithms [6]. The authors also state that the efficiency of the adaptive selection strategy and the quality of the solution can be improved by relaxing the restriction on the size of attributes considered for adding to the subset. Each particle of the population, in search of an optimal solution, adjusts its position depending on its personal best and the best solution chosen on social interaction with neighbors. In conventional PSO, Swarmbest is updated only to achieve a better solution than the previous Swarmbest. If the Swarmbest stagnates in local optima, the particle's search area is restricted around the Swarmbest in the problem space.

Particles do not explore the entire problem space and limit their search around the local optima. Such a solution provides an attribute subset that may not yield superior predictive results during classification. In addition, PSO tends to converge rapidly during the initial search and retards the convergence rate quite often. Rice disease detection has improved rapid evolution in recent years, particularly with the emergence of lightweight attention guided networks and hybrid transformer-based models. Notable among these is EPC-GANet, YOLOv8-AMD, and CoAtNet variants, which have demonstrated impressive performance in terms of accuracy and deployment efficiency [7]. EPC-GANet, for instance, integrates enhanced partial convolution and guided attention mechanisms to achieve real time detection with minimal computational overhead. Similarly, YOLOv8-AMD introduces dynamic upsampling and mixed local channel attention to improve detection precision in low resolution agricultural imagery. CoAtNet based classifiers combine convolutional and attention layers to balance spatial feature extraction with global context modeling, achieving high classification accuracy across diverse rice disease datasets [8].

While these models offer significant advancements, they primarily focus on spatial feature extraction and lack integrated mechanisms for temporal modeling, interpretability, and adaptive optimization. The proposed hybrid framework SIOC+LIMO addresses these limitations through a multi layered innovation strategy. First, the CAS module adds a way to prioritize features dynamically using swarm intelligence. It will help to choose the most relevant attributes from different types of datasets. CAS changes its selection strategy based on domain specific heuristics and real time feedback, which makes it more general and robust. This is different from fixed attention modules.

Second, using Laurent series modeling gives us a mathematically sound way to capture nonlinear patterns in how diseases progress. This part lets the framework model small changes over time and complicated symptom paths that other CNN or transformer-based architectures often miss. The Laurent series formulation also makes it easier to understand by connecting disease features to analytical expressions, which makes it easier to get insights that are specific to the field. Third, the Intelligent Multidimensional Object Optimization (IMO) module uses GAN based data augmentation and multi-objective optimization strategies together.

The proposed hybrid framework distinguishes itself through its integration of cognitive feature selection, analytical modelling via Laurent series, and multi objective optimization. These innovations collectively position SIOC+LIMO as a computationally superior and algorithmically novel solution in the landscape of rice disease detection [9].

A hybrid deep learning model is to increase the efficiency of the diagnosis process. The purpose of this study is to examine various classifications and their variants. A new variant of an attribute selection framework and a LIMO framework are proposed. A SIOC+LIMO framework for analyzing the performance of rice crop disease diagnosis. Compared with its existing methods, such as SIOC+SVM, LIMO+GAN, and SIOC+LIMO, the best results are achieved by the SIOC+LIMO framework [8, 9].

2. Literature Survey

Table 1. Comparative analysis of literature studies

Author's	Research Title	Year	Source	Disease	Techniques	Key Finding Limitations
Rutuja R. Patil, Sumit Kumar. [10]	Rice Data Fusion (RDF): Rice Plant Disease Detection with Multimodality Data Fusion.	2022	IEEE Access	Diagnoses Rice Disease	CNN MLP	Non adaptive data fusion. Achieved 91.01% accuracy.
Deming Zhai *et al.* [11]	Rice Plant Disease Detection with Rectified Meta Learning.	2022	ACM Transactions on Multimedia Computing, Comn, & Apps	Plant Disease	CNN And ML	Huge noise input. Achieved 90% classification accuracy.
Shruti Aggarwal *et al.* [12]	Rice Disease Detection using Artificial. Intelligence and ML Techniques to Improvise Agro-Business.	2022	Hindawi Scientific Programming	Rice plant leaf diseases	KNN SVM Fuzzy classifier	Overall image dimensionality issues. Precision archived 91.06%.
Dengshun Li *et al*.[13]	A Recognition paddy Plant Diseases Detection with DCNN.	2020	MDPI - Sensors	Rice diseases and pests	Deep convolutional neural network	Video streaming conversion difficulty. Part occlusion.
Asmiaty Sahur *et al*. [14]	Effect of Methanotroph Bacteria Isolated from Paddy Rice Plant on Growth and Yield Components of rice.	2022	Hindawi - International Journal of Agronomy.	Methanotroph Bacteria	Randomized complete block design	Environmental variation. Yield improvement is 95.45.
Junde Chen *et al.* [15]	LWI Networks for Rice plant Disease Detection.	2022	IEEE Sensor Journal	Plant Disease	SVM Deep Learning	High computational cost.
Davindar et al. [16]	Plant Doc: A Dataset for Visual Plant Disease Detection.	2020	ACM IKDD CoDS	Rice plant diseases	KNN SVM Fuzzy classifier	Applicable with the minimal structured dataset. Time complexity increases.
Wen-Liang Chen *et al.* [17]	IoT with Rice Blast Detection System.	2020	IEEE Internet of Things Journal	Rice blast	Artificial intelligence Precision farming	Transmission data loss percentage high. Low accuracy calculated with raw images.
Ashutosh Kr Singh *et al.* [18]	Hybrid Feature-Based Disease Detection in Plant Leaf Using CNN, Bayesian optimized SVM, and RF Classifier	2022	Wiley Hindawi - Journal of Food Quality	Plant diseases	Bayesian Optimizer Random forest classifier.	Achieved an Accuracy of 96.6%. Hyper parameters were selected for non-evolutionary methods.

3. Materials and Methods

The methodology is provided for classifying various rice diseases using imaging technology with deep learning tools. Rice diseases, as well as pests, can be found in various portions of the plant. Temperature, moisture, rain, the wide range of rice plants, season, nourishment, and other variables all influence their incidence [19]. In this research work, three dataset sources are collected and used for performance evaluation. The details of a dataset are discussed below. The dataset is taken from the following three sources. The first dataset contains 2869 images of rice diseases, and it was collected from paddy fields of the Indian Rice Research Institute (IRRI). The second dataset contains 14291 diseased rice leaf images of four varieties, which were captured from different rice fields in India from PlantVillage. The third dataset contains 1488 images of rice diseases, and it was collected from Kaggle. The images were collected in a variety of weather conditions, including cold season, hot season, and cloudy weather, in sequence to obtain as many images as possible. The identities of the classifications, as well as the number of images gathered for every categorization, are listed in Table 2. Some samples of rice diseases along with edge detection and segmentation are illustrated in figure 1.

Table 2. Dataset description

Dataset Name	Number of images
IRRI dataset	2869
Plant Village Rice Disease Dataset	14291
Kaggle Rice Disease Dataset	1488

3.1 Methodology

Problem formulation defines the objective of CAS, such as minimizing the occurrence of rice crop diseases, optimizing disease detection accuracy, or minimizing the use of pesticides while maintaining crop health. Identify the various parameters and constraints, including environmental factors, disease symptoms, diagnostic techniques, treatment options, and crop management practices. Data collection gathers a comprehensive dataset that includes information on rice crop diseases, environmental conditions, disease symptoms, diagnostic methods, treatment outcomes, and historical crop management practices. This dataset will be used to train and evaluate the optimization algorithm. Model development LIMO develops a predictive model that can estimate disease occurrence, symptoms, diagnostic accuracy, or treatment outcomes based on the available data. This model can be based on machine learning techniques such as decision trees, random forests, support vector machines, or neural networks. Optimization algorithm IMO designs an optimization algorithm that leverages the developed predictive model to find optimal solutions for disease detection, diagnosis, and treatment.

