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Coconut Disease Prediction Using Neural Attention Mechanism With Adamax Optimizer Based Convolutional Neural Network

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Abstract:- *Accurate coconut disease prediction systems become most important in developing effective disease mitigation strategies, encouraging cost-effective crop protection for small-scale farming. The farmers utilize only the conventional methods like laboratory view and experts for the identification of diseases in coconut. However, these techniques are inadequate for an effective and timely detection of diseases in the coconut. Hence, this research proposes the Neural Attention Mechanism with AdaMax Optimizer based Convolutional Neural Network (NAM-AMO-CNN) approach for prediction of coconut disease. This article is comprises of different levels: Initially, the dataset is collected from the real-world of various images of coconut diseases. Next, pre-processing is conducted through data augmentation and noise removal through Quaternion Non-local Means Denoising Algorithm (QNLM) approach. Then, segmentation is performed through DeepLabV3+ and Feature extraction is employed by Residual DenseNet. Finally, prediction is performed through NAM-AMO-CNN approach, which allows the classifier to concentrate on critical disease-infected regions, leading to improved accuracy. Experimental results demonstrates that the proposed NAM-AMO-CNN approach attains the superior accuracy of 98.43% as compared to the existing methods like Artificial Intelligence Enabled Coconut Tree Disease Detection and Classification (AIE-CTDDC) and Enhanced Visual Geometry Group (EVGG16).*
Keywords: *AdaMax Optimizer, Coconut disease prediction, Convolutional Neural Network, Neural Attention Mechanism, DeepLabV3+, Quaternion Non-local Means Denoising Algorithm.*

1 INTRODUCTION

Coconuts become the most important fruit in South Asia and Pacific Border countries. The coconuts can be utilized for various household things like food, cosmetics, oil, medicines and so on [1]. Globally, a coconut palm is highly produced in pantropical as well as tropical regions. In worldwide, the cultivation spans of the coconut palm comprise about 12 million hectares, offering livelihood support to nearly 80 million people across about 90 countries [2]. Accurate prediction and classification of various plant pets are important for the development of accurate organic farming as well as agriculture. Identifying and detecting the plant diseases by human perceptions of leaf symptoms and depending on experience is most independent, ineffective, and vulnerable to faults in decision making [3][4]. However, Inadequate endeavors have focused on developing an acoustical system for predicting the maturity levels of coconut fruits. Such a system is most siniifcantly benefit companies involved in large-scale coconut exports by saving both time and costs [5][6]. Nutrient deficiencies, particularly in young coconut trees, have resulted in tree diseases, further impacting the country’s economic growth. The onslaught of pests, notably the coconut caterpillar and red palm weevil, has also plagued coconut cultivation [7-9].

To hinder the formidable challenges confronting farmers, early pest detection and management have emerged as indis pensable components of sustainable coconut cultivation [10]. This project introduces an innovative hybrid approach which leverages image processing, data augmentation, and deep learning al gorithms to help farmers identify pests early in the growth cycle [11][12]. Through the integration of cutting-edge technology, it equips farmers to take timely precautionary measures, thereby contributing to enhanced crop yields and overall sustainability. The core of this innovative approach lies in advanced image analysis [13]. Conventional methods mayencounter issues in identification and feature extraction during an occurrence of large backgrounds, shadows as well as lighting conditions in the collected image

