

IGWO-Driven DeepForestNet: A Hybrid Shallow Fusion Model for Multiclass Leaf Disease Classification

Shantilata Palei*, Puspanjali Mohapatra

International Institute of Information Technology,
Department of CSE, Bhubaneswar,
India

{c122011, puspanjali}@iiit-bh.ac.in

Abstract. Modern deep learning (DL) techniques, especially convolutional neural networks (CNNs), have greatly increased the precision of multiclass classification tasks used to diagnose plant diseases. To detect multiclass leaf diseases in corn and apple plants, this study aims to develop a reliable and effective model. The proposed DeepForestNet integrates mid-level feature representations from DenseNet201 and MobileNetV2 through a shallow fusion mechanism. The fused feature vector is classified using a Random Forest (RF) classifier to enhance generalization and robustness. To further optimize model performance, the hyperparameters are fine-tuned using the Particle Swarm Optimization (PSO) and Improved Grey Wolf Optimization (IGWO) algorithms. The effectiveness of these optimization techniques is validated through comparative statistical analysis using the Wilcoxon signed-rank test and convergence evaluation. The IGWO-optimized DeepForestNet achieves a classification accuracy of 97.59% for apple leaf diseases (13 classes) and 97.19% for corn leaf diseases (4 classes), outperforming baseline and PSO-tuned variants. The proposed IGWO-driven DeepForestNet demonstrates high accuracy, stability, and convergence, making it a promising framework for automated and precise plant leaf disease identification in precision agriculture.

Keywords. Multiclass leaf disease classification, deep-ForestNet, feature fusion, IGWO, statistical analysis.

1 Introduction

Current agricultural production struggles to meet the rapidly increasing demand for food, necessitating improved productivity and sustainability. Leaf

infections can cause significant economic and environmental losses by reducing crop quality, underscoring the importance of early disease detection [53]. Traditionally, professional visual inspections have been the primary method for diagnosing plant diseases, but this approach can be costly and time-consuming, particularly for small producers in emerging regions [26].

To address these challenges, automated methods for detecting leaf diseases are becoming increasingly critical. As a powerful tool for analyzing leaf images for disease detection, machine learning (ML) is gradually replacing traditional visual inspections, providing more efficient and timely disease control in agriculture [30]. Vision-based methods have been developed recently to identify leaf diseases. These techniques usually entail using Convolutional Neural Networks (CNNs) based on deep learning (DL) for disease diagnosis and extracting visual information from leaf images. However, these techniques often suffer from lower recognition efficiency due to the complexity of feature extraction and the need for extensive image preprocessing [5]. Despite leveraging large image datasets to identify distinguishing features, these approaches still face challenges in achieving high accuracy.

The CNN model relies on a trial-and-error approach to enhance performance and reduce processing time by tuning hyperparameters using optimization algorithms [31]. These innovative optimization techniques offer a robust solution to the challenge of disease identification. Various optimization strategies have been found to greatly

improve the performance of the majority of models, especially when handling high-dimensional real-world problems [26].

The contributions of this paper include:

- Developed DeepForestNet, a hybrid shallow fusion model that integrates mid-level features extracted from DenseNet201 and MobileNetV2 through feature concatenation. The fused representation is classified using a Random Forest (RF) classifier, enhancing multiclass leaf disease identification performance.
- Propose an improved method of the GWO algorithm to optimize with the DeepForestNet model.
- PSO, GWO, and IGWO algorithms are used to tune DeepForestNet hyperparameters to maximize performance.
- IGWO-driven DeepForestNet model performs better in comparison to the standard optimization algorithms, i.e., PSO and GWO classification accuracy and reduced model complexity.
- Conducted detailed statistical analyses with the Wilcoxon signed rank test to compare PSO, GWO, and IGWO impacts on model performance.

The structure of this study: Literature review is included in Section 2. The suggested method is explained in Section 3. The results are evaluated in Section 4. Conclude the study in Section 5.

2 Literature Review

DL models have significantly advanced leaf disease detection and crop recognition. Jiang et al. [17] developed an improved CNN model to classify five types of apple leaf disease. Waheed et al. [48] introduced an optimized DenseNet model that efficiently recognizes corn leaf diseases with high accuracy, using fewer parameters than other CNN architectures such as EfficientNet, VGG19, NASNet, and Xception Net.

In a comparative analysis of ML and CNN models for identifying soybean disease, Nikith et al. [27] demonstrated the better accuracy of CNN. Banerjee

et al. [8] examined a hybrid CNN and RF model for diagnosing bitter Orange leaf diseases, demonstrating improved diagnostic accuracy. Kilicarslan et al. [18] proposed ML models with CNN models such as MobileNetV2 and EfficientNetV2B0 to classify apple varieties.

Optimization algorithms have been integrated with DL models to enhance plant disease classification performance. Raja et al. [38] incorporated Red Deer optimization and PSO to boost the performance of MobileNetV3, XGBoost, and neural network models, leading to improved accuracy and convergence rates. Sowmiya et al. [45] used quantum whale optimization with AlexNet, VGG16, ResNet50, and DenseNet121 models for Tomato leaf disease detection, demonstrating significant improvements in classification accuracy.

Naik et al. [26] explored the CNNs for paddy grain recognition, focusing on improving the model's performance by integrating GWO. By using GWO, the CNN was able to more effectively tune its hyperparameters, leading to improvements in both training and testing accuracy, demonstrating the potential of optimization algorithms in boosting DL models.

Similarly, Tamilvizhi et al. [47] optimized SqueezeNet and Deep Stacked Autoencoders with PSO to identify sugarcane leaf diseases. PP et al. [35] applied Harris Hawks Optimization (HHO) to DenseNet-121 and DenseNet-201 models for weed identification. HHO enabled more effective hyperparameter tuning, which improved the deep feature extraction capabilities of DenseNet models. As a result, these models achieved high classification accuracy. Prasannakumar et al. [36] employed a Dynamic Differential Annealed Optimization algorithm to enhance a Contextual Mask Auto-Encoder for plant disease identification. This approach significantly improved detection accuracy.

The growing use of ML-DL hybrid models with optimization strategies for plant disease diagnosis is highlighted. Table 1 summarises the pertinent previous research conducted during the past five years.

Table 1. Review of Prior Studies

Ref.	ML and DL Model Applied	Optimization Algorithm	Objective
[12]	LSTM, BiLSTM, GRU, RNN	Red Fox Optimization	Crop selection and yield prediction
[38]	MobileNetV3, XGBoost, NN models	Red Deer Optimization, PSO	Plant Disease Detection
[49]	EfficientNetB5	-	Assessment of baby corn quality
[45]	AlexNet, VGG16, ResNet50, DenseNet121, PCA	Quantum Whale Optimization	Tomato leaf disease detection
[26]	CNN	Grey Wolf Optimization	Recognition of Paddy grains
[47]	SqueezeNet, Deep Stacked Autoencoder	Particle Swarm Optimization	Identification of Diseases in Sugarcane Leaves
[35]	DenseNet-121, DenseNet-201	Harris Hawks Optimization	Weed Identification
[4]	DCNN, GoogleNet	Dipper Throated Optimization, Modified Sine Cosine Algorithm	Crop classification
[3]	MobileNetv2, GRU	Improved Artificial Ecosystem Optimization	Insect detection
[19]	MobileNetV2	-	Diagnosis of Diseases in Plant Leaves
[7]	MobileNetV2, DenseNet121, InceptionResNetV2	Genetic Algorithm	Crop Pests classification
[43]	Mask-R-CNN, SqueezeNet, Deep Q-Net	Adaptive Snake Optimization	apple, tomato, and corn disease detection
[20]	DCNN	-	Crop Leaf disease detection
[22]	UNet, Deep Batch Normalized AlexNet	Bald Eagle Search Optimization, Mayfly Algorithm	Leaf disease detection
[34]	-	Grasshopper Optimization, Modified Artificial Bee Colony Optimization	Leaf disease detection
[40]	EfficientNet, RF, AdaBoost, Stochastic Gradient Boosting	-	Crop Leaf disease detection
[23]	ELM, k-means	-	Leaf disease detection
[11]	EfficientNet(B0–B7), kNN, AdaBoost, RF, LR, Stochastic Gradient Boosting	-	Tomato disease detection
[5]	Dilated Residual Network, CNN-Gated Recurrent Unit	Salp Swarm Optimization	Grape leaf classification
[1]	CNN	Ant Colony Optimization	Plant Leaf disease detection
[2]	ELM, RF	Ant Colony Optimization	Wheat yield prediction
[10]	U-net, Mask RCNN	-	Leaf disease detection
[14]	kNN, SVM, RF, CNN	Artificial Plant Optimization	Leaf disease detection
[15]	DNN, Speeded up robust feature	Grasshopper Optimization	Leaf Disease Detection

3 Proposed Methodology

Multiclass leaf disease classification includes describing the dataset, preprocessing, hyperparameter tuning, feature extraction, and classification.

3.1 Dataset Description

In this study, an automated apple and corn disease classification has been implemented. The Kaggle and Plantvillage databases contain the apple

and corn leaf dataset used in this study [32] [39]. This study examines a 4-class maize leaf disease dataset and a 13-class apple dataset. Figs 1 and 2 show the samples of each class of the leaf dataset.

Dataset preprocessing uses several steps to prepare images for model training. Initially, images are decoded and converted into the JPEG format for consistency. Data augmentation is performed by rotating images at angles of 30°, 60°, 90°, 120°, and 180° to increase diversity and model robustness. The images, originally in varying dimensions



Fig. 1. Apple Leaf Image Dataset Samples

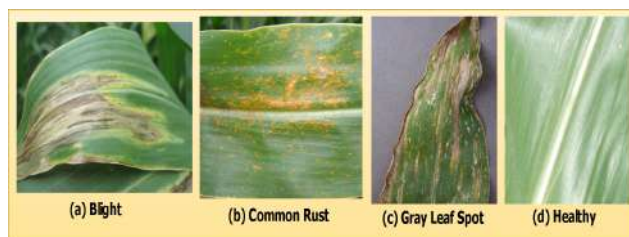


Fig. 2. Corn Leaf Image Dataset Samples

are resized uniformly to $[224 \times 224]$ pixels. Color conversion, such as RGB to grayscale or other transformations, is applied to simplify processing. Lastly, the dataset is divided into X_{train} , X_{val} , and X_{test} (80%, 20%, respectively).