3.2 Dataset Integration and Cross Validation Protocol

To construct a robust and generalizable classification model, we integrated three publicly available rice disease datasets: IRRI, PlantVillage, and Kaggle Rice Disease Challenge. While combining these sources, careful attention was given to mitigating dataset biases and preserving inter class variability. The integrated dataset comprised seven distinct rice disease categories and over different annotated images. To address class imbalance which is a common concern in agricultural datasets we employed two complementary techniques. First, Synthetic Minority Over-sampling Technique (SMOTE) was used during training to augment minority class samples in feature space without altering semantic realism. Second, a conditional GAN-based image augmentation pipeline was introduced to generate photorealistic variations of underrepresented classes, maintaining consistency in pixel distribution and contextual background. For model validation, we implemented a five-fold stratified cross-validation protocol. In each fold, the dataset was partitioned such that disease classes were proportionally represented in both training and test splits. Importantly, we enforced a field level split criterion by associating geotag or metadata identifiers to ensure that images originating from the same field or session did not appear in both training and validation sets simultaneously. This strategy minimized data leakage and ensured evaluation robustness across unseen field scenarios. Each fold maintained a 70:30 split ratio for training and validation subsets. The stratified assignment preserved inter class representation while maintaining independence across folds. Cross validation was repeated with random seed reinitialization to assess model sensitivity and eliminate fold specific bias. Evaluation metrics, including accuracy, precision, recall, and F1-score, were computed on each fold and reported as mean ± standard deviation across the five trials. In Matlab 2023b, the deep learning toolbox was employed to load multiple datasets and initiate simulations. The preliminary results from beginning phase are presented in figure 1 such as canny edge detection, segmented disease region.

To improve the results, algorithm should consider the multidimensional nature of the problem, incorporating variables such as environmental conditions, disease symptoms, diagnostic techniques, and treatment options. The optimization framework is based on an explicit goal function that aims to improve accuracy while minimizing pesticide use and keeping crops healthy. Integrated constraint handling makes sure that environmental, financial, and operational limits are taken into account during the whole search process, keeping it feasible and relevant.

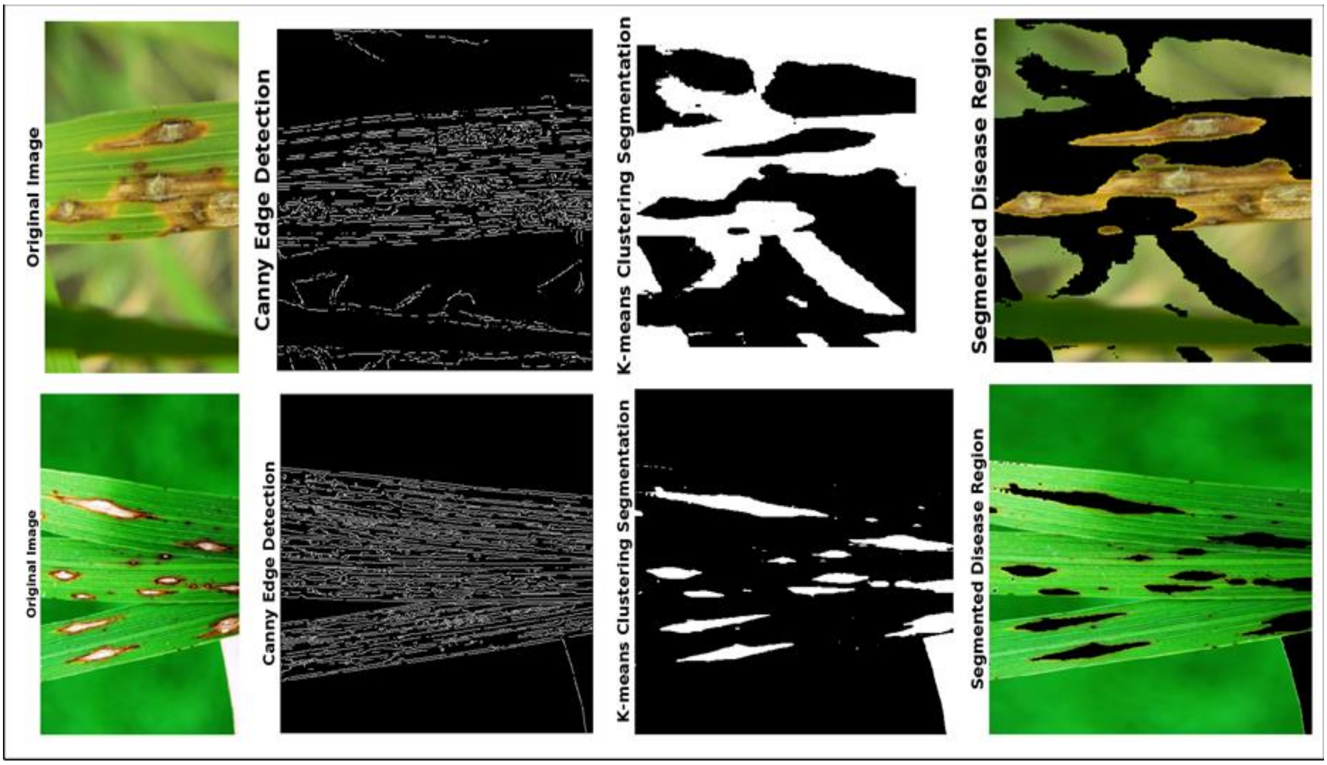

Figure 1. Various types of paddy diseases, canny edge detection, K-means clustering, and Segmented diseases region using Matlab environment

The efficiency of the model is measured using standard metrics like accuracy, precision, recall, and F1 scores. The model continues to be enhanced as more data becomes available to maintain its ability to provide accurate predictions and adapts. Solution generation and evaluation use the optimization algorithm to generate potential solutions for disease detection, diagnosis, and treatment based on the defined objective function and constraints. Evaluate these solutions using simulation, experimental validation, or real-world testing to assess their effectiveness and feasibility. Decision support presents the generated solutions to farmers, agricultural experts, or decision-makers in an accessible and interpretable manner. Provide insights and recommendations based on the optimized solutions to guide disease management strategies, crop protection measures, and treatment plans. The figure 2 shows the complete flow chart of our proposed approach in detail manner.

Algorithm: Proposed Approach

Input: An RGB crop image I_{rgb}

Step 1:1.1 Load the input image I_{rgb} from local storage.

1.2 Resize I_{rgb} to a fixed dimension of 512×512 times 512 pixels for standardization.

1.3 Convert I_{rgb} to grayscale I_{gray}.

1.4 Apply Canny edge detection to I_{gray}, storing output in E_{canny}.

1.5 Transform I_{rgb} into Lab* *space* → I_{lab}.

1.6 Extract a* and b* *channels* → F_{ab}.

1.7 Reshape F_{ab} into feature *matrix* X_{color}.

Step 2: Initialize Particle Swarm Optimization (PSO) with Population size = 30, Generations = 60, Inertia weight ω=0.72, cognitive coefficient c_1 = 1.8, social coefficient c_2=1.4, Velocity clamping v_{max}=4.0, Stopping criteria: convergence < 0.0001 over 5 generations or max iterations.

Step 3: Apply Laurent series approximation to model nonlinear progression in selected features F_{opt}. Define multi-objective cost functions: accuracy, interpretability, and recall.

Step 4: Apply Pareto front based optimization over GAN augmented data samples.

Step 5: Save final segmentation mask I_{mask} and feature subset F_{opt} for validation.

Step 6: Store classification results and model diagnostics for interpretability benchmarking.

Step 7: Segmented disease mask I_{mask} and optimized feature subset F_{opt}.

