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Research Article

Development of an AI-Based Pyramid Convolutional Neural Network Model with ResNet and Coati Optimization for Multi-Crop, Multi-Disease Identification in Leaf Images

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ABSTRACT

The rapid advancement of artificial intelligence has paved the way for innovative solutions in agriculture, particularly in crop disease detection. Diagnosing plant diseases often rely on manual inspection and expert knowledge that time-consuming and prone to errors. As agriculture faces increasing challenges from pests, diseases and climate change, there is a pressing require for efficient, automated systems to monitor crop health. In this manuscript, Development of an AI-Based Pyramid Convolutional Neural Network Model with ResNet and Coati Optimization for Multi-Crop, Multi-Disease Identification in Leaf Images is (PCNN-ResNet-COA) proposed. Initially the data is collected from Plant Disease Classification Merged Dataset. This dataset includes both healthy and diseased leaves for various crop types. The collected images are organized into categories based on the crop type such as crop, grape and soybean and disease condition healthy or various types of diseases. Then the categorized images are fed to Pyramid Convolutional Neural Network with Residual Network (PCNN-ResNet), for identifying and classifying the Leaf Images as Corn_healthy, Corn_northern_leaf_blight, Corn_gray_leaf_spot, Grape_healthy, Grape_leaf_blight, Grape_black_rot, Grape_black_measles, corn_common_rust, soybean_bacterial_blight, Soybean_downy_mildew, Soybean_mosaic_virus, Soybean_powdery_mildew, Soybean_healty, Soybean_rust, and Soybean_southern_blight. In general, PCNN-ResNet does not express any adaption of optimization methods for determining optimal parameters to assure precise detection and classification of Leaf Images. Coati Optimization Algorithm (COA) is proposed for improving the weight parameter of PCNN-ResNet classifier that accurately predicts crop yield. The proposed PCNN-ResNet-COA method is implemented and analyzed with help of performance metrics like accuracy, precision, F1-score, computational time is evaluated. The proposed ResNet-COA approach attains 18.97%, 24.57% and 32.68% higher accuracy and 19.84%, 24.93% and 31.62% lower computational time with existing method respectively.

Keywords: Artificial Intelligence, Coati Optimization Algorithm, Leaf Images, Pyramid Convolutional Neural Network, Residual Network.

1. INTRODUCTION

Variations in the temperature, soil properties, and fertiliser use can cause crop yields to vary from year to year. Many countries have made specialised pest and disease protection for the crop industry a top agricultural goal. Production in agriculture is severely harmed by agricultural diseases and pests [1]. A key component of agricultural output has always been agricultural pest control, and the foundation for both disease and pest prevention and control is the efficient identification and tracking of agricultural pests and illnesses [2]. In smart agricultural systems, computer vision (CV)-based automatic methods for identifying pests or diseases are frequently used because of their high cost-effectiveness and effective automation [3]. Diseases of grape leaves, maize, and soybeans can have a major effect on crop quality and output, which can considerably reduce a farmer's revenue [4]. Farmers can take the necessary steps to limit crop damage and reduce the spread of these diseases by detecting and managing them early [5]. For instance, if treatment is not received, soybean diseases like leaf blight and soybean yellow mosaic can cut crop output by as much as 50%. In a similar vein, diseases of maize as northern corn leaf blight and grey leaf spot can lower yields by as much as 30% [6]. Crop yields and quality can also be greatly impacted by grape diseases such Leaf Blight, Black Rot, and Black Measles [7]. Farmers can take the necessary steps to limit crop damage and reduce the spread of these diseases by detecting and managing them early [8]. If left untreated, soybean diseases including leaf blight and soybean yellow mosaic can cut crop yields by as much as 50% [9]. In a similar vein, diseases of maize as northern corn leaf blight and grey leaf spot can lower yields by as much as 30%. Crop yields and quality can also be greatly impacted by grape diseases like Leaf Blight, Black Rot, and Black Measles [10].

1.1 Problem Statement and Motivation

Identifying multiple diseases across various crops remains a complex challenge in agriculture, primarily due to the vast diversity of crops, the similarity in visual symptoms among different diseases and the overlapping presence of multiple diseases on the same plant. In existing methods, it relies heavily on expert knowledge, such as delay in time-consuming, expensive and not readily accessible to all farmers especially in remote regions. Variations in environmental factors, lighting conditions and leaf textures further complicate disease detection, leading to inconsistent and inaccurate results. This challenge is compounded by the scarcity of large, annotated datasets covering multiple crops and diseases limiting the effectiveness of existing detection methods. This research motivates to address these limitations by exploring the potential of PCNN-ResNet technique model, which can predict the multi-crop, multi-disease identification in leaf images more effectively.

The novelty of this work lies in the innovative application of coati optimizing algorithm to optimize parameters of Pyramid Convolutional Neural Network with ResNet, which has not been explored for multi-crop, multi-disease identification in leaf. This approach uniquely combines spatial-temporal features with attention mechanisms to improve the efficiency of identification in leaf image based crop diseases.

1.2 Contribution

Major contribution of this manuscript is;

- Initially, developed and organized a comprehensive dataset with healthy and diseased leaf images, categorized by crop types and disease conditions, enabling robust and scalable for crop disease prediction.
- The aim is to propose an identification of multi-crop, multi-disease identification from leaf image utilizing Pyramid Convolutional Neural Network with Residual Network categorized by crop types and disease conditions.
- Developed an AI-based PCNN-ResNet model for multi-crop, multi-disease identification, enabling efficient and precise classification of different leaf diseases across crops like corn, grape and soybean.
- COA optimizes PCNN-ResNet's weight parameters by fine-tuning for enhanced accuracy of adaptive leaf image.

Remaining section is arranged as below: fragment 2 defines literature review, fragment 3 shows proposed technique, fragment 4 proves result with discussions, fragment 5 gives conclusion.

2. LITERATURE SURVEY

Numerous researches were presented in literature based on Multi-Crop, Multi-Disease Identification in Leaf Images utilizing DL; some recent studies were reviewed here,
In 2023 K. M. Hosny, et.al, [11] have presented Multi-Class Categorization of Plant Leaf Diseases Utilizing Feature Fusion of DCNN with Local Binary Pattern; A high-level hidden feature representations can be obtained using new lightweight DCNN method. The deep features were combined by conventional constructed LBP features to extract local texture information from plant leaf images. Three publicly accessible dataset such as Tomato Leaf, Apple Leaf, Grape Leaf—were utilized to train and evaluate the method. It provides high accuracy, low precision.

In 2023, R. ArumugaArun and S. Umamaheswari, [12] have presented effectual multi-crop disease prediction utilizing pruned complete concatenated DL method. Multi-crop disease identification models that can categories crop illnesses regardless of crop type are presented utilizing Complete Concatenated Deep Learning structure. The Complete Concatenated Block uses a fundamental functional unit in the presented design. To limit amount of parameters produced in the method, point convolution layer was positioned before all convolution layer in this unit. The entire concatenation process was applied to convolution layers inside CCB. The architecture was trained using reconstructed Plant Village dataset. It provides high precision, low FI-score.