3.2 Methods Used in the Study

This study introduces DeepForestNet, a shallow fusion-based multiclass leaf disease classification model that integrates DenseNet201 and MobileNetV2 for efficient mid-level feature representation. The proposed framework takes an input leaf image of size $(224 \times 224 \times 3)$, which is processed independently by both CNN backbones.

From DenseNet201, feature maps are extracted from an intermediate convolutional block `conv3_block12_out`, approximately $28 \times 28 \times 512$, and a Global Average Pooling (GAP) operation is applied to obtain a 512-dimensional feature vector (F_1). Similarly, from MobileNetV2, the intermediate feature maps `block_6.expand_relu`, approximately

$28 \times 28 \times 256$ are extracted and processed using GAP to generate a 256-dimensional feature vector (F_2).

These two mid-level feature vectors are then concatenated to form a fused representation ($F = [F_1, F_2]$) of dimension approximately 768. Instead of relying on a fully connected or softmax layer, the fused features are fed into an RF classifier, which leverages an ensemble of decision trees and majority voting to perform the final classification.

The model is evaluated on two datasets—comprising 13 apple leaf disease classes and 4 corn disease classes—to validate its robustness and generalization capability. By performing feature fusion at intermediate layers, DeepForestNet effectively captures both fine-grained and structural information, leading to improved accuracy and stability compared to conventional CNN-based classifiers. Fig. 3 illustrates the proposed DeepForestNet model.

DeepForestNet uses PSO and GWO as standard optimization algorithms to tune hyperparameters with optimal values. PSO and GWO individually operate to find the best hyperparameter values for the DeepForestNet model. The model leverages both PSO and GWO optimizers and the optimized hyperparameter values identified by these two algorithms. DeepForestNet extracts features from the dataset using the best-tuned hyperparameters.

The GWO algorithm was inspired by the hunting behavior and social hierarchy of grey wolves and was first proposed by Seyedali Mirjalili in 2014 [41]. Grey wolves exhibit a strict social hierarchy with alpha (X_α), beta (X_β), delta (X_δ), and omega wolves (X_i). This hierarchy influences their hunting strategy, where alpha wolves lead, followed by beta and delta wolves, and finally omega wolves [29]. During a hunt, wolves encircle their victim, as illustrated in Eqs. (1) and (2) [24]:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right|, \quad (1)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D}. \quad (2)$$

Here, wolf's position vector is $\vec{X}(t)$, $\vec{X}_p(t)$ is the prey's position, and current iteration (t) . Eqs. (3) and (4) are show coefficient vectors \vec{A} and \vec{C} [21]:

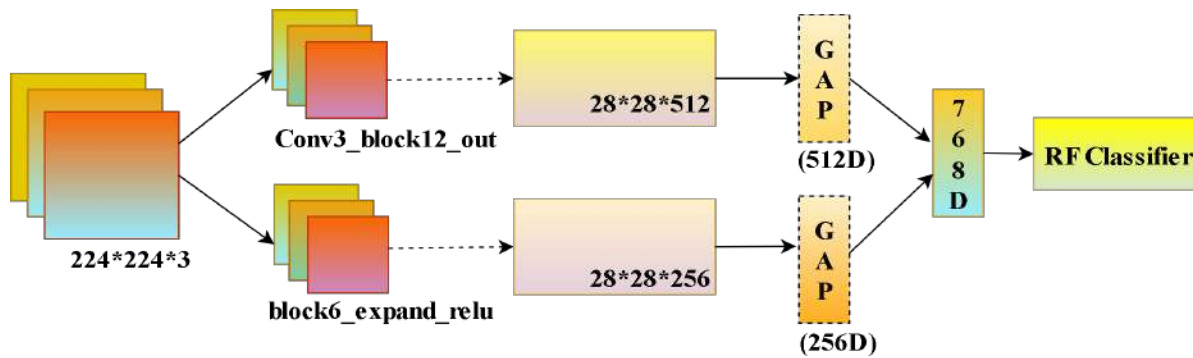


Fig. 3. Proposed DeepForestNet Model

$$\vec{C} = 2\vec{a} \cdot \vec{r}_1 - \vec{a}, \quad (3)$$

$$\vec{A} = 2 \cdot \vec{r}_2, \quad (4)$$

where random values are r_1 and r_2 in $[0, 1]$, and control parameter \vec{a} that drops from 2 to 0 linearly, as shown in Eq. (5):

$$\vec{a} = 2 \left(1 - \frac{t}{t_m} \right). \quad (5)$$

Where the maximum number of iterations is t_m . The three best solutions so far, \vec{X}_α , \vec{X}_β , and \vec{X}_δ , guide the position update of the remaining wolves through Eqs. (6)–(12) [13]:

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|, \quad (6)$$

$$\vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|, \quad (7)$$

$$\vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}|, \quad (8)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha, \quad (9)$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta, \quad (10)$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta, \quad (11)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}. \quad (12)$$

To improve performance, the GWO is modified into an IGWO. The first enhancement adjusts the parameter \vec{a} using a non-linear decay, as shown in Eq. (13), replacing the linear Eq. (5):

$$\vec{a} = 2 \left(1 - \left(\frac{t}{t_m} \right)^{2.5} \right). \quad (13)$$

This non-linearity helps maintain a better balance between exploration and exploitation during iterations. The updated position vector of a search agent is also refined using weighted contributions from the three best wolves, as defined in Eq. (14):

$$\vec{X}(t+1) = \frac{3\vec{X}_1 + 2\vec{X}_2 + \vec{X}_3}{6}. \quad (14)$$

Algorithm 1 presents the step-by-step process of IGWO-driven DeepForestNet, and Fig. 4 illustrates the IGWO algorithm in detail.

Fig. 5 illustrates the multiclass image leaf disease classification model comprising phases named P1 to P5. In P1, the apple and corn dataset is collected.

P2 shows the 13 classes of an apple leaf dataset and 4 for the corn datasets. In P3, preprocessing techniques are applied to the datasets. The pre-processed data are given to the proposed model in P4. In P4 (A) and P4 (B), DenseNet201 and MobileNetV2 are individually trained using both datasets. In P4 (C) DeepForestNet trains the model.

This method needs time to tune and build the model as it is found to determine the model parameters on the trial-and-error method. To overcome the

Algorithm 1 Proposed IGWO-driven DeepForest-Net Model

- 1: **Input:** Apple and Corn dataset X , Labels y , DeepForestNet Model
- 2: **Output:** Optimized hyperparameters for the model
- 3: **Initialize** GWO parameters: bounds lb , ub , max_iterations, population size n
- 4: Split data into X_{train} , X_{val} , and X_{test}
- 5: **Define** fitness function:
- 6: **function** FITNESSFUNCTION(position)
- 7: Decode position to hyperparameters: learning rate, decay rate, epochs, dropout, $n1$, $n2$, $n3$, $n4$
- 8: Initialize model with these hyperparameters
- 9: Train model on X_{train} , y_{train} with early stopping based on validation loss
- 10: **return** Validation accuracy
- 11: **end function**
- 12: **Initialize** the wolf population x_i ($i = 1, 2, \dots, n$) with random hyperparameters
- 13: Calculate FITNESSFUNCTION
- 14: Identify (X_α), (X_β), and (X_δ) search agents
- 15: **for** $t = 1$ to max_iterations **do**
- 16: **for** each search agent i **do**
- 17: **for** each dimension d of the search agent's position **do**
- 18: Modify the agent's location using Eq (14)
- 19: **end for**
- 20: **end for**
- 21: Adaptively revise parameters a , A , and C
- 22: Assess fitness for every search agent
- 23: Refresh X_α , X_β , X_δ with the new best solutions
- 24: **end for**
- 25: **Return** X_α (the best hyperparameter values)
- 26: Initialize and train the final model with the optimized hyperparameters on the combined training and validation set
- 27: Evaluate the DeepForestNet's performance on X_{test}

limitations that arise due to the randomly chosen hyperparameters, evolving algorithms like PSO, GWO, and IGWO are utilized to determine the optimal hyperparameters. The RF classifier categorizes features extracted by combined DeepForestNet model, optimized through tuned hyperparameters, into multiple disease classes. In P5, the model performance is shown using various classification measures.

4 Results Evaluation

4.1 Experimental Setup

The experiment uses a Kaggle Notebook Disk Space of 73.1 GB, RAM of 13 GB, GPU Memory of 15.4 GB, and Accelerator - GPU P100. The batch size of 128, maximum epoch of 50, a validation frequency of 1 and an Adam optimizer used for training. Table 2 shows the optimal value of the hyperparameters after applying the proposed optimization algorithms.

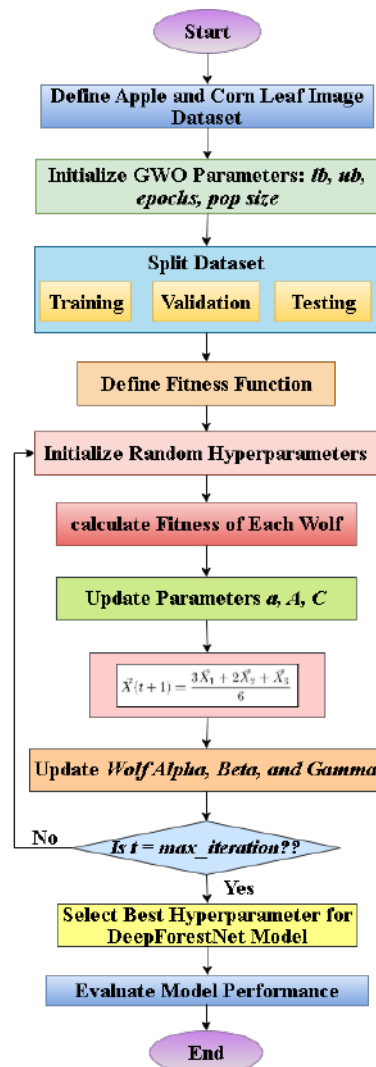


Fig. 4. Flowchart of the IGWO-Driven DeepForestNet model for hyperparameter tuning

This paper uses parameters such as *Accuracy*, *macro* and *micro Precision*, *macro* and *micro recall*, *macro* and *micro F1*, Matthews Correlation Coefficient (*MCC*) and Kappa Coefficient (*Kappa*).