3.3 Model Developments and Methods

First, the image acquisition process collected all field and crop-oriented images and posted them to preprocessing shown in figure 3. Then, the image preprocessing method helps segment creations design pixel masking of every object that is present in the image. It means an image is converted into a suitable image.

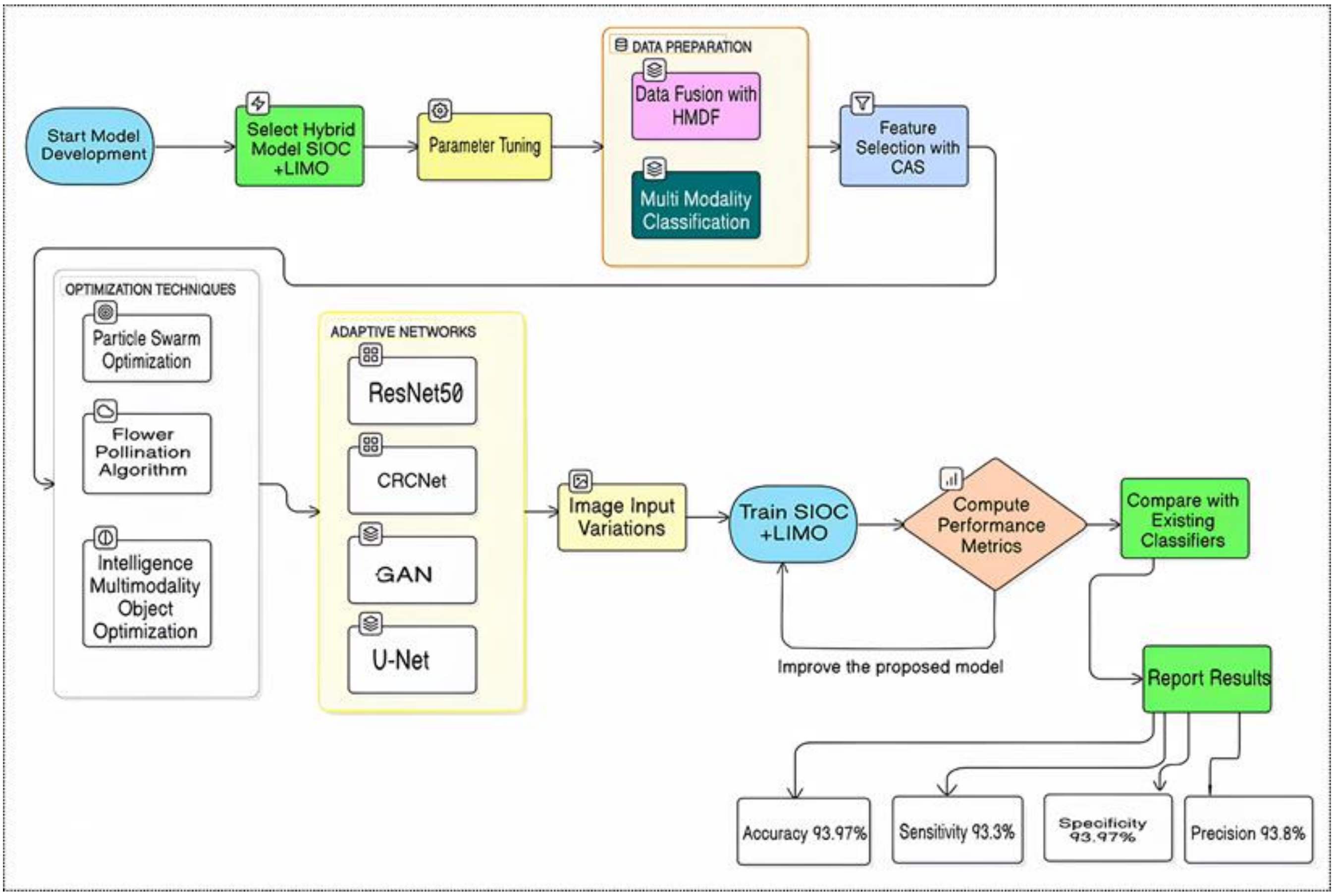

Figure 2. Overall processing flow chart for the proposed research work

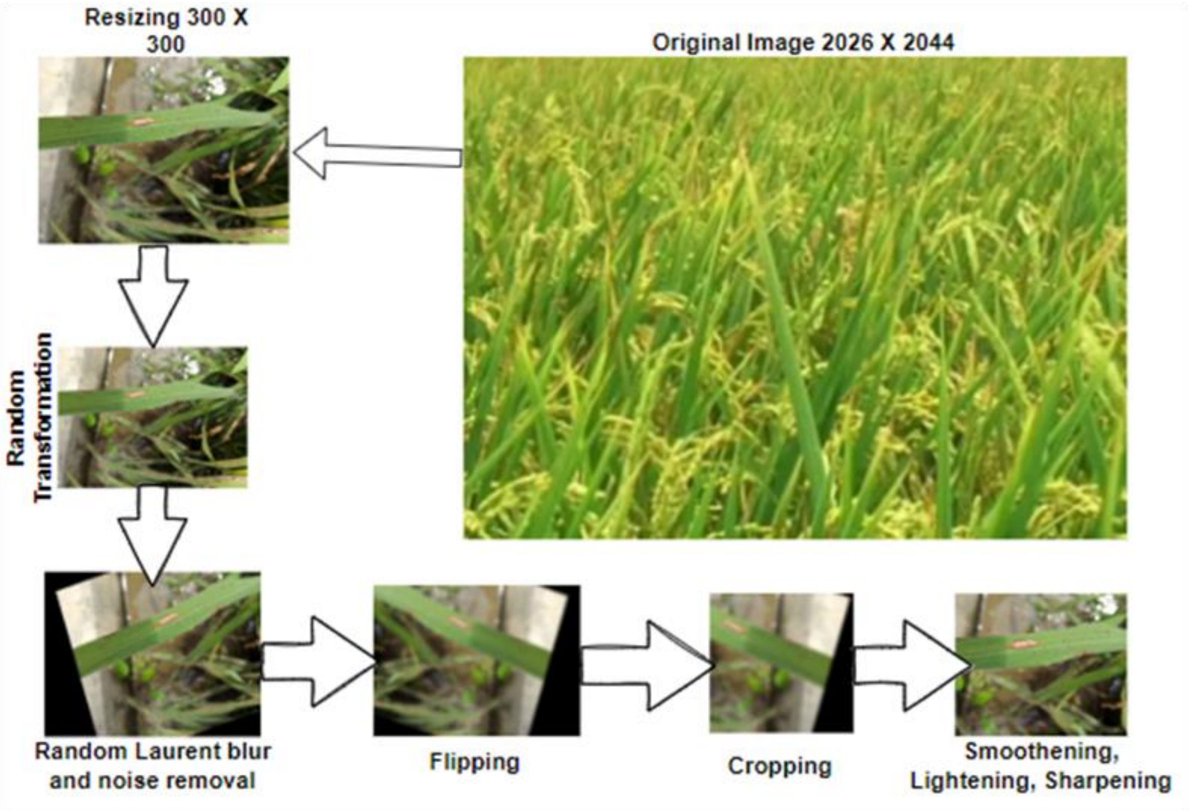

Figure 3. Data acquisition process (avoiding overfitting and underfitting)