In 2023, V. Sharma, A., et.al, [13] have presented DLMC-Net: Deeper lightweight multi-class categorization method for PLD identification. Here, DLMC-Net, cutting-edge lightweight CNN for predicting plant leaf diseases in various crops in real time. To improve feature extraction and solve the vanishing gradient issue, the model uses collective blocks and passage layer. Trainable parameters were also decreased via point-wise with separable convolution blocks. It performs better with seven state-of-the-art techniques in validation on dataset of tomatoes, cucumbers, citrus, and grapes. It attains higher f1-score and lower computational time.

In 2023, Ahmad, A., et.al, [14] have presented towards generalization of DL-dependent plant disease detection using controlled and field conditions. DL models were used to identify plant diseases utilizing five dataset comprise images of foliar illnesses in maize: Plant Village, Digipathos, PlantDoc, the northern leaf blight dataset, custom-acquired CD&S dataset. These models generalise across various datasets and environmental situations. With various dataset combinations, many DL-dependent image classification methods were trained and assessed. For four distinct studies, TL was applied 5 distinct pre-trained DNN architectures such as InceptionV3, DesneNet169, VGG16, ResNet50 and Exception. It attains lower computational time and it attains lower accuracy.

In 2023, Kulkarni, P. and Shastri, S., [15] have presented rice leaf illness prediction utilizing ML. Here a model of a CNN for classification of common illness of rice leaves. Rice leaf diseases can be identified by an algorithm from a range of image backgrounds and capture scenarios. Here, it categorise images of disease in rice leaves with complex backgrounds and different lighting. 95% accuracy was achieved with the CNN-based model. The result shows effective the proposed method is for identifying diseases in rice. Index terms include machine learning, CNN algorithm, rice leaf, and disease detection. It attains higher accuracy and it attains higher f1-score.

Khandagale and Patil (2023) analyzed different neural network approaches for leaf image processing in disease identification. The study compared traditional machine learning techniques with advanced deep learning models, emphasizing the superiority of CNN-based architectures. The findings revealed that neural networks play a crucial role in feature extraction, segmentation, and classification of diseased leaves, thereby contributing to precision agriculture and automated disease detection [20].

In another study, Khandagale and Patil (2023) conducted a performance evaluation of retrained Convolutional Neural Network (CNN) models for grape leaf disease identification. Their study explored the effectiveness of various CNN architectures in detecting and classifying grape leaf diseases, demonstrating that retraining CNN models significantly improves classification accuracy. The research provided insights into model selection for agricultural applications, highlighting the role of deep learning in plant disease detection [21].

Meshram et al. (2024) presented a comprehensive review of medicinal plant classification systems, focusing on various machine learning and deep learning techniques used for classification. The study discussed different image processing methods, feature extraction techniques, and classification algorithms, demonstrating how AI-driven models improve plant identification. Their findings emphasized the importance of dataset quality, preprocessing techniques, and model optimization in achieving high classification accuracy for medicinal plant species [22].

Khandagale et al. (2025) proposed a CNN-based system, FourCropNet, for efficient multi-crop disease detection and management. Their study designed and implemented a deep learning-based framework capable of detecting multiple crop diseases with high accuracy. The research emphasized the need for robust and scalable CNN architectures in precision agriculture, showcasing how FourCropNet enhances early disease detection and improves crop health monitoring ([23].

3. PROPOSED METHODOLOGY

In this section, an AI-based PCNN with ResNet and COA is presented for the accurate identification of multiple crops and diseases in leaf images. This process comprises of three steps: Data Collection, Identification and Optimization. The proposed method used to analyze and gather data from Plant Disease Classification Merged Dataset for further analysis. Then in the next step it involves employing a PCNN-ResNet to identify the crop disease from leaf images. The COA method is introduced for optimizing the PCNN-ResNet. Figure 1 illustrates the proposed PCNN-ResNet-COA technique and detailed description of every step is given below,

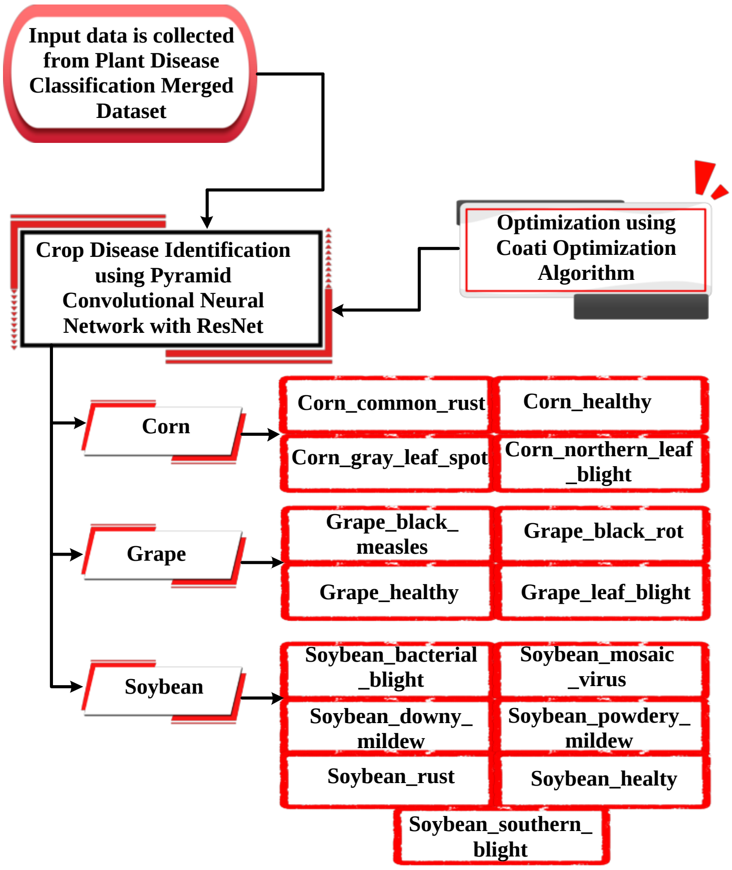

Figure 1: Block Diagram for PCNN-ResNet-COA Technique

3.1 Data Acquisition

The input data are obtained from Plant Disease Classification Merged Dataset [17]. A huge number of images, at least one healthy plant and one disease per plant, the most prevalent diseases, annotated images, laboratory and field photographs, significant staple foods and the plant species with the highest worldwide production were the self-imposed conditions for the dataset. Both field and lab photos are included in the dataset. Watermarked photographs, classes with fewer than 50 examples, images of non-food plants, and classes with a single criterion were eliminated. The project's final dataset, which was used for training, has 88 classes and more than 76,000 photos totalling 17.6GB in size. Since diverse shooting settings were sometimes employed for the photographs (e.g. classes with predominantly laboratory images or varied soil in the background), bias among the classes is something that cannot be prevented in general. Also, this dataset includes both healthy and diseased leaves for various crop types. Then organized the collected images into categories based on the crop type (grape, maize, soybean) and disease condition (healthy or various types of diseases). Then the each image is labeled with the correct class (e.g., “Healthy,” “Leaf Spot,” “Rust” for the respective crops). This labeled dataset will be used for training method. Split labeled dataset into 3 subsets: training set (66%), validation set (14%), test set (20%) for training, fine-tuning, and evaluation of the model.

