Coconut Tree Disease Detection Using the Piecewise Linear Chaotic Map-Based Cuckoo Search Optimization with Convolutional Neural Networks

Kavitha Magadi Gopalakrishna
Department of Computer Science and Engineering, Kalpataru Institute of Technology, Tiptur, Visvesveraya Technological University, Belagavi, India
kavitha.magadi1@gmail.com (corresponding author)

Raviprakash Madenur Lingaraju
Department of Artificial Intelligence & Machine Learning, Kalpataru Institute of Technology, Tiptur, Visvesveraya Technological University, Belagavi, India
raviprakashml@gmail.com

Ananda Babu Jayachandra
Department of Information Science and Engineering, Malnad College of Engineering, Hassan, India
abj@mcehassan.ac.in

Received: 26 June 2025 | Revised: 18 August 2025 | Accepted: 30 August 2025

 DOI: https://doi.org/10.48084/etasr.12960

ABSTRACT

Coconut trees are vital staple crops that are widely grown in coastal regions, contributing significantly to the national economy. However, diverse types of diseases affect coconut tree health, including leaf spot diseases, which affect crop health and productivity. To address these challenges, a Deep Learning (DL)-based detection model, combining a Piecewise Linear Chaotic Map-based Cuckoo Search Optimization (PCSO) algorithm with a Convolutional Neural Network (CNN), referred to as PCSO-CNN, is proposed for coconut tree disease detection. By optimizing the hyperparameters of the CNN, the network effectively learns subtle differences in diseased portions, enabling the PCSO-CNN model to accurately detect coconut tree diseases. The coconut tree images are preprocessed, and then multi-scale features are extracted using the EfficientNet-B7 to enhance disease detection through its fine-tuned architecture. Experimental results show that the proposed PCSO-CNN method achieves an accuracy of 98.53% on the coconut tree disease dataset, which is higher than that of the existing ResNet-50 approach.

Keywords-coconut tree disease detection; Convolutional Neural Network (CNN); Deep Learning (DL); EfficientNet-B7; Piecewise Linear Chaotic Map-based Cuckoo Search Optimization (PCSO) algorithm

I. INTRODUCTION

Coconut (Cocos nucifera) is an important cash crop grown year-round, mainly in coastal regions of South America and Asia. Coconut tree products such as leaves, coconuts, and related items have become a crucial part of our daily lives and industry in many parts of the world because of their high nutritional value [1, 2]. Coconut trees are found across the globe, especially in coastal regions, and have become economically important crops worldwide. The scientific name for the coconut tree is Cocos nucifera, which belongs to the palm family and is the only living species of the Cocos genus. The coconut tree produces oil, coconut milk, desiccated coconut, and many other commercial products with high market demand [3-5].

However, cultivating coconut trees is challenging because of pests and diseases that spread and affect tree health, reducing yield [6]. Addressing these issues can increase coconut yield and improve market value. The leaves, nuts, stems, and roots are susceptible to various diseases that can ultimately kill the tree [7]. Early identification of these diseases can reduce infection spread among coconut trees.

Nonetheless, the manual identification of coconut tree diseases by humans is a difficult and time-consuming task that requires significant effort and may lead to inaccurate results in certain circumstances [8]. To overcome these limitations, Artificial Intelligence (AI)-based methods like Machine Learning (ML) and Deep Learning (DL) are used for disease detection and classification [9-11]. However, existing ML algorithms often fail to detect diseases accurately because they depend only on training data and extracted features that may contain irrelevant information [12, 13]. Therefore, automated classification systems have been developed to overcome these limitations by accurately detecting coconut tree diseases and assisting in their analysis [14].

Hence, DL models are used to identify coconut tree diseases, where the models are trained using images of diseased trees and tested to predict infections accurately based on sample data [15]. DL-based approaches such as deep neural networks and time series-based models are widely used for various applications. However, existing DL-based detection models often struggle to detect diseases accurately due to imbalanced data, irrelevant features, and ineffective hyperparameter tuning, all of which degrade detection performance.

To overcome these issues, a Piecewise Linear Chaotic Map-based Cuckoo Search Optimization (PCSO) with a Convolutional Neural Network (CNN), referred to as PCSO-CNN, is proposed for coconut tree disease detection. The DL model undergoes several stages, including the collection of coconut leaf image datasets, preprocessing, feature extraction, and finally classification to identify the specific disease type.

The main contributions of this research are:

- Preprocessing techniques such as median filtering, normalization, and resizing are employed to enhance image quality and remove noise for effective feature extraction and detection.
- The EfficientNet-B7 is used for feature extraction, where multi-scale features containing important disease-related information are extracted to improve detection accuracy under various conditions.
- The proposed PCSO-CNN effectively learns complex patterns associated with distinct coconut tree diseases, resulting in improved detection and classification accuracy.

II. RELATED WORK

The advantages and limitations of detection and classification approaches used for coconut tree or leave disease detection are discussed below.

Authors in [16] developed a DL-based pre-trained model for disease detection and classification of coconut trees. The pre-trained models such as VGG-16, ResNe-t50 and MobileNetV2 architectures were utilized to analyze disease classification. Due to several advantages such as skip connections and residual learning, the ResNet-50 model effectively detected coconut tree diseases compared with the other two pre-trained models. However, the ResNet-50 model struggled to generalize new disease data, leading to overfitting and degraded detection performance under certain conditions.