Here, True Positives (p), True Negatives (q), False Positives (r), and False Negatives (s) is used to calculate the values. In the *Kappa* measures, class no. (i), total no. of class (w), truth class i values ($x_{i,i}$), total prediction value (z_i) and total truth values (y_i) [32]. Eqs. (15) to (26) shows all the mathematical formulae. The loss function

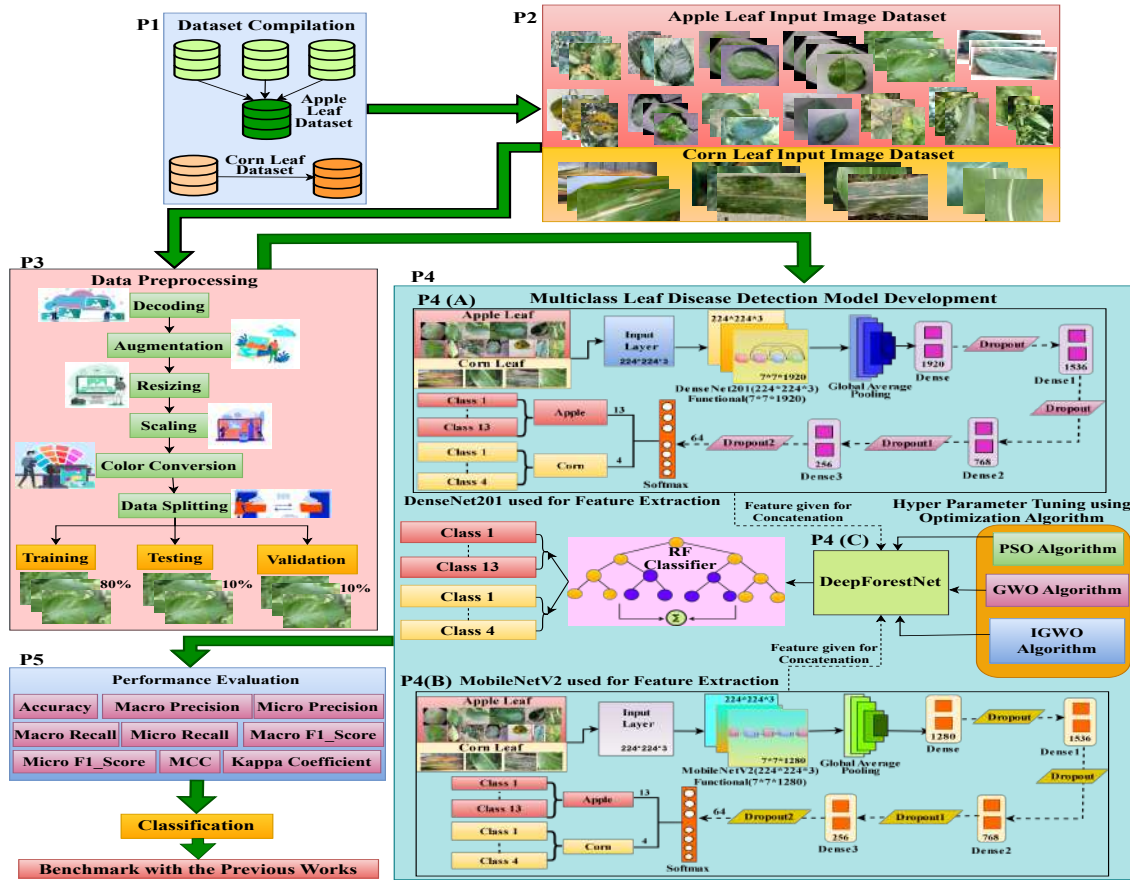


Fig. 5. Workflow of Proposed Model for Multiclass Leaf Disease Detection

(L) is given in Eq. (27). In L , C is the no. of classes. Binary indicator is y_c if class c is the correct classification for the sample. Predicted probability (\hat{y}_c) of class c :

$$Accuracy = \frac{p + q}{p + q + r + s}, \quad (15)$$

$$Precision = \frac{p}{p + r}, \quad (16)$$

$$Micro_Precision = \frac{\sum_{i=1}^m p_i}{\sum_{i=1}^m p_i + r_i}, \quad (17)$$

$$Macro_Precision = \frac{1}{m} \sum_{i=1}^m PR_i, \quad (18)$$

$$Recall = \frac{p}{p + s}, \quad (19)$$

$$Micro_Recall = \frac{\sum_{i=1}^m p_i}{\sum_{i=1}^m p_i + s_i}, \quad (20)$$

$$Macro_Recall = \frac{1}{m} \sum_{i=1}^m Recall_i, \quad (21)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}, \quad (22)$$

$$Micro_F1 = 2 \times \frac{Micro_Precision * Micro_Recall}{Micro_Precision + Micro_Recall}, \quad (23)$$

$$Macro_F1 = 2 \times \frac{Macro_Precision \times Macro_Recall}{Macro_Precision + Macro_Recall}, \quad (24)$$

Table 2. Optimal Hyperparameter Values

Optimization Algorithm	Hyperparameters	Range	Previous Value	Optimal Value
DeepForestNet + PSO (Apple)	Learning Rate	[0.0001 – 0.005]	0.001	0.00093765
	Dropout Rate	0.1-0.4	0.2	0.25684264
	Decay Rate	0.7 – 0.99	0.9	0.93268459
	Number of Neurons (n1, n2, n3, n4)	[1024, 512, 256, 16] to [2048, 1024, 512, 256]	[1536, 768, 256, 64]	[1949, 588, 475, 43]
DeepForestNet + PSO (Corn)	Learning Rate	[0.0001 – 0.005]	0.001	0.00063789
	Dropout Rate	0.1-0.4	0.2	0.27589623
	Decay Rate	0.7 – 0.99	0.9	0.96854263
	Number of Neurons (n1, n2, n3, n4)	[1024, 512, 256, 16] to [2048, 1024, 512, 256]	[1536, 768, 256, 64]	[1113, 566, 452, 246]
DeepForestNet + GWO (Apple)	Learning Rate	[0.0001 – 0.005]	0.001	0.00127689
	Dropout Rate	0.1-0.4	0.2	0.23758612
	Decay Rate	0.7 – 0.99	0.9	0.94126584
	Number of Neurons (n1, n2, n3, n4)	[1024, 512, 256, 16] to [2048, 1024, 512, 256]	[1536, 768, 256, 64]	[1245, 650, 432, 126]
DeepForestNet + GWO (Corn)	Learning Rate	[0.0001 – 0.005]	0.001	0.00058902
	Dropout Rate	0.1-0.4	0.2	0.28569134
	Decay Rate	0.7 – 0.99	0.9	0.96125698
	Number of Neurons (n1, n2, n3, n4)	[1024, 512, 256, 16] to [2048, 1024, 512, 256]	[1536, 768, 256, 64]	[2009, 977, 358, 100]
DeepForestNet + IGWO (Apple)	Learning Rate	[0.0001 – 0.005]	0.001	0.00090217
	Dropout Rate	0.1-0.4	0.2	0.26892543
	Decay Rate	0.7 – 0.99	0.9	0.93658725
	Number of Neurons (n1, n2, n3, n4)	[1024, 512, 256, 16] to [2048, 1024, 512, 256]	[1536, 768, 256, 64]	[1366, 938, 400, 247]
DeepForestNet + IGWO (Corn)	Learning Rate	[0.0001 – 0.005]	0.001	0.00061253
	Dropout Rate	0.1-0.4	0.2	0.27589623
	Decay Rate	0.7 – 0.99	0.9	0.95486312
	Number of Neurons (n1, n2, n3, n4)	[1024, 512, 256, 16] to [2048, 1024, 512, 256]	[1536, 768, 256, 64]	[1918, 720, 260, 177]

$$MCC = \frac{p \cdot q - r \cdot s}{\sqrt{(p+r)(p+s)(q+r)(q+s)}}, \quad (25)$$

$$Kappa = \frac{w \sum_{i=1}^n x_{i,i} - \sum_{i=1}^n (y_i, z_i)}{w^2 - \sum_{i=1}^n (y_i, z_i)}, \quad (26)$$

$$L = \sum_{c=1}^C y_c \log(\hat{y}_c). \quad (27)$$

4.2 Performance Analysis

This section presents the results obtained from the implemented models. The training and validation loss and accuracy of DenseNet201 and

MobileNetV2 on the apple and corn datasets are shown in Figs 6 and 7.

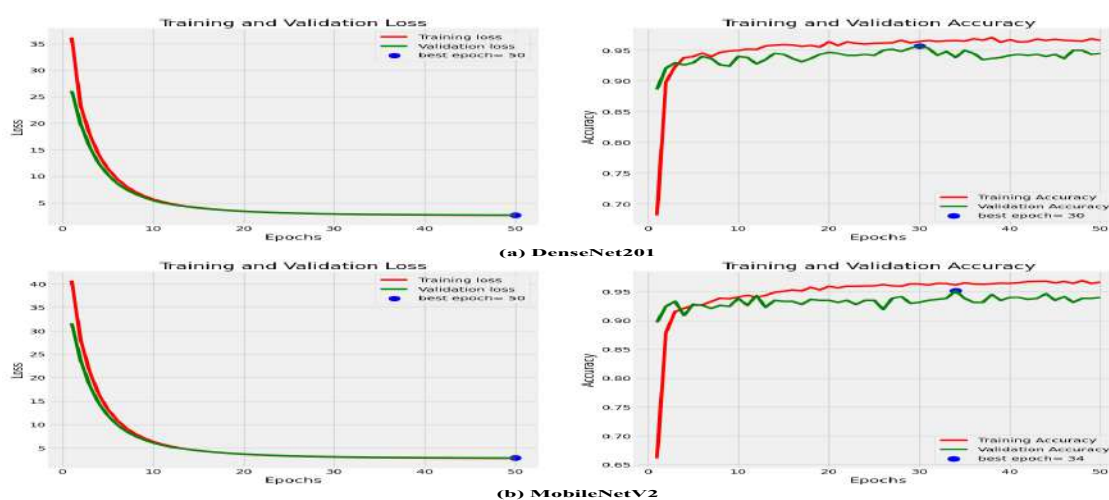
The confusion matrix, along with the accuracy and loss graph over epochs for the DeepForestNet model, is illustrated in Figs 8, 9, and 10.

