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Disease detection on coconut tree using golden jackal optimization algorithm

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ABSTRACT

Millions of people depend on coconut palms for their food and livelihoods, making them one of the most essential crops in tropical countries. However, Diseases may significantly reduce the output of coconut trees and possibly result in their death. To overcome this, a novel golden jackal optimized disease detection in COCOnut tree (GOD-COCO) has been proposed for detecting diseases in coconut trees. First, the input dataset images are pre-processed in pre-processing image rotation, image rescaling, and image resizing, and the enhanced images are gathered. The enhanced images are segmented using the PSP-Net. From the segmented images, the features are extracted using the Dense-Net. Then the features needed are selected using the golden jackal optimization algorithm (GJOA). Finally, the deep belief network (DBN) classifier classifies whether it is normal or abnormal. The experimental analysis of the proposed GOD-COC has been evaluated using the Plant Pathology datasets based on the accuracy, precision, and recall standards. By this, the proposed GOD-COCO achieves an accuracy rate of 99.31% and it achieves an overall accuracy rate of 0.77%, 0.31% and 1.17% by the existing methods such as AIE-CTDDC, DL-WDM, and CLS. Similarly, the proposed GOD-COCO model takes less time, 1.13 milliseconds to detect the disease, than the existing methods, which take 3.04, 2.5, and 2.67 milliseconds, respectively.

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1. INTRODUCTION

Globally, coconut trees grow extensively and provide a significant source of income for numerous individuals in tropical places. Among various tropical developing countries and other Pacific Island nations, the coconut tree has significant ecological and economic benefits [1], [2]. These coconut trees have suffered from numerous diseases in recent years [3], [4]. The coconut tree is not only gorgeous but also incredibly practical [5], [6]. Many kinds of problems with coconut trees could prevent this tree from growing healthily [7], [8]. Therefore, for a coconut tree to flourish, proper diagnosis and treatment of problems are essential [9], [10]. A variety of pests frequently inflict serious harm to coconut trees [11], [12].

Infestations and diseases that afflict coconut trees most frequently in the central Philippines include yellowing, flaccidity, leaflet drying, caterpillars, and leaflets [13], [14]. The coconut tree's leaves can be used to detect nutrient deficits based on color changes [15], [16]. The majority of farmers are unable to identify the disease as long as several plants and identical symptoms are present in multiple nutritional shortages [17]. Since several fertilizers on the market contain more nutrients than others, choosing the right fertilizer is also crucial.

Figure 1 describes the diseases that affect coconut trees in various countries. Finally, the discussion will highlight the model's implications for detecting diseases in coconut trees.

- How can coconut tree diseases be accurately detected and classified using advanced deep learning techniques?
- What are the impacts of feature selection using the golden jackal optimization algorithm (GJOA) on disease classification performance?
- How does the proposed GOD-COCO method improve time efficiency compared to existing approaches?

In this, the trees affected by the coconut trees are increasing year by year in various ways. This work's primary contribution has been successfully completed by:

- A novel GOD-COCO has been proposed for detecting diseases on coconut trees whether it is normal or abnormal.
- First, the input dataset images are pre-processed to image rotation, image rescaling, and image resizing, and the enhanced images are gathered.
- The enhanced images are segmented using the PSP-Net. From the segmented images, the features are extracted using the Dense-Net.
- Then the features needed are selected using the GJOA. Finally, the deep belief network (DBN) classifier classifies whether it is normal or abnormal.

The format for the remainder of the study report was as follows. Section 2 provides an overview and a full summary of the relevant works. A thorough description of the proposed GOD-COCO system for identifying coconut tree diseases is provided in Section 3. Section 4 contains discussion and experimental fallouts. Section 5 concludes with some thoughts for future development.