Authors in [17] designed a DL model for whitefly identification in coconut tree leaves. The designed VGG-16 model was utilized for whitefly detection by segmenting abnormal portions of the leaves. The model extracted relevant features related to the disease to enhance detection. However, the VGG-16 model failed to detect accurately due to class imbalance in the dataset, which negatively affected accuracy.

Authors in [18] explored a detection model based on an Artificial Neural Network (ANN) and a Support Vector Machine (SVM) for coconut trees. The strengths of ANN and SVM approaches were combined to detect pest-related diseases, and features extracted using the gray-level co-occurrence matrix method enhanced the detection of pest diseases in coconut trees. However, integrating two detection models made it difficult to identify diseases effectively due to the challenge of selecting the most important and relevant features.

Authors in [19] presented a work on disease and pest infection detection in coconut trees using DL approaches. The main objective was to develop a framework for disease detection using DL. Several pre-trained CNN models like VGGNet, DenseNet, and InceptionV3 were used to analyze the dataset, along with the k-means clustering method for segmentation, which increased classification accuracy. However, the model became overfitted during training, which was mitigated using a regularization technique.

Authors in [20] proposed a hybrid model based on an SVM and CNN for coconut disease prediction. The model utilized pre-trained networks such as ResNet-50, VGG-16, and EfficientNetB0 for feature extraction and early disease identification. The integrated SVM and CNN models enhanced classification accuracy. However, noise in the coconut tree and leaf images reduced image quality, which negatively affected feature extraction and detection performance.

Authors in [21] aimed to develop a Hybrid Attention Convolutional Neural Network (HACNN) for avocado ripeness classification on resource-constrained devices. This model uses attention mechanisms to identify local and global information for classification. The model's ability to capture long-range dependencies and global contextual information is enhanced by self-attention. Fine-tuning is still required to achieve optimal model performance.

Authors in [22] aimed to develop CNN models for classifying diseases on rose leaves using hybrid DL techniques with an SVM. The developed model, based on the VGG-16 architecture, applied early and late fusion techniques to combine outputs from fully connected layers. The results showed that the early-fusion-based models achieved the highest training, validation, and testing performance, followed by the late-fusion-based and VGG-16-based models.

III. METHODOLOGY

The proposed coconut tree disease detection framework includes four phases: dataset preparation, preprocessing, feature extraction, and proposed classification. The block diagram of the proposed framework is illustrated in Figure 1. At first, coconut leaf images are obtained from the dataset and preprocessed to remove noise, resize the images, and normalize them using min–max normalization to transform raw images into a suitable format for further processing and to improve model performance.

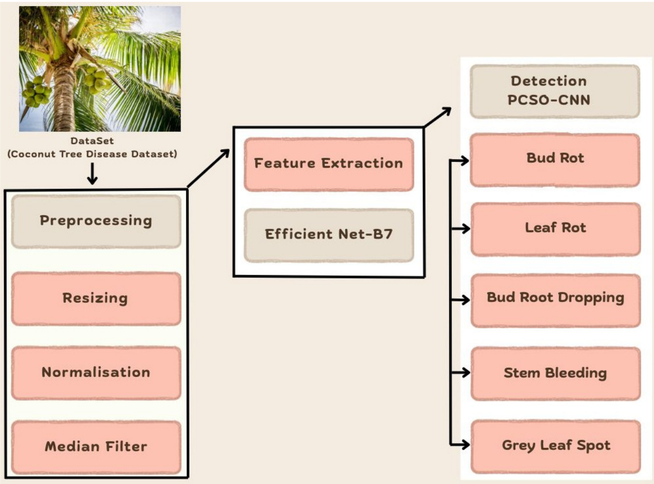

Fig. 1. Block diagram of the proposed coconut tree disease detection model.

After preprocessing, the feature extraction process is performed by utilizing a pre-trained model based on EfficientNet-B7, which extracts several multi-scale features corresponding to various diseases. The extracted features are then fed as input to the proposed PCSO-CNN model for efficient classification and detection of coconut tree diseases. Finally, the performance of the proposed method is evaluated by comparing it with existing detection and classification approaches.

A. Dataset

The Coconut Tree Disease Dataset [23] is utilized in this research, which provides high-quality images of various disease types to support effective tree disease detection. This dataset includes high-resolution images, where each image has a dimension of 768 pixels in width and 1024 pixels in height to represent the disease clearly. The coconut diseases are categorized into five different classes: Bud Rot, Leaf Rot, Bud Root Dropping, Stem Bleeding, and Gray Leaf Spot. The challenges associated with each class are summarized as follows:

- Bud Rot: A fungal disease that, if not identified and managed correctly, can destroy entire groves.
- Leaf Rot: This disease directly affects vitality by compromising the photosynthesis capacity of coconut trees.
- Bud Root Dropping: It affects the early growth phase, leading to reduced development and yield.
- Stem Bleeding: A prolonged condition that weakens the structural integrity of coconut trees.
- Gray Leaf Spot: A serious disease that spreads rapidly and leads to widespread defoliation.

The total number of images in each class is presented in Table I. The acquired images are fed into the preprocessing stage to convert them into useful formats for feature extraction and classification.