A comparison of performance results between standard DL models and DeepForestNet is shown in Fig. 11, where DeepForestNet demonstrates superior performance.

The detailed performance of all models is provided in Table 3, which highlights the effectiveness of DeepForestNet across both datasets.

Table 3. Classification Performance of DL Models (in %)

Dataset	Model	Accuracy	Macro Precision	Micro Precision	Macro Recall	Micro Recall	Macro F1 Score	Micro F1 Score	MCC	Kappa
Apple Leaf	DenseNet201	93.15	93.61	93.15	92.65	93.15	92.83	93.15	92.61	92.57
	MobileNetV2	92.32	91.89	92.32	92.32	92.32	91.65	92.32	91.67	91.66
	DenseNet201+	94.15	94.03	94.15	93.69	94.15	93.82	94.15	93.667	93.66
	DeepForestNet	95.35	94.95	95.35	94.77	95.35	94.78	95.35	94.96	94.95
Corn Leaf	DenseNet201	94.75	93.21	94.75	92.68	94.75	92.92	94.75	92.83	92.82
	MobileNetV2	93.00	92.51	93.00	89.76	93.00	90.73	93.00	90.50	90.38
	DenseNet201+	94.91	95.5	94.91	92.91	94.91	93.18	94.91	93.04	93.03
	DeepForestNet	95.23	93.92	95.23	93.33	95.23	93.6	95.23	93.48	93.47

**Fig. 6.** Validation and Training Accuracy and Loss over Epochs with the Apple Leaf Dataset

4.2.1 Simulation Results of PSO-driven DeepForestNet Model

The confusion matrices using the apple and corn leaf dataset are shown in Fig. 12. Table 4 show the PSO-driven DeepForestNet of all the experimental parameter results. This table shows that PSO-driven DeepForestNet using the corn dataset displays better results with 96.06%.

4.2.2 Simulation Results of GWO-driven DeepForestNet Model

Confusion matrices of this model using both datasets are illustrated in Fig. 13. Table 5 represents the experimental results. It shows that

GWO-driven DeepForestNet using the corn dataset achieves better overall performance, with an accuracy of 96.44%.

4.2.3 Simulation Results of IGWO-driven DeepForestNet Model

The confusion matrices for IGWO-driven DeepForestNet are shown in Fig. 14.

The apple dataset shows fewer severe misclassifications overall.

The validation and training accuracy and loss graphs for the apple and corn datasets are shown in Figs 15 and 17.

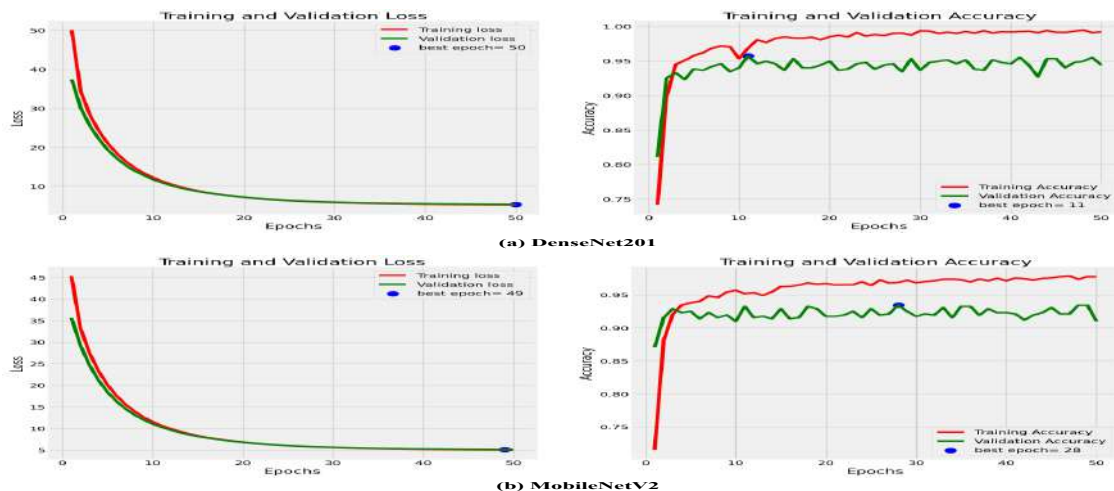


Fig. 7. Validation and Training Accuracy and Loss over Epochs using Corn Leaf Dataset

Table 4. Results of PSO-driven DeepForestNet on Apple and Corn Leaf Datasets (in %)

Dataset	Accuracy	Macro Precision	Micro Precision	Macro Recall	Micro Recall	Macro F1 Score	Micro F1 Score	MCC	Kappa
Apple Leaf	95.86	95.61	95.86	95.49	95.86	95.51	95.86	95.52	95.51
Corn Leaf	96.06	96.22	96.06	93.53	96.06	94.52	96.06	94.75	94.59

Table 5. Results of GWO-driven DeepForestNet on Apple and Corn Leaf Datasets (in %)

Dataset	Accuracy	Macro Precision	Micro Precision	Macro Recall	Micro Recall	Macro F1 Score	Micro F1 Score	MCC	Kappa
Apple Leaf	96.21	96.10	96.21	95.86	96.21	95.91	96.21	95.897	95.892
Corn Leaf	96.44	96.52	96.44	94.22	94.44	95.1	96.44	95.25	95.11

Table 6. Results of IGWO-Driven DeepForestNet on Apple and Corn Leaf Datasets (in %).

Dataset	Accuracy	Macro Precision	Micro Precision	Macro Recall	Micro Recall	Macro F1 Score	Micro F1 Score	MCC	Kappa
Apple Leaf	97.59	97.39	97.59	97.37	97.59	97.37	97.59	97.389	97.386
Corn Leaf	97.19	97.14	97.19	95.59	97.19	96.23	97.19	96.25	96.15

Table 6 illustrate the experimental results of IGWO-driven DeepForestNet on apple and corn datasets.

he apple dataset with this proposed model shows superior results with an accuracy of 97.59%.

4.3 Convergence Analysis

The objective is to achieve the minimum possible misclassification rate. The convergence graphs for models concerning the apple leaf and corn leaf datasets are presented in Fig. 18.

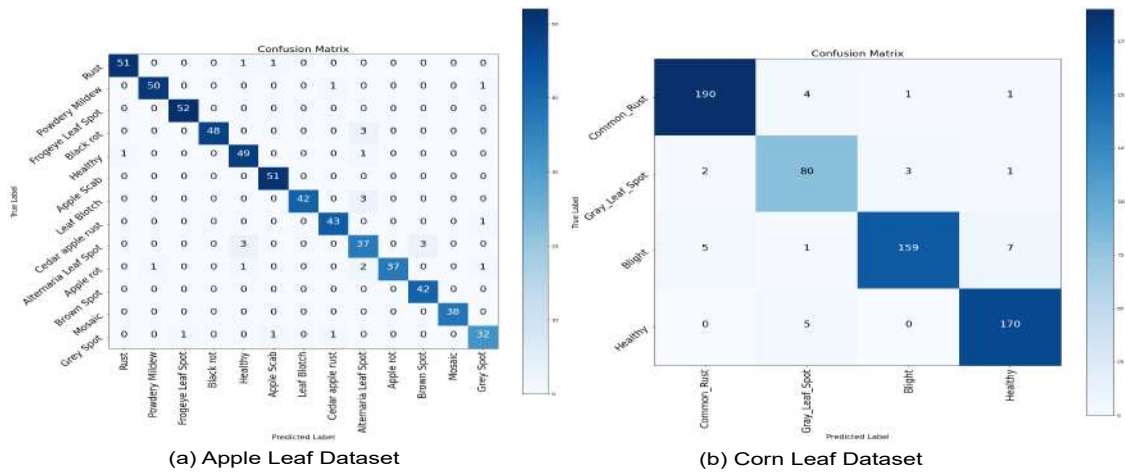


Fig. 8. Confusion Matrices of DeepForestNet on both the Datasets

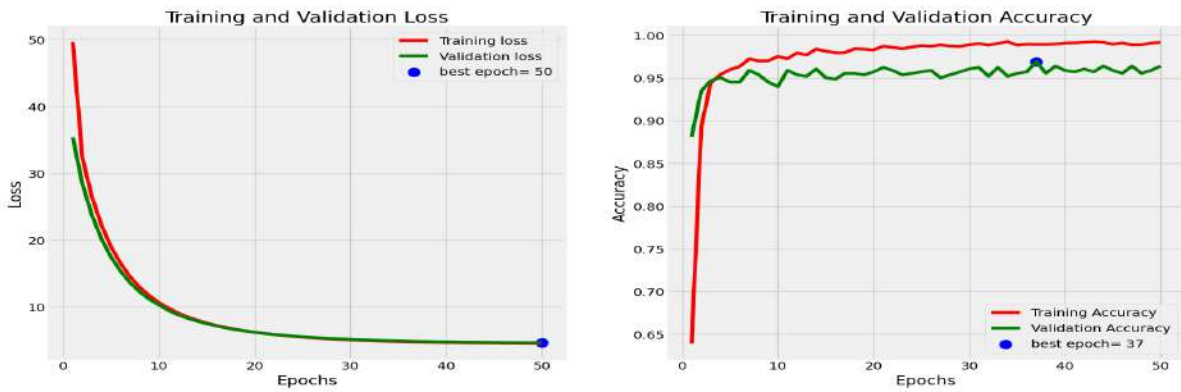


Fig. 9. Accuracy and Loss Over Epochs for DeepForestNet on the Apple Leaf Dataset