3.2 Crop Disease Identification utilizing Pyramid Convolutional Neural Network with ResNet

PCNN, [12][17] is discussed for identifying and classifying the crop diseases from leaf image. PCNN efficiently captures multi-scale features, improving the accuracy of crop disease identification across varying image resolutions. Its hierarchical structure enhances both fine-grained and global feature extraction, leading to better generalization of disease classification. The input layer accepts high-resolution images of crops, typically captured under varying conditions. The first convolutional layer uses small filters to input image to capture low-level features like textures, edges, simple shapes. This layer is processed by activation function with pooling layers to decrease spatial dimensions, retain important features of image utilizing equation (1).

$$X_L^{[P]} = \sigma(u_z * E_L) \tag{1}$$

Where, $X_L^{[P]}$ represents the location on the crop leaves; P symbolize the fine-grained images; L denotes the number of blocks in image pixel; σ represents the sigmoid function; u_z captures the low-level features in edges; Z locates the discriminative regions; $*$ signifies the notes de-convolution and E_L indicates the generated spatial attention mask in each layer. In the pyramid convolutional blocks, multiple convolutional operations are applied at different scales [17]. This enables the PCNN to extract features at varying levels of granularity, which is particularly useful in identifying diseases that might present themselves at different spatial resolutions. Each block consists of multiple convolution layers and capture fine details and global patterns of image using equation (2).

$$GAP(E_L) = \frac{1}{V \times G} \sum_{i=1}^{G} \sum_{j=1}^{V} E_L(i, j) \tag{2}$$

Where, GAP represents global average pooling layer; V denoted as the weight matrices of each layer; G symbolize the spatial dimensions of pixel and i *and* j indicates the i^{yh} and j^{th} pixel of each image. After the pyramid convolutional blocks, the features at different scales are fused together. This layer typically combines the multi-scale feature maps using concatenation. By combining features from different scales, the PCNN gain a comprehensive understanding of the disease, irrespective of its size or location on the crop leaves. Additional deep convolutional layers employed to refine the learned representations. These layers focus on capturing more complex patterns and interactions between various visual elements of the disease using equation (3).

$$E'_L = E_L \,.\left(X_L^{[P]} \oplus X_L^{(Z)}\right) \tag{3}$$

Where, E'_L indicates the different scales of each dimension; $\oplus$ denotes the addition operation and $X_L^{(Z)}$ symbolize the size of image. The dense layers process the higher-level features extracted by convolutional layers. Such layers are responsible for interpreting the complex relationships between the extracted features and classifying input image as one of several disease classifications. The fully connected layer usually comprises of softmax activation function that identifies probability of each class using equation (4).

$$C_n = \varphi(F_n[t_{b1} : t_{b2}, t_{a1} : t_{a2}]) \tag{4}$$

Where, C_n denotes sent to refined-stage to conduct more detection; φ signifies bilinear up-sample operation; F_n represents the dropped feature maps and $t_{b1} : t_{b2}$ *and* $t_{a1} : t_{a2}$ represented as minimum and maximum coordinates of each terms. ResNet [13] is used replacing convolutional layer of PCNN with comprises dense activation layer of ResNet. Then convolutional layer of PCNN is collected of 1000 neurons, is swapped out for two neurons to utilize ResNet. A new fully connected layer using 256 neurons is followed using a dense layer. To avoid over fitting, dropout layer at 0.4 values is included. The convolutional layer of the PCNN, which included 1000 neurons, was swapped out for ResNet. In top layer, inputs were sorted into expected labels using Softmax layer. To capture complex linkages and long-range interactions between crop images, graph convolution is enhanced with ResNet algorithms. It is shown in equation (5).

$$b = E(a, V + a) \tag{5}$$

Where, b signifies output layer; E indicates the function of the residual map; a represents the input layer and V signifies the particular crop disease class. This architecture uses a PCNN with ResNet for crop disease identification. The input image is processed through Feature Pyramids, which extract multi-scale features using ResNet and down-sampling operations. These features are refined by a Spatial Gate for spatial information and a Channel Gate, which includes Global Average Pooling to generate channel descriptors. Two fully connected layers with a sigmoid activation produce channel-wise attention weights, which recalibrate the features. Finally, the refined features from all pyramid levels are fused and passed through a Channel Attention Pathway for classification, outputting the probability for each class label. The method effectively combines multi-scale features and attention mechanism [17]. Figure 2 represents the architecture diagram of PCNN-ResNet.

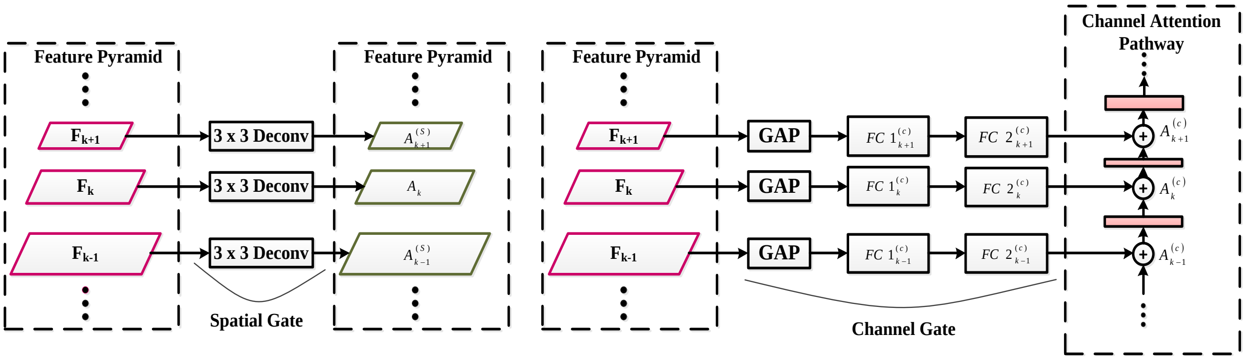

Figure 2: Architecture Diagram of proposed PCNN-ResNet

Several residual blocks are traversed before the global average pooling layer is employed. It reduces spatial dimensions according to feature maps by calculating the average of all feature maps. ResNet effectively condenses the feature map into a single value per feature, which reduces overfitting and provides a compact representation of the image. The outcomes from global average pooling is given into fully connected layer. It contains a large number of neurons to capture complex patterns and the weights of layer are mapped the extracted features to the class scores of different crop diseases using equation (6).

$$\Delta v_{ij} = -\eta\, \delta F / \left(\delta v_{ij}\right) \tag{6}$$

Where, Δ indicates the complex patterns in neurons; v_{ij} considered as i^{th} and j^{th} layer of neurons in ResNet; η represents parameter size stewarding learning level of NNs and δ reduces the over fitting issues. The final layer is softmax activation function that outputs probability distribution over the possible classes. Each outcome corresponds to likelihood that image belong to particular crop disease class. The class with high probability is selected as predicted disease label. In the case of crop disease identification, output can correspond to multiple disease categories and model classifies diseases dependent on the class using equation (7).

$$\Delta v_{ij}(t+1) = -\eta\, \delta Q / \left(\delta v_{ij}\right) + \alpha \Delta v_{ij}(t) \tag{7}$$

Where, Q identifies the multiple disease categories and α represents the softmax activation function. Finally, PCNN-ResNet identifies and classifies the crop diseases such as Corn_northern_leaf_blight, corn_common_rust, Corn_gray_leaf_spot, Grape_black_measles, Corn_healthy, Grape_healthy, Grape_black_rot, Grape_leaf_blight, Soybean_downy_mildew, Soybean_rust, soybean_bacterial_blight, Soybean_mosaic_virus, Soybean_powdery_mildew, Soybean_healty and Soybean_southern_blight. Here COA is employed to enhance PCNN. The COA is utilized for tuning weight, bias parameter of PCNN.