TABLE I. NUMBER OF IMAGES IN EACH CLASS OF THE COCONUT TREE DISEASE DATASET

Class	No of images
Gray Leaf Spot	2135
Bud Rot	470
Leaf Rot	1673
Stem Bleeding	1006
Bud Root Dropping	514

B. Preprocessing

The coconut tree images obtained from the dataset are considered as input in this preprocessing stage to transform them into a useful format. For preprocessing, resizing, median filtering, and min-max normalization techniques are applied to enhance the image quality for further processing. The preprocessing steps for coconut tree images are as follows:

- Resizing: Resizing converts all images into uniform dimensions for better detection and classification performance. The raw coconut tree and leaf images are resized from 768 × 1024 pixels to 256 × 256 pixels. These resized images ensure consistent input dimensions for training the PCSO-CNN model, which prevents the model from being biased towards images of certain sizes and improves the generalization ability of the proposed detection framework.
- Normalization: Normalization is a widely used preprocessing technique in image processing that scales the intensity values in images to a uniform range between 0 and 1. In this work, min-max normalization is applied, as given in (1):

$$X_{new} = (X - X_{min})/(X_{max} - X_{min}) \quad (1)$$

where X_{new} denotes the normalized value, and X_{min} and X_{max} represent the minimum and maximum pixel values, respectively.

- Noise removal: The normalized image pixels are filtered using a median filter to remove noise from coconut tree and leaf images, enhancing the detection performance of the proposed model [24]. The median filter with an $n \times n$ kernel replaces the central pixel value with the median of all pixel values within the kernel. The mathematical representation of the median filter is given in (2):

$$H_{med}(X,Y) = \underset{i,j \in k_{n,n}}{\text{med}} \left[k_{n,n}(i,j) \otimes H_{enh}[X+i, Y+j] \right] \quad (2)$$

where $H_{med}(X,Y)$ denotes the noise-free image at pixel coordinates X and Y. The preprocessed images are then passed to the feature extraction process.

C. Feature Extraction

The preprocessed images are passed to the feature extraction stage to extract relevant features by utilizing a pre-trained model based on the EfficientNet-B7 architecture. The EfficientNet-B7 model is a CNN architecture with a scaling technique applied evenly in all dimensions of width, depth, and resolution utilizing a compound coefficient [25]. This scaling strategy of the EfficientNet-B7 model extracts several multi-scale features corresponding to various diseases, including fine-grained details of pest infections in coconut leaves and trees. The scaling parameters, depth, width, and resolution, refer to the network's layer count, layer size, and resolution of the preprocessed images, respectively. Based on these parameters, the model precisely extracts features even from small diseased regions of the trees and leaves. The scaling relations in EfficientNet-B7 are represented in (3) to (5):

$$\partial = \alpha^{\phi} \quad (3)$$

$$\omega = \beta^{\phi} \quad (4)$$

$$r = \delta^{\phi} \quad (5)$$

where ∂, ω, and r represent the depth, width, and image resolution, and ϕ denotes the user-specified compound coefficient. The EfficientNet-B7 architecture efficiently minimizes overfitting issues which are caused by insufficient labeled data of coconut trees through its optimized architecture. The fine-tuned EfficientNet-B7 model efficiently extracts multi-scale features to identify the subtle differences between the texture, color, and shape of coconut tree diseases. These extracted features are then passed to the proposed PCSO-CNN model for disease detection.

D. Proposed Detection Model

The extracted features are fed into the proposed PCSO-CNN model for coconut tree disease detection. The CNN effectively learns spatial and temporal patterns from complex image data. Each convolutional layer generates a feature map by performing element-wise multiplication between the input data and trainable filters, followed by summation and activation, as given in (6):

$$F(i,j) = \sigma(\textstyle\sum_m \sum_n K(m,n)\, I\,(i+m, j+n) + b) \quad (6)$$

where F represents the feature map, I denotes the input data, K indicates the filter set, and b and σ represent the bias and activation function, respectively, of the CNN model.

However, CNNs involve various hyperparameters, such as learning rate, number of filters, batch size, and number of layers, which greatly influence detection performance. Improper tuning can cause overfitting or underfitting, leading to poor results. Thus, a search-based optimization algorithm with a chaotic strategy is utilized for efficient hyperparameter tuning.

1) Piecewise Linear Chaotic Map-Based Cuckoo Search Optimization

The Cuckoo Search Optimization (CSO) algorithm is inspired by the parasitic brood behavior of cuckoo birds, which lay eggs in the nests of host birds. This natural strategy is adapted to enhance CNN hyperparameter tuning for effective disease detection. The CSO algorithm models this behavior under three main conditions, as follows:

- Each cuckoo lays one egg at a time in a randomly placed nest and places it in a host bird's nest. This egg represents a candidate solution to the problem, addressing the challenge of hyperparameter tuning.
- The most suitable nest with the top-quality egg is carried over to the next generation according to the survival-of-the-fittest rule.
- After initializing the number of host nests with the best quality, the cuckoo birds find their eggs through parasitic behavior based on a probability $0 \leq P \leq 1$, which may result in cuckoo egg desertion or host nest abandonment.

Figure 2 illustrates the process of the proposed PCSO algorithm.