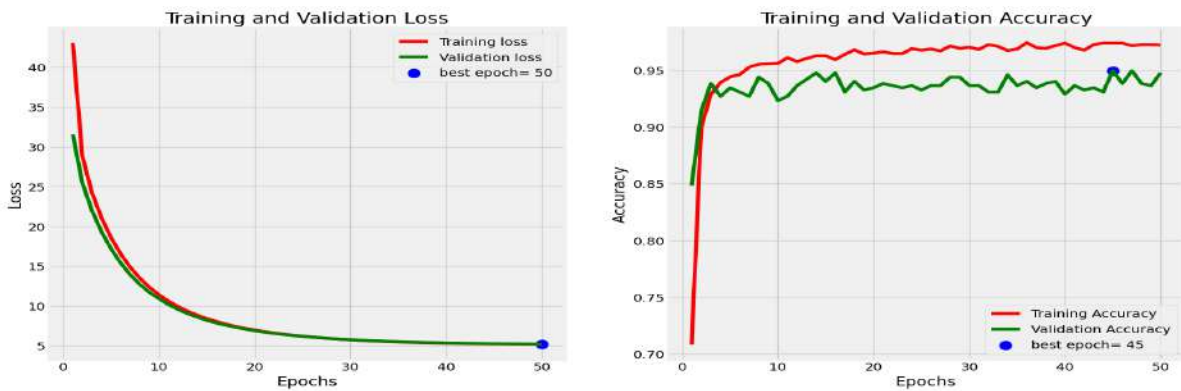


Fig. 10. Accuracy and Loss Over Epochs for DeepForestNet on the Corn Leaf Dataset

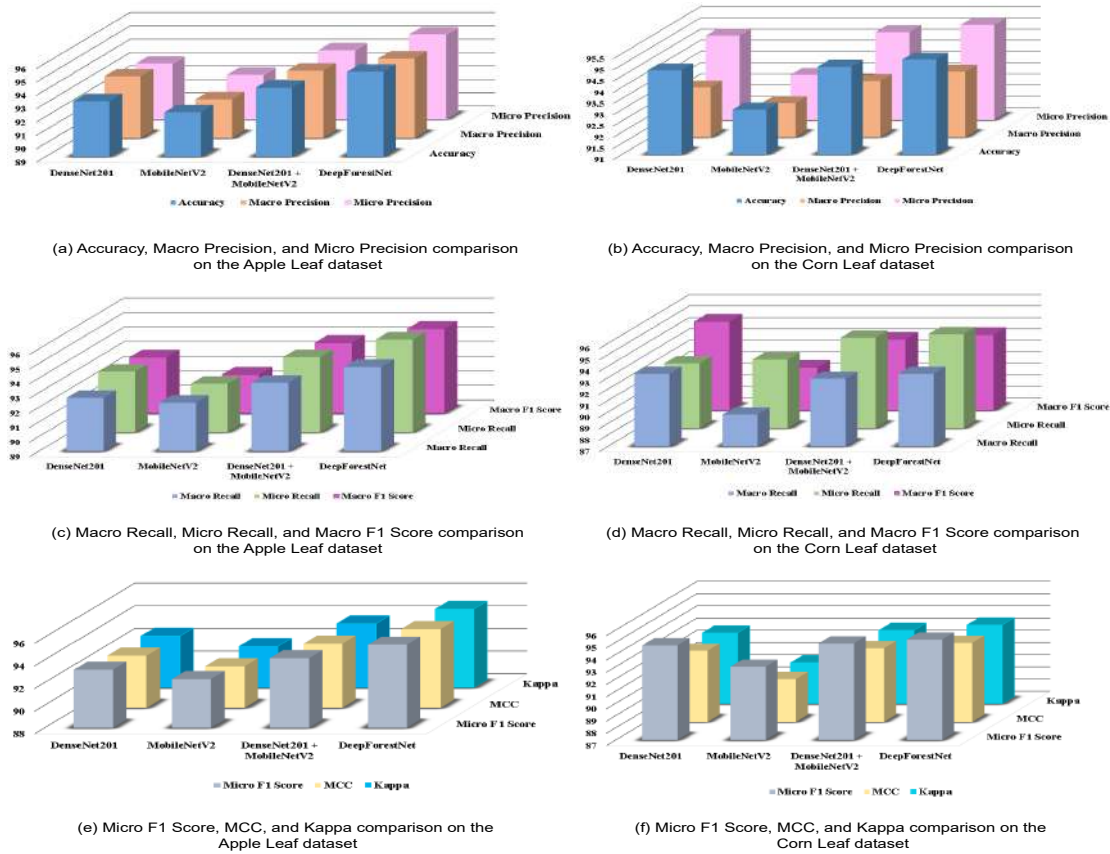


Fig. 11. DenseNet201 vs. MobileNetV2 vs. DenseNet201+MobileNetV2 vs. DeepForestNet on Apple and Corn Leaf Dataset w.r.t all the Performance parameters

Table 7. Statistical Analysis of Classification Accuracy and Average Running Time (mins) for All Models on Both Datasets

Models	Apple Leaf Dataset				Corn Leaf Dataset					
	Min	Max	Avg	Std	Time (mins)	Min	Max	Avg	Std	Time (mins)
DenseNet201	87.07	93.67	93.15	2.412	20.34	88.71	94.89	94.75	2.360	17.53
MobileNetV2	86.24	92.84	92.32	1.622	22.41	86.96	93.28	93.00	1.577	18.02
DenseNet201 + MobileNetV2	88.17	94.67	94.15	1.515	17.52	88.87	94.95	94.91	1.445	14.36
DeepForestNet	89.37	95.42	95.35	1.356	14.32	89.19	95.33	95.23	1.390	11.45
DeepForestNet + PSO	88.69	96.38	95.86	1.302	10.43	90.02	96.89	96.06	1.299	8.98
DeepForestNet + GWO	90.03	96.73	96.21	1.151	8.29	90.40	97.22	96.44	1.147	6.87
DeepForestNet + IGWO	91.15	98.07	97.59	0.998	5.09	91.01	98.02	97.19	1.027	4.97

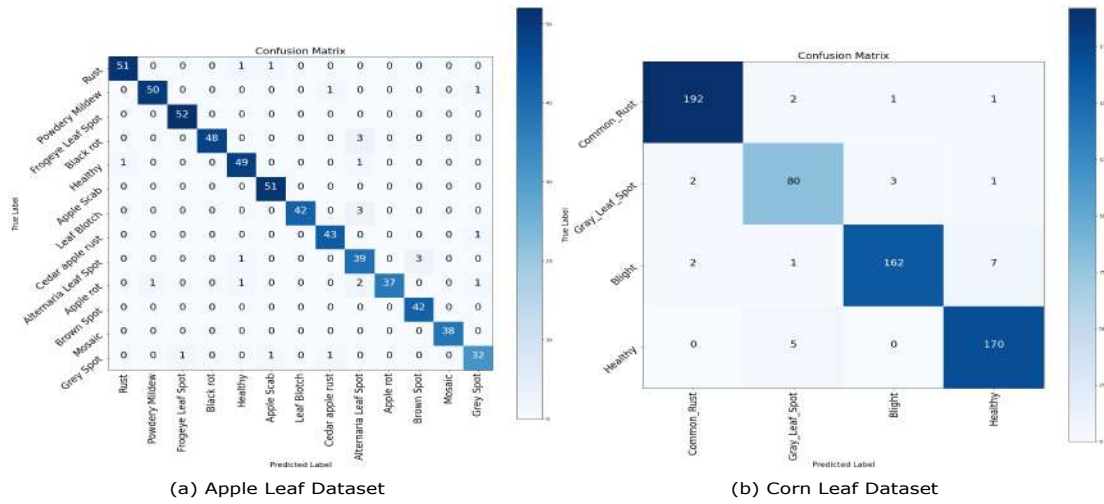


Fig. 12. Confusion Matrices of PSO-Driven DeepForestNet on both the Datasets

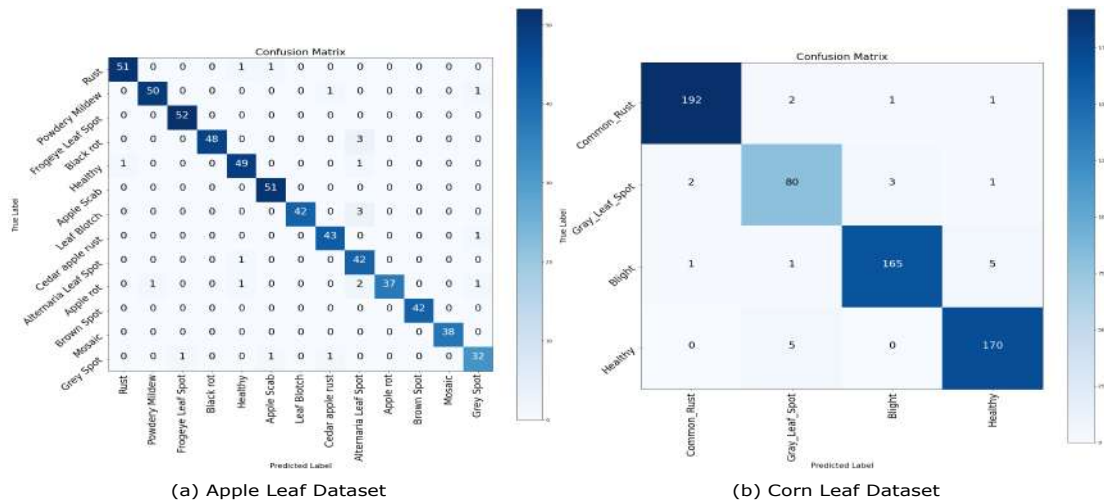


Fig. 13. Confusion Matrices of GWO-Driven DeepForestNet on both the Datasets

The IGWO-driven DeepForestNet model achieves a faster convergence rate than the other models on both datasets.