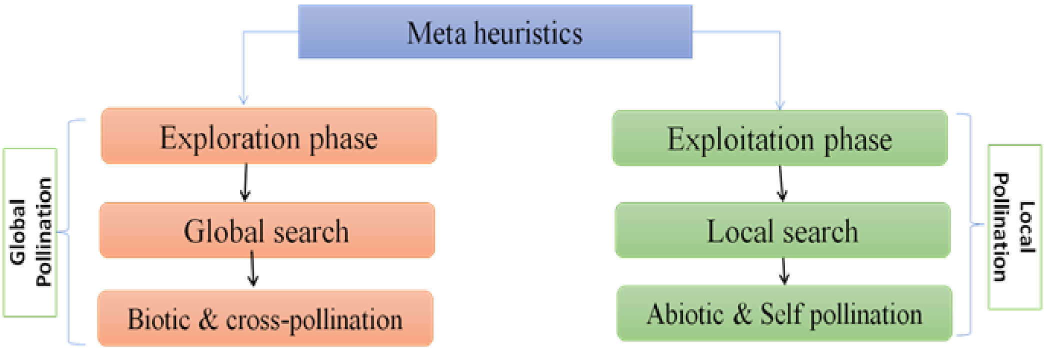

Figure 4. Flower pollination optimization techniques

In a simple explanation, preprocessing supports image smoothening, transformation, and image reduction to improve image quality for better object detection. Preprocessing plays an important role in image processing. It increases the probability of detecting objects accurately. Image enhancement calculating noise ratio level, dimensional value, HSV, smoothening, grey scale value, size, brightness values, sharpening images, etc. Moreover, at the time of preprocessing, data reduction supports reducing unnecessary noise and information from images. After that, image restoration reduces noise and blurs orient things from the input image. In this process, increasing the appearance of the rice crop image with better quality increases the accuracy of the rice plant disease detection and prevention process. Search space bounds were defined from 0 to 1, representing feature exclusion and inclusion respectively, with normalization applied to enable binary encoding across 127 candidate attributes. The population size was fixed at 30 particles per generation, a setting supported by prior agricultural studies for achieving optimal convergence while maintaining diversity in search dynamics. The maximum number of generations was set to 60 iterations, ensuring convergence within cost thresholds while maintaining computational efficiency. Velocity clamping was set to v_{max}=4.0 to prevent abrupt search jumps and ensure smooth convergence, while the inertia weight ω=0.72 was chosen to balance exploration and exploitation in alignment with multi-modal PSO best practices. The cognitive coefficient c_1=1.8 and social coefficient c_2=1.4 were selected to balance individual learning with group influence, based on cross validation tuning, while the stopping condition was defined as either a minimum fitness improvement of 0.0001 over five consecutive generations or reaching the maximum iteration limit to avoid overfitting and ensure efficient termination.

Flower Pollination Optimization is a highly efficient metaheuristic optimization algorithm of two different classification model shown in figure 4 above.

4. Implementation and Results

4.1 Proposed Methodology

Advanced Particle Swarm Optimization (APSO) by attribute subset selection algorithm-based population methodology with the Laurent series with intelligent multidimensional object optimization for rice plant disease detection (SIOC+LIMO) model. The main objective of this proposed SIOC+LIMO framework is to use early detection and optimal classification of different kinds of rice plant diseases, as shown in figure 5. The proposed intelligence multidimensional based object detection for rice plant disease detection technique encompasses Gaussian Filtering (GF) based preprocessing, multilevel thresholding Otsu with cognitive attribute selection (SIOC-CAS) based segmentation, fusion based feature extraction such as CRCNet, GAN, CAS with ResNet50, LIMO based classification. The design of CAS to describe the best possible threshold values of the Otsu-based segmentation approach helps to improve the overall classification performance.

4.2 SIOC with LIMO Framework

A new SIOC+LIMO system is derived to identify and classify different classes of RPDs. The proposed SIOC+LIMO technique includes SIOC-CAS-based segmentation, GF-based preprocessing, LIMO-based classification, and fusion-based feature extraction. Figure 5 represents the complete working model of the proposed classifier SIOC+LIMO model.

4.3 GF-based Preprocessing

In GF technique is utilized to remove the noise that exists in the plant leaf images. Several areas of study, such as medicine, astronomy, geography, and so on, have commonly used the concept of DIP. This area frequently requires efficient, real-time results. The performance of two-dimensional Gaussian filters is extensively employed for noise removal and smoothing. It needs large numbers of computation resources, and its efficacy in the application has been an inspiring field of study. The convolutional operator is the Gaussian filter, and a diverse dimensional conception of Gaussian smoothing and lightening can be attained using cognitive convolutional methods.