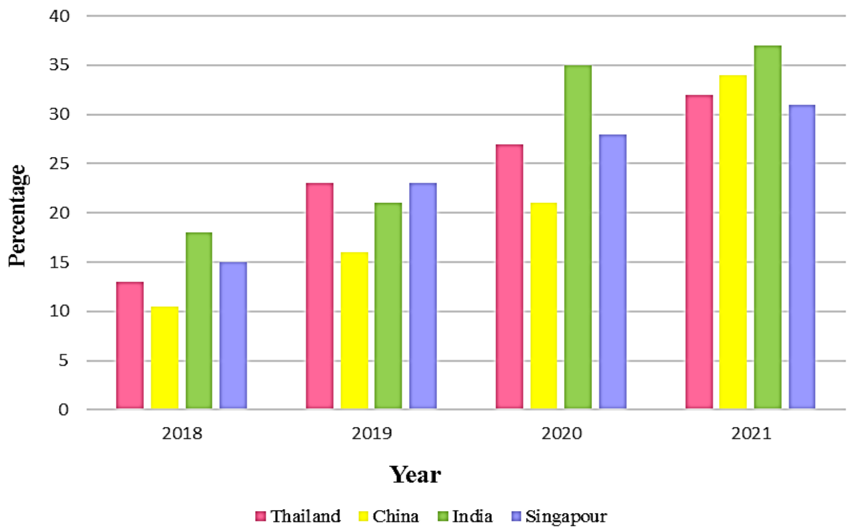

Figure 1. Diseases affected coconut trees in various countries

2. LITERATURE REVIEW

Kadethankar *et al.* [18] proposed an exhaustive pipeline for identifying a specific insect in coconut trees. The primary goal is to recognize and differentiate every single tree crown from an image that might have up to thirty crowns. Convolution neural network (CNN)-based algorithms have several problems when it comes to unmanned aerial vehicle (UAV) navigation and image processing in wooded regions. Singh *et al.* [19] proposed the identification of nutritional deficits and insect infestations in the coconut leaves. Coconut leaves have been seen applying the newest techniques in image processing and machine learning following the application of pesticides and fertilizers. It is not possible to enhance this system by adding other features like water level and soil type, this is one of the major drawbacks.

Maray *et al.* [20] suggested the AIE-CTDDC concept for intelligent farming, which is an artificial intelligence-enabled method for identifying and categorizing coconut tree illnesses. It identifies diseases that affect coconut trees in an intelligent farming setting to increase crop output. The main drawback of this approach is that it does not help to ensure the industry's sustainability. In 2022, Banerjee *et al.* [21] developed a method for identifying and categorizing the degrees of coconut leaf yellowing disease using CNN and support vector machine (SVM). In order to recognize and classify the various degrees of severity of the coconut leaf yellowing illness, the suggested CNN and SVM methodology is a viable and efficient technique.

Kavithamani and Maheswari [22] introduced the deep learning-assisted whitefly detection model (DL-WDM) a model effective in finding illnesses of coconut trees like insect infestation, dirty blades, and bleeding roots. The suggested DL-WDM achieves an accuracy rate of 95.71%. One of the main disadvantages could be the difficulty in compiling a large dataset covering a variety of illnesses affecting coconut trees. In 2023 Brar *et al.* [23] suggested a deep learning (DL)-based version of ResNext50 for the coconut sector. The system achieves a 91.77% overall accuracy rate in correctly identifying automatic detection and classification of CLS disease. The suggested approach has promises for greatly enhancing the efficacy and precision of detecting and tracking CLS disease.

Yogabalajee and Kaliappan [24] proposed that MConvnextV2 utilizes a Swin optimizer to detect and classify coconut tree leaf diseases to enable precision farming. The principal aim of this study is to promote sustainable agricultural methods by using cutting-edge technologies to accurately classify plant diseases. Applying a swim optimizer the proposed MConvnextV2 achieves 99% accuracy.

3. PROPOSED METHOD

This research proposes a novel GOD-COCO has been proposed for detecting diseases on coconut trees, whether it is normal or abnormal. First, the input dataset images are pre-processed in pre-processing image rotation, image rescaling, and image resizing, and the enhanced images are gathered. The enhanced images are segmented using the PSP-Net. From the segmented images, the features are extracted using the Dense-Net. Then the features needed are selected using the GJOA. Finally, the DBN classifier classifies whether it is normal or abnormal. Figure 2 illustrates the general procedure of the GOD-COCO method.