4.4 Statistical Analysis

Max is computed by Eq. (28).

$$\text{Max.} = \max_{1 \leq i \leq t_m} f. \quad (28)$$

Where f indicates the accuracy:

Min is computed by Eq. (29):

$$\text{Min.} = \min_{1 \leq i \leq t_m} f_i. \quad (29)$$

Avg of f . f is computed by Eq. (30):

$$\text{Avg.} = \frac{\sum_{i=1}^{t_m} (f_i)}{t_m}. \quad (30)$$

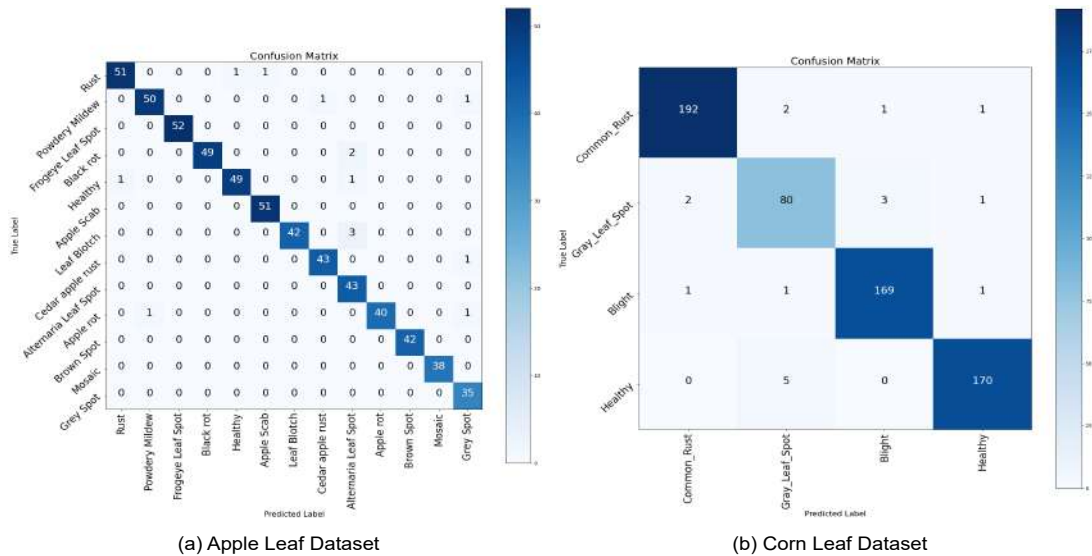


Fig. 14. Confusion Matrices of IGWO-Driven DeepForestNet on both the Datasets

Table 8. Performance Comparison Using Wilcoxon Rank Analysis

Models	Apple Dataset		Corn Dataset	
	P-Value	Sig_diff	P-Value	Sig_diff
DenseNet201	0.0149	++	0.0156	++
MobileNetV2	0.0078	++	0.0065	++
DenseNet201 + MobileNetV2	0.0191	++	0.0233	==
DeepForestNet	0.0696	==	0.0821	==
DeepForestNet + PSO	0.1736	==	0.1988	==
DeepForestNet + GWO	0.4057	==	0.3643	==

The Std evaluated by Eq. (31):

$$\text{Std.} = \sqrt{\frac{\sum_{i=1}^N (f_i - \text{Mean})^2}{N - 1}} \quad (31)$$

The statistical evaluation includes Maximum (Max), Minimum (Min), Average (Avg), Standard Deviation (Std), and Avg Running Time (in minutes) [32]. Table 7 presents the comparative analysis of model accuracies.

4.5 Wilcoxon Signed Rank Test

This paper presents a comparative analysis of model misclassification rates using the Wilcoxon

signed-rank test at a 0.05 significance level, with results summarized in Table 8.

The symbols '++', '-', and '==' denote cases where the IGWO-driven DeepForestNet performs significantly better, significantly worse, or shows no significant difference compared to other models, respectively.

As shown in Table 8, IGWO-driven DeepForestNet generally outperforms the other models across both datasets, with a few cases indicating comparable performance.

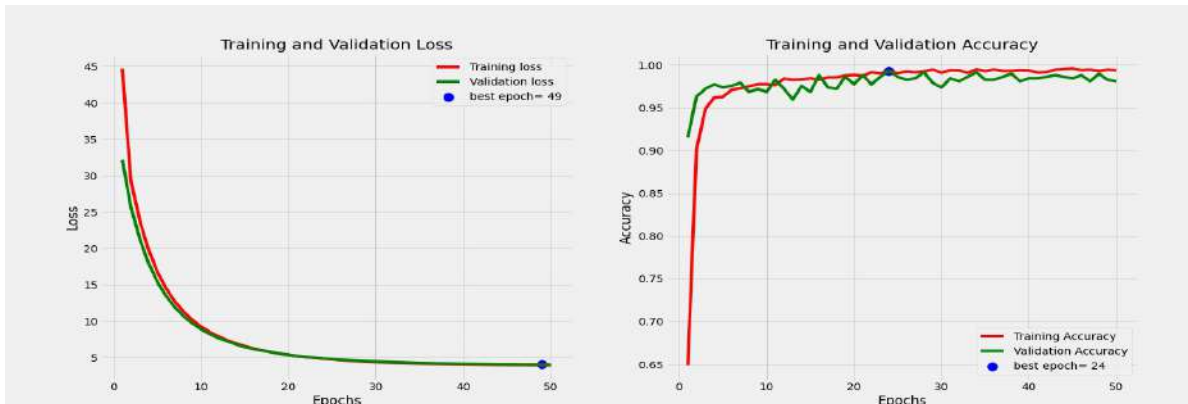


Fig. 15. Accuracy and Loss over Epochs for IGWO-driven DeepForestNet on the Apple Leaf Dataset

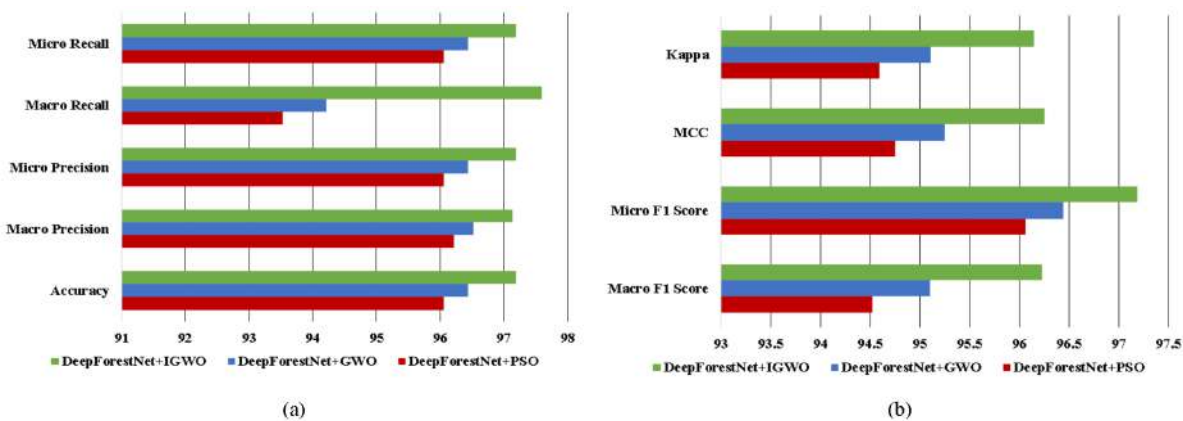


Fig. 16. PSO-driven DeepForestNet vs. GWO-driven DeepForestNet vs. IGWO-driven DeepForestNet on Corn Leaf Dataset

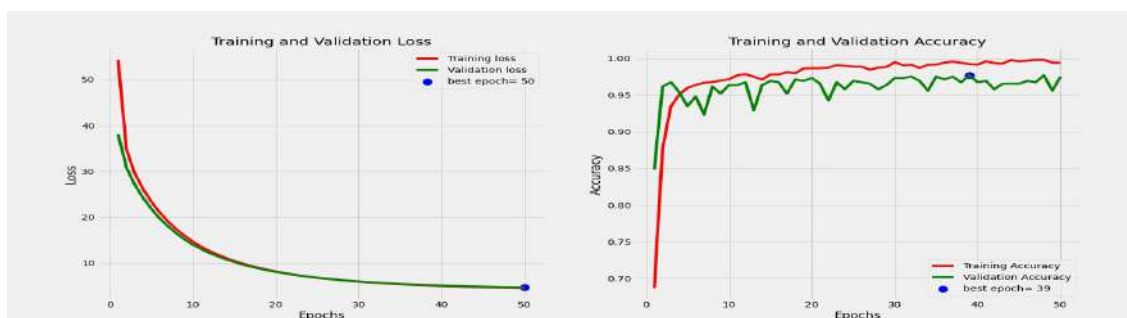


Fig. 17. Accuracy and Loss over Epochs for IGWO-driven DeepForestNet on the Corn Leaf Dataset

4.6 Discussion and Comparison

Fig. 19 (a) and (b) illustrate the detailed performance metrics for Apple leaves, where IGWO-

driven DeepForestNet achieved 97.59% accuracy, 97.39% macro_precision, 97.59% micro_precision, 97.37% macro_recall, 97.59% micro_recall, 97.37%