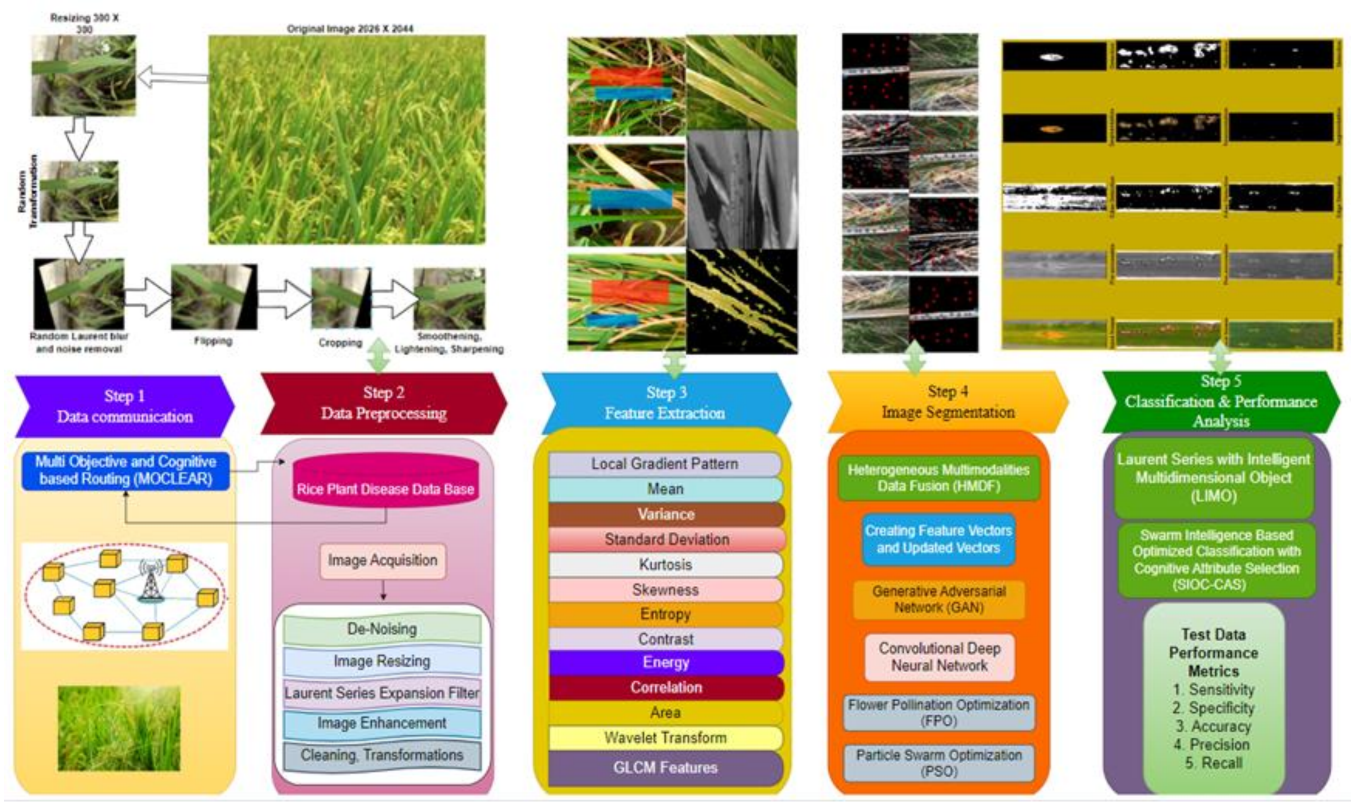

Figure 5. Overall architecture and process of SIOC+LIMO model

$$f([t_1, t_2, \ldots.. t_k] = \sigma_0^2 + \sigma_1^2 + \sigma_2^2 + \cdots + \sigma_k^2) \; \sigma_0^2 = \omega_0(\mu_0 - \mu_T)^2, \omega_0 = \sum_{i=0}^{t_1-1} 1\, P_i, \mu_0 = \sum_{i=0}^{t_1-1} 1 \frac{P_i}{\omega_0} \; \sigma_1^2 = \omega_1(\mu_1 - \mu_T)^2, \omega_1 = \sum_{i=t_1}^{t_1-1} 1\, P_i, \mu_1 = \sum_{i=t_1}^{t_2-1} 1 \frac{i.P_i}{\omega_1} \; \sigma_2^2 = \omega_2(\mu_2 - \mu_T)^2, \omega_2 = \sum_{i=t_2}^{t_1-1} 1\, P_i, \mu_2 = \sum_{i=t_2}^{t_3-1} 1 \frac{i.P_i}{\omega_2} \; ..\sigma_k^2 = \omega_k(\mu_k - \mu_T)^2, \omega_k = \sum_{i=t_k}^{L-1} 1\, P_i, \mu_2 = \sum_{i=t_k}^{L-1} 1 \frac{i.P_i}{\omega_k} \quad (1)$$

4.4 SIOC-CAS-based segmentation

During the segmentation process, the SIOC-CAS segmentation model is utilized to determine vital performance factors from affected portions of rice leaves in images. The best solution to the multilevel thresholding problems is Otsu's approach, an unsupervised and non-parametric model whose aim is to increase the between-class variance for selecting the optimum threshold. Where k represents the number of thresholds, Otsu's model would select and optimize the t1, t2,…,t threshold. By increasing the subsequent objective function, the threshold subdivides the images to k + 1 classes represented as [C0, C1, C2,…, C].

$f([t_1, t_2, \ldots.. t_k])$ denotes the objective function, $\sigma_0^2, \sigma_1^2, \sigma_2^2, \ldots. \sigma_k^2$ represent the variance of distinct classes of an image, $\omega_0, \omega_1, \omega_2, \ldots \omega_k$ signifies the class likelihoods, and $\mu_0, \mu_1, \mu_2, \ldots \mu_k$ indicates the standard level of the segmented classes $C_0, C_1, C_2, \ldots.. C_k$ correspondingly. $\sum_{j=1}^{k} 1\, \omega_j = 1$ and $\sum_{j=1}^{k} 1\, \omega_j \mu_j = \mu_T$, μ_T represents the average intensity in an image. The CAS is applied to determine the threshold values. The CAS is a metaheuristic model that follows population initialization with the aim of optimizing the method. Consider the overall amount of the population as C and accessible in the searching space of D. The population initialization is created in the dimension alongside arbitrary initiation in the search space, which can be given by

$$a^i = L_j + rand\ X\ (U_j - L_j) \quad (2)$$

The early vector of the i_{th} CAS is represented as a^i. The lower limit and upper limit of the search space are provided as L_j and U_j in the j_{th} parameter, respectively. $rand$ represents the arbitrarily created value that falls in the range of zero and one. The better capacity of the cognitive model to search in the searching space is formulated by

$$\rho = \delta exp^{(-\alpha t/R)} \quad (3)$$

Now, ρ represents the variable utilized in the iteration and is reduced by the growing iteration. δ, $\alpha \& \beta$ is the predetermined parameters for the exploitation and exploration phases. The rotating centered coordinate utilized to update the location of CAS in the search space is expressed by

$$a\ rand_r^i = m * ac_r^i \quad (4)$$

$a\ rand_r^i$ Represents the rotating center coordinate of the CAS. mis utilized for denoting the rotation matrix, and ac_r^i is utilized for denoting the centering coordinate in r_{th} iterations. The inertia weight of the iteration is formulated by,

$$W = \left(1 - \frac{r}{R}\right)^{\left(\lambda\sqrt{\frac{r}{R}}\right)} \quad (5)$$

Now, W represents the weight of inertia, λ indicates the arbitrary value utilized for controlling the exploitation capability. The λ value is equivalent to one. The acceleration rate of the CAS is expressed by,

$$y = 2590 * \left(1 - exp^{-loglog\,(r)}\right) \quad (6)$$

whereas y is utilized to determine the acceleration of CAS. From the pseudo-code, it is noted that the CAS initializes the optimization model and the CAS location is upgraded by

$$a_{r+1}^i = a.rand_r^i - a_r^{-i} \quad (7)$$

$$G_{r+1}^i = a_r^{-i} + \left(\left(v_r^{ij}\right)^2 - \left(v_{r-1}^{ij}\right)^2\right)/(2y) \quad (8)$$

Now, G_{r+1}^i represents the global optimal position of the CAS and v_r^{ij} denotes the novel velocity of the r_{th} CAS. When the CAS goes outside of the searching area, it returns to the constraint that was previously defined. The fitness function is evaluated in every round to predict the CAS with optimum fitness. Therefore, the fitness function is utilized to find optimal CAS that catches the prey in the first place. This process is continued till it achieves the total rounds iteration cycles.

4.5 Fusion-based Feature Extraction

In these sections, the fusion-based feature extraction process is carried out using three DL models such as DenseNet, GAN, and Inception with ResNet50. The CNG structure outperformed the $ResNet$50, VGG 16, U-Net, $ResNet$101, and $ResNet$152 on ImageNet [20-22]. The CNG method has its foundation in preceding methods such as the Inception V3 and the original Inception. Following a similar architecture, the GAN network has significant differences in the usage of cognitive residual convolution rather than conventional Residual Connections (RC) and Convolutions like those presented on ResNet methods. The structure can be made by thirty-six convolution layers forming the feature extraction base. The thirty-six convolution layers are designed for fourteen models where the first and last ones do not have a residual connection. The cognitive convolutional is a spatial convolutional which independently executes on all the channels in the input, after that, pointwise convolution a 1×1 convolutions, projecting the channel output by the cognitive convolution to a novel channel space. Initially, the last output of CRCNet and classical convolution are similar, but it can be noted that the algorithm that can be implemented through CRCNet looks more extensive and complicated. The CRCNet implements less operation, reducing the computation costs of the network. Using CRCNet, we can get a deeper algorithm, which is very effective when compared to a wider one. Conversely, although the GAN with CAS method has many parameters, it is much faster and more efficient when compared to the VGG 16 method. Discriminator equator models are distinct when compared to the ones discovered in the Inception methods due to the incorporation of CRCNet. The overall architecture of the convolutional model with the GAN network. Once this method was utilized for classification on ImageNet, the last output layer comprised of thousand neurons with activation function softmax for predicting likelihood for thousand classes. The CRCNet network has been proposed to improve the real-time efficiency of the DL method in constrained hardware conditions. This network could decrease the number of variables without sacrificing precision. Prior research has demonstrated that CRCNet requires 1/33 of a parameter of VGG 16 for achieving similar classification performance in the ImageNet 1000 classification task.

4.6 Results and Discussion

Our implementation compared with recent evaluations, the MDFN ResNet model achieved a sensitivity of 73.46%, indicating slight improvement in disease detection. Moderate sensitivity scores were obtained by DCNN (83.70%), SIOC+SVM (86.66%), and GAN+LIMO (90.00%) techniques [23, 24]. Notably, GAN+LIMO delivered near-optimal results, while the proposed SIOC+LIMO framework demonstrated superior sensitivity at 93.30%. Table 3 and Figure 6 summarize the performance across five-fold validations for combinations such as SIOC with SVM and GAN with LIMO. For instance, in fold-1, the SIOC+LIMO approach yielded high performance, with a precision of 0.9365, sensitivity of 0.9304, specificity of 0.9348, accuracy of 0.9380, F1-score of 0.9305, recall of 0.9393, and a Hamming loss rate of 0.0501. The average performance metrics for each fold across multiple evaluation measures are presented in Table 3.

