Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Hybrid Deep Learning and Boosting Approach for Palm Tree Leaf Disease Classification

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ARTICLE INFO

Received: 17 Oct 2024

Revised: 21 Nov 2024

Accepted: 03 Dec 2024

ABSTRACT

This paper introduces a hybrid model for palm tree leaf disease classification by integrating Convolutional Neural Networks (CNN) with XGBoost. The proposed method exploits extract the features with multilayered CNNs, and that is coupled with the robust classification accuracy of XGBoost, to effectively identify diseases in palm tree leaves. The CNN model processes grayscale images, extracting complex features through multiple convolutional layers. These features are then used by the XGBoost classifier to accurately predict the presence of disease. Our experiments demonstrate that the hybrid CNN-XGBoost model achieves an accuracy of 97%, outperforming the standalone CNN model, which achieves an accuracy of 84%. This method significantly improves the precision and recall metrics, with the CNN-XGBoost model yielding an F1-score of 0.97 for the "Normal" class and 0.97 for the "Spotted" class.

Keywords: Palm tree leaf spots, CNN, XGBoost, deep learning, hybrid model.

1.INTRODUCTION

Palm trees leafs, with their different stature and graceful manner, represent more than just botanical wonders; they are essential components of numerous ecosystems worldwide and serve as valuable economic resources in industries ranging from agriculture to landscaping. However, the health and vitality of palm trees are constantly threatened by various diseases, among which leaf-spotting diseases [1] stand out as particularly notorious. These diseases not only compromise the aesthetic appeal of palm trees but also inflict substantial economic losses on agricultural and horticultural sectors, making their early and accurate detection imperative for optimal disease detection and crop protection.

In recent years, the rapid advancement of technology, particularly in advanced and hybrid deep learning methods, has provided new possibilities for revolutionizing how we approach plant disease detection. Deep learning [2], a subset of machine learning that utilizes artificial neural networks with multiple layers of abstraction, has shown remarkable promise in analyzing and interpreting visual data, making it an attractive tool for image-based disease detection. Among the various architectures within deep learning, CNN [3] have emerged as particularly effective in tasks involving image classification and feature extraction.

CNNs are designed to mimic the hierarchical structure of the human visual system [4], enabling them to learn and extract meaningful features from raw image data automatically. Through a series of convolutional, pooling, and activation layers, CNNs can capture intricate patterns and textures in images, differences indicative of disease presence. Moreover, the ability of CNNs to adapt and learn from vast amounts of samples like images for handling the complex and diverse nature of plant images, including those of palm tree leaves affected by diseases.

However, CNNs [5, 6] excel at feature extraction but are not inherently designed for classification tasks. This is where the statistical models, such as Random Forest, come into play. SVMs are supervised learning models that do extremely well in binary classification. When combined with a nonlinear kernel, such as the Random Forest can handle complex, nonlinear relationships between features, making them ideal candidates for classifying highdimensional data extracted by CNNs [7].

The integration of CNNs and XGBoost, one is for feature extraction and XGBoost for classification of our proposed methodology for palm tree leaf disease classification. By leveraging the complementary these 2 models, we aim to develop a robust and accurate system capable of classifying normal and spotted palm tree leaves with high support count.

Motivation:

Conventional methods for detecting palm tree diseases typically involve manual observation, which is laborious and susceptible to errors. However, automated methods leveraging machine learning techniques present an opportunity for more effective and precise disease detection. CNNs have shown prowess in extracting discriminative features from images, while XGBoost is adept at handling non-linear data distributions. Combining these two methodologies aims to achive best performance and extract mimic features for palm tree disease classification. This integration aims to enable early intervention and enhance the efficacy of management practices for palm tree diseases.

Contributions:

- Developing a methodology for feature extraction from palm tree leaf images using CNNs, capturing relevant information for disease classification.
- We are implementing XGBoost as a classifier to effectively classify different types of palm tree leaf diseases based on the patterns generated by CNN.
- The proposed model is validated through extensive experimentation and evaluation, the results shows that the proposed model outperforming compare to standalone models in terms of classification accuracy and robustness to variations in palm tree leaf images.