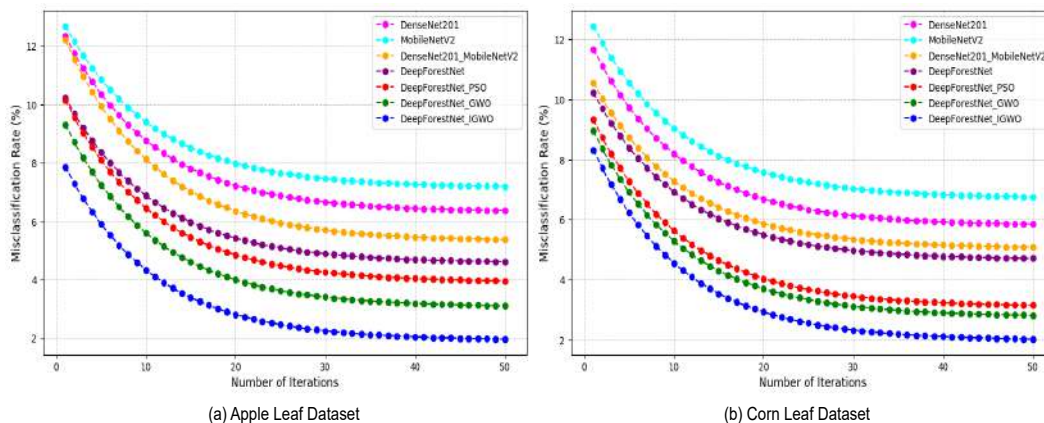


Fig. 18. Convergence Graph

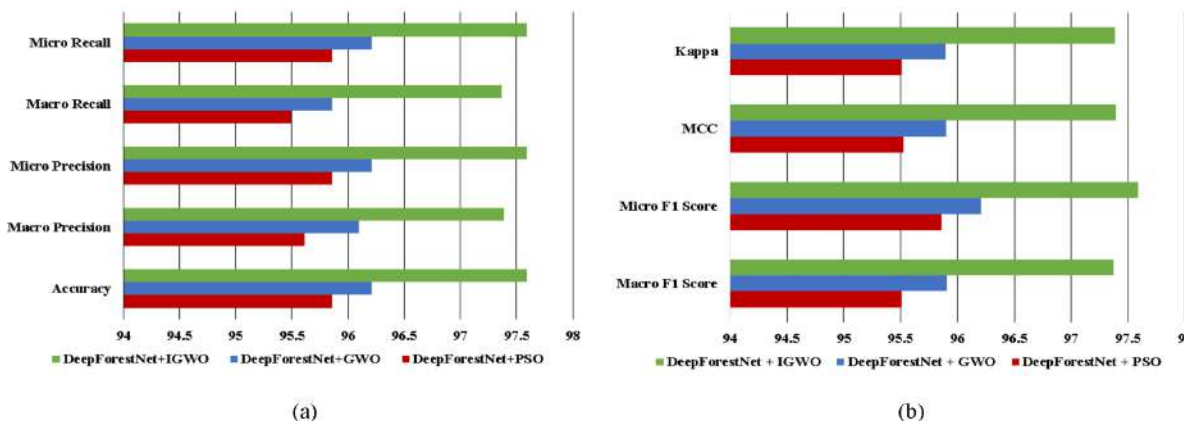


Fig. 19. PSO-driven DeepForestNet vs. GWO-driven DeepForestNet vs. IGWO-driven DeepForestNet on Apple Leaf Dataset

macro_F1, 97.59% micro_F1, 97.389% MCC, and 97.386% Kappa.

Similarly, Fig. 20 (a) and (b) show results for corn leaves, with IGWO-driven DeepForestNet obtaining 97.19% accuracy, 97.14% macro_precision, 97.19% micro_precision, 95.59% macro_recall, 97.19% micro_recall, 96.23% macro_F1, 97.19% micro_F1, 96.25% MCC, and 96.15% Kappa.

Comparative analysis demonstrates that IGWO-driven DeepForestNet outperforms other models in all metrics. In the past five years, limited research has explored apple and corn leaf disease detection

using DL models with metaheuristic-based hyperparameter tuning.

Therefore, prior studies were selected for benchmarking. Table 9 highlights the superiority of the proposed IGWO-driven DeepForestNet over state-of-the-art methods for both datasets.

5 Conclusion

This study proposed the IGWO-driven DeepForestNet model for multiclass classification of apple and corn leaf diseases. IGWO, GWO, and PSO were employed for hyperparameter tuning, with IGWO

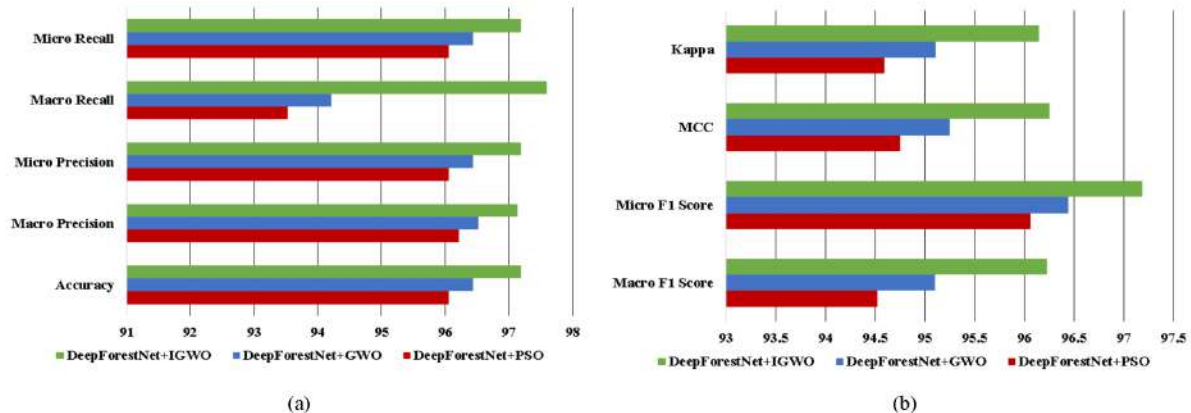


Fig. 20. PSO-driven DeepForestNet vs. GWO-driven DeepForestNet vs. IGWO-driven DeepForestNet on Corn Leaf Dataset

and GWO outperforming PSO. The IGWO-driven DeepForestNet achieved the highest classification accuracy of 97.59% on the apple leaf dataset and 97.19% on the corn leaf dataset, outperforming other models. Statistical and computational analyzes confirmed the effectiveness of the model for the practical detection of plant disease.

The future recommendation will focus on expanding the applicability of the model to other plant species and disease data sets to evaluate its generalizability. Additionally, recently proposed metaheuristic algorithms will be explored for hyperparameter tuning and compared with IGWO to further enhance classification accuracy. The model will also be integrated into a real-time plant health recommender system to enable early disease diagnosis and provide actionable treatment recommendations for farmers.

References

1. Abd Algani, Y. M., Caro, O. J. M., Bravo, L. M. R., Kaur, C., Al Ansari, M. S., Bala, B. K. (2023). Leaf disease identification and classification using optimized deep learning. *Measurement: Sensors*, Vol. 25, pp. 100643.
2. Ali, M., Deo, R. C., Xiang, Y., Prasad, R., Li, J., Farooque, A., Yaseen, Z. M. (2022). Coupled online sequential extreme learning machine model with ant colony optimization algorithm for wheat yield prediction. *Scientific Reports*, Vol. 12, No. 1, pp. 5488.
3. Aljebreen, M., Mengash, H. A., Kouki, F., Motwakel, A. (2023). Improved artificial ecosystem optimizer with deep-learning-based insect detection and classification for agricultural sector. *Sustainability*, Vol. 15, No. 20, pp. 14770.
4. Alotaibi, Y., Rajendran, B., Rajendran, S., et al. (2024). Dipper throated optimization with deep convolutional neural network-based crop classification for remote sensing image analysis. *PeerJ Computer Science*, Vol. 10, pp. e1828.
5. Alsubai, S., Dutta, A. K., Alkhayyat, A. H., Jaber, M. M., Abbas, A. H., Kumar, A. (2023). Hybrid deep learning with improved salp swarm optimization based multi-class grape disease classification model. *Computers and Electrical Engineering*, Vol. 108, pp. 108733.
6. Austria, Y. C., Mirabueno, M. C. A., Lopez, D. J. D., Cuaresma, D. J. L., Macalisang, J. R., Casuat, C. D. (2022). Ezm-ai: A yolov5 machine vision inference approach of the philippine corn leaf diseases detection system. *2022 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAET)*, IEEE, pp. 1–6.
7. Ayan, E. (2024). Genetic algorithm-based hyperparameter optimization for convolutional

Table 9. The proposed work is compared to state-of-the-art techniques

Ref.	Name of Species	No. of Images	Methods	Metaheuristic Algorithm	Accuracy
[25]	Apple	2,539	CNN	No	97.3%
[28]	Corn	8,506	Proposed CNN architecture	No	97.09%
[17]	Apple	26,377	VGGNet + Inception	No	78.80%
[42]	Corn	400	CNN	No	92.85%
[46]	Corn	200	AlexNet and SVM	No	93.5%
[33]	Corn	1,103	RF	No	79.23%
[44]	Apple	100	PSO and SVM	Yes	85.5%
[51]	Apple	2,516	MSO-ResNet	No	95.7%
[6]	Corn	561	YOLO V5	No	97%
[9]	Apple	334	MobileNet	No	73.50%
[50]	Apple and Corn	250 and 400	CNN + Salp Swarm Optimization	Yes	84% and 75%
[37]	Corn	4,118	ResNet-50	No	95.59%
[16]	Corn	7,316	Memetic Salp Swarm Optimization	Yes	90.6%
[52]	Corn	124	Long-short attention neural network	No	94.35%
Proposed Model	Apple and Corn	5867 and 4184	IGWO-Driven DeepForest-Net	Yes	97.59% and 97.19%

neural networks in the classification of crop pests. *Arabian Journal for Science and Engineering*, Vol. 49, No. 3, pp. 3079–3093.

8. **Banerjee, D., Sharma, N., Chauhan, R., Singh, M., Kumar, B. V. (2024).** Hybrid cnn & random forest model for effective bitter orange leaf disease diagnosis. *2024 4th International Conference on Innovative Practices in Technology and Management (ICIPTM)*, IEEE, pp. 1–6.
9. **Bi, C., Wang, J., Duan, Y., Fu, B., Kang, J.-R., Shi, Y. (2022).** Mobilenet based apple leaf diseases identification. *Mobile Networks and Applications*, pp. 1–9.
10. **Buakum, B., Kosacka-Olejnik, M., Pitakaso, R., Srichok, T., Khonjun, S., Luesak, P., Nanthasamroeng, N., Gonwirat, S. (2024).** Two-stage ensemble deep learning model for precise leaf abnormality detection in *Centella asiatica*. *AgriEngineering*, Vol. 6, No. 1, pp. 620–644.
11. **Chug, A., Bhatia, A., Singh, A. P., Singh, D. (2023).** A novel framework for image-based plant disease detection using hybrid deep learning approach. *Soft Computing*, Vol. 27, No. 18, pp. 13613–13638.
12. **Gopi, P., Karthikeyan, M. (2024).** Red fox optimization with ensemble recurrent neural network for crop recommendation and yield prediction model. *Multimedia Tools and Applications*, Vol. 83, No. 5, pp. 13159–13179.
13. **Gopi, S., Mohapatra, P. (2025).** A modified grey wolf optimization algorithm to solve global optimization problems. *OPSEARCH*, Vol. 62, No. 1, pp. 337–367.
14. **Gupta, D., Sharma, P., Choudhary, K., Gupta, K., Chawla, R., Khanna, A., Albuquerque, V. H. C. d. (2021).** Artificial plant optimization algorithm to detect infected leaves using machine learning. *Expert Systems*, Vol. 38, No. 6, pp. e12501.

