

Areacanut Yellow Leaf Disease Detection Using CNN

Ashwini S P¹, KAVYASHREE S J², NIRANJAN B R³, RITISH M TILAVALLI⁴, SUNIL V⁵

¹Associate Professor, Department of Computer Science and Engineering, JNNCE, Shivamogga, Karnataka, India

^{2,3,4,5}UG Students, Department of Computer Science and Engineering, JNNCE, Shivamogga, Karnataka, India

Abstract - Areacanut cultivation plays an important role in the agricultural economy of India, but crop productivity is severely affected by diseases such as Yellow Leaf Disease (YLD). Early identification of this disease is challenging due to gradual symptom development and reliance on manual inspection. This paper presents the implementation of an automated image-based detection system for identifying Yellow Leaf Disease in arecanut plants using Convolutional Neural Networks (CNN). The proposed system processes leaf images through preprocessing, feature extraction, and deep learning-based classification to distinguish between healthy and diseased leaves. The model is trained and evaluated using standard performance metrics, and the final system is deployed through a simple web interface for real-time usage. Experimental results demonstrate that the system provides reliable accuracy and supports early disease detection, helping farmers take timely preventive measures.

Key Words: Areacanut, Yellow Leaf Disease, CNN, Deep Learning, Image Processing, Smart Agriculture.

1. INTRODUCTION

Areacanut is one of the most widely cultivated plantation crops in India, especially in regions such as Karnataka and Kerala. The crop contributes significantly to rural livelihoods, making disease management a critical concern. Among various diseases affecting arecanut, Yellow Leaf Disease is particularly harmful as it weakens the plant gradually and leads to long-term yield reduction.

Traditional disease identification methods rely on visual inspection by farmers or experts. This approach is time-consuming, subjective, and often ineffective during early stages of infection. With the advancement of artificial intelligence, image-based disease detection has emerged as a promising alternative. Convolutional Neural Networks are especially effective in analyzing visual patterns such as color changes, texture variations, and leaf deformities. This project focuses on implementing a CNN-based system that automates YLD detection and supports precision agriculture.

2. RELATED WORK

Several studies have explored the application of machine learning and deep learning techniques for plant disease detection. Earlier approaches relied on handcrafted features combined with classifiers such as SVM and KNN. Although

effective to some extent, these methods struggled with complex visual variations.

Recent research highlights the superiority of CNN-based approaches, which automatically learn discriminative features from images. Transfer learning models such as MobileNet, VGG, and ResNet have been widely adopted due to their high accuracy and reduced training time. Studies on arecanut disease detection confirm that CNN-based models outperform traditional techniques, especially when combined with data augmentation and proper preprocessing. These findings motivate the implementation of a CNN-driven system for Yellow Leaf Disease detection.

3. PROBLEM STATEMENT AND OBJECTIVES

3.1. Problem Statement

Manual detection of Yellow Leaf Disease in arecanut plantations is inefficient and prone to error, particularly during early stages of infection. Delayed diagnosis results in disease spread and significant crop loss. Existing automated systems are either costly or not easily accessible to farmers. Therefore, there is a need for an accurate, affordable, and easy-to-use image-based disease detection system.

3.2. Objectives

The objectives of this project are:

- To design and implement a CNN-based model for detecting Yellow Leaf Disease in arecanut leaves
- To preprocess and enhance leaf images for improved classification accuracy
- To evaluate the model using standard performance metrics
- To deploy the trained model through a simple user interface for real-time prediction

4. PROPOSED SYSTEM

This section explains the overall design and working of the proposed Areacanut Yellow Leaf Disease Detection System. The system is designed to automatically identify Yellow Leaf Disease in arecanut plants using image processing and deep learning techniques. It converts raw leaf images into meaningful predictions by following a structured pipeline consisting of data preparation, preprocessing, CNN-based classification, and result visualization. The primary objective of the system is to provide an accurate, fast, and user-friendly solution that supports early disease diagnosis in agricultural environments.