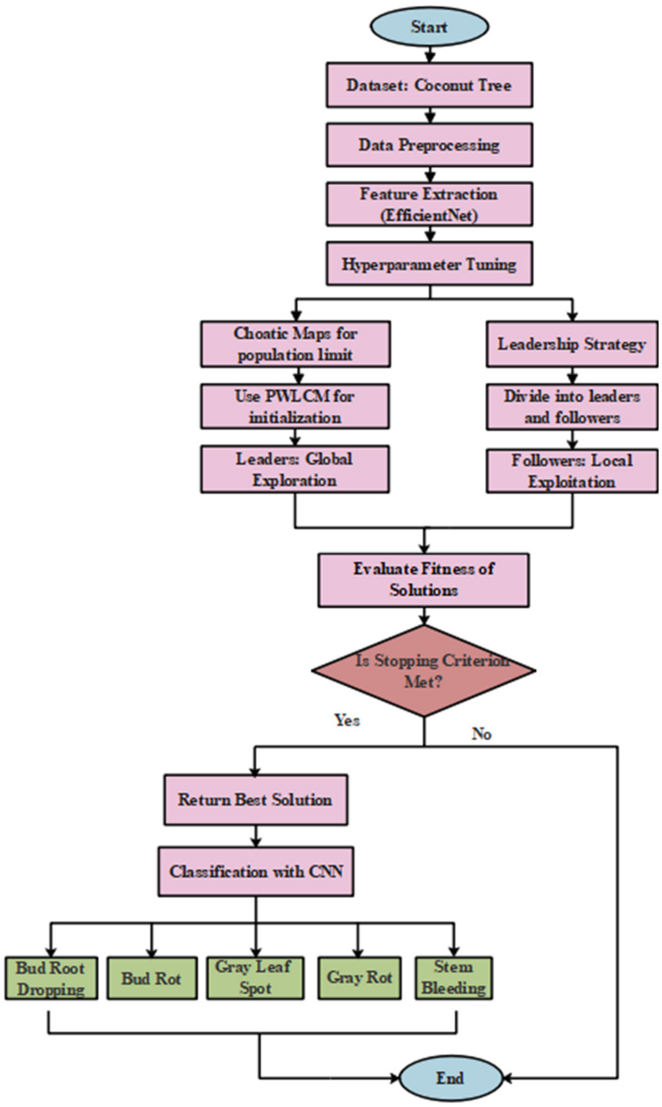

Fig. 2. Flowchart of the proposed PCSO-CNN model.

a) Piecewise Linear Chaotic Map Strategy

The piecewise linear chaotic map enhances the balance between global exploration and local exploitation during the search for optimal hyperparameters. It allows the algorithm to effectively explore the search space and fine-tune promising regions, preventing it from being trapped in local optima and ensuring a more optimal search within the CNN's parameter space. This chaotic map strategy is mathematically expressed in (7):

$$X(+1) = F_p(X(T)) = \begin{cases} \frac{X(T)}{p}, \ 0 < X(T) < p \\ \frac{X(T)-p}{0.5-p}, \ p \leq X(T) < 0.5 \\ \frac{1-X(T)-p}{0.5-p}, \ 0.5 \leq X(T) < 1-p \\ \frac{1-X(T)}{p}, \ 1-p \leq X(T) < 1 \end{cases} \quad (7)$$

The PCSO technique helps in fine-tuning the CNN parameters effectively to avoid overfitting issues and allows the model to generalize well for unseen data. Additionally, the PCSO algorithm improves the robustness of the CNN model in detecting various diseases in coconut trees. The PCSO-CNN combination ensures optimal utilization of computational resources by identifying the best-performing hyperparameters with minimal effort, leading to faster and more accurate detection processes. Table II illustrates the hyperparameter settings of the proposed PCSO-CNN model.

TABLE II. HYPERPARAMETER SETTINGS OF THE PROPOSED PCSO-CNN MODEL

Parameter	Value
Batch size	32
Epochs	20
CNN layers	3 Layers (max pooling, fully connected, and dropout layers)
Loss function	Categorical cross-entropy loss function
Learning rate	0.001
Optimizer	Adam optimizer
Alpha	0.01
Lambda	1.5
Iterations	100

The PCSO algorithm was trained for 20 epochs with a batch size of 32. The CNN architecture consists of three max pooling layers, a dropout layer to prevent overfitting, and a fully connected layer for output classification. The model uses a categorical cross-entropy loss function, an Adam optimizer with a learning rate of 0.001, and is configured with an alpha of 0.01 and a lambda of 1.5 over 100 iterations.

IV. III. RESULTS AND DISCUSSION

The experimental outcomes of the proposed PCSO-CNN model for coconut tree disease detection are presented in this section. The model utilized the Coconut Tree Disease dataset which was split into training, validation and testing sets in a ratio of 70:20:10. The proposed detection method was simulated using Python 3.9 on a system with Windows 10 OS, Intel i5 processor, and 16 GB RAM. To evaluate the performance of the PCSO-CNN model, various performance metrics were used, namely accuracy, precision, recall, and F1-score. Their mathematical formulations are given in (8) to (11):

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \quad (8)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (9)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (10)$$

$$\text{F1} - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \quad (11)$$

where: TP= True Positive, TN = True Negative, FP = False Positive, and FN = False Negative

A. Quantitative and Qualitative Analysis

The performance of the proposed PCSO-CNN method is evaluated through both quantitative and qualitative analyses. The PCSO-CNN framework is compared with existing DL approaches and optimization algorithms used for classification, feature extraction, and feature selection in coconut tree disease detection. Tables III to V present the quantitative and qualitative performance comparisons. Table III presents the performance comparison of PCSO-CNN with existing classifiers, including VGG-19, Recurrent Neural Network (RNN), and Deep Neural Network (DNN). The proposed PCSO-CNN method achieved a high classification accuracy of 98.53%, which is greater than existing DL-based classifiers.