[14]. The computer vision, image processing Machine Learning (ML) and Deep Learning (DL) methods are efficient for an accurate detection of plant diseases, supports the farmers to enhance better crop yield production. Emerging innovations in DL have allowed an integration with other AI techniques, designing it progressively helpful in agricultural applications like crop monitoring and disease detection [14]. The farmers utilize only the conventional methods like laboratory view and experts for the identification of diseases in coconut. However, these techniques are inadequate for an effective and timely detection of diseases in the coconut. Hence, this research proposes the Neural Attention Mechanism with AdaMax Optimizer based Convolutional Neural Network (NAM-AMO-CNN) approach for prediction of coconut disease.
The primary contributions of the research are as trails:
- This manuscript develops a NAM-AMO-CNN approach for coconut diseases prediction. A combination of NAM allows the network to concentrate on complex disease-infected regions, while the AMO make sures stable and efficient convergence during training, resulted in enhanced accuracy and faster prediction of coconut diseases.
- In segmentation, the DeepLabV3+ approach is employed to effectively localize the disease affected regions. Moreover, it significantly captures multi-scale contextual data and preserves fine object boundaries, designing it ideal for accurately segmenting diseased regions on coconut leaves.
- In feature extraction, the Residual DenseNet approach is introduced approach for the extraction of important features. This approach integrates the dense and residual connections, allowing efficient feature reuse and deep representation learning, which improves an extraction of complex disease-specific features.

The other sections of manuscript are given as trails: Section 2 gives the literature survey. Section 3 presents the proposed methodology. Section 4 illustrates the results and discussion. Section 5 provides a conclusion.

2 LITERATURE SURVEY
Here, the ML and DL assisted coconut and their leaf disease prediction is described, along with their advantages and limitations.
Mohammed Maray et al. [16] introduced the Artificial Intelligence Enabled Coconut Tree Disease Detection and Classification (AIE-CTDDC) approach for the smart agriculture. A purpose of introduced AIE-CTDDC approach was to categorize coconut tree diseases in a smart farming area for improve a better yield of a crop. Initially, the AIE-CTDDC approach utilized the median filtering -assisted noise removal approach. Next, Bayesian fuzzy clustering-assisted segmentation approach was performed to detect the disease affected portions. Then, Capsule Network (CapsNet) approach was utilized for the feature extraction. A Harris Hawks Optimization via Gated Recurrent Unit (HHO-GRU) approach was introduced for disease detection in coconut trees. However, an AIE-CTDDC approach relied on handcrafted segmentation and feature extraction methods which lacked the robustness, leads to poor performance.
Samitha Vidhanaarachchi et al. [17] implemented the transfer learning-based CNN and Mask Region-based-CNN (Mask R-CNN) for detection of Weligama Coconut Leaf Wilt Disease (WCWLD) as well as Coconut Caterpillar Infestation (CCI) at primary level of pest development. Then, the objection detection approach of YOLO was utilized for produce amount of caterpillars. The implemented approaches were estimated and tested through different collected datasets from various places. However, a combination of various DL approaches enhanced the system complexity and inference time, resulted in poor performance.
Xiaocun Huang et al. [18] presented the transfer learning based Enhanced EVGG16 model for detection of disease in coconut trees. An EVGG16 architecture obtained a significant training through less amount of data, employing weight parameters of convolution as well as pooling layer from pre-training architecture to employ transfer VGG16 architecture. The presented approach obtained the better prediction performance through employing the hyperparameter tuning and training batch configuration optimizations, this offered the most stable and robust prediction approaches. However, the EVGG16 model's accuracy was heavily depend on the quality of pre-trained weights, and its performance was degraded when exposed to unseen disease types in new environments.
Utpal Barman et al. [19] presented a Gray Level Co-occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRLM) approaches for an extraction of texture feature of the diseases. Then, Binary Artificial Neural Network (ANN) approaches were utilized for classification of extracted data features of