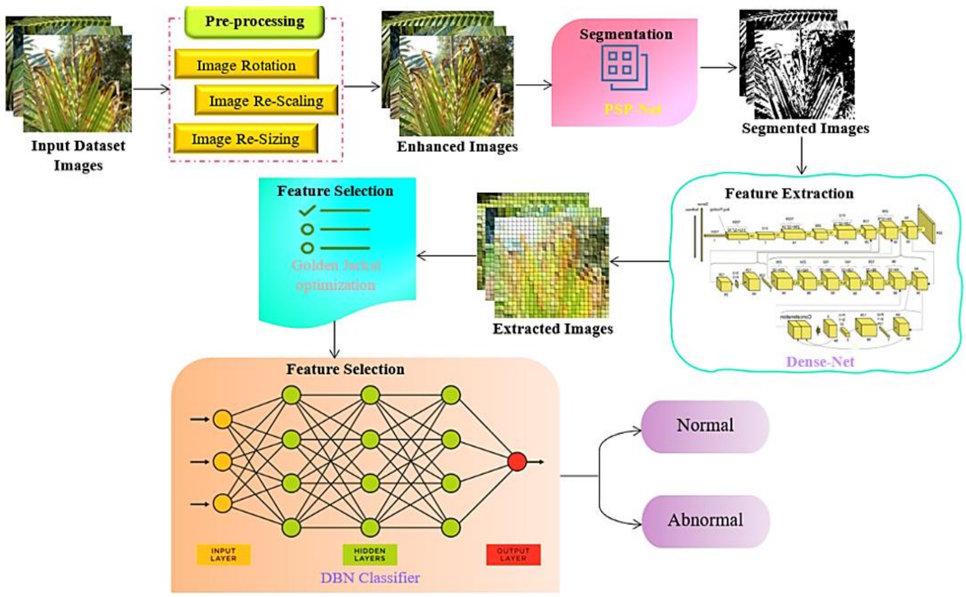

Figure 2. Block diagram of proposed GOD-COCO method

3.1. Pre-processing

The image pre-processing steps are as follows.

a. Image rotation: Image rotation is a rudimentary image processing method that modifies the image orientation by a predetermined angle. The tendency of the model to generalize and identify patterns more precisely can be enhanced by rotating images to better align the characteristics inside them with the model's learning objectives.

b. Image re-scaling: Resizing involves either expanding or decreasing the dimensions of the images is known as image re-scaling. To ensure that models can handle images of different dimensions efficiently, standardize inputs, and reduce computational complexity, rescaling is essential.
c. Image re-sizing: Image resizing is a basic image processing technique that entails adjusting the dimensions of images. This alteration modifies the image's pixel count, causing it to either get smaller or larger. Resizing photos also aids in the creation of consistent datasets, making it easier to train and use predictive algorithms on a variety of image inputs.

3.2. Segmentation

Partitioning the image into meaningful parts or objects for analysis and comprehension is known as segmentation. Segmenting an image facilitates analysis and makes it easier to retrieve important information. In this, the pre-processed images are image datasets are segmented using the PSP-Net.

3.2.1. PSP-Net

A multi-scale network is used in the PSP-Net pyramid scene processing system. The pyramid pooling module is used in the semantic segmentation area to increase segmentation accuracy and effectively learn the global context of the scene. The PSP-Net acquires a background priority and enriches semantic segmentation with context information. This PSP-Net network model measures the training error as the average of the total of the output errors for each pixel in the sample image. By employing pooling of various sizes and having the ability to increase the network's real receptive field, the spatial pyramid pooling module successfully mitigates this issue. The PSP-Net network uses this benefit to its full potential. Figure 3 depicts its network structure.