TABLE III. COMPARISON OF THE PROPOSED PCSO-CNN METHOD WITH EXISTING CLASSIFIERS

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
VGG-19	71.13	72.59	69.31	70.02
Recurrent Neural Network (RNN)	87.67	93.55	85.98	88.75
DNN	95.95	97.32	95.31	96.25
PCSO-CNN (proposed)	98.53	98.57	98.48	98.52

Table IV shows the performance of EfficientNet- B7 compared with existing feature extraction methods, including VGG-16, MobileNet, and ResNet. EfficientNet-B7 achieved an accuracy of 98.53%, which is greater than that of existing DL-based feature extraction approaches. Table V presents the performance comparison of the proposed PCSO algorithm with existing optimization approaches, including the Whale Optimization Algorithm (WOA), Dragonfly Optimization Algorithm (DOA), Grasshopper Optimization Algorithm (GOA), and CSO. The PCSO algorithm used in conjunction with the CNN achieved an accuracy 98.53%, which is greater than that of existing optimization-based detection models.

TABLE IV. COMPARISON OF FEATURE EXTRACTION METHODS FOR COCONUT TREE DISEASE DETECTION

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
VGG-16	85.23	86.14	84.78	85.45
MobileNet	90.67	91.45	89.83	90.63
ResNet	82.80	83.12	82.34	82.73
EfficientNet-B7 (proposed)	98.53	98.57	98.48	98.52

TABLE V. COMPARISON OF CNN-BASED DETECTION MODELS WITH DIFFERENT OPTIMIZATION ALGORITHMS

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
WOA-CNN	88.34	90.12	88.56	89.33
DOA-CNN	84.45	85.34	83.67	84.50
GOA-CNN	93.13	94.56	92.78	93.66
CSO-CNN	96.48	95.76	94.89	95.32
PCSO-CNN (proposed)	98.53	98.57	98.48	98.52

The accuracy curve, loss curve, confusion matrix, and Receiver Operating Characteristic (ROC) curve of the proposed PCSO-CNN model are illustrated in Figures 3 to 6. These graphical representations clearly demonstrate the model's effective learning behavior and stability. Overall, the proposed PCSO-CNN model achieved superior performance compared to existing DL approaches and optimization algorithms.

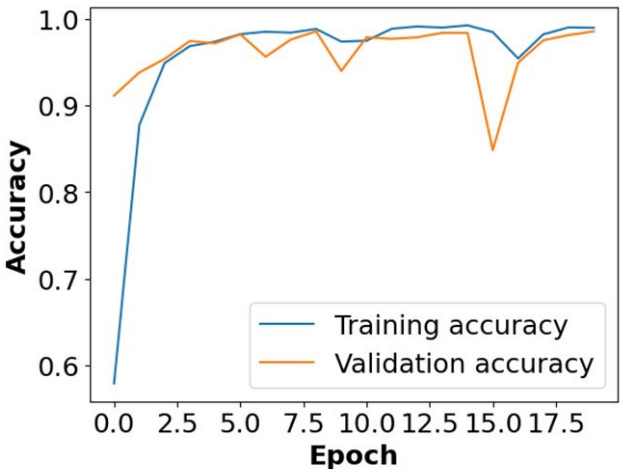

Fig. 3. Accuracy curve of the proposed PCSO-CNN model for coconut tree disease detection.

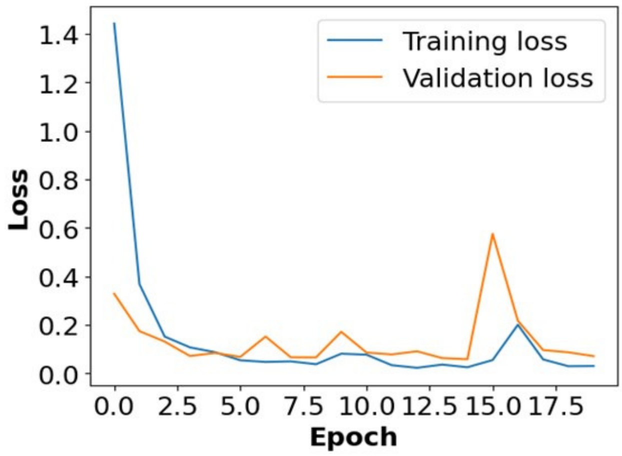

Fig. 4. Loss curve of the proposed PCSO-CNN model for coconut tree disease detection.