the damage into various classes. The coconut pest infection samples were gathered through the DSLR camera in a natural environment. The ML approaches like ANN, Support Vector Machine (SVM), Decision Tree (DT) and Naïve Bayes (NB) approaches were exported for a determination of pest damage infection. However, the GLCM-based approaches extracted only texture features and often miss contextual or spatial relationships, led to lower accuracy in complex or overlapping disease patterns.
Dr. Rajesh Kannan Megalingam et al. [20] introduced the deep learning-based approach demonstrates significant potential for revolutionizing coconut tree pest diag nosis and agricultural management. A combination of Convolutional Neural Networks (CNN) as well as autoencoders for feature extraction, coupled with the developed model's high accuracy, paves the way for effective pest identification. The results and discussions indicate promising outcomes, highlighted the model's robustness in classifying coconut tree pests. However, the GLCM-based feature extraction was sensitive to noise and lighting variations, and does not effectively capture the complex patterns or spatial hierarchies in diseased regions.
While existing literature demonstrates promising AI-based techniques for coconut disease detection, most methods face challenges like high data dependency, limited generalization, and computational overhead. Therefore, there's a need for lightweight, scalable, and adaptive models which perform reliably across diverse field conditions. Hence, NAM-AMO-CNN approach is proposed for the coconut disease prediction.

3 PROPOSED METHODOLOGY

This research develops a NAM-AMO-CNN approach for prediction of coconut diseases. This research comprises of various levels like data acquisition, pre-processing using data augmentation and QNLM, segmentation using DeepLabV3+, Feature extraction using Residual DenseNet and Finally prediction using NAM-AMO-CNN approach. Figure 1 portrays a block diagram of proposed approach.

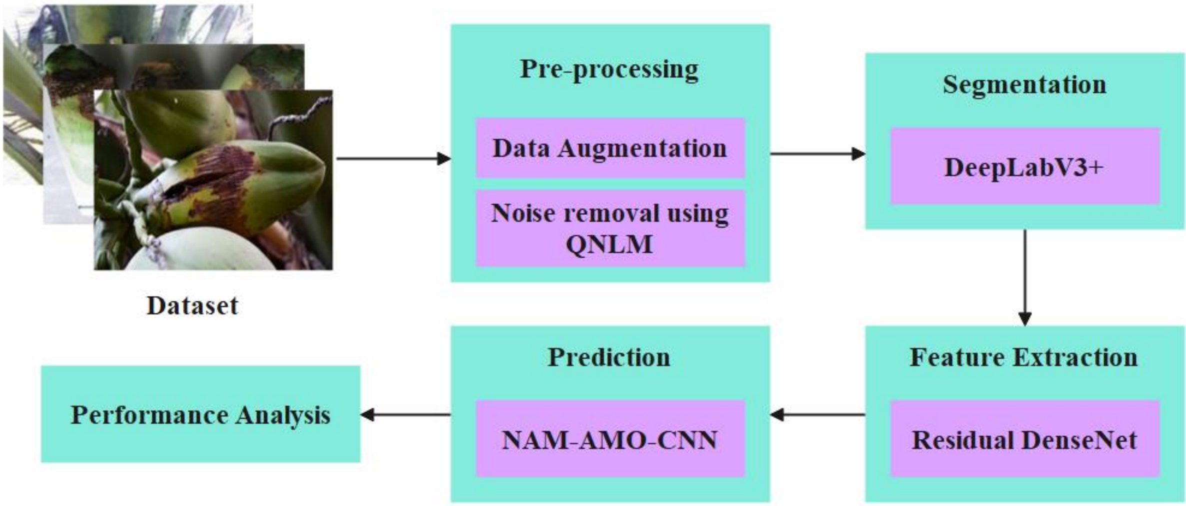

Figure 1. Block diagram of the proposed method

3.1 Dataset

The Coconut Tree (Coconut nucifera) disease dataset is utilized in this research which provides high-quality images of various types of diseases which help in detecting the leaf disease effectively. 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 in images.

3.2 Pre-processing

The gathered actual image has to pre-processed by different techniques to enhance the overall performance as well as to reduce computational complexity. Hence, this research employs the binary pre-processing steps like data augmentation and noise removal through QNLM approach. The details of these approaches are discussed below.