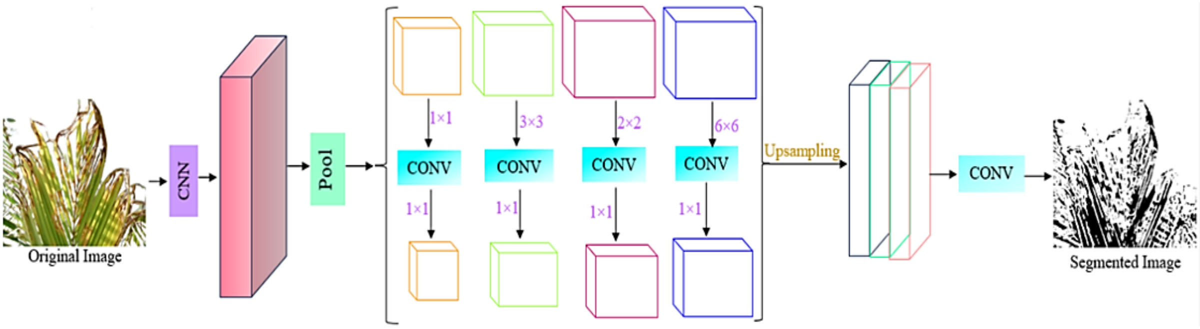

Figure 3. Architecture of PSP-Net

3.3. Feature extraction

Feature extraction is the method of identifying and removing relevant patterns or characteristics from visual data so that it can be expressed succinctly and unambiguously. Several computer vision applications use the collected features as the basis for more complex evaluation and analysis. From the segmented image dataset, the features are extracted using the Dense-Net method.

3.3.1. Dense-Net

DenseNet is an innovative, parameter-light version of the CNN architecture for visual object recognition. DenseNet and ResNet are relatively similar, with a few key differences. It can improve feature map propagation, lessen the number of parameters required, and solve the vanishing-gradient problem. Direct connections from any layer to any following layer are a novel connectivity pattern in the DenseNet model compared to previous CNNs, and they can significantly enhance the information flow across layers. Therefore, the feature maps of every previous layer are transmitted to the ℓ^{th} layer, and (1) is computed:

$$a^{\ell} = \mathcal{M}^{\ell}[(a^0, a^1, \dots \dots .. a^{\ell-1})] \tag{1}$$

where a^1 indicates the ℓ^{th} layer's output and ℓ indicates the layer. $[a^0, a^1, \dots \dots . a^{\ell-1}]$ denotes the joining of feature maps made in layers 0, 1, 2... l − 1. Additionally, $\mathcal{M}^1$ may be a combination of various uses an identity function-based skip-connection to circumvent the non-linear transformations.

$$a^{\ell} = \mathcal{M}^{\ell}(a^{\ell}) + a^{\ell-1} \tag{2}$$

The model DenseNet201 (TTA) indicates that the test set has been expanded while the training set still uses the DenseNet201 model. To obtain sufficient diversity in samples and derive a deep network from the images, data augmentation is an essential phase.

3.4. Feature selection

Feature selection includes determining the most relevant and useful characteristics from the extracted image collection in order to enhance the model's efficacy and performance. It is a critical processing step in disease detection on coconut trees by identifying and retaining only the most relevant attributes from the data. The detection system has the ability to focus on special visual patterns and biomarkers that are symptomatic of particular diseases of coconuts. In this, the required features are selected from the image dataset using GJOA.

3.4.1. Golden jackal optimization algorithm

The GJO algorithm is a meta-heuristic optimization technique that is based on golden jackal hunting behavior. These crafty predators are known for their ability to adapt to a variety of environmental conditions, and this algorithm attempts to mimic their hunting approach. Equation (3) illustrates how the GJO is a population-based method that, like other meta-heuristics, starts with a randomized distribution of the first answer over the search space.

$$Y_0 = Y_{Min} + rand * Y_{Max} - Y_{Min} \tag{3}$$

where Y_{Max} is the Upper limit and Y_{Min} is the lower limit, and rand indicates that a consistently random number is contained in [0,1]. An objective function determines each prey's fitness value throughout the optimization phase. The fitness value is found in the following (4).

$$Fitprey = \begin{bmatrix} \mathcal{F}(Y_{1,1} & Y_{1,2} & \cdots & Y_{1.d}) \\ \mathcal{F}(Y_{2,1} & Y_{2,2} & \cdots & Y_{2,d}) \\ \vdots & \vdots & \vdots & \vdots \\ \mathcal{F}(Y_{r,1} & Y_{r,2} & \cdots & Y_{r,d}) \end{bmatrix} \tag{4}$$

The fitness values of every prey are collected in a matrix, with the F matrix storing the fitness values of each prey, as explained in (4). $Y_{r,d}$ denotes the r^{th} dimension value of the d^{th} prey. The male golden jackal is regarded as the most suited prey in its hunting tactics, with the female jackal coming in second. The jackal pair obtains the prey's placements by instructions.