3.3 Optimization utilizing Coati Optimization Algorithm

COA [14][19] is a nature-inspired optimization approach mimics foraging behaviour of coatis and utilized to enhance weights parameters $X_L^{[P]}$ and v_{ij} of proposed PCNN- ResNet. The parameter $X_L^{[P]}$ is used for increasing the Accuracy and v_{ij} Lessing the Computational Time. The COA is used to fine-tune weight parameters in PCNN-ResNet for crop disease identification. By leveraging its exploration-exploitation balance, COA identifies optimal parameter values that enhance the model's predictive accuracy. COA fine-tunes the weight parameters of the PCNN-ResNet by simulating the foraging behavior of coatis. COA employs a multi-phase search mechanism to explore and exploit the solution space, optimizing key hyper parameters such as learning rates, layer weights, and activation functions. It uses a balance between broad search and focused refinement to achieve optimal model performance. The optimization process ensures that PCNN-ResNet method is finely tuned for improved accuracy and efficiency in tasks like image classification and feature extraction [18]. The stepwise procedure for acquiring suitable PCNN- ResNet values utilizing COA is described. To makes uniformly distributed population for optimizing ideal PCNN- ResNet parameters. Each step method is given in follows,

Step 1: Initialization

Initial population of COA is initially created by randomly. It is given in equation (8).

$$A = \begin{bmatrix} A_{1,1} & \cdots & A_{1,j} & \cdots & A_{1,m} \\ \vdots & \ddots & \vdots & \cdot^{\cdot^{\cdot}} & \vdots \\ A_{i,1} & \cdots & A_{i,j} & \cdots & A_{i,m} \\ \vdots & \ddots & \vdots & \cdot^{\cdot^{\cdot}} & \vdots \\ A_{N,1} & \cdots & A_{N,j} & \cdots & A_{N,m} \end{bmatrix}_{N \times m} \tag{8}$$

Here, A mathematically represents the coatis population in COA; $A_{i,j}$ considered as the best value of j^{th} decision variable; A_i represents i^{th} position of the coati in search space N denotes total coatis, M signifies decision variables.

Step 2: Random generation

Input weight parameter V_{gz} and v_{ij} developed randomness via COA technique.

Step 3: Fitness Function

It makes random solution from initialized values. It is computed by optimizing parameter. It is given in equation (9).

$$Fitness\ \ Function = optimizing\ \ [X_L^{[P]}\ and\ \beta_{(i)}^{g}] \tag{9}$$

Where, $X_L^{[P]}$ is utilized for increasing accuracy, v_{ij} is utilized to Lessing Computational Time.

Step 4: Hunting and Attacking Strategy on Iguana for optimizing $X_L^{[P]}$

Initial stage of updating coati's population at search space is based on model that mimics approach to iguana attacks. A group of coatis scale trees approach the iguana and threaten it by using this tactic. Under the tree, several more jackets wait until the iguana touches down. When the iguana hits the ground, coatis attack and pursue it. This strategy shows how COA can explore globally in problem-solving space by causing coatis to move to diverse places inside search space using equation (10). A_i^{S2}

$$A_i^{S1} : A_{i,j}^{S1} = \begin{cases} A_{i,j} + r \cdot \left(\dfrac{Iguana_j^H}{X_L^{[P]}} - I \ . \ A_{i,j} \right), & E_{iguana^H} < E_i \\ A_{i,j} + r \cdot \left(A_{i,j} - Iguana_j^H \right), & else \end{cases} \tag{10}$$

Where, A_i^{S1} indicates novel position computed for i^{th} coati; $A_{i,j}^{S1}$ represents j^{th} dimension; r considered as random real number at $[0,1]$ interval; $Iguana$ symbolises iguana position at search space of best member's position; I denotes the integer, which randomly selects the set $\{1,2\}$; $Iguana_j^H$ considered as j^{th} dimension of coati; E_{iguana^H} signifies value of objective function; $X_L^{[P]}$ represents the location on the crop leaves and E_i is its objective functional value obtained dependent on i^{th} coati.

Step 5: The Process of Escaping from Predators for optimizing v_{ij}

The second stage is the process of updating their location at search space is mathematically represented by using coatis' natural behaviour during encounter and then escape from predators. A coati will leave its area if it is attacked by a predator. This strategy's manoeuvres put Coati in a safe location near its present position, representing COA's capacity for local search operation using equation (11).

$$A_i^{S2} : A_{i,j}^{S2} = A_{i,j} + (1-2r) \cdot \left(ly_j^{Local} + \frac{r}{v_{ij}} \cdot \left(uy_j^{Local} - ly_j^{Local} \right) \right) \quad (11)$$

Where, A_i^{S2} denotes new location computed for i^{th} coati, dependent on second phase of coati optimization algorithm; $A_{i,j}^{S2}$ is its j^{th} dimension and uy_j^{Local} *and* ly_j^{Local} represents local lower, local upper bound of j^{th} decision variable, v_{ij} considered as i^{th} and j^{th} layer of neurons in ResNet.

Step 6: Termination

The weight parameter value of generator $X_L^{[P]}$ *and* v_{ij} from Pyramid Convolutional Neural Network is enhanced by COA; it will repeat step 3 until halting criteria $A = A+1$ is obtained. The PCNN defectively identifies the crop diseases by increasing the accuracy and lessening computational time. Figure3 represents the Flow Chart of COA for Optimizing PCNN.

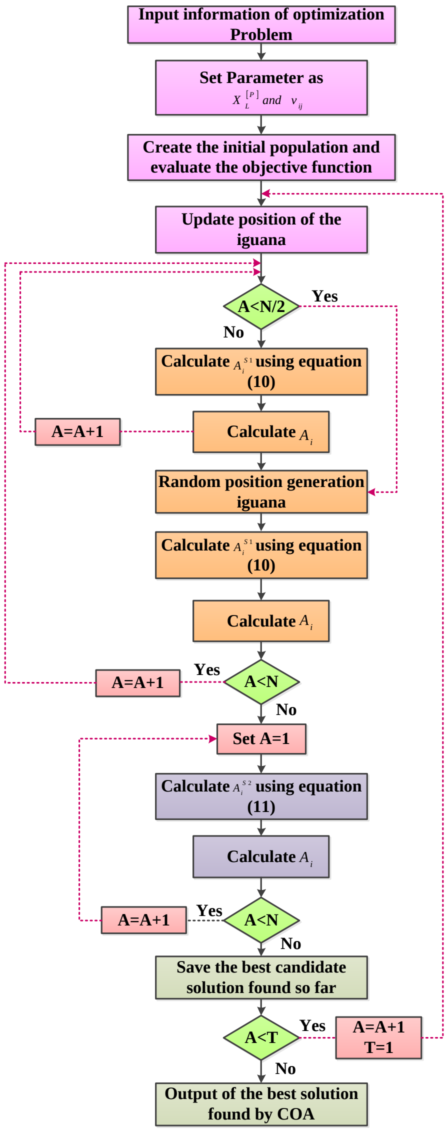

Figure3: Flow Chart of COA for Optimizing PCNN

4. RESULT WITH DISCUSSION

The simulation outcomes of PCNN-ResNet-COA are discussed. The simulation is implemented within Python utilizing PC through Intel core i5, 2.50GHz CPU, windows 7, 8GB RAM, utilizing Plant Disease Classification Merged Dataset. The PCNN-ResNet-COA model is tested against several performance metrics. Attained result proposed method is analyzed with existing techniques like Multi-Class Categorization of Plant Leaf Diseases Utilizing Feature Fusion of DCNN with LBP (LD-DCNN), effectual multi-crop disease detection utilizing pruned complete concatenated DL method (MCDD-CCDL) and DLMC-Net: Deeper lightweight multiple class categorization method for PLDD (PLDD-DLMC-Net). The Figure 4 and 5 display the output of proposed PCNN-ResNet-COA method.