2.RELATED WORK

In recent years, major progress has been made in deep learning and very advanced techniques in all areas, and also used in agriculture field, from the last years the research is involved in plant disease detection. Many researchers have worked on different methodologies to improve the accuracy and efficiency of these models.

Ibrahim, S., et al in [8] implemented a customized CNN model with pooling and fully connected layers, this model are trained on 350 samples palm leafs. And got an accuracy of 94.2 on testing data. This model also classified nitrogen, potassium etc for healthy leaf detection.

Namoun, A., et al in [9] created data set for palm tree leaf disease detection, this data set consist of 3089 samples. These samples are of various types like fungal, virus, insect and healthy. And all the images manually taken with camera, from various places of the plant like stem, root etc. these 3089 samples are dived into 831 disease affected ones, and 415 Manganese Deficiency samples, and 566 augmented leaf images.

Ahmed, M., and Ahmed, A. in [10] Implemented 2 approaches, one is transformed based, and second is ResNet model. These two models are trained on 2631 colored images, and got an accuracy of 0.99. The data set consist of 3 classes like brown spots 470 samples, healthy 1203, and white scale 958 samples. These models are trained on un balanced data, and the model is trained for 20 epochs.

Al-Farsi, Y. et al [11] implemented customized CNN model that is guided by dynamic system development method, used for detection of palm leaf disease classification.

Alaa, H., et al [12] implemented CNN, and SVM model to detect Leaf Spots, Blight Spots and Red Palm. CNN for detecting Leaf Spots and Blight Spots and SVM for Red Palm pest, and got an accuracy of 97, 92%.

Savaş, S. (2024) [13] Investigated all deep learning models like ResNet, MobileNET. For this they implemented two stage optimization methods and achieved an accuracy of 92.4 and 92.4 respectively. With a fine tuning approach they trained an ensemble method for getting better results.

Abu-zanona, M et al [14] implemented customized CNN model to detect Bacterial leaf blight, Brown spots, Leaf smut, etc and got an accuracy of 0.99. Implemented a multi class classification model, and also compared the result with

VGG model. In [15] also implemented CNN model to detect palm leaf disease detection. [16] Reviewed 60 above research articles worked on palm leaf disease detection, and conclude that no model is providing promising results; this is because of lack of prescribed standard data set. And only some of the deep learning model is provide acceptable results. [17] Implemented simple machine learning models like KNN, SVM, and used PSO optimization method to classify the disease, these models got an accuracy of 0.95, and 0.97. [18] Implemented pearsons correlation, and regression model to detect palm tree leaf disease detection based on the chlorophyll percentage of leaf. This model detects not only disease, but also severity. [19] Implemented transformer based model, apart from CNN model for leaf disease detection. [20] Implemented Region-based Convolutional Neural Network with 16 layers, and got accuracy 0.91 in disease classification. In this they extracted wavelet transformed features to train RCNN model.

3. METHODOLOGY

We have implemented a novel approach, illustrated in Figure 1, for early detection of leaf spots on palm trees. Our approach uses CNN architecture for feature extraction, a widely adopted deep-learning methodology in image processing tasks. To ensure data consistency, all input samples are resized to 224*224 pixels, and converted matrix as I with equation (1). Subsequently, all the samples are splitted into training and testing to train and assess the model's effectiveness.