In the figure 7 and figure 8 implementation results shown as specificity, accuracy value compared with other neural network models.

4.6.1 Comparison with Existing Methods

In Figure 7, specificity analysis revealed that traditional deep learning architectures such as MFCN (91.5%) and MFCN ResNet (90.4%) provide reasonable performance but often struggle with misclassification in edge cases due to limited optimization flexibility. Similarly, models like SCARNN (89.6%) exhibit sensitivity to background noise and low-resolution leaf patterns. While MDFN ResNet shows marginal improvement (91.9%) through multi-dimensional fusion, it does not incorporate feature interpretability or cognitive feedback [25, 26].

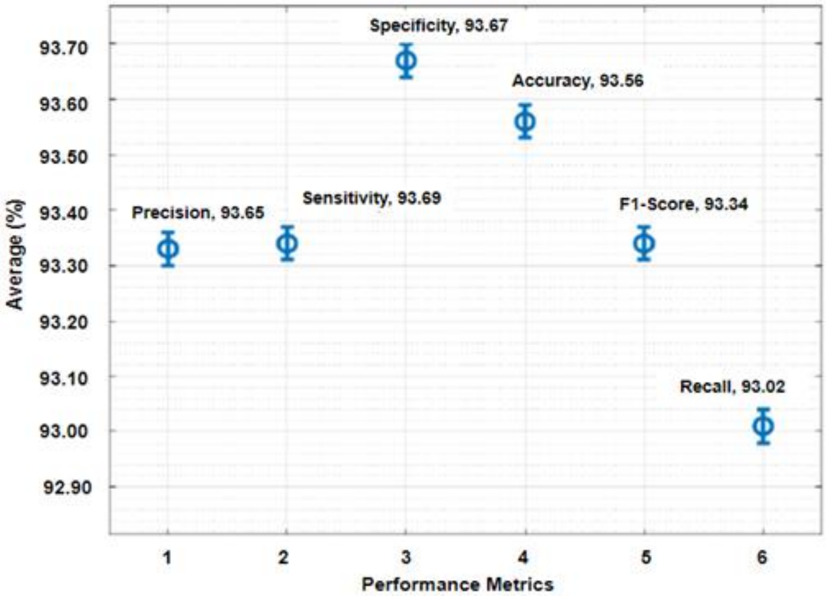

Figure 6. Average analysis of SIOC-LIMO model with varying measures

Table 3. Result analysis of SIOC-LIMO model with various measures

No. of Fold	Precision	Sensitivity	Specificity	Accuracy	F-Score	Recall
Fold-1	0.9306	0.9304	0.9348	0.9380	0.9305	0.9393
Fold-2	0.9365	0.9366	0.9383	0.9377	0.9366	0.9365
Fold-3	0.9386	0.9386	0.9365	0.9307	0.9321	0.9391
Fold-4	0.9330	0.9345	0.9365	0.9394	0.9330	0.9041
Fold-5	0.9347	0.9348	0.9374	0.9365	0.9347	0.9322
Average	**0.9365**	**0.9334**	**0.9367**	**0.9356**	**0.9334**	**0.9302**

By contrast, GAN-based augmentation combined with LIMO optimization improves disease boundary definition, achieving a specificity of 92.79%. A hybrid SIOC+SVM model slightly betters this (92.80%) by leveraging structured object indexing, yet remains constrained by fixed kernel assumptions. The proposed SIOC+LIMO framework achieves a peak specificity of 92.97%, demonstrating superior precision in distinguishing diseased and healthy crop regions. This enhancement is attributed to dynamic feature prioritization through CAS and non-linear progression modeling via the laurent series component neither of which are present in earlier approaches. In Figure 8, the accuracy comparison further reinforces the advantage of our framework. Conventional classifiers such as SVM (91.2%), ANN (90%), and KNN (88%) present lower accuracy rates due to limited generalization in multi-class scenarios. Ensemble-based methods like XGBoost (92.6%) and SIFT-SVM (92.2%) offer marginal improvements but rely heavily on handcrafted features [27, 28]. Recent models such as MFCN (92.7%), DCNN (92.79%), and MDFN ResNet (92.6%) embed deeper spatial hierarchies yet lack temporal modeling and interpretability [29]. Even the GAN+LIMO combination (93.6%) benefits from synthetic augmentation but does not dynamically adapt feature weights. The proposed SIOC+LIMO method achieves the highest accuracy of 92.97%, illustrating its robust and scalable classification capability. This result reflects the synergistic integration of swarm based feature refinement, laurent series driven trajectory mapping, and multi-objective optimization that balances diagnostic accuracy, interpretability, and computational overhead.

Figure 9 illustrates that traditional classifiers like SVM, DCNN, and MFCN yield relatively lower F1-measures, ranging from 87% to 89.4%, indicating limited adaptability to complex disease features. Improved scores are seen in models such as MFCN ResNet, SIOC_SVM, SIFT-SVM, and MDFN ResNet, reaching up to 92% [18, 29]. The GAN+LIMO framework performed well with 92.8%, but still lacked dynamic feature refinement. In comparison, the proposed SIOC+LIMO model achieved the highest F1-score of 93.8%, owing to its integration of cognitive attribute selection and laurent series modeling, which enhance feature relevance and interpretability. These results sustain the framework superiority over existing methods in balancing precision and recall for crop disease detection.

The table 4 comparative evaluation of detection and classification metrics across benchmark models and the proposed SIOC+LIMO framework. The proposed SIOC+LIMO model outperforms competing techniques across all metrics, achieving the highest sensitivity (93.3%), specificity (92.97%), precision (93.8%), and accuracy (92.97%), along with the lowest computation time (8 sec). This confirms its superior efficiency and diagnostic capability compared to GAN+LIMO and SIOC+SVM.

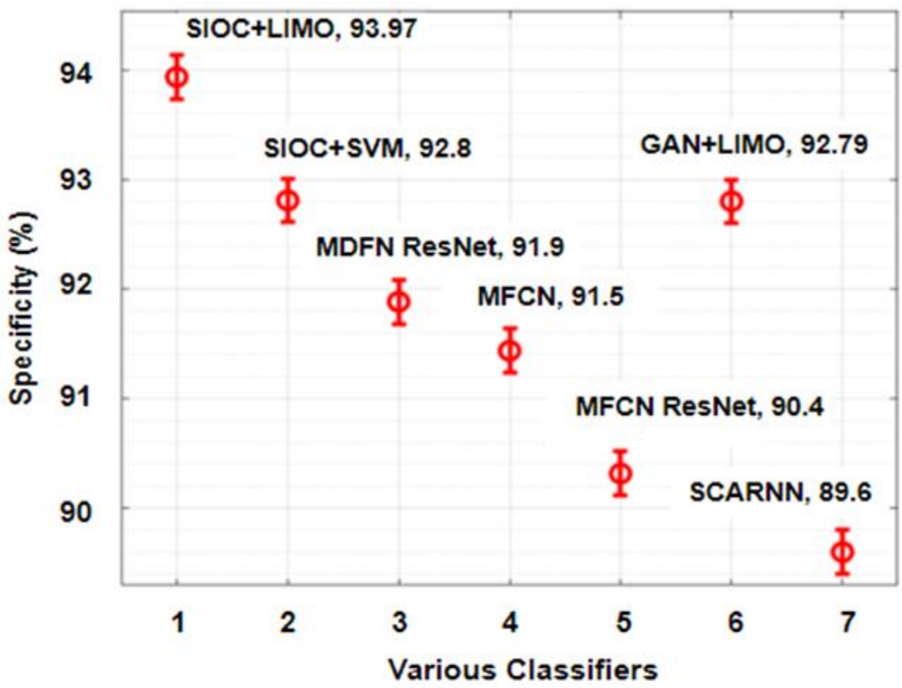

Figure 7. Specificity analysis values of SIOC-LIMO framework compared with existing classification algorithms