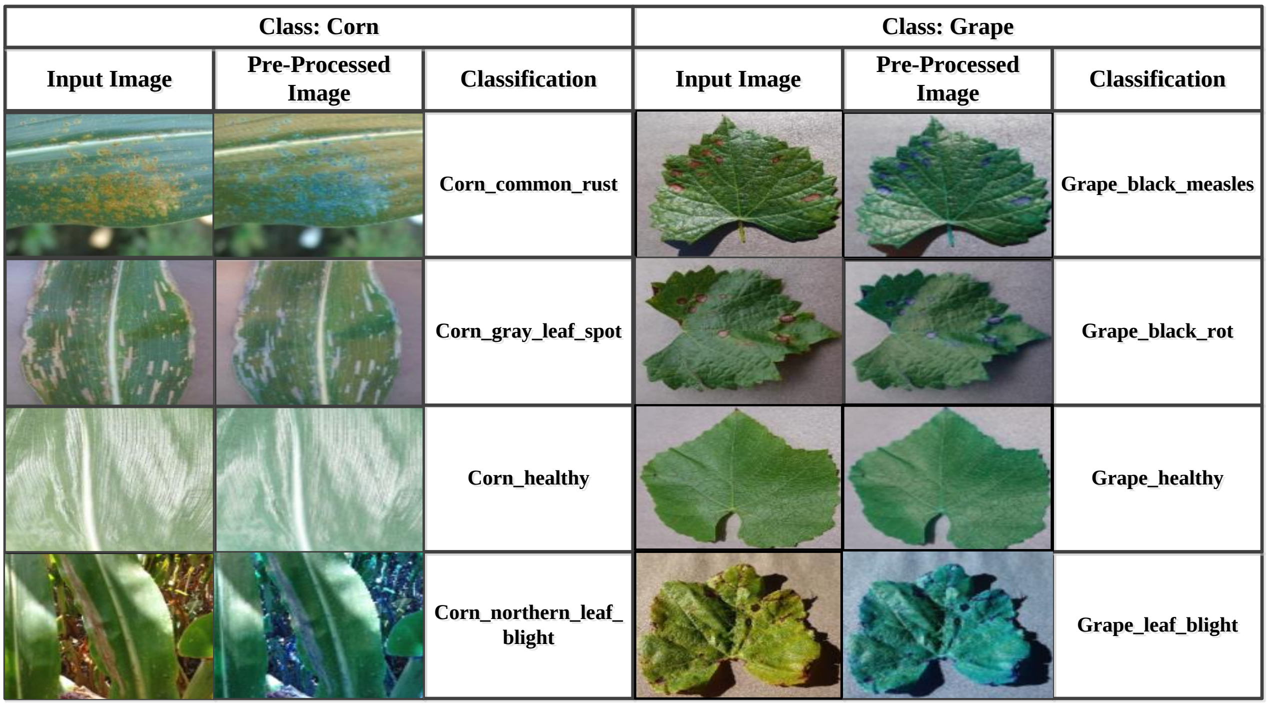

Figure 4: Display the output of PCNN-ResNet-COA proposed method

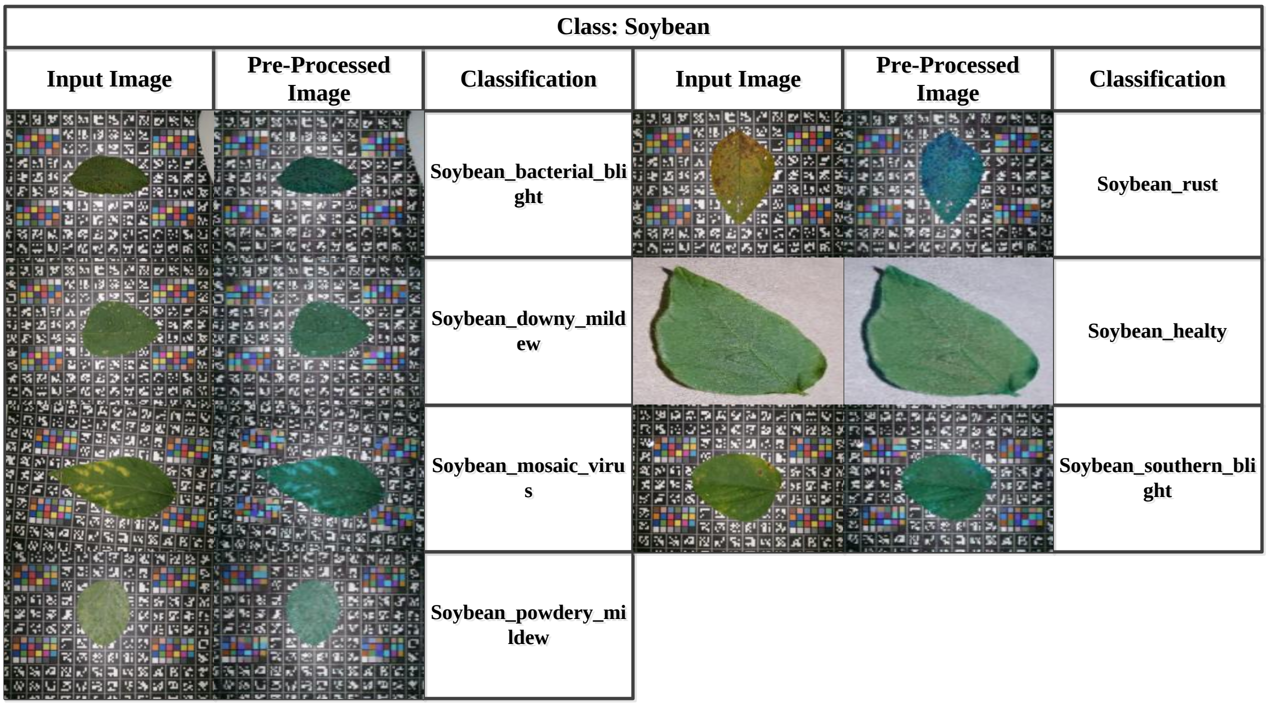

Figure 5: Display the output of PCNN-ResNet-COA proposed technique

4.1 Performance Measures

The proposed approach is evaluated under performance metrics like accuracy, precision, F1-score, computational time.