4.1. System Architecture

The proposed system follows a modular architecture in which each module performs a specific task in the disease detection pipeline. The architecture is designed to ensure clarity, scalability, and ease of deployment.

The major components of the system include:

1. Image Acquisition Module

This module is responsible for collecting input images of arecanut leaves. Images are obtained from publicly available datasets and can also be captured using cameras or mobile devices in real-world scenarios. The collected images include both healthy and Yellow Leaf Disease-affected samples under different lighting and background conditions.

2. Image Preprocessing Module

The raw input images may contain noise, background variations, or inconsistent dimensions. Therefore, preprocessing is performed to standardize the images before model training and prediction. This module performs operations such as resizing images to a fixed resolution, normalizing pixel values, and removing irrelevant noise. Data augmentation techniques are also applied to increase dataset diversity and improve model generalization.

3. Feature Extraction and CNN Classification Module

In this module, a Convolutional Neural Network is used to automatically extract meaningful features from preprocessed leaf images. The CNN learns hierarchical features such as edges, textures, color patterns, and disease-specific visual symptoms. These learned features are then used to classify the leaf images into two categories: healthy or affected by Yellow Leaf Disease.

4. Prediction and Result Display Module

The final module presents the prediction results to the user. Once an image is classified by the CNN model, the system displays the predicted class along with a confidence score. This module ensures that results are easily understandable, enabling users to take timely action.

The overall architecture ensures smooth data flow from image input to disease prediction, making the system suitable for real-time agricultural applications.

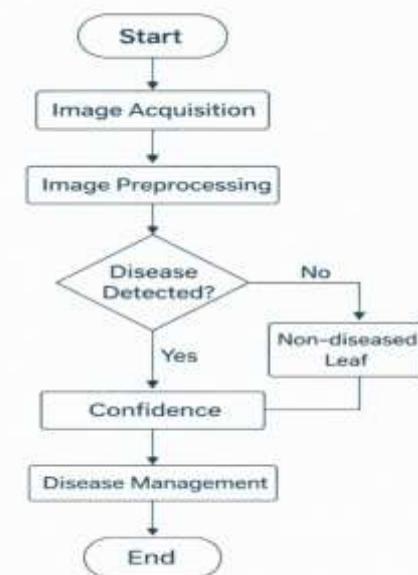


Fig. 1. Workflow of the proposed Arecanut Yellow Leaf Disease Detection

4.2. Methodology

The methodology of the proposed system describes the step-by-step process used to detect Yellow Leaf Disease from arecanut leaf images.

The process begins with the **input of a leaf image** into the system. The image is first passed to the preprocessing stage, where it is resized to a standard dimension and normalized to ensure consistency across all samples. To enhance robustness, data augmentation techniques such as rotation, flipping, and zooming are applied during training.

After preprocessing, the image is fed into the **Convolutional Neural Network**. The CNN consists of multiple convolutional layers that apply filters to the input image to extract important visual features. Activation functions introduce non-linearity, allowing the network to learn complex patterns. Pooling layers reduce spatial dimensions and help the model focus on dominant features.

The extracted features are then passed to fully connected layers that perform classification. The final output layer uses an activation function suitable for binary classification, producing a probability score that indicates whether the leaf is healthy or affected by Yellow Leaf Disease.

During training, the model learns by minimizing classification error using an optimization algorithm. Once trained, the model is evaluated on unseen test images to measure its performance. The trained model is then deployed for real-time prediction.

4.3. Workflow of the Proposed System

The workflow of the proposed Yellow Leaf Disease detection system is illustrated in Figure 4 and can be summarized as follows:

1. Start

The system initializes by loading the trained CNN model and required libraries.

2. Image Input

The user uploads an arecanut leaf image through the application interface.

3. Preprocessing

The uploaded image undergoes resizing, normalization, and noise reduction.

4. Feature Extraction

The CNN extracts visual features related to leaf colour, texture, and disease symptoms.

5. Disease Classification

The extracted features are classified into healthy or Yellow Leaf Disease categories.

6. Result Generation

The system generates the final prediction along with a confidence value.

7. Output Display

The result is displayed to the user, enabling timely decision-making.