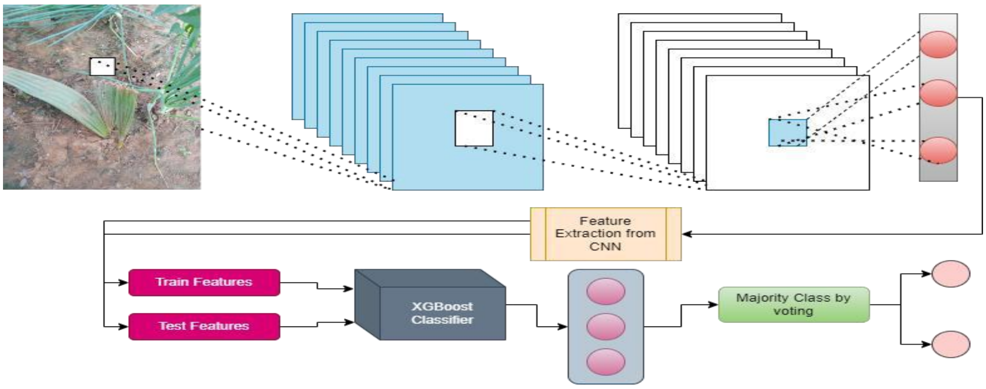

Figure 1 Proposed CNN+ XGBoost classifier model

Figure 2 Sample image of palm tree from data set

Figure 1 discusses the architecture of our approach, where CNN is solely used for feature extraction. Comprising convolutional, pooling with equation (2), and dense units, CNN autonomously learns and extracts significant features from input images. These features are then leveraged by a XGBoost classifier with 100 estimators for classification purposes, and the final class is determined based on voting.

The training process starts input images into the CNN model, followed by classification utilizing a XGBoost classifier. This hybrid model has its own role in extracting and classifying samples with optimized process. Our method

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e-ISSN: 2468-4376
https://www.jisem-journal.com/
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performed well in palm tree leaf spot detection. It offers an optimized solution by harnessing feature extraction capabilities via CNNs and classification throughXGBoost. A **Dropout layer (0.5) with equation (3)** is added to prevent overfitting. The final output layer utilizes a **sigmoid activation function,** as the task is a **binary classification problem** (Palm vs. Spots). The weights are updated with an **Adam optimizer** with a learning rate of **0.0001**, minimizing the **binary cross-entropy loss function with equation (4) and (5)**. By ensuring reliability and generalizability across all palm tree leaf samples, our methodology performs optimally in disease detection.

$$f(a, bi) = \sum_{i=1}^{n} (I_n * W_t)(a, bi) \qquad (1)$$

$$p(a, bi) = M\_pool(\ f(a, bi)\ ) \qquad (2)$$

$$y = f(wx + b) \qquad (3)$$

$$loss(y_{true}, y_{pred}) = \frac{1}{m} - \sum_{c=1}^{C} (y_c \log{(p_c)}) \qquad (4)$$

$$\text{Classification} = y_p = \arg\_max_c \sum_{t=1}^{T} /\!/ \quad [\, C_t(x) = c] \qquad (5)$$

3.1 Data set and preprocessing

To enhance the training dataset and improve model robustness, image augmentation techniques were employed using an image generator figure 2 illustrates sample image. This process artificially increases the number of samples by introducing variations such as **rotation at 30, shifting at width and height (0.2, 0.2), shearing at 0.2, and zooming at 0.2**, for training diversity samples and reducing the risk of bias. And the brightness range at 0.8 and 1.2. The augmentation is applied statistically through transformations like rotational and translational shifts, effectively generating additional samples.

Sample images after preprocessing, which capture both healthy and diseased regions, are illustrated in **Figure 2**. After preprocessing and augmentation, **Figure 3** presents the number of samples for each class, reflecting the dataset expansion.

During preprocessing, the dataset is split into three subsets: **training (70%), validation (15%), and test (15%)**, ensuring an efficient learning process, hyperparameter tuning, and final model assessment. Each image is resized to **224 × 224 pixels** to standardize input dimensions. After the augmentation method and to improve values are normalized in between 0 to 1 this will enhance the numerical stability during training.