4.1.1 Accuracy

Accuracy describes detection rate are correctly analyze the identification of crop diseases. The formula is derived in equation (12).

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{12}$$

Here, TP signifies true positive, TN implies true negative, FP implies false positive, FN implies false negative.

4.1.2 Precision

It calculates the number of positive results while analysing agricultural disease identification. It is shown in equation (13).

$$\Pr ecision = \frac{TP}{(TP + FP)} \tag{13}$$

4.1.3 F1-Score

The performance equation is given in and evaluation parameter of F1-score is analyzed. It is given in equation (14).

$$F1 - Score = 2 \times \frac{recall \times precision}{recall + precision} \tag{14}$$

4.2 Performance Metrics

Table 2-5 and Figure 4-11 portrays simulation outcomes of PCNN-ResNet-COA technique. The performance metrics are compared with existing LD-DCNN, MCDD-CCDL and PLDD-DLMC-Net techniques.

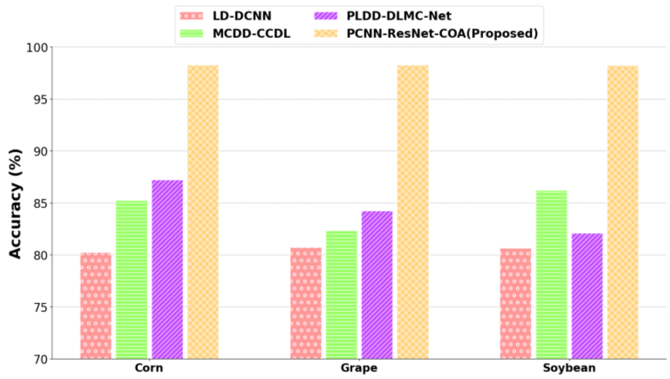

Figure 6: Accuracy analysis

Figure 6 illustrates the accuracy analysis. The higher accuracy of the PCNN-ResNet-COA model is due to its integration of PCNN-ResNet, which enhances feature extraction and model learning. The COA optimizes the model's weight parameters, improving convergence and overall performance. These combined advancements enable the model to achieve superior accuracy in multi-crop, multi-disease classification. It indicates that the PCNN-ResNet-COA Proposed model performs the best in all multi-crop, multi-disease identification in leaf images as 18.97%, 24.57% and 32.68% higher accuracy for corn; 22.50%, 17.21% and 32.35% higher accuracy for Grape and 18.40% , 20.64% and 30.12% higher accuracy for soybean which is analyzed with existing LD-DCNN, MCDD-CCDL and PLDD-DLMC-Net methods respectively.

Table 2-: Precision Analysis

Precision (%)					
Identified Class	Classification	Methods			
		LD-DCNN	MCDD-CCDL	PLDD-DLMC-Net	PCNN-ResNet-COA (Proposed)
Corn	corn_common_rust	89.4	72.5	76.4	98.4
	Corn_gray_leaf_spot	71.3	83.1	84.2	99.1
	Corn_healthy	83.2	88.2	79.3	98.2

	Corn_northern_leaf_blight	63.5	79.5	63.2	98.9
Grape	**Grape_black_measles**	74.8	84.3	88.9	98.4
	Grape_black_rot	89.5	83.9	78.5	99.6
	Grape_healthy	77.1	80.2	69.2	99.1
	Grape_leaf_blight	86.3	69.7	68.3	98.9
Soybean	**soybean_bacterial_blight**	68.3	82.3	72.9	98.1
	Soybean_downy_mildew	77.2	90.2	77.5	98.9
	Soybean_mosaic_virus	84.9	82.6	80.4	99.2
	Soybean_powdery_mildew	75.7	76.3	86.9	98.1
	Soybean_rust	73.2	66.2	72.2	97.9
	Soybean_healty	86.1	86.1	89.3	99.2
	Soybean_southern_blight	68.4	84.3	76.3	98.7

Table 2 illustrates the precision analysis. Precision is higher in proposed PCNN-ResNet-COA model due to ResNet's ability to capture more refined features through its residual connections, reducing the risk of false positives. The ResNet architecture enables better differentiation between healthy and diseased leaves, enhancing true positive predictions. It indicates that the PCNN-ResNet-COA proposed model performs the best in all multi-crop, multi-disease identification in leaf images as 17.46%, 23.94% and 33.42% higher precision for corn_common_rust; 23.89%, 16.94% and 33.49% higher precision for Corn_gray_leaf_spot; 33.14%, 22.69% and 17.20% higher precision for Corn_healthy; 24.28%, 32.05% and 17.21% higher precision for Corn_northern_leaf_blight; 17.81%, 25.99% and 32.24% higher precision for Grape_black_measles; 16.28% , 33.57% and 24.66% higher precision for Grape_black_rot, 36.40% , 19.74% and 27.88% greater precision for Grape_healthy; 18.97% , 24.82%, 30.19% greater precision for Grape_leaf_blight; 16.70% , 26.08% and 35.16% higher precision for soybean_bacterial_blight; 30.93% , 24.02% and 18.28% higher precision for Soybean_downy_mildew; 18.48% , 23.95% and 34.28% higher precision for Soybean_mosaic_virus; 25.97% , 19.82% and 34.78% higher precision for Soybean_powdery_mildew; 34.15% , 19.37% and 24.79% higher precision for Soybean_rust, 23.12% , 19.65%, 32.46% greater precision for Soybean_healty and 18.25% , 24.66%, 32.86% greater precision for Soybean_southern_blight which is analyzed with existing LD-DCNN, MCDD-CCDL and PLDD-DLMC-Net methods respectively.

Table 3: F1-Score Analysis

Precision (%)					
Identified Class	**Classification**	**Methods**			
		LD-DCNN	**MCDD-CCDL**	**PLDD-DLMC-Net**	**PCNN-ResNet-COA (Proposed)**
Corn	**corn_common_rust**	68.4	84.2	75.2	97.9
	Corn_gray_leaf_spot	64.2	75.7	84.3	98.6
	Corn_healthy	77.6	83.2	72.8	97.3
	Corn_northern_leaf_blight	71.2	69.3	69.1	97.8
Grape	**Grape_black_measles**	73.9	74.2	68.3	98.2
	Grape_black_rot	73.2	61.9	72.8	99.1
	Grape_healthy	86.5	67.1	78.6	98.5
	Grape_leaf_blight	62.3	84.6	65.3	97.2
Soybean	**soybean_bacterial_blight**	67.5	73.8	68.2	98.8
	Soybean_downy_mildew	79.8	84.9	83.7	98.6
	Soybean_mosaic_virus	83.4	76.3	69.5	97.5
	Soybean_powdery_mildew	82.9	67.4	68.3	97.7
	Soybean_rust	76.1	62.3	67.1	98.7
	Soybean_healty	63.3	71.5	64.9	97.1