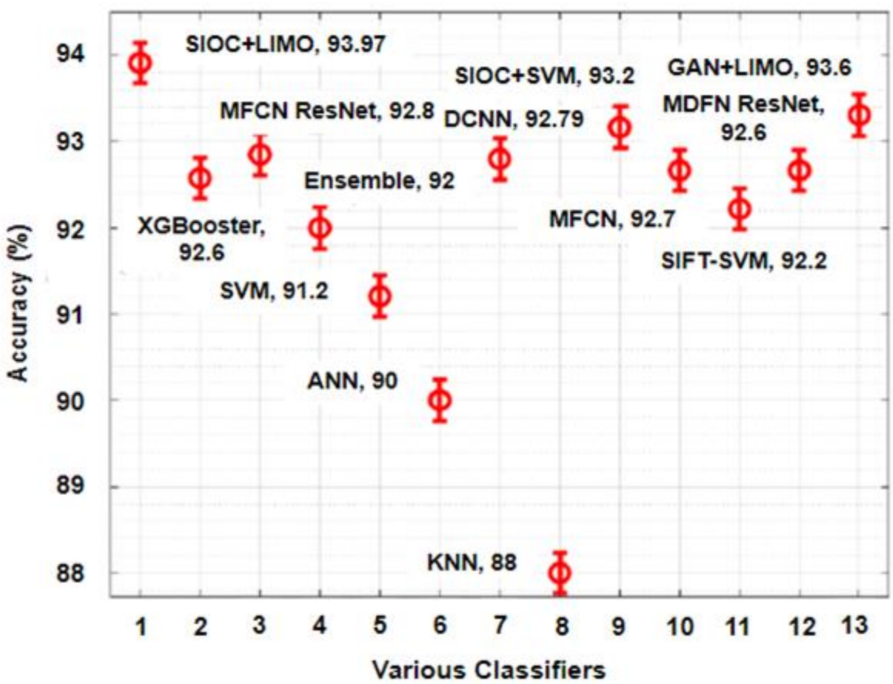

Figure 8. Accuracy of SIOC-LIMO framework with various disease detection classifiers

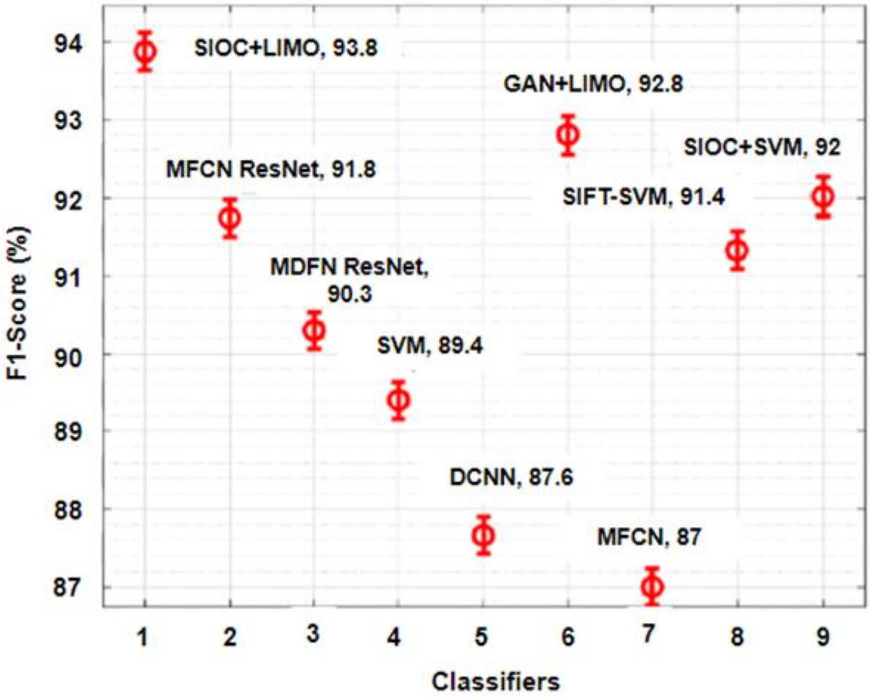

Figure 9. F1-score measure of SIOC-LIMO model with various machine learning algorithms

Table 4. Various detection and classification model metrics compared with SIOC+LIMO

Performance Metrics	Sensitivity Value (%)	Specificity Value (%)	Precision rate (%)	Accuracy Level (%)	F1Measure (%)	Computation Time(sec)
SIOC+SVM	86.6	92.80	92.1	93.2	92	11
GAN+LIMO	90	92.79	92.8	93.6	92.8	10
Proposed SIOC+LIMO	93.3	92.97	93.8	92.97	93.8	8

5. Conclusion

In our research work, a fine-tuning hybrid model termed SIOC+LIMO was evaluated and compared with various rice plant disease detection classifiers. SIOC+LIMO framework, the cognitive tuning of parameters such as activation function and loss function was done. This shows improvement over the results of the second stage analysis in terms of accuracy and trainable parameters. The accuracy, sensitivity, specificity, precision, recall, and F1-Score for SIOC+LIMO in our work for data fusion and multi-modality classification. Also, their performance is evaluated based on the performance parameter. This SIOC+LIMO model provided results with the best filtering methodologies, attribute selection model (CAS), various combinations of optimization techniques (particle swarm optimization, flower pollination algorithm, intelligence multimodality object optimization), adaptive network availability (ResNet50, CRCNet, GAN, U-Net) and finally various dimensional image input. It also additionally introduced HMDF for data fusion and the MOCLEAR algorithm used for data communication. The above-mentioned features improve the quality of the RPD system, as well as very quick detection and optimal classification. For SIOC+LIMO, Accuracy is 92.97%, sensitivity value is 93.3%, specificity value is 92.97%, precision rate is 93.8%, recall is 93.9%, and F1 Score is 93.8%. In the future, we will enhance with various deep learning algorithms that can be suitable for unstructured, more noisy images to improve the exact rice crop disease prevention and detection in real-time environment.

References

[1] P.K. Guru, P. Sahu, P. Shukla, P. Diwan, G. Panwar, P. Tiwari, A. Nagori, G. Carpenter, R. Sanodiya, B.S. Meena, M. Kumar, A critical review on rice cultivation and mechanization level in Indian perspective. Results in Engineering, 26, (2025) 105632. https://doi.org/10.1016/j.rineng.2025.105632

[2] Government of India (2023) Price policy for Kharif crops: The marketing season 2023-24, New Delhi India.