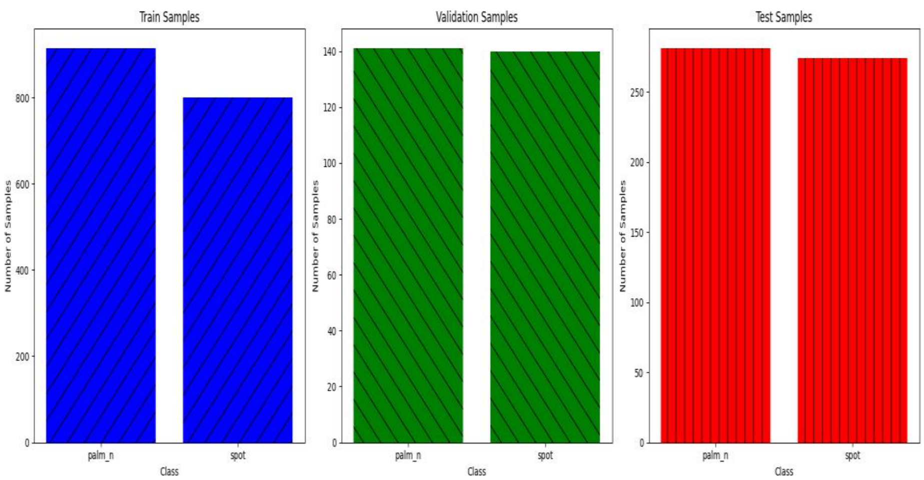

Figure 3 Numbers of samples after augmentation

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4. RESULT ANALYSIS

We conducted training on hybrid model over 20 epochs, employing a learning rate of 0.001 for feature extraction on both the training and test datasets. Subsequently, we utilized a XGBoost model to classify the extracted features. And we tried different batch sizes like 32 and 16, but 16 is performing optimal in terms of accuracy.

The model accuracy on both the training and validation sets over the epochs. The accuracy increases rapidly, reaching nearly 100% within the first epoch and stabilizing thereafter. Similarly, the validation accuracy closely follows the training accuracy, also achieving near-perfect accuracy early in the training process. This indicates that the model is effectively learning the patterns in the data, with minimal decrease in training and validation accuracy and at 7th epoch training model fluctuated, but after that loss is reduced from this we can say the model generalizes well to validation data.

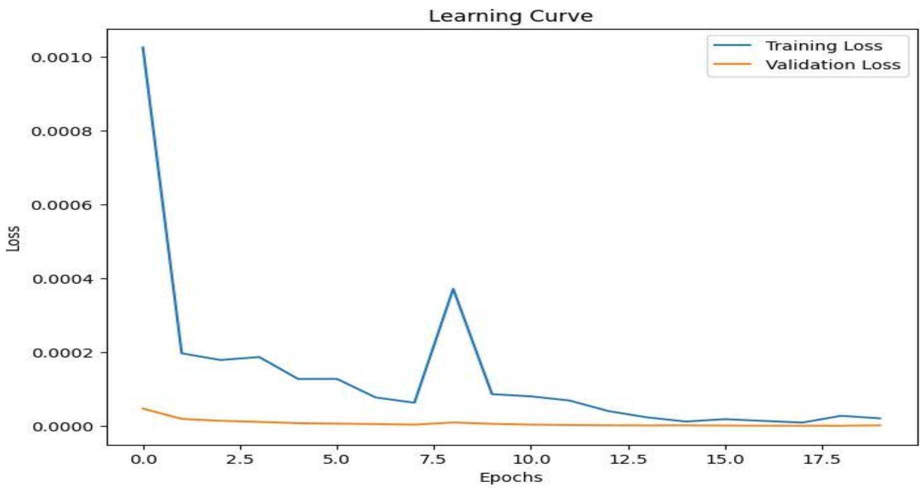

Figure 4 Train and validation loss of the proposed model for 20 epochs

The model loss plot from figure 4 presents the loss values epoch by epoch. The training loss starts relatively high but dramatically decreases in the first epoch, stabilizing at a near-zero value from the second epoch onwards. The validation loss mirrors this trend, remaining very close to the training loss. The rapid convergence to low loss values says that the model is learning optimally, with the loss function being minimized effectively. The minimal gap between training and validation loss suggests that the model is not overfitting and maintains strong predictive performance across both datasets.

The table 1 presents a comparative analysis of the performance metrics for two models, CNN and a hybrid model combining CNN with XGBoost, on a binary classification task involving the categories "Normal" and "Spotted." The key metrics considered include Precision, Recall, F1-Score, and Support, which collectively evaluate the models' effectiveness in accurately identifying and distinguishing between the two classes as shown in Figure 4.