3.4.2. Exploration phase

In GJO, the process of exploring is accomplished by imitating the movements of a pack of golden jackals looking for food in an unknown territory. Although jackals are capable of seeing and singing their prey, the prey occasionally manages to escape capture. In general, a male jackal leads the hunt, with the female following in his wake:

$$Y_1(h) = Y_N(h) - G|Y_N(h) - kj * prey(h)| \tag{5}$$

$$Y_2(h) = Y_{\mathbb{F}N}(h) - G|Y_{\mathbb{F}N}(h) - kj * prey(h)| \tag{6}$$

where the position vector is indicated by prey(h), the present iterations are represented by h, and the male and female jackals' locations within the search area are denoted by $Y_N(h)$ and $Y_{\mathbb{F}N}(h)$ respectively. G is calculated using (7), which is the prey's escape energy.

$$G = G_1 * G_0 \tag{7}$$

where G_0 and G_1 symbolize the beginning and decreasing energy levels of the prey, respectively.

$$G_0 = 2 * k - 1 \tag{8}$$

$$G_1 = a_1 * (1 - h|H) \tag{9}$$

The random number K in this case is between [0,1]. and h and H stand for the current iteration and maximum iteration, respectively. a_1 is the constant, with a value of 1.5. G_1 gradually drops throughout the course of the iterations, from 1.5 to 0. Eventually, the golden jackal's most recent location is established to be (10).

$$Y(h+1) = \frac{Y_1(h)+Y_{2(h)}}{2} \quad (10)$$

Equation (11) represents the male and female jackals' most recent positions based on the averages of (6) and (7).

3.4.3. Exploitation phase

The prey found in the previous phase is surrounded by the jackal couples following their ability to flee. They surround their victim, then jump on it to eat it. Together with the male and female jackals, the mathematical expression for this hunting activity is:

$$Y_1(h) = Y_N(h) - G.|kj.Y_N(h) - prey(h)| \quad (11)$$

$$Y_2(h) = Y_{\mathbb{F}N}(h) - G.|kj.Y_{\mathbb{F}N}(h) - prey(h)| \quad (12)$$

In order to emphasize exploration and prevent local optimum, the goal of kj in (11) and (12) are to generate random behaviour during the exploitation phase.

3.5. Classification

The process of categorization entails the arrangement of data points into discrete groups or classes according to specific features or attributes. Coconut tree disease classification involves categorization of various diseases affecting coconut trees based on visual symptoms. In this classification process, the diseases on the coconut trees are classified by the DBN classifier. It improves recognition performance by handling complex, nonlinear data and reducing classification errors in coconut disease detection tasks.

3.5.1. DBN

A particular sort of generative model called a deep belief network (DBN) makes use includes several processing layers to extract intricate structures and abstractions from input. A stack of multiple independently trained restricted Boltzmann machines (RBMs) makes up the system. The network's visible layer (w) is formed up of an enormous number of observable entities $(w_1, w_2, \dots \dots . w_j)$, which are taught using the unlabeled pattern structures that were provided to it, and several invisible beings $(p_1, p_2 \dots \dots p_i)$. Network nodes that are not visible have binary values and can rebuild patterns by receiving information from visible nodes (p). As a two-way weight matrix that is symmetric (G_{ji}), all the obvious nodes communicate with all the other obvious nodes in addition to the preexisting biases (b_j) and (c_i).

$$H(w,p) = \sum_{j \in wjG} \frac{(w_i - e_i)^2}{2\lambda_j^2} - \sum_{i \in pjd} c_i p_i - \sum_{ji} \frac{w_j}{\lambda_j} p_i G_{ji} \quad (13)$$

where λ is the Gaussian noise dispersion in the j^{th} visible dimension. If both the exposed and hidden units are Gaussians, the learning gradient might increase.