3.2.1 Data Augmentation

The data augmentation approaches are important for enhancing large number of images in the coconut disease dataset. The transformations involved in this technique are zooming, rotation, scaling, translation, shearing, etc, which supports to produce large images rather than the randomized discrepancy of contrasting, saturating and brightness [21]. This approach supports to enhance the training data samples and keep identical number of samples over class for producing effective approach. Hence, this technique is performed before an approach is developed to minimize the model over-fitting.

3.2.2 Noise Removal using QNLM

Primarily, a noise present in coconuts and their leaves is eliminated to improve image quality. Thus, this research employed the QNLM) for removing the noises from the collected datasets. As the QNLM denoising approach utilizes an essential large self-similarity into images for noise defeat, a selection of a similarity metric between image covers becomes most important in the approach's noise reduction efficiency. Here, a new technique is developed through exchanging a conventional Euclidean distance through QNLM approach as an index for estimating the similarities among image covers. Temporarily, an image data basically involves particular repeativeness, as self-resemblance methods at distribution of noise is random. Thus, an aim of QNLM is to design self-resemblance methods to devastate noises precent in the images. So, a QNLM approach enhances the denoising procedure from level of pixel to cover stage. A noise involved image is expressed as $\mathfrak{Y} = \mathfrak{X} + \mathfrak{N}$ and a denoised image $\mathfrak{X}$ through QNLM is scientifically formulated in equation (1) as follows:

$$\hat{\mathfrak{X}}_{(\rho)} = \frac{\sum_{q \in \delta_\rho} \varpi(\rho, q) \times \mathfrak{Y}(q)}{\sum_{q \in \delta_\rho} \varpi(\rho, q)} \qquad (1)$$

Here, δ_ρ demonstrates the search window along with centre ρ. $\varpi(\rho, q)$ illustrates the weight, which is formulated in equation (2) as follows:

$$\varpi(\rho, q) = \exp\left(\frac{\mathfrak{d}(\rho, q)/\alpha_n^2}{\mathfrak{H}^2}\right) \qquad (2)$$

Where, $\mathfrak{d}(\rho, q)$ illustrates an Euclidean distance between binary image patches through the centre ρ and q in δ_ρ. Similarly, the coconut images are denoised for image betterment. Then, the pre-processed images are provided to the segmentation process.

3.3 Segmentation using DeepLabV3+

In this portion, the pre-processed images are utilized as input to the segmentation to effectively localize the affected regions. Deeplabv3+ has illustrated better performance in different areas through its robust, Fully CNN (FCN) encoder-decoder structure. This approach has been significantly utilized for the detection of objections in different applications, offering reliable visual considerations. Similarly, Deeplabv3+ obtained the important segmentation as well as identification outcomes, providing accurate image analysis support for image prediction. To localize and identify the disease affected regions, an encoder of Deeplabv3+ becomes most widely utilized in features extraction associated through morphological dispersal of crop diseases. This structure performs an Atrous Spatial Pyramid pooling (ASPP) module to seizure contextual data at various scales, allowing a more complete handling of coconut diseases of different sizes and shapes and improving the model's considerate of image semantics. By up sampling tasks, a decoder keeps feature maps extracted through an encoder to a resolution of an input image, eventually producing precise segmentation outcomes.

3.4 Feature Extraction using Residual DenseNet

An income of Residual DenseNet is coconut disease image, and an outcome is a vigorous feature vector of disease affected coconut image. The Residual-DenseNet is partitioned into binary kinds: initially, a backbone network is utilized for image feature maps extraction. After that, a feature output component which operates feature maps result through a backbone network.

i. **Backbone Network:** According to DenseNet-121 architecture, which pre trained on ImageNet, the residual connection at DenseBlock4 is added to acquire backbone network of Residual DenseNet.
ii. **Feature Output Module:** It involves a2D convolutional (kernel size: 1×1), a global average pooling as well as 1D convolutional layer. Later to an extraction of feature maps through backbone network which operated through feature output module, a feature vector through length of 64 is acquired. It is a robust feature vector $\mathrm{PFV(i)}$ of an input data.