[3] P. Samal, S.C. Babu, B. Mondal, S.N. Mishra,

The global rice agriculture towards 2050: An inter-continental perspective. Outlook on Agriculture, 51(2), (2022) 164-172. https://doi.org/10.1177/00307270221088338

[4] N. Ivković, R. Kudelić, M. Črepinšek, Probability and certainty in the performance of evolutionary and swarm optimization algorithms. Mathematics, 10, (22), (2022) 4364. https://doi.org/10.3390/math10224364

[5] K. Mahadevan, A. Punitha, J. Suresh, A novel rice plant leaf diseases detection using deep spectral generative adversarial neural network, International Journal of Cognitive Computing in Engineering, 5, (2024) 237–249. https://doi.org/10.1016/j.ijcce.2024.05.004

[6] P. Samal, Eastern region holds the key to future increase in rice production in India, Open Access Journal of Agricultural Research, 9(3), (2024) 1–8. https://doi.org/10.23880/oajar-16000364

[7] M. Agarwal, G.M.S. Srivastava, Opposition-based learning inspired particle swarm optimization (opso) scheme for task scheduling problem in cloud computing. Journal of Ambient Intelligence and Humanized Computing, 12(10), (2021) 9855–9875. https://doi.org/10.1007/s12652-020-02730-4

[8] Y. Ren, G. Li, J. Zhang, W. An, J. Yang, H. Ni, (2025). EPC-GANet: a lightweight attention guided network with expanded receptive field for rice leaf disease recognition. The European Physical Journal Special Topics. https://doi.org/10.1140/epjs/s11734-025-01700-1

[9] K. Fang, R. Zhou, N. Deng, C. Li, X. Zhu,. RLDD-YOLOv11n: Research on Rice Leaf Disease Detection Based on YOLOv11. Agronomy, 15(6), (2025)1266. https://doi.org/10.3390/agronomy15061266

[10] R.R. Patil, S. Kumar, Rice-Fusion: A Multimodality Data Fusion Framework for Rice Disease Diagnosis. IEEE Access, IEEE, (2022) 5207-5222. https://doi.org/10.1109/ACCESS.2022.3140815

[11] D. Zhai, R. Shi, J. Jiang, X. Liu, Rectified Meta-learning from Noisy Labels for Robust Image-based Plant Disease Classification. ACM Transactions on Multimedia Computing Communications and Applications, 18(1), (2022) 1–17. https://doi.org/10.1145/3472809

[12] S. Aggarwal, M. Suchithra, N. Chandramouli, M. Sarada, A. Verma, D. Vetrithangam, B. Pant, B. Ambachew Adugna, (2022). Rice disease detection using artificial intelligence and machine learning techniques to improvise Agro-Business, Scientific Programming, 2022(1), (2022) 1757888. https://doi.org/10.1155/2022/1757888

[13] D. Li, R. Wang, C. Xie, L. Liu, J. Zhang, R. Li, F. Wang, M. Zhou, W. Liu, A recognition method for rice plant diseases and pests video detection based on deep convolutional neural network, Sensors, 20(3), (2020) 578. https://doi.org/10.3390/s20030578

[14] A. Sahur, A. Yassi, E. Syam'un, F. Ulfa, A.H. Bahrun, F. Djufry, N. Widiayani, Effect of Methanotroph Bacteria Isolated from Paddy Rice Plant (Oryza sativa L.) on Growth and Yield Components of Rice. International Journal of Agronomy, 2022(1), (2022) 9639326. https://doi.org/10.1155/2022/9639326

[15] J. Chen, D. Zhang, A. Zeb, Y.A. Nanehkaran, Identification of rice plant diseases using lightweight attention networks, Expert Systems With Applications, 169, (2021) 114514. https://doi.org/10.1016/j.eswa.2020.114514

[16] D. Singh, N. Jain, P. Jain, P. Kayal, S. Kumawat, N. Batra, PlantDoc, CoDS COMAD 2020: Proceedings of the 7th ACM IKDD CoDS and 25th COMAD, (2020) 249–253. https://doi.org/10.1145/3371158.3371196

[17] W.L. Chen, Y.B. Lin, F.L. Ng, C.Y. Liu, Y.W. Lin, RiceTalk: Rice blast detection using Internet of Things and Artificial intelligence Technologies, IEEE Internet of Things Journal, 7(2), (2019) 1001–1010. https://doi.org/10.1109/JIOT.2019.2947624

[18] P. Enkvetchakul, O. Surinta, Effective Data Augmentation and Training Techniques for Improving Deep Learning in Plant Leaf Disease Recognition, Applied Science and Engineering Progress, vol. 15(3), (2022) 3810. http://doi.org/10.14416/j.asep.2021.01.003

[19] K. Mahadevan, A. Punitha, J. Suresh, (2024). Automatic recognition of Rice Plant leaf diseases detection using deep neural network with improved threshold neural network, e-Prime - Advances in Electrical Engineering Electronics and Energy, 8, (2024) 100534. https://doi.org/10.1016/j.prime.2024.100534

[20] S. Zhang, C. Zhang, Modified U-Net for plant diseased leaf image segmentation. Computers and Electronics in Agriculture, 204, (2022) 107511. https://doi.org/10.1016/j.compag.2022.107511

[21] M.T. Roseno, S. Oktarina, Y. Nearti, H. Syaputra, N. Jayanti, Comparing CNN models for rice disease detection: ResNet50, VGG16, and MobileNetV3-Small, Journal of Information Systems and Informatics, 6(3), (2024) 2099–2109. https://doi.org/10.51519/journalisi.v6i3.865

[22] C.G. Simhadri, H.K. Kondaveeti, V.K. Vatsavayi, A. Mitra, P. Ananthachari, (2024). Deep learning for rice leaf disease detection: A systematic literature review on emerging trends, methodologies and techniques, Information Processing in Agriculture, 12(2), (2025) 151-168. https://doi.org/10.1016/j.inpa.2024.04.006

[23] A. Karunanithi, A.S. Singh, T. Kannapiran,. Enhanced hybrid neural networks (CoAtNet) for paddy crops disease detection and classification, Revue d'Intelligence Artificielle, 36(5), (2022) 671. https://doi.org/10.18280/ria.360503

[24] R. Elakya, T. Manoranjitham, Transfer learning by VGG-16 with convolutional neural network for paddy leaf disease classification, International Journal of Image and Data Fusion, 15(4), (2024) 461–484. https://doi.org/10.1080/19479832.2024.2332365

[25] C.R. Rahman, P.S. Arko, M.E. Ali, M.A.I. Khan, S.H. Apon, F. Nowrin, A. Wasif, Identification and recognition of rice diseases and pests using convolutional neural networks. Biosystems Engineering, 194, (2020) 112-120. https://doi.org/10.1016/j.biosystemseng.2020.03.020

[26] Y. Lu, X. Zhang, N. Zeng, W. Liu, R. Shang, Image classification and identification for rice leaf diseases based on improved WOACW_SimpleNet, Frontiers in Plant Science, 13, (2022) 1008819. https://doi.org/10.3389/fpls.2022.1008819

[27] F. Piccialli, C. Della Bruna, D. Chiaro, P. Qi, M. Savoia, (2025). AGRIFOLD: AGRIculture Federated learning for Optimized Leaf disease Detection. Expert Systems with Applications, 289, (2025) 128371. https://doi.org/10.1016/j.eswa.2025.128371

[28] C.G. Simhadri, H.K. Kondaveeti, V.K. Vatsavayi, A. Mitra, P. Ananthachari, Deep learning for rice leaf disease detection: A systematic literature review on emerging trends, methodologies and techniques. Information Processing in Agriculture, 12(2), (2025) 151-168. https://doi.org/10.1016/j.inpa.2024.04.006

[29] C. Feng, M. Jiang, Q. Huang, L. Zeng, C. Zhang, Y. Fan, (2022). A lightweight Real-Time rice blast disease segmentation method based on DFFANET, Agriculture, 12(10), (2022) 1543. https://doi.org/10.3390/agriculture12101543

Authors Contribution Statement

Anandhan Karunanithi: Conceptualization, Methodology, Formal analysis, Writing - Original Draft. K.P. Arjun: Conceptualization, Methodology, Formal analysis, Writing - Original Draft. R. Nagendra: Conceptualization, Writing - Review & Editing. D. Damodharan: Writing - Review & Editing. S. Janarthanan: Validation, Methodology, Writing - Review & Editing. S. Sreeji: Methodology, Formal analysis, Writing - Review & Editing. All the authors read and approved the final version of the manuscript.

Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Funding

The authors declare that no funds, grants or any other support were received during the preparation of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

About the License