4. RESULTS AND DISCUSSION

Plant pathology from Kaggle datasets [25] provide a wide selection of excellent images depicting plant leaves with various diseases. These databases are essential for creating and refining machine learning algorithms that automate plant disease identification and diagnosis. Figure 4 describes the experimental classification result of the proposed GOD-COCO method. Column 1 describes the input image. The enhanced images of the coconut tree are displayed in column 2. The segmented images if the coconut tree is shown in column 3. Column 4 displays the feature extracted image and finally the classification result of the coconut tree disease are shown in column 4.

4.1. Performance analysis

The evaluation metrics mentioned previously described can be generated with simple parameters such as true positive $(T_{\mathcal{P}o})$, true negative $(T_{\mathcal{N}e})$, false positive $(F_{\mathcal{P}o})$, and false negative $(F_{\mathcal{N}e})$.

$$Accuracy = \frac{T_{\mathcal{P}o}+T_{\mathcal{N}e}}{T_{\mathcal{P}o}+T_{\mathcal{N}e}+F_{\mathcal{P}o}+F_{\mathcal{N}e}} \times 100 \quad (14)$$

$$Precision = \frac{T_{\mathcal{P}o}}{T_{\mathcal{P}o}+F_{\mathcal{P}o}} \quad (15)$$

$$Recall = \frac{T_{\mathcal{P}o}}{T_{\mathcal{P}o}+F_{\mathcal{N}e}} \quad (16)$$

The effectiveness evaluation of the proposed GOD-COCO including normal and abnormal is described in the Table 1. Accuracy, precision, and recall are used to calculate performance. The proposed GOD-COCO archives an accuracy rate of 99.34% in the normal classes and 99.28% in the abnormal classes. Additionally, the proposed GOD-COCO archives a precision and recall rate of 98.63% and 99.19% in normal classes and 98.57% and 99.08% in the abnormal classes. The performance evaluation of the proposed GOD COCO approach is shown in Figure 5. The detection accuracy of the proposed GOD-COCO model with 100 training epochs was 99.48, and it had a low rate of errors.