In Residual-DenseNet, leverages a strong feature extraction capability of DenseNet-121 to generate multi-scale feature maps from input images. As associated DenseBlock3 and DenseBlock4 through skip connections, large semantic data among disease images can be effectively mined, with high-level features offering enhanced robustness. An important aim of zero-watermark approach is to integrate image features through watermark, and strength of coconut image features extracted through an approach directly. Hence, in the Feature Output Module, 1×1 convolution is performed to minimize number of feature maps, global average pooling is used to minimize the dimensionality, and finally a vigorous 64 length feature vector $\mathrm{PFV(i)}$ is acquired through 1D convolution.

Employ a mean binarization task on a vigorous feature vector $\mathrm{PFV(i)}$ extracted through Residual-DenseNet to acquire a vigorous hash vector $\mathrm{FV(i)}$, which is formulated in equation (3) as follows:

$$FV(i) = \begin{cases} 1, PFV(i) \geq \mu \\ 0, \text{otherwise} \end{cases}, \mu = \frac{1}{64}\sum_{i=0}^{63} PFV(i) \quad (3)$$

3.5 Prediction using NAM-AMO-CNN

3.5.1 Convolutional Neural Network

A CNN is a kind of Deep Neural Network (DNN) which is specially developed for the image categorization tasks. The CNN involves 224×224 Leaflets 795 fundamental operations: convolution and pooling. Through performing different filters in 224×224 convolution operation, distinctive features can be extracted from the input signals, such as Drying of Leaflets (1088 samples) and Flaccidity (1079 samples), while retaining their spatial information. Figure 2 illustrates an architecture of CNN.

1. Input layer: CNNs is specially made to operate on high-dimensional data effectively. Lower-dimensional convolutions are utilized for low-dimensional arrays, while higher-dimensional convolutions handle more complex, high-dimensional data. Here, color images are utilized, utilizing more RGB channels dimensionality for improved feature extraction as well as estimation.

2. Convolution Layer: This layer is the core of a CNN, designed for extraction of features from input images through various convolution kernels. Each kernel slides over the image, producing feature maps which models local patterns. Key parameters involve kernel size, stride, and padding, which describes a scanning region and control how the kernel processes the input.

3. Pooling Layer: This layer minimizes spatial dimensions of feature maps, supports to obtaining significant data while lowering computational complexity. It performs sliding window to summarize regions, characteristically by operations like max or average pooling, and outputs a compressed version of the input.

4. Activation Layer: This layer uses activation function (e.g., ReLU) to produce non-linearity into a network, allowing the model to learn complex patterns. It identifies how the input from one layer is transformed before passing to the next, designing the network capable of modelling more sophisticated relationships.

5. Output Layer: This layer produces the final prediction, usually through fully connected layers pursued through an softmax activation function. It assigns class labels based on the extracted features, completing the classification task.