8. End

The process terminates after successful prediction.

This structured workflow ensures accurate and efficient disease detection with minimal user effort.

5. IMPLEMENTATION AND RESULTS

This section describes the practical implementation of the proposed **Arecanut Yellow Leaf Disease Detection System** and presents the experimental results obtained during evaluation. The implementation focuses on developing a reliable deep learning model, testing its performance under different conditions, and analyzing its effectiveness in detecting Yellow Leaf Disease from leaf images.

5.1. Implementation Details

The proposed system is implemented using **Python** as the primary programming language due to its extensive support for machine learning and image processing libraries. The deep learning model is developed using **TensorFlow and Keras**, which provide flexible tools for designing and training Convolutional Neural Networks.

Leaf images used for the project are collected from publicly available datasets. The dataset contains both healthy and Yellow Leaf Disease-affected arecanut leaf images. Before training, the images are carefully filtered to remove low-quality samples. Each image is resized to a fixed resolution to maintain uniformity across the dataset.

Image preprocessing includes normalization of pixel values to improve convergence during training. Data augmentation techniques such as rotation, horizontal flipping, zooming, and brightness adjustment are applied to increase dataset diversity and reduce overfitting. The dataset is then split into training and testing sets using an appropriate ratio.

The CNN model consists of multiple convolutional layers followed by activation and pooling layers to extract hierarchical features from the leaf images. Fully connected layers are used for final classification. The model is trained using an optimization algorithm that minimizes classification error. After training, the model is saved and integrated into a lightweight application that allows users to upload images and receive predictions in real time.

5.2. Experimental Setup

The experimental evaluation is carried out to measure the accuracy and reliability of the proposed system. The experiments are conducted by providing different arecanut leaf images as input to the trained model. These images include variations in lighting, background, and disease severity to test the robustness of the system.

The dataset is divided into training and testing subsets. During training, the model performance is monitored using validation data. Key training parameters such as batch size, number of epochs, and learning rate are selected based on empirical observation to achieve stable convergence.

The trained model is evaluated using standard performance metrics including **accuracy**, **precision**, **recall**, and **F1-score**. A confusion matrix is also generated to visualize the classification performance and identify misclassification cases.

5.3. Results and Performance Analysis

The proposed CNN-based system demonstrates effective performance in detecting Yellow Leaf Disease from arecanut leaf images. The model achieves good classification accuracy on the test dataset, indicating its ability to generalize well to unseen data.

Data augmentation plays a significant role in improving robustness by exposing the model to a wide range of image variations. The confusion matrix shows that the system correctly identifies most healthy and diseased samples, with minimal false predictions. Precision and recall values further confirm that the model maintains a good balance between detecting diseased leaves and avoiding incorrect classification of healthy samples.

The system produces predictions within a short response time, making it suitable for real-time usage. The results confirm that CNN-based feature extraction is effective in capturing disease-related visual patterns such as yellow discoloration and texture changes in arecanut leaves.