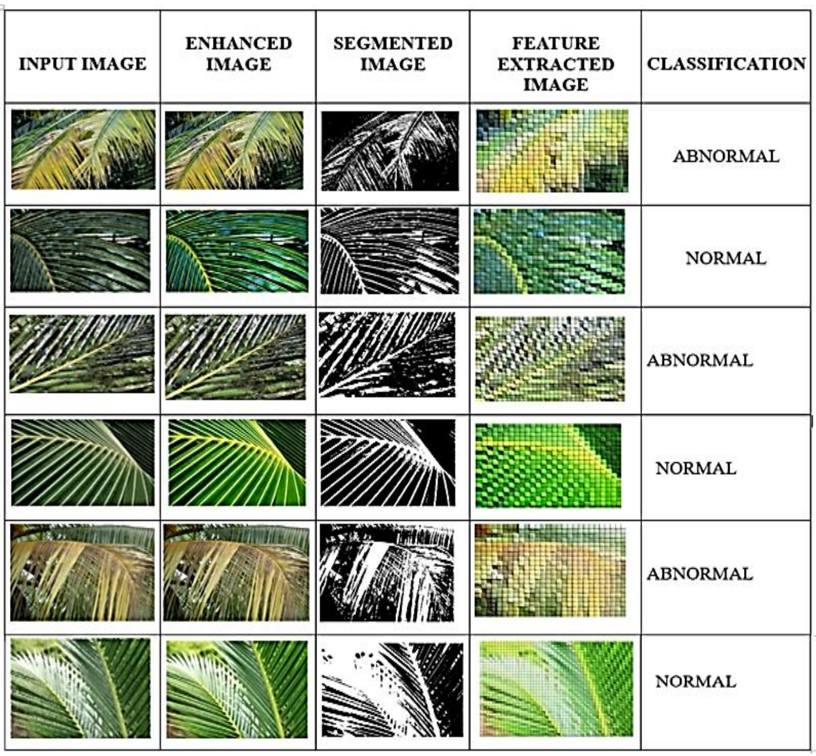

Figure 4. Simulation result of the proposed GOD-COCO method

Table 1. Evaluation outcome of the proposed method

Classes	Accuracy	Precision	Recall
Normal	99.34%	98.63%	99.19%
Abnormal	99. 28%	98.57%	99.08%

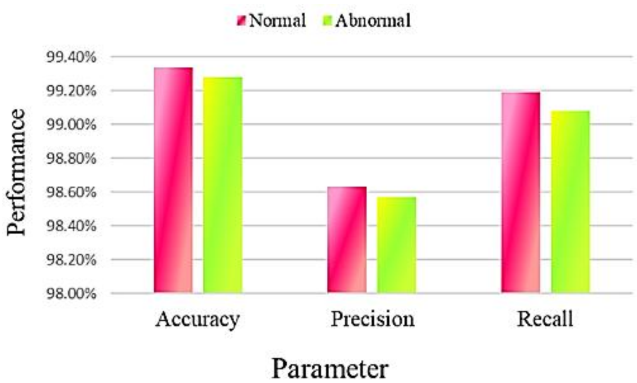

Figure 5. Performance evaluation of the proposed GOD-COCO model

In Figure 6, the accuracy graph was generated using 100 epochs and an accuracy range. The accuracy of the proposed GOD-COCO similarly improves as the number of epochs rises. Figure 7 describes the epoch and loss graph of the proposed GOD COCO method. To achieve optimal accuracy for testing in this study. The detection accuracy of the proposed GOD-COCO model with 100 training epochs was 99.48, and it had a low rate of errors.

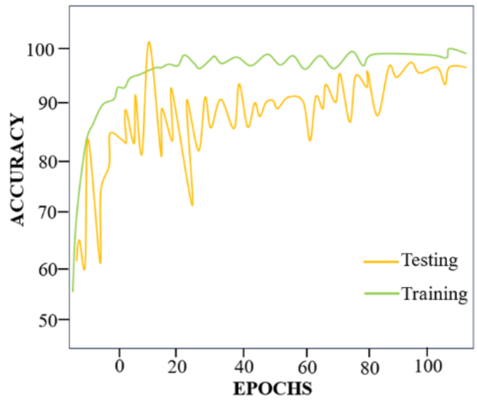

Figure 6. Accuracy graph of the proposed GOD-COCO method

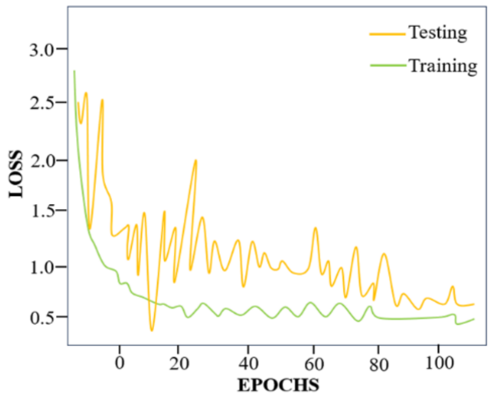

Figure 7. Loss of the proposed GOD-COCO method

4.1.1. Time efficiency

Time taken to detect the disease in the coconut tree using both the proposed and the existing methods is described in Figure 8. The performance levels are indicated on the vertical axis, while the evaluated methods are presented on the horizontal axis. The proposed GOD-COCO method taken less time for coconut tree disease detection than the existing techniques. It shows that the proposed GOD-COCO model takes less time 1.13 milliseconds to detect the disease than the existing methods which take 3.04, 2.5 and 2.67 milliseconds to detect the disease.