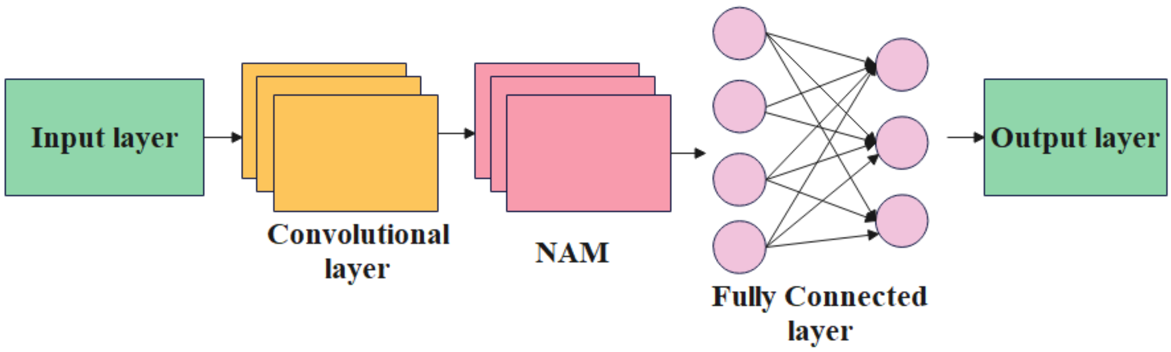

Figure 2. Architecture of CNN

3.5.2 Neural Attention Mechanism

NAM achieves global interaction by calculating the similarity between each loca tion in the input feature map and other locations. Subsequently, based on the weights derived from the similarity calculations, the input feature map is weighted and summed to produce a feature representation containing global inter action information. By doing so, the model can effectively leverage global contextual information in the image, thereby enhancing performance. It utilizes modules from the CBAMand reveals a channel as well as spatial attention sub modules. Subsequently, an NAM module is embedded at an end of every network block. A residual network is entrenched at an end of residual structure. A Batch Normalization (BN) scaling factor was performed in channel attention submodule, which is formulated in equation (4) as follows:

$$B_{out} = BN(B_{in}) = \gamma \frac{B_{in} - \mu\mathcal{B}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} + \beta \quad (4)$$

Here, $\mu\mathcal{B}$ illustrates the mean; $\sigma_{\mathcal{B}}^2$ denotes a variance; γ and β depicts a trainable transformation parameters.

3.5.3 AdaMax

A factor $v(t)$ in an Adam approach adjusts the gradient inversely proportionate to the l2 norm of past $(v(t-))$ and present $t(\partial E/ \partial\varphi(t))$, which is formulated in equation (5) as follows:

$$v(t) = \beta_2 v(t-1) + (1-\beta_2)\left|\frac{\partial E}{\partial \varphi(t)}\right|^2 \quad (5)$$

A generalization of this update to the lp norm is formulated in equation (6) as follows:

$$v(t) = \beta_2^p v(t-1) + \left(1-\beta_2^p\right)\left|\frac{\partial E}{\partial \varphi(t)}\right|^2 \quad (6)$$

To eliminate being numerically unstable, l1 and l2 norms are the most basic in practices. Nevertheless, in common, l∞ also demonstrates the stable action. Thus, this research introduces the AdaMax and illustrates that $v(t)$ through l∞ converges to the more stable value, which is formulated in equations (7) to (9) as follows:

$$u(t) = \beta_2^\infty v(t-1) + (1-\beta_2^\infty)\left|\frac{\partial E}{\partial \varphi(t)}\right|^\infty \quad (7)$$

$$= \max\left(\beta_2 . v(t-1), \left|\frac{\partial E}{\partial \varphi(t)}\right|\right) \quad (8)$$

$$\varphi(t+1) = \varphi(t) - \alpha\frac{\hat{z}(t)}{u(t)} \quad (9)$$

4 Experimental Results

The significance of the proposed NAM-AMO-CNN approach for the coconut disease prediction is implemented on Python 3.11 tool through system configuration of intel i5 processor, windows 10 OS and 16GB RAM. An importance of proposed approach is estimated by using different performance indices like accuracy, precision, sensitivity/recall and F1-score. The mathematical expressions of these performance indices are given in equations (10) to (13) as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (10)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (11)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (12)$$

$$F1-\text{score} = \frac{2TP}{2TP+FP+FN} \quad (13)$$

Where, TP – True Positive; TN – True Negative; FP – False Positive and FN – False Negative;

4.1 Performance Evaluation

The significance of the proposed approach is estimated and compared with the various existing approaches. This research employed the various experiments for the verification of the estimation of the proposed NAM-AMO-CNN approach for the coconut disease prediction.