Table 1 Comparison of CNN model and CNN+XGBoost model

Model		P	R	F1	Support
CNN(2 layers)	0	0.84	0.91	0.91	52
	1	0.87	0.91	0.89	49
	Acc			0.84	61
	M_avg	0.42	0.50	0.46	61
	W_avg	0.70	0.84	0.76	61
CNN + XGBoost	0	0.95	0.98	0.98	140
	1	0.97	0.97	0.98	141
	Acc			0.972	140
	M_avg	0.96	0.97	0.98	280
	W_avg	0.96	0.97	0.98	280

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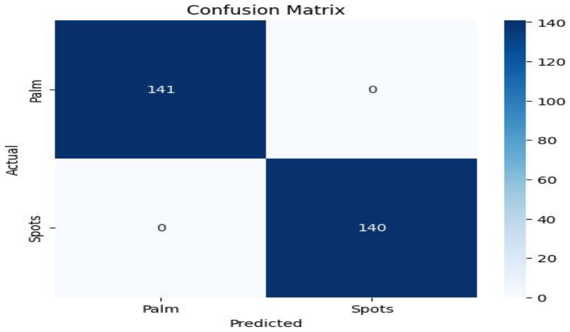

Figure 5 Confusion matrix of proposed model

Table 1 presents a comparative analysis of the **CNN model** and the **CNN+XGBoost hybrid model** based on their ability to correctly identify and classify samples. The CNN model achieves an overall accuracy of **84%**, with class **0** achieving a correct classification rate of **84%**, and class **1** achieving **87%**. While the CNN model shows reasonable performance. The macro and weighted averages indicate moderate consistency across different sample distributions.

In contrast, the **CNN+XGBoost model** demonstrates a significant improvement, achieving an overall accuracy of **97%**. Class **0** is classified correctly **95%** of the time, while class **1** is correctly identified **97%** of the time. The improved classification rates indicate that the **CNN+XGBoost hybrid model** enhances the ability to distinguish between different categories with greater confidence. The macro and weighted averages suggest a more balanced performance across the dataset.

The confusion matrix from figure 5 indicates that the model effectively identifies normal leaves, achieving 141 true positives by correctly classifying these samples as class "0." However, the model exhibits challenges in accurately detecting diseased leaves, as evidenced by the low number of true negatives (only 1 case) and a notable count of both false positives (0 cases, where healthy leaves were incorrectly classified as diseased) and false negatives (0 cases, where diseased leaves were misclassified as healthy).