15. **Hameed Al-bayati, J. S., Üstündağ, B. B. (2020).** Evolutionary feature optimization for plant leaf disease detection by deep neural networks. *International Journal of Computational Intelligence Systems*, Vol. 13, No. 1, pp. 12–23.
16. **Jain, S., Dharavath, R. (2023).** Memetic salp swarm optimization algorithm based feature selection approach for crop disease detection system. *Journal of Ambient Intelligence and Humanized Computing*, Vol. 14, No. 3, pp. 1817–1835.
17. **Jiang, P., Chen, Y., Liu, B., He, D., Liang, C. (2019).** Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks. *IEEE Access*, Vol. 7, pp. 59069–59080.
18. **Kılıçarslan, S., Dönmez, E., Kılıçarslan, S. (2024).** Identification of apple varieties using hybrid transfer learning and multi-level feature extraction. *European Food Research and Technology*, Vol. 250, No. 3, pp. 895–909.
19. **Kumar, R., Chug, A., Singh, A. P. (2023).** Plant foliage disease diagnosis using light-weight efficient sequential CNN model. *Optical Memory and Neural Networks*, Vol. 32, No. 4, pp. 331–345.
20. **Kurmi, Y., Saxena, P., Kirar, B. S., Gangwar, S., Chaurasia, V., Goel, A. (2022).** Deep CNN model for crops' diseases detection using leaf images. *Multidimensional Systems and Signal Processing*, Vol. 33, No. 3, pp. 981–1000.
21. **Ladi, S. K., Panda, G., Dash, R., Ladi, P. K., Dhupar, R. (2022).** A novel grey wolf optimization based cnn classifier for hyperspectral image classification. *Multimedia Tools and Applications*, Vol. 81, No. 20, pp. 28207–28230.
22. **Mishra, M., Choudhury, P., Pati, B. (2024).** IoT enabled plant leaf disease segmentation and multi-classification using mayfly bald eagle optimization-enabled machine learning. *Multimedia Tools and Applications*, pp. 1–35.
23. **Mishra, R., Kavita, Rajpal, A., Bhatia, V., Rajpal, S., Agarwal, M., Kumar, N. (2024).** I-LDD: an interpretable leaf disease detector. *Soft Computing*, Vol. 28, No. 3, pp. 2517–2533.
24. **Mohakud, R., Dash, R. (2022).** Designing a grey wolf optimization based hyper-parameter optimized convolutional neural network classifier for skin cancer detection. *Journal of King Saud University-Computer and Information Sciences*, Vol. 34, No. 8, pp. 6280–6291.
25. **Nachtigall, L. G., Araujo, R. M., Nachtigall, G. R. (2016).** Classification of apple tree disorders using convolutional neural networks. *2016 IEEE 28th international conference on tools with artificial intelligence (ICTAI)*, IEEE, pp. 472–476.
26. **Naik, N. K., Sethy, P. K., Devi, A. G., Behera, S. K. (2024).** Few-shot learning convolutional neural network for primitive indian paddy grain identification using 2D-DWT injection and grey wolf optimizer algorithm. *Journal of Agriculture and Food Research*, Vol. 15, pp. 100929.
27. **Nikith, B., Keerthan, N., Praneeth, M., Amrita, T. (2023).** Leaf disease detection and classification. *Procedia Computer Science*, Vol. 218, pp. 291–300.
28. **Ouppaphan, P. (2017).** Corn disease identification from leaf images using convolutional neural networks. *2017 21st International computer science and engineering conference (ICSEC)*, IEEE, pp. 1–5.
29. **Padhy, S., Panda, S., Mahapatra, S. (2017).** A modified gwo technique based cascade pi-pd controller for agc of power systems in presence of plug in electric vehicles. *Engineering Science and Technology, an International Journal*, Vol. 20, No. 2, pp. 427–442.
30. **Palei, S., Mohapatra, P. (2025).** Cutting-edge approaches to plant disease detection: a survey of machine learning models and optimization methods. *Journal of Ambient Intelligence and Humanized Computing*, Vol. 16, No. 10, pp. 1073–1086.
31. **Palei, S., Mohapatra, P. (2025).** Hyperparameter optimization of cnn models for plant leaf disease classification using optuna. *2025 International Conference on Microwave, Optical, and Communication Engineering (ICMOCE)*, IEEE, pp. 1–4.

32. **Palei, S., Mohapatra, P. (2025).** Metaheuristic-integrated densenomobileforestnet for apple leaf disease identification. *Applied Fruit Science*, Vol. 67, No. 3, pp. 1–16.
33. **Panigrahi, K. P., Das, H., Sahoo, A. K., Moharana, S. C. (2020).** Maize leaf disease detection and classification using machine learning algorithms. *Progress in Computing, Analytics and Networking: Proceedings of ICCAN 2019*, Springer, pp. 659–669.
34. **Pavithra, P., Aishwarya, P. (2024).** 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.
35. **PP, F. R., Ismail, W. N., Ali, M. A. (2023).** A metaheuristic Harris hawks optimization algorithm for weed detection using drone images. *Applied Sciences*, Vol. 13, No. 12, pp. 7083.
36. **Prasannakumar, M., Latha, K. (2024).** Plant disease identification using contextual mask auto-encoder optimized with dynamic differential annealed optimization algorithm. *Microscopy Research and Technique*, Vol. 87, No. 3, pp. 484–494.
37. **Rachmad, A., Fuad, M., Rochman, E. M. S. (2023).** Convolutional neural network-based classification model of corn leaf disease.. *Mathematical Modelling of Engineering Problems*, Vol. 10, No. 2.
38. **Raja, D., Karthikeyan, M. (2023).** Red deer optimization with deep learning enabled agricultural plant disease detection and classification model.. *International Journal of Intelligent Engineering & Systems*, Vol. 16, No. 5.
39. **Rashid, R., Aslam, W., Aziz, R. (2024).** An early and smart detection of corn plant leaf diseases using iot and deep learning multi-models. *IEEE Access*.
40. **Sahu, P., Chug, A., Singh, A. P., Singh, D. (2023).** Classification of crop leaf diseases using image to image translation with deep-dream. *Multimedia Tools and Applications*, Vol. 82, No. 23, pp. 35585–35619.
41. **Shauqee, M. N., Rajendran, P., Suhadis, N. M. (2021).** Proportional double derivative linear quadratic regulator controller using improvised grey wolf optimization technique to control quadcopter. *Applied Sciences*, Vol. 11, No. 6, pp. 2699.
42. **Sibiya, M., Sumbwanyambe, M. (2019).** A computational procedure for the recognition and classification of maize leaf diseases out of healthy leaves using convolutional neural networks. *AgriEngineering*, Vol. 1, No. 1, pp. 119–131.
43. **Singh, V., Kaushik, V. D. (2024).** Adaptive snake optimization-enabled deep learning-based multi-classification using leaf images. *Signal, Image and Video Processing*, pp. 1–10.
44. **SK, P. K., Sumithra, M., Saranya, N. (2021).** Particle swarm optimization (pso) with fuzzy c means (pso-fcm)–based segmentation and machine learning classifier for leaf diseases prediction. *Concurrency and Computation: Practice and Experience*, Vol. 33, No. 3, pp. e5312.
45. **Sowmiya, M., Krishnaveni, S. (2023).** lot enabled prediction of agriculture’s plant disease using improved quantum whale optimization drdnn approach. *Measurement: Sensors*, Vol. 27, pp. 100812.
46. **Syarief, M., Setiawan, W. (2020).** Convolutional neural network for maize leaf disease image classification. *Telkomnika (Telecommunication Computing Electronics and Control)*, Vol. 18, No. 3, pp. 1376–1381.
47. **Tamilvizhi, T., Surendran, R., Anbazhagan, K., Rajkumar, K. (2022).** Quantum behaved particle swarm optimization-based deep transfer learning model for sugarcane leaf disease detection and classification. *Mathematical Problems in Engineering*, Vol. 2022, No. 1, pp. 3452413.
48. **Waheed, A., Goyal, M., Gupta, D., Khanna, A., Hassanien, A. E., Pandey, H. M. (2020).** An optimized dense convolutional neural network model for disease recognition and classification in corn leaf. *Computers and Electronics in Agriculture*, Vol. 175, pp. 105456.

49. **Wonggasem, K., Chakranon, P., Wongchaisuwat, P. (2024).** Automated quality inspection of baby corn using image processing and deep learning. *Artificial Intelligence in Agriculture*, Vol. 11, pp. 61–69.
50. **Xie, X., Xia, F., Wu, Y., Liu, S., Yan, K., Xu, H., Ji, Z. (2023).** A novel feature selection strategy based on salp swarm algorithm for plant disease detection. *Plant Phenomics*, Vol. 5, pp. 0039.
51. **Yu, H., Cheng, X., Chen, C., Heidari, A. A., Liu, J., Cai, Z., Chen, H. (2022).** Apple leaf disease recognition method with improved residual network. *Multimedia Tools and Applications*, Vol. 81, No. 6, pp. 7759–7782.
52. **Zhang, F., Bao, R., Yan, B., Wang, M., Zhang, Y., Fu, S. (2024).** Lsannet: A lightweight convolutional neural network for maize leaf disease identification. *Biosystems Engineering*, Vol. 248, pp. 97–107.
53. **Zhang, Y., Cheng, W., Wang, Y., Lu, Z., Cheng, M. (2025).** Research on plant leaf disease detection method based on improved yolov11. *Journal of Biosystems Engineering*, pp. 1–11.

*Article received on 19/10/2025; accepted on 16/12/2025.
Corresponding author is Shantilata Palei.