Table 1 demonstrates the performance evaluation of DeepLabV3+ with different segmentation approaches. The different segmentation approaches like U-Net, SegNet, Mask Residual CNN (Mask R-CNN), DeepLabV1 are estimated and compared with the utilized DeepLabV3+ methods. As compared to these approaches, DeepLabV3+ has better capability to model multi-scale contextual data through ASPP and deep encoder-decoder architecture. This allows the model to accurately segment fine details and complex patterns typical of coconut diseases like small lesions and irregular shapes on leaves or fruits. Table 1 results proven that the DeepLebV3+ image attains superior performance in all performance metrices.

Table 1. Performance evaluation of DeepLabV3+ with different segmentation approaches

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
U-Net	89.67	90.56	89.64	90.54
SegNet	91.56	92.32	91.54	92.33
Mask R-CNN	93.37	94.98	93.43	94.32
DeepLabV1	96.38	96.54	95.63	96.65
DeepLabV3+	98.43	98.65	97.83	98.12

Table 2 demonstrates the performance evaluation of Residual DenseNet with different feature extraction approaches. The different feature extraction approaches like InceptionV3, ResNet50, VGG16 and DenseNet are estimated and compared with the Residual DenseNet approach. As compared to other feature extraction methods, the Residual DenseNet performs well through integrating the benefits of residual connections and dense connectivity. This architecture allows deeper feature propagation, encourages feature reuse, and effectively mitigates the vanishing gradient issue.

Table 2. Performance evaluation of Residual DenseNet with different feature extraction approaches

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
InceptionV3	90.32	87.65	89.76	88.71
ResNet50	92.48	91.43	90.44	90.43
VGG16	94.38	93.83	92.48	92.89

DenseNet	97.66	96.43	94.53	95.32
Residual DenseNet	98.43	98.65	97.83	98.12

Table 3 demonstrates the performance evaluation of NAM-AMO-CNN with different classifiers. The different classifiers such as DNN, ANN, MobileNetV2 and CNN are estimated and compared through developed NAM-AMO-CNN approach. A developed NAM-AMO-CNN demonstrates superior performance over traditional classifiers through combining NAM with AMO into the CNN architecture. This integration enhances the feature discrimination, focuses on the most relevant regions of the input image, and improves generalization. The proposed NAM-AMO-CNN approach attains the better accuracy of 98.43%, precision of 98.65%, recall of 97.83% and F1-score of 98.12% respectively.

Table 2. Performance evaluation of Residual DenseNet with different feature extraction approaches

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
DNN	86.38	91.32	89.54	88.76
ANN	90.47	93.98	91.49	91.89
MobileNetV2	94.32	94.21	93.45	94.12
CNN	96.54	97.56	95.67	96.55
NAM-AMO-CNN	98.43	98.65	97.83	98.12

Figure 3 illustrates the performance evaluation of different attention mechanism and different optimizers with CNN approach. The attention mechanisms like Spatial Attention (SA), Channel Attention (CA), Self Attention and Multi-head Attention (MHA) are estimated and compared with NAM. Then, the different optimizers such as Adam, Stochastic Gradient Descent (SGD), AdaGrad and Adadelta are estimated and compared with the AMO.