Fig. 2. User interface of the Areca YLD Detector

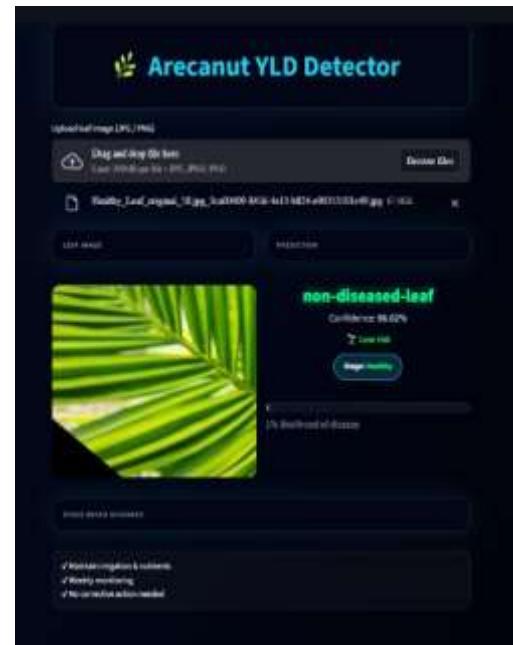


Fig. 4. Non-Diseased leaf output of the Areca YLD Detector

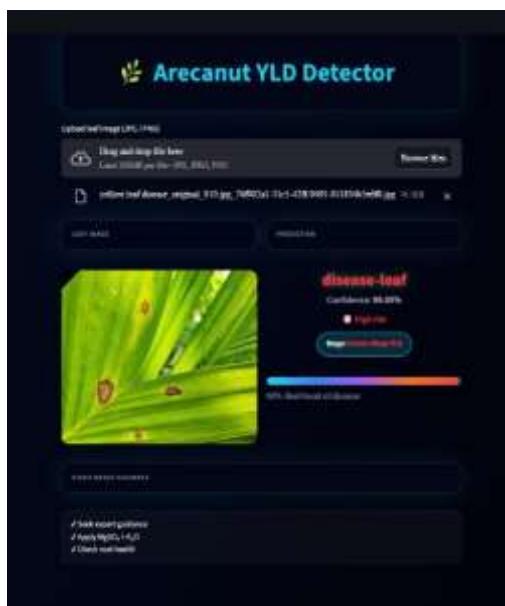


Fig. 3. Diseased leaf output of the Areca YLD Detector

5.4. Discussion

The experimental results highlight the effectiveness of the proposed system in automating the detection of Yellow Leaf Disease. Compared to traditional manual inspection, the system provides faster and more consistent results. While the current implementation focuses on binary classification (healthy and diseased), the architecture can be extended to support multi-class disease detection.

Some limitations include dependency on image quality and dataset diversity. However, these can be addressed in future work by expanding the dataset and incorporating advanced preprocessing techniques. Overall, the results demonstrate that the proposed system is a practical and scalable solution for disease detection in arecanut plantations.

6. APPLICATIONS

The proposed Areca YLD Detector has practical applications in multiple areas of agriculture and research. The primary application is in **early disease identification** for arecanut plantations, where farmers can upload leaf images and quickly determine whether the plant is affected by Yellow Leaf Disease. Early detection enables timely preventive measures, reducing crop loss and improving overall yield.

The system can also be used by **agricultural officers and extension workers** for field-level disease monitoring and advisory services. By automating disease diagnosis, the system minimizes dependence on expert visual inspection and reduces human error.

In **research and academic environments**, the proposed system serves as a useful tool for studying plant disease

patterns and evaluating the effectiveness of deep learning techniques in agricultural applications. Additionally, the model can be integrated into **smart farming platforms** and decision-support systems to promote precision agriculture.

7. CONCLUSION

This paper presented the design and implementation of a **Convolutional Neural Network-based system for detecting Yellow Leaf Disease in arecanut plants**. The proposed approach combines image preprocessing techniques with deep learning-based feature extraction to accurately classify leaf images as healthy or diseased. The system was implemented using widely adopted machine learning frameworks and evaluated using standard performance metrics.

Experimental results demonstrate that the CNN model effectively captures disease-related visual features such as color variation and texture changes. The automated detection process provides faster and more consistent results compared to traditional manual inspection methods. Overall, the proposed system proves to be a reliable, efficient, and user-friendly solution for early detection of Yellow Leaf Disease, supporting improved crop management and productivity.

8. FUTURE SCOPE

Although the proposed system provides effective results, there is scope for further enhancement. Future work can extend the system to **detect multiple arecanut diseases** instead of focusing only on Yellow Leaf Disease. Severity-level classification (mild, moderate, severe) can also be incorporated to assist farmers in selecting appropriate treatment measures.

The system can be enhanced by **expanding the dataset** with images collected from different regions and environmental conditions, which would improve model generalization. Deployment as a **mobile application** would make the solution more accessible to farmers in rural areas. Additionally, integrating the system with **IoT-based monitoring devices** and real-time field data could further strengthen its role in smart and precision agriculture.