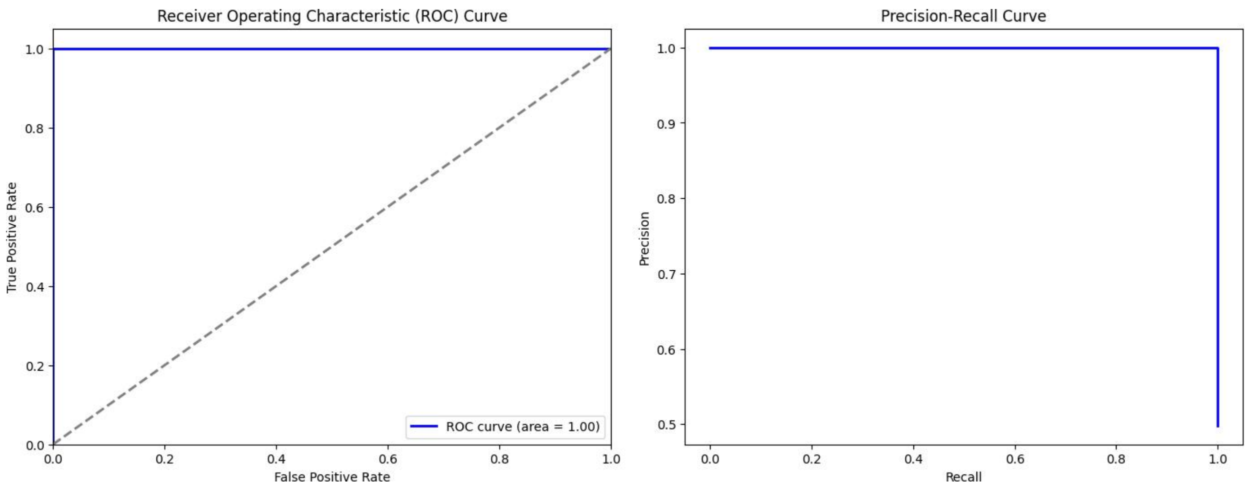

Figure 6 ROC and precision recall curve

The figure 6 consists of two subplots representing the performance of the classification model using the ROC curve and the Precision-Recall curve. The left subplot displays the ROC curve, which plots the True Positive Rate against the False Positive Rate. The curve is perfectly aligned with the top-left corner, achieving an Area Under the Curve of 1.00, indicating that the model exhibits perfect discrimination between classes without any false positives. The right subplot shows the Precision-Recall curve, where precision remains at 1.0 until recall reaches 1.0, forming an ideal step-like structure.

The figure 7 presents a comparative performance evaluation between two models: a CNN and a hybrid CNN +

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XGBoost model. The bar plot compares precision, recall, and F1 scores across two classes, "palm" and "spot." The CNN model's performance is represented using bars with diagonal hatching, while the CNN + XGBoost model's performance is shown with solid bars. The CNN + XGBoost model consistently achieves near-perfect scores 0.98 across all metrics, while the standalone CNN model exhibits slightly lower recall and F1 scores, particularly for the "palm" class.