	Soybean_southern_blight	79.5	77.2	84.7	98.7

Table 3 illustrates the f1-score analysis. The COA improves the f1-score by optimizing the weight parameters of the PCNN-ResNet model, ensuring better balance between each value. COA reduces model bias and enhances generalization, leading to more accurate predictions across both classes. It indicates that the PCNN-ResNet-COA proposed model performs the best in all multi-crop, multi-disease identification in leaf images as 19.21%, 25.68% and 35.21% higher f1-score for corn_common_rust; 22.97%, 18.68% and 34.68% higher f1-score for Corn_gray_leaf_spot; 32.93%, 25.25%, 18.57% greater FI-score for Corn_healthy; 23.68%, 33.10% and 16.99% higher f1-score for Corn_northern_leaf_blight; 19.23%, 24.80% and 33.68% greater f1-score for Grape_black_measles; 18.64% , 32.36% and 25.90% greater f1-score for Grape_black_rot, 35.11% , 18.49% and 24.36% greater f1-score for Grape healthy; 17.66% , 22.70% and 32.17% greater f1-score for Grape_leaf_blight; 17.52% , 27.12% and 34.21% greater f1-score for soybean_bacterial_blight; 32.36% , 23.20% and 19.80% greater f1-score for Soybean_downy_mildew; 19.61% , 24.48% and 32.14% greater f1-score for Soybean_mosaic_virus; 23.12% , 17.96% and 32.84% higher f1-score for Soybean_powdery_mildew; 31.25% , 18.94% and 23.23% greater f1-score for Soybean_rust, 25.58% , 18.23%, 33.11% greater FI-score for Soybean_healty and 16.98% , 23.62% and 33.19% greater FI-score for Soybean_southern_blight that is analyzed with existing LD-DCNN, MCDD-CCDL and PLDD-DLMC-Net methods respectively.

Table 4: Computational Time Analysis

Methods	Computational Time (Sec)
LD-DCNN	190
MCDD-CCDL	220
PLDD-DLMC-Net	260
PCNN-ResNet-COA (Proposed)	99

Table 4 illustrates the computational time analysis The PCNN-ResNet reduces computational time by efficiently extracting multi-scale features, eliminating the need for redundant processing. The integration of ResNet's residual connections accelerates learning, reducing training complexity. This performs faster without compromising accuracy, leading to lower computational time compared to existing methods. It indicates that the PCNN-ResNet-COA proposed model performs the best in all multi-crop, multi-disease identification in leaf images as 19.84%, 24.93% and 31.62% lower computational time which is analyzed with existing LD-DCNN, MCDD-CCDL and PLDD-DLMC-Net methods respectively.

Figure 7 illustrates the performance analysis of ROC. The ROC achieves higher in PCNN-ResNet-Coati is due to enhanced feature extraction via Pyramid CNN and ResNet, which captures multi-scale disease patterns effectively. The COA fine-tunes hyper parameter, improving classification accuracy and reducing false positives. Better class balance handling and transfer learning enhance generalization, leading to a higher TPR**.** In contrast, existing methods struggle with suboptimal feature extraction and weaker optimization, resulting in lower ROC performance. It indicates that the PCNN-ResNet-COA proposed model performs the best in all multi-crop, multi-disease identification in leaf images as 0.94%, 0.92% and 0.98% higher ROC which is analyzed with existing LD-DCNN, MCDD-CCDL and PLDD-DLMC-Net methods respectively.

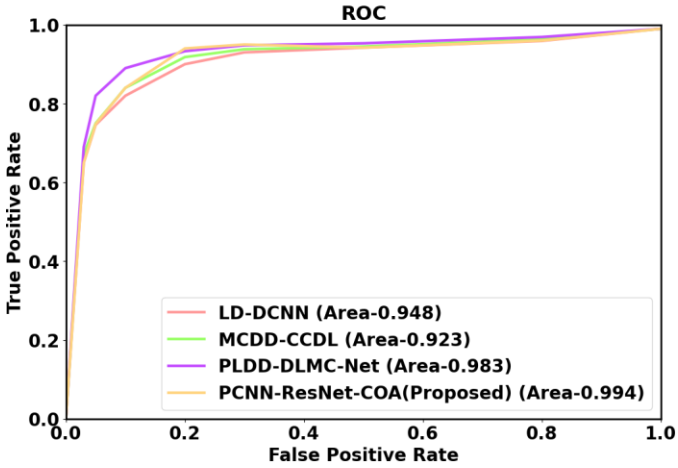

Figure 7: Performance Analysis of ROC

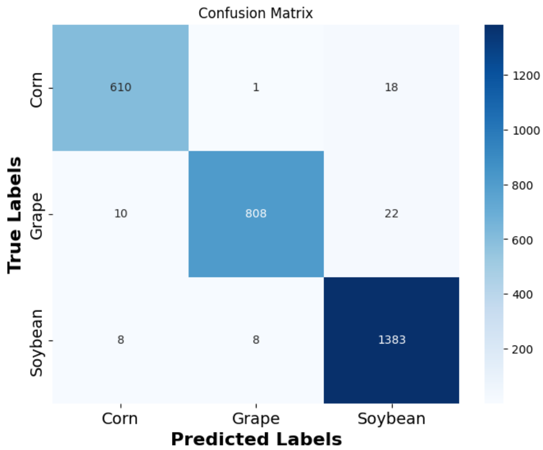

Figure 8: Confusion Matrix

Figure 8 illustrates the confusion matrix, the overall classification performance of the -Based PCNN with ResNet and COA for multi-crop, multi-disease identification. The model accurately classifies most samples, with 610 Corn, 808 Grape, and 1383 Soybean instances correctly identified. Minimal misclassifications occur, such as 18 Corn samples predicted as Soybean and 22 Grape samples misclassified as Soybean. The strong diagonal values indicate high classification accuracy, confirming the model's robustness in identifying different crop diseases.

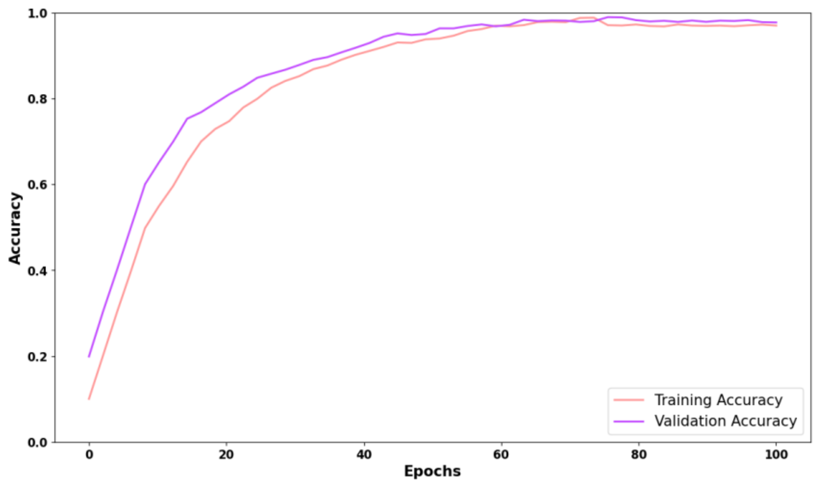

Figure 9: Performance Analysis of Accuracy vs Epoch

Figure 9 illustrates the accuracy vs epoch graph. The accuracy progression of an AI- PCNN, integrated with ResNet, for multi-crop, multi-disease identification in leaf images. The training and validation accuracy curves indicate a steady improvement, indicating effective learning. Initially, validation accuracy surpasses training accuracy, representing strong generalization. Both curves converge near 100 epochs, approaching near-perfect classification performance. The minimal gap between them suggests low overfitting, implying the robustness of the model with ResNet and COA Optimization.