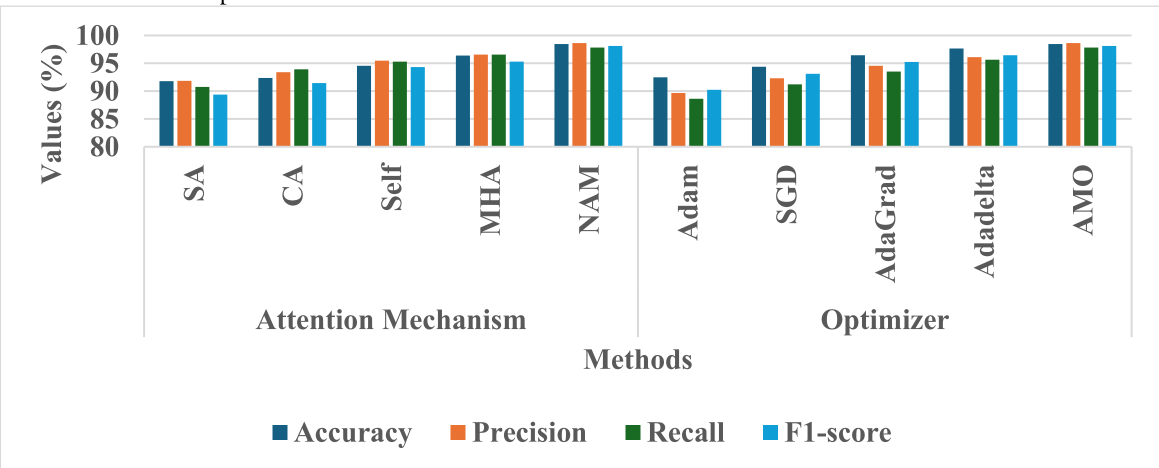

Figure 3. Graphical representation of different attention mechanism and different optimizers with CNN approach

4.2 Comparative Analysis

In this section, an effectiveness of proposed NAM-AMO-CNN approach is estimated and compared with existing approaches based on the simulation. The existing methods like AIE-CTDDC [16], YoloV5 [17] and EVGG16 [18] are estimated compared with the proposed NAM-AMO-CNN approach using various performance metrices.

Table 4. Comparative Analysis of proposed NAM-AMO-CNN through existing methods

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
AIE-CTDDC [16]	97.75	NA	95.64	95.43
YoloV5 [17]	NA	93	92.5	NA
EVGG16 [18]	97.78	97.70	96.77	97.46
Proposed NAM-AMO-CNN	98.43	98.65	97.83	98.12

4.3 DISCUSSION

This portion describes the drawbacks of existing methods and befits of proposed NAM-AMO-CNN approach is discussed. The limitation of AIE-CTDDC [16], the AIE-CTDDC approach relied on handcrafted segmentation and feature extraction methods which lacked the robustness, leads to poor performance. A combination of various DL approaches [17] enhanced the system complexity and inference time, resulted in poor performance. The EVGG16 model's [18] accuracy was heavily depend on the quality of pre-trained weights, and its performance was degraded when exposed to unseen disease types in new environments. The GLCM-based approaches [19] extracted only texture features and often miss contextual or spatial relationships, led to lower accuracy in complex or overlapping disease patterns. The GLCM-based feature extraction [20] was sensitive to noise and lighting variations, and does not effectively capture the complex patterns or spatial hierarchies in diseased regions. Hence, the new NAM-AMO-CNN approach is proposed for the prediction and classification of coconut tree diseases with respect to enhance the productivity of a crop. The NAM-AMO-CNN effectively reduces irrelevant background noise and enhances the model's capability to simplify across varying lighting and environmental conditions, designing it highly appropriate for real-world coconut disease detection in diverse field scenarios.

5 CONCLUSION

In this research, the new NAM-AMO-CNN approach is proposed for prediction and classification of coconut tree diseases with respect to enhance the productivity of a crop. The integration of a NAM enables the model to focus on critical disease-infected regions, while the AMO ensures stable and efficient convergence during training, leading to improved accuracy and faster prediction of coconut diseases. The NAM-AMO-CNN approach exploits the data augmentation and noise removal through QNLM approach as the pre-processing step. Moreover, the DeepLabV3+ approach is performed for an identification of disease affected regions. Furthermore, the Residual DenseNet approach for the extraction of important features. The proposed NAM-AMO-CNN approach is experimentally tested and the outcomes are evaluated over various perceptions. Experimental results demonstrates that the proposed NAM-AMO-CNN approach attains the superior accuracy of 98.43% as compared to the existing methods like Artificial Intelligence AIE-CTDDC and EVGG16. The results of comparative analysis established the significant effectiveness of proposed NAM-AMO-CNN approach over the various existing approaches. The future work will involve the hybrid DL approach to enhance the overall effectiveness of proposed method.

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