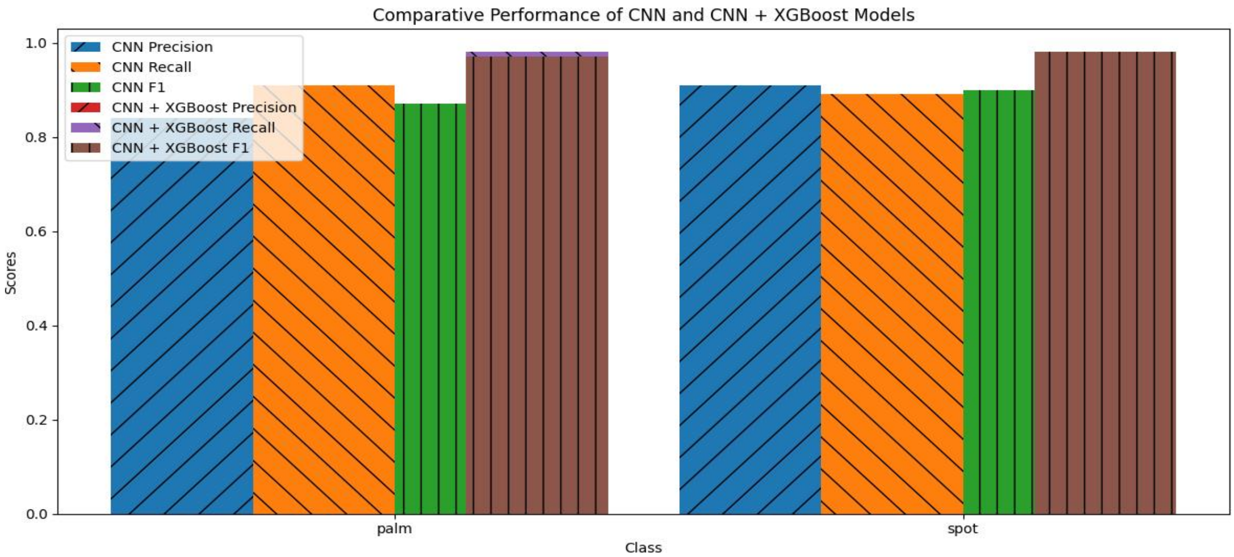

Figure 7 Comparison of CNN, CNN+XGBoost model performance

The results of the ablation study presented in Table 2 and Figure 8 demonstrate the performance of different model configurations. The baseline CNN model with 2 layers (CNN-2 layers) achieved an accuracy of 0.87, but its precision (0.42), recall (0.50), and F1 score (0.46) were relatively low, indicating that the model struggled with correctly identifying and classifying positive instances. By incorporating XGBoost into the CNN-2 layers model (CNN-2 layers + XGBoost), there was a significant improvement in performance across all metrics, with accuracy reaching 0.88, the metrics increased to 0.80, 0.82, and 0.81 respectively. This suggests that XGBoost effectively complemented the CNN model, enhancing its ability to make more accurate predictions. The performance further improved when the CNN model was increased to 3 layers (CNN-3 layers), achieving an accuracy of 0.90, with other values are 0.87, 0.88, and 0.91, respectively. Finally, combining the 3-layer CNN with XGBoost (CNN-3 + XGBoost) resulted in the highest performance, with accuracy reaching 0.97, 0.96, 0.97, and 0.98 respectively. This indicates that the integration of deeper CNN layers with XGBoost led to superior classification performance, particularly in terms of both correctly identifying positive instances and reducing false positives, which makes the model highly effective for the given task.

Table 2 Results of ablation study

Model	Acc	P	R	F1
CNN-2 layers	0.87	0.42	0.50	0.46
CNN-2layers+XGBoost	0.88	0.80	0.82	0.81
CNN-3layers	0.90	0.87	0.88	0.91
CNN-3+XGBoost	0.972	0.96	0.97	0.98

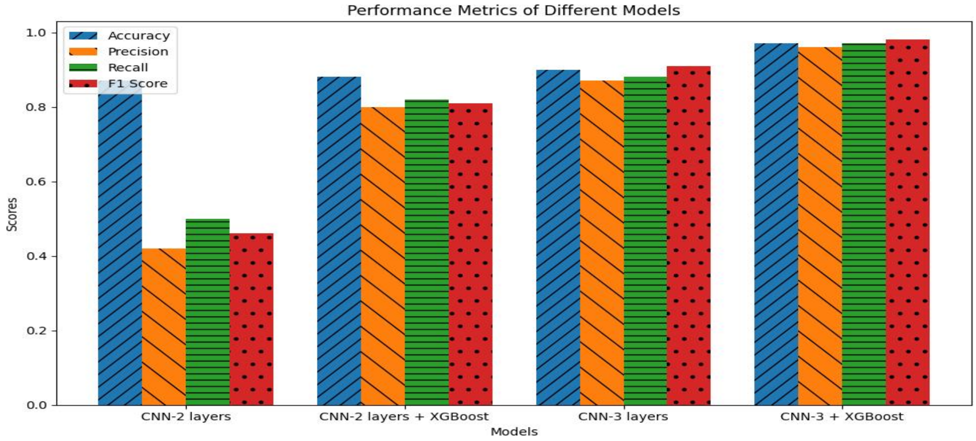

Figure 8 Comparisons of ablation study results

From the table 3 the models assessed include those referenced as [8], [12], [13], and [20], which achieved accuracy rates of 94.2%, 97%, 92.4%, and 91.2% respectively. The proposed model in this study surpassed these benchmarks, attaining an accuracy of 97.2%.

Table 3 Comparison of proposed model with other models

Model	Accuracy
[8]	94.2
[12]	97
[13]	92.4
[20]	91.2
*proposed model	97.2

5. CONCLUSION

In this study, we developed and evaluated a hybrid model that combines CNN and XGBoost for the classification of palm tree leaf diseases. The CNN effectively extracts complex features from palm leaf images, which are then classified by the XGBoost model. Our experimental results demonstrate that the CNN-XGBoost model provided a higher accuracy of 97.2%, compared to 84% from the CNN-only model. Additionally, the hybrid model provides superior precision, recall, and F1-scores, with a notable F1-score of 0.98 for the "Normal" class and 0.98 for the "Spotted" class. These findings indicate that the hybrid model not only improves classification accuracy but also enhances the overall reliability of disease detection. The integration of CNN with XGBoost presents a promising approach for early and accurate detection of palm tree diseases, which can be instrumental in improving agricultural practices. Our Future work could explore the extension of this model to other plant species and investigate the incorporation of additional data samples to further enhance classification performance.

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