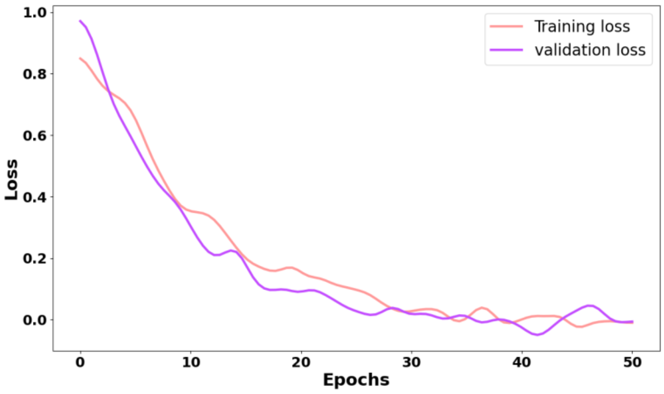

Figure 10: Performance Analysis of Training Loss vs Validation Loss

Figure 10 illustrates training loss Vs validation Loss graph. The training and test loss curves over 50 epochs for the AI-Based PCNN with ResNet and COA for multi-crop, multi-disease identification. The training loss decreases significantly during the early epochs, stabilizing near 0.2 by epoch 50. Similarly, the test validation loss follows a similar trend, though it slightly lags behind the training loss. Both curves suggest that the model is successfully learning, with minimal overfitting, as the test loss also continues to decline and stabilize.

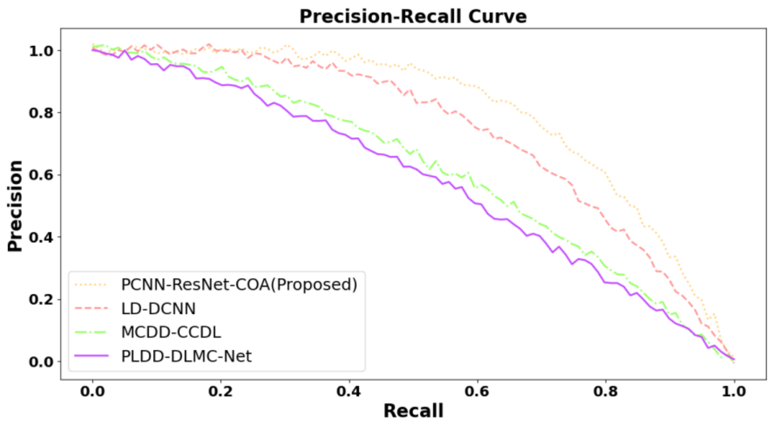

Figure 11: Performance Analysis of Precision-Recall

Figure 11 illustrates the Precision-Recall curve comparing various models for multi-crop, multi-disease identification in leaf images. The proposed PCNN-ResNet-COA outperforms other methods with higher precision at corresponding recall values. The existing models LD-DCNN, MCDD-CCDL and PLDD-DLMC-Net, have lower precision, especially as recall increases. Thus proposed model provides better overall performance, particularly in balancing precision and recall for the task at hand.

Table 5: Comparative analysis and state-of-the-art methods

Performance Analysis	Authors'					
	K. M. Hosny, et.al, [11]	R. ArumugaArun and S. Umamaheswar	V. Sharma, A., et.al, [13]	Ahmad, A., et.al, [14]	Kulkarni, P. and Shastri, S., [15]	PCNN-ResNet-COA (Proposed)

		i, [12]				
Accuracy (%)	89.2	84.6	79.1	85.7	90.1	99.6
Precision (%)	78.4	86.8	80.8	83.3	76.3	98.2
F1-Score (%)	84.7	75.9	81.6	72.9	86.4	97.5
ROC	0.948	0.923	0.983	0.957	0.948	0.994
Computational Time (Sec)	190	220	260	199.9	216.8	99

Table 5 illustrates comparative analysis of PCNN-ResNet-COA with several state-of-the-art techniques regards key performance metrics. The accuracy the PCNN-ResNet-COA model significantly outperforms the other methods, achieving 99.6%, which is notably higher than the best-performing model, Kulkarni et al. [15], with 90.1%. Precision, F1-Score values for proposed method also demonstrate superior performance, with values of 98.2% and 97.5%, respectively, compared to the other methods that range from 75.9% to 86.4%. Also, PCNN-ResNet-COA model achieves a lower computational time of 99 seconds, providing a significant improvement in efficiency over the other models, where computational times range from 190 to 260 seconds. This highlights the effectiveness of proposed technique regards both accuracy and efficiency.

4.3 Discussion

A novel PCNN-ResNet-COA model to multi-crop, multi-disease identification in leaf images using Plant Disease Classification Merged Dataset is developed. The PCNN-ResNet-COA method involves encompasses PCNN-ResNet dependent crop diseases identification on multi-crop, multi-disease in leaf image. Finally, PCNN-ResNet model utilized for performing identification process which identify the crop diseases. The instance of Plant Disease Classification Merged Dataset, average highest results of method is analyzed with average results given in existing techniques like LD-DCNN, MCDD-CCDL and PLDD-DLMC-Net. It is lesser expensive than comparing to proposed technique. It uses a faster PCNN-ResNet in conjunction by COA, resulting in more effectual collection of data with better ability to deal by method over-fitting problem. The PCNN-ResNet method lies in its ability to capture multi-scale features and enhance learning through residual connections, leading to improved classification accuracy and robustness for multi-crop, multi-disease identification. The limitation of COA demands the significant computational resources for parameter tuning, especially when applied to large-scale datasets. The accuracy values of PCNN-ResNet-COA are 18.97%, 24.57% and 32.68% respectively higher than existing methods such as LD-DCNN, MCDD-CCDL and PLDD-DLMC-Net respectively. Similar to this, the accuracy of proposed technique is 99.6% analyzed with accuracy and precision of comparison methods of 98.2%.The PCNN-ResNet-COA has higher accuracy, precision evaluation metrics than existing techniques. The comparative methods are expensive than proposed method. Accordingly, it identifies multi-crop, multi-disease identification in leaf images more efficiently.

5. CONCLUSION

In this section, PCNN-ResNet-COA is successfully executed. The proposed PCNN-ResNet-COA method is simulated in Python utilizing Plant Disease Classification Merged Dataset. By conducting a number of tests to the Multi-Crop, Multi-Disease identification in leaf images; then the data is extracted from Plant Disease Classification Merged Dataset, for identifying the accurate crop diseases in leaf images. The PCNN-ResNet-COA performed better with the Co-training technique than using separately Accuracy and Computational Time. The performance of identification in leaf images approach attains 17.46%, 23.94% and 33.42% higher precision and 19.21%, 25.68% and 35.21% higher F1-Score when analyzed with existing methods like LD-DCNN, MCDD-CCDL and PLDD-DLMC-Net respectively. In future work, it focus on developing a real-time, low-cost sensing system for monitoring crop health using simple handheld devices, enabling farmers in remote areas to easily detect diseases without requiring specialized equipment. By investigating environmental and genetic factors influencing disease resistance in crops can provide deeper insights into developing disease-resistant varieties, enhancing crop yield and sustainability.

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