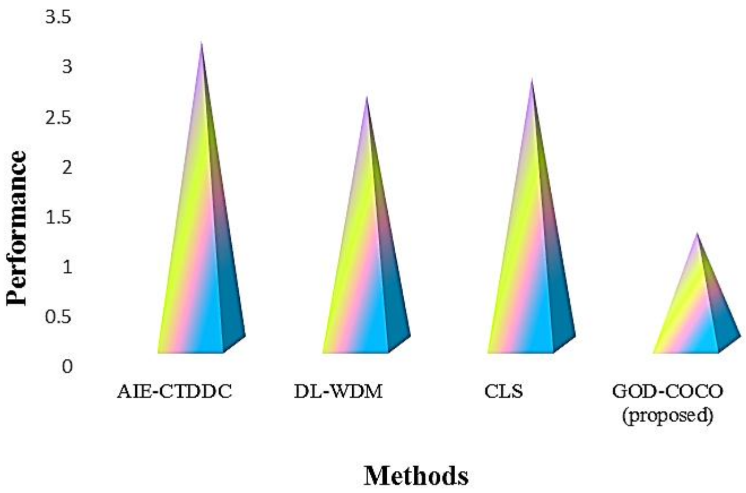

Figure 8. Comparison of time efficiency

4.1.2. Comparative analysis

The comparison analysis of existing methods with the proposed GOD-COCO is described in the Table 2. The accuracy rating of 99.31% achieved by the suggested GOD-COCO is higher than that of the current techniques. In this, the proposed GOD-COCO achieves an overall accuracy rate of 0.77%, 0.31% and 1.17% over the existing methods such as AIE-CTDDC, DL-WDM and CLS, respectively.

4.2. Discussion

In this section, the comparison evaluation of the proposed method on results is described. Figure 1 describes the diseases that affect coconut trees in various countries. The experimental classification result of the proposed GOD-COCO method is described in Figure 4. Figure 5 describes the performance evaluation of the proposed GOD COCO method. The accuracy and loss graph with 100 training epochs attain highest accuracy of 99.48%. The time efficiency comparison of the proposed method in both the proposed and the existing methods is described in Figure 8. Finally, the comparison analysis of existing methods with the proposed GOD-COCO is described in the Table 2.

Table 2. Performance comparison of existing method with proposed method

Methods	Accuracy	Precision	Recall
AIE-CTDDC [20]	98.54%	97.48%	97.21%
DL-WDM [22]	99.00%	98.19%	98.82%
CLS [23]	98.14%	97.57%	97.49%
GOD-COCO (Proposed method)	99.31%	98.61%	99.13%

5. CONCLUSION

In this paper, a novel golden jackal optimized disease detection in COCOnut tree (GOD-COCO) has been proposed for detecting diseases in coconut trees. First, the input dataset images are pre-processed in pre-processing image rotation, image rescaling, and image resizing, and the enhanced images are gathered. The enhanced images are segmented using the PSP-Net. From the segmented images, the features are extracted using the Dense-Net. Then the features needed are selected using the Golden Jackal Optimization algorithm. Finally, the DBN classifier classifies whether it is normal or abnormal. The experimental analysis of the proposed GOD-COC has been evaluated using the Plant pathology datasets based on the accuracy, precision, and recall precision standards. By this, the proposed GOD-COCO achieves an accuracy rate of 99.31% and it achieves an overall accuracy rate of 0.77%, 0.31%, and 1.17% by the existing methods such as AIE-CTDDC, DL-WDM, and CLS. Future research and development efforts should be guided by an evaluation of the model's impact on coconut farming methods and its potential to contribute to the industry's sustainability.

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AUTHOR CONTRIBUTIONS STATEMENT

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Anish Pon Yamini Kumareson	✓		✓	✓	✓		✓		✓	✓	✓		✓	✓

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

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

I certify that I have explained the nature and purpose of this study to the above-named individual, and I have discussed the potential benefits of this study participation. The questions the individual had about this study have been answered, and we will always be available to address future questions.

ETHICAL APPROVAL

My research guide reviewed and ethically approved this manuscript for publishing in this journal.

DATA AVAILABILITY

Data sharing is not applicable to this article as no datasets we regenerated or analyzed during the current study.

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