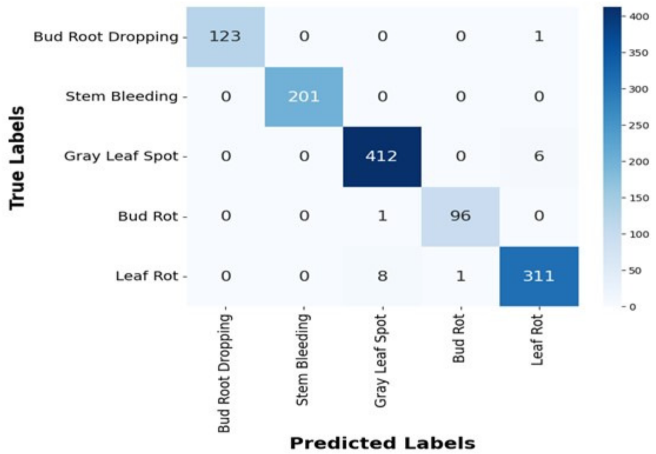

Fig. 5. Confusion matrix of the proposed PCSO-CNN model for coconut tree disease detection.

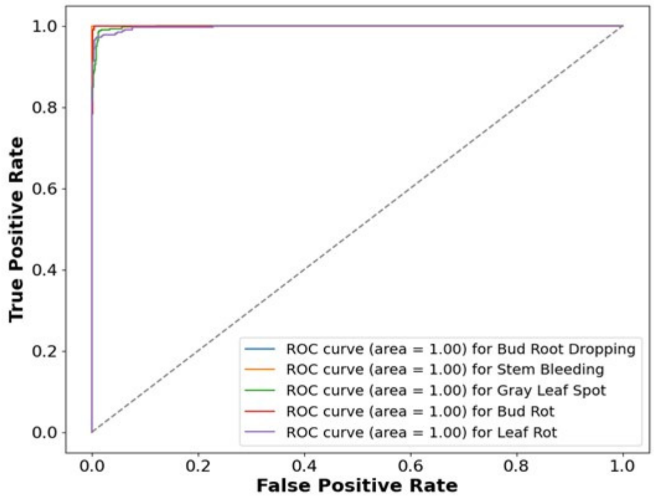

Fig. 6. ROC curve of the proposed PCSO-CNN model for coconut tree disease detection.

B. Comparative Analysis

The performance of the proposed PCSO-CNN method is compared with existing detection approaches in Table VI. The comparison includes methods applied to different datasets, such as the white leaf infection dataset and pest infection dataset. The proposed PCSO-CNN model achieved an accuracy of 98.53%, precision of 98.57%, recall of 98.48%, and an F1-score of 98.52%. The PCSO algorithm fine-tunes key hyperparameters of the convolutional layers, enabling the CNN model to effectively capture disease-specific patterns, including discoloration and leaf spots, in coconut tree images.

C. Discussion

The proposed PCSO-CNN detection model achieved superior performance in detecting coconut tree diseases using leaf images. The existing detection approaches have several limitations. ResNet-50 [16] struggles to generalize to new disease data, resulting in overfitting and degraded performance under certain conditions. The VGG-16 [17] model fails to detect diseases accurately due to class imbalance in the dataset, which reduces detection accuracy. The hybrid ANN-SVM [18] approach faces difficulties in identifying the diseases accurately because of the selection of features with irrelevant information, reducing the disease detection performance. To overcome these limitations, a PCSO-CNN model is proposed for accurate detection of coconut tree disease detection using a piecewise linear chaotic map strategy. With the integration of chaotic dynamics, PCSO introduces randomness and non-repetitive behavior into the CSO optimization process, which improves the capability to explore CNN's complex hyperparameter space more effectively.

TABLE VI. COMPARISON OF THE PROPOSED PCSO-CNN METHOD WITH EXISTING DETECTION APPROACHES

Method	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
ResNet-50 [16]	Coconut tree disease dataset	94	92.25	93.42	93.88
VGG-16 [17]	White leaf disease dataset	95.71	N/A	N/A	N/A
ANN-SVM [18]	Pest infection dataset	95	98	92	95
PCSO-CNN (proposed)	Coconut tree disease dataset	98.53	98.57	98.48	98.52

V. CONCLUSION

The proposed Piecewise Linear Chaotic Map-based Cuckoo Search Optimization with a Convolutional Neural Network (PCSO-CNN) method was developed for effective detection of coconut tree diseases by addressing limitations in CNNs. By optimizing the hyperparameters of the CNN model, the network effectively learns subtle differences from diseased portions, resulting in highly accurate detection of coconut tree diseases. The coconut tree images are preprocessed through resizing, normalization, and noise removal to enhance feature extraction from diseased areas. A fine-tuned neural network architecture, EfficientNet-B7, is then used to extract multi-scale features from the preprocessed images, allowing the model to effectively capture subtle differences between diseased and healthy images. Based on these extracted features, the proposed PCSO-CNN model achieves highly accurate disease detection.

Experimental results demonstrate that the PCSO-CNN method achieved an accuracy of 98.53%, outperforming previous disease detection approaches such as ResNet-50 on the Coconut Tree Disease dataset. In future work, advanced Deep Learning (DL) models incorporating attention mechanisms will be explored to further improve coconut tree disease detection.

REFERENCES

[1] W. C.D, I. K.C, P. S.D.N, P. T.J.N, B. Harshanath, and S. Rajapaksha, "Coconut Plant Disease Identified and Management for Agriculture Crops using Machine Learning," *International Journal of Engineering and Management Research*, vol. 13, no. 5, pp. 79–88, Oct. 2023, https://doi.org/10.31033/ijemr.13.5.13.