9. REFERENCE

- [1] Hegde, V. S. Sadanand, C. G. Hegde, K. M. Naik, and K. D. Shastri, "Identification and categorization of diseases in arecanut: a machine learning approach," *Indonesian Journal of Electrical Engineering and Computer Science*, Vol. 31, No. 3, pp. 1803–1810, Sep. 2023.
- [2] A. Karthik V., J. Shivaprakash, and R. D., "Disease detection in arecanut using convolutional neural network," *Proceedings of International Conference, SRM Institute of Science and Technology, Chennai, India*, 2023.
- [3] Dhanuja K. C. and H. P. Mohan Kumar, "Areca nut disease detection using image processing technology," *Proceedings of Conference on Computer Applications, PES Engineering College, Mandya, India*, 2023.
- [4] J. Guo, Y. Jin, H. Ye, W. Huang, J. Zhao, B. Cui, F. Liu, and J. Deng, "Recognition of Areca Leaf Yellow Disease Based on PlanetScope Satellite Imagery," *Agronomy*, Vol. 12, No. 1, p. 14, Dec. 2021.
- [5] Latif Ullah Khan, R. Zhao, H. Wang, and X. Huang, "Recent advances of the causal agent of yellow leaf disease (YLD) on areca palm," *Tropical Plants*, Vol. 2, No. 7, pp. 1–12, 2023.
- [6] Madhu B. G., R. Kumar G., S. S. Rao, A. R. Shetty, and C. M., "Detection of diseases in arecanut using convolutional neural network," *Proceedings of 2024 Second International Conference on Advances in Information Technology (ICAIT), Chikmagaluru, India*, 2024.
- [7] P. A. Chougale, A. Ammanagi, M. T. Hussain, A. K., and B. K. Byregowda, "Classification and detection of diseases of areca nut and leaf using machine learning," *Journal of Emerging Technologies and Innovative Research (JETIR)*, Vol. 10, No. 5, pp. 376–382, May 2023.
- [8] K. Premalatha, G. Naik, M. K. Naik, V. Hegde, B. C. Dhananjaya, and S. K. M., "Exploring yellow leaf disease patterns in areca plantations in Chikkamagaluru District of Karnataka," *Saudi Journal of Pathology and Microbiology*, Vol. 9, No. 3, pp. 63–70, Mar. 2024.
- [9] J. S. N. Hegde and H. S. Vijaya Kumar, "Karnataka Malenadu region arecanut leafspot disease severity assessment using machine learning," *Proceedings of 2025 3rd International Conference on Smart Systems for Applications in Electrical Sciences (ICSSES), Tumkur, India*, 2025.
- [10] M. Balipa, P. Shetty, A. Kumar, P. B. R., and A. Hebbar, "Arecanut disease detection using CNN and SVM algorithms," *Proceedings of International Conference on Artificial Intelligence and Data Engineering (AIDE), Nitte, Karnataka, India*, 2022.
- [11] S. Chikkanayakanahalli, S. B. Srinivas, P. D. Ravindra, V. Singh, V. Gangadhar, and A. K. Dwivedi, "Disease Diagnosis and Sustainable Prevention in Areca Nut Farming," *2025 International Conference on Electronics and Renewable Systems (ICEARS), Bengaluru, India*, 2025.
- [12] L. M. Mohammed and Y. Yusoff, "Detection and classification of plant leaf diseases using digital image processing methods: A review," *ASEAN Engineering*

Journal, Vol. 13, No.1, pp. 1–9, Feb. 2023.

- [13] Beena K., Nidhi G. D., Sangeetha V., Varshini S., H. K. Lohar, and Y. K. N., "Arecanut disease prediction using MobileNet V2, ResNet and VGG-16 framework," Proceedings of 2024 4th International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS), Bangalore, India, 2024.
- [14] J. V. R. K., S. G. Prasad, S. Karegoudra, L. K. N. D., S. S. Shetty, S. S. Poojary, and H. Koten, "Deep learning-based classification of areca nut yellow leaf disease with ResNet-50 CNN," 2024 International Conference on Recent Advances in Science and Engineering