[2] E. El-Shafeiy, A. A. Abohany, W. M. Elmessery, and A. A. A. El-Mageed, "Estimation of coconut maturity based on fuzzy neural network and sperm whale optimization," *Neural Computing and Applications*, vol. 35, no. 26, pp. 19541–19564, Sep. 2023, https://doi.org/10.1007/s00521-023-08761-0.

[3] S. K. Manoharan, R. K. Megalingam, A. H. Kota, V. K. T. P., and K. S. Sankardas, "Hybrid fuzzy support vector machine approach for Coconut tree classification using image measurement," *Engineering Applications of Artificial Intelligence*, vol. 126, no. A, Nov. 2023, Art. no. 106806, https://doi.org/10.1016/j.engappai.2023.106806.

[4] F. Sattar, "Predicting Maturity of Coconut Fruit from Acoustic Signal with Applications of Deep Learning," *Biology and Life Sciences Forum*, vol. 30, no. 1, Mar. 2024, Art. no. 16, https://doi.org/10.3390/IOCAG2023-16880.

[5] P. R. De Silva, C. N. Perera, B. W. Bahder, and R. N. Attanayake, "Nested PCR-Based Rapid Detection of Phytoplasma Leaf Wilt Disease of Coconut in Sri Lanka and Systemic Movement of the Pathogen," *Pathogens*, vol. 12, no. 2, Feb. 2023, Art. no. 294, https://doi.org/10.3390/pathogens12020294.

[6] B. Patil *et al.*, "Exploring the Impact of Climatic Variables on Arecanut Fruit Rot Epidemic by Understanding the Disease Dynamics in Relation to Space and Time," *Journal of Fungi*, vol. 8, no. 7, Jul. 2022, Art. no. 745, https://doi.org/10.3390/jof8070745.

[7] L. G. Divyanth, P. Soni, C. M. Pareek, R. Machavaram, M. Nadimi, and J. Paliwal, "Detection of Coconut Clusters Based on Occlusion Condition Using Attention-Guided Faster R-CNN for Robotic Harvesting," *Foods*, vol. 11, no. 23, Dec. 2022, Art. no. 3903, https://doi.org/10.3390/foods11233903.

[8] A. Descals *et al.*, "High-resolution global map of closed-canopy coconut palm," *Earth System Science Data*, vol. 15, no. 9, pp. 3991–4010, Sep. 2023, https://doi.org/10.5194/essd-15-3991-2023.

[9] L. Yu *et al.*, "A non-destructive coconut fruit and seed traits extraction method based on Micro-CT and deeplabV3+ model," *Frontiers in Plant Science*, vol. 13, Dec. 2022, Art. no. 1069849, https://doi.org/10.3389/fpls.2022.1069849.

[10] M. Maray *et al.*, "Artificial intelligence-enabled coconut tree disease detection and classification model for smart agriculture," *Computers and Electrical Engineering*, vol. 104, no. A, Dec. 2022, Art. no. 108399, https://doi.org/10.1016/j.compeleceng.2022.108399.

[11] J. A. Caladcad and E. Piedad, "Deep learning classification system for coconut maturity levels based on acoustic signals," in *2024 IEEE 12th Region 10 Humanitarian Technology Conference*, Kuala Lumpur, Malaysia, 2024, pp. 1–6, https://doi.org/10.1109/R10-HTC59322.2024.10778826.

[12] M. Tzec-Simá *et al.*, "Potential of Omics to Control Diseases and Pests in the Coconut Tree," *Agronomy*, vol. 12, no. 12, Dec. 2022, Art. no. 3164, https://doi.org/10.3390/agronomy12123164.

[13] S. Vigneshwaran and V. N. Tamburi, "Identification of coconut palm trees using single shot detector deep learning model," *Spatial Information Research*, vol. 31, no. 6, pp. 695–707, Dec. 2023, https://doi.org/10.1007/s41324-023-00542-0.

[14] R. K. Megalingam, S. Kuttankulangara Manoharan, D. H. T. A. Babu, G. Sriram, K. Lokesh, and S. Kariparambil Sudheesh, "Coconut trees classification based on height, inclination, and orientation using MIN-SVM algorithm," *Neural Computing and Applications*, vol. 35, no. 16, pp. 12055–12071, Jun. 2023, https://doi.org/10.1007/s00521-023-08339-w.

[15] R. N. Alkhawaji *et al.*, "Enhanced Coconut Yield Prediction Using Internet of Things and Deep Learning: A Bi-Directional Long Short-Term Memory Lévy Flight and Seagull Optimization Algorithm Approach," *Applied Sciences*, vol. 14, no. 17, Sep. 2024, Art. no. 7516, https://doi.org/10.3390/app14177516.

[16] S. Thite, Y. Suryawanshi, K. Patil, and P. Chumchu, "Coconut (*Cocos nucifera*) tree disease dataset: A dataset for disease detection and classification for machine learning applications," *Data in Brief*, vol. 51, Dec. 2023, Art. no. 109690, https://doi.org/10.1016/j.dib.2023.109690.

[17] V. Kavithamani and S. UmaMaheswari, "Investigation of deep learning for whitefly identification in coconut tree leaves," *Intelligent Systems*

with Applications, vol. 20, Nov. 2023, Art. no. 200290, https://doi.org/10.1016/j.iswa.2023.200290.

[18] U. Barman, C. Pathak, and N. K. Mazumder, "Comparative assessment of Pest damage identification of coconut plant using damage texture and color analysis," *Multimedia Tools and Applications*, vol. 82, no. 16, pp. 25083–25105, Jul. 2023, https://doi.org/10.1007/s11042-023-14369-2.

[19] P. Singh, A. Verma, and J. S. R. Alex, "Disease and pest infection detection in coconut tree through deep learning techniques," *Computers and Electronics in Agriculture*, vol. 182, Mar. 2021, Art. no. 105986, https://doi.org/10.1016/j.compag.2021.105986.

[20] D. Nesarajan, L. Kunalan, M. Logeswaran, S. Kasthuriarachchi, and D. Lungalage, "Coconut Disease Prediction System Using Image Processing and Deep Learning Techniques," in *2020 IEEE 4th International Conference on Image Processing, Applications and Systems*, Genova, Italy, 2020, pp. 212–217, https://doi.org/10.1109/IPAS50080.2020.9334934.

[21] S. Nuanmeesri, "Enhanced hybrid attention deep learning for avocado ripeness classification on resource constrained devices," *Scientific Reports*, vol. 15, no. 1, Jan. 2025, Art. no. 3719, https://doi.org/10.1038/s41598-025-87173-7.

[22] S. Nuanmeesri, "Utilization of Multi-Channel Hybrid Deep Neural Networks for Avocado Ripeness Classification," *Engineering, Technology & Applied Science Research*, vol. 14, no. 4, pp. 14862–14867, Aug. 2024, https://doi.org/10.48084/etasr.7651.

[23] K. Patil, S. Thite, Y. Suryawanshi, and P. Chumchu, "Coconut Tree Disease Dataset." Mendeley Data, Aug. 01, 2023, https://doi.org/10.17632/gh56wbsnj5.1.

[24] S. Alsubai, A. K. Dutta, A. H. Alkhayyat, M. M. Jaber, A. H. Abbas, and A. Kumar, "Hybrid deep learning with improved Salp swarm optimization based multi-class grape disease classification model," *Computers and Electrical Engineering*, vol. 108, May 2023, Art. no. 108733, https://doi.org/10.1016/j.compeleceng.2023.108733.

[25] A. Ghosh, B. Soni, and U. Baruah, "Transfer Learning-Based Deep Feature Extraction Framework Using Fine-Tuned EfficientNet B7 for Multiclass Brain Tumor Classification," *Arabian Journal for Science and Engineering*, vol. 49, no. 9, pp. 12027–12048, Sep. 2024, https://doi.org/10.1007/s13369-023-08607-w.

AUTHORS PROFILE

Kavitha Magadi Gopalakrishna is a research scholar with a background in Electronics Engineering, Computer Science, AI, and ML. She is currently working as an Assistant professor, with over 10 years of experience in the Computer Science field. Her current research focuses on applying AI and ML techniques to agriculture, particularly in disease prediction. Her current research delves into harnessing the power of AI and ML algorithms for the critical task of identifying and predicting diseases in trees. This innovative approach has the potential to revolutionize the coconut industry by enabling earlier detection and intervention, ultimately improving crop health and yield. Her areas of interest include AI, ML, and the Internet of Things (IoT), with a focus on algorithms well-suited to DL, CNNs, image recognition, and pattern recognition. These techniques can be applied to analyze visual data of coconut trees, such as photographs, to detect signs of disease and predict future outbreaks. She can be contacted at: Kavitha.mg@kittiptur.ac.in.

Raviprakash Madenur Lingaraju has completed his Ph.D. in Computer Science &Engineering from Visvesvaraya Technological University. He has over 13 years of teaching experience in various fields such as ML and DL, Data Science, Cloud Computing, Wireless Ad hoc Networks, Image Processing. He has published various research papers in reputed journals and conferences, including IEEE and Springer. He has delivered various talks on ML, Data Science and its applications, and Cyber Security. He has reviewed many national and international journals and conference papers. He has received certificates of appreciation as a Session Chair in international conferences, and from the IEEE Bangalore Section for outstanding dedication and support in IEEE conferences. Research scholars have been awarded Ph.D. under his guidance, and he is currently guiding over six research scholars in various fields, including ML, Network Security, and DL. He holds patents in "An Effective Method for Fake Medicine Detection and Recommendation System" and "Anomaly Detection in Cloud Environment using Deep Learning Applications". He can be contacted at: raviprakashml@kittiptur.ac.in.

Ananda Babu Jayachandra worked as a Research Scholar in the area of Wireless Sensor Networks. He has over 13 years of teaching experience in various fields. His research has been widely recognized, with publications in leading journals and conferences. His areas of interest include Data Science, AI, Cloud Computing, and Wireless Ad hoc Networks. His strength is ML and DL, with hands-on experience in R-Hadoop and the CISCO Packet Tracer network simulator. He has received the Faculty Excellence Award from the International Conference on Engineering Trends in Science, Engineering & Management for best contribution in academic research and development. He has contributed to the academic community by guiding over six Ph.D. students. He can be contacted at: abj@mcehassan.ac.in.