# Areca Nut Disease Detection Using Deep Learning

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## ABSTRACT

The detection of areca nut diseases is a critical challenge faced by farmers due to the reliance on manual inspection, limited datasets, and the complex visual symptoms to diseases such as Mahali Koleroga, Yellow Leaf Diseases and Stem Bleeding. These issues lead to inefficiencies, inaccuracies and delays in disease management. To address these problems, we developed an automated detection system leveraging deep learning and image processing. Utilizing a pre-trained ResNet-50 model, the system effectively classifies diseases by employing preprocessing techniques such as resizing, normalization and data augmentation to enhance the robustness of the input data. By integrating diverse datasets and advanced feature extraction, our approach achieves consistent and accurate classification under varied real-world conditions. The results demonstrate high accuracy in detecting and differentiating between disease states, empowering farmers with timely and actionable insights to manage crop health.

## I. INTRODUCTION

Areca nut, which is widely distributed over countries such as India, China, Malaysia etc, is a plantation crop. India is the world’s leading producer of areca nuts, providing a vital source of livelihood for many farmers [1]. Areca nut is popular and important in Taiwan. Areca is typically cultivated on mountainsides with mild air circulation. This makes it exposed to numerous pathogens like bacteria, fungi etc. The manual cost and sorting time always impacts the income of farmers [2]. Areca nut cultivation often suffers substantial losses due to diseases such as bud rot, inflorescence dieback, leaf spot, and fruit rot [3]. To limit the labour cost in classifying and detecting these diseases, image processing is one among the most significant technologies used. Image processing is a method utilized to apply operations to an image for the purpose of improving it or retrieving valuable information from it [4].

There are many various hurdles exist which limit the efficiency of these papers. These challenges include, manual inspection dependency which involves traditional sorting that is labor-intensive and susceptible to human error [1]. Other challenges like dataset size is also a limitation as the data set contains only 181 images which may not fully capture all types of diseases and conditions [2]. Image quality dependency which involves variations in image resolution, lighting and angles during capture affect the model’s performance [3]. Complex disease symptoms which include the overlapping visual symptoms of diseases such as fruit rot and fruit crack increase classification complexity [5].

This work rectifies these shortcomings in various ways. Automated disease detection which uses a pre-trained ResNet-50 model to automate the disease detection process, eliminating the dependency on manual inspection and ensuring consistency and accuracy. We utilise an augmented dataset that incorporates more diverse and representative samples of areca nuts, improving the model's ability to generalize across different scenarios. Unlike other systems our system is tested on diverse samples and conditions to ensure robust performance in real world scenarios. Instead of a decision tree like in a majority of papers, we use a deep learning model that dynamically adapts to diverse dataset and disease severity, enhancing robustness.

# II. RELATED WORKS

Areca nut Disease Detection Using CNN and SVM Algorithms [4] employs CNN and SVM for disease detection in areca nut. Images are preprocessed, with data augmentation methods such as rotation and color shifting applied to improve dataset diversity. CNN automates feature extraction, while SVM relies on texture-based features such as Wavelet and GLCM for classification. This approach is the integration of CNN and SVM, which leverages the strengths of both methods for improved accuracy. However, this involves the increased computational complexity and resource requirements due to combining these techniques. Detection of Disease in Areca nut Using CNN [5] [6] involves preprocessing like resizing images, Disease classification utilizes CNNs or ResNet architectures to obtain features from RGB images, achieving notable accuracy in detecting diseases. One key advantage of these approaches is the automation of disease detection, reducing manual labor and improving the precision and efficiency of diagnosis. However, these papers relied on limited datasets, which may hinder generalizability and robustness in real-world conditions. Constructing and Optimizing RNN Models to predict Fruit Rot Disease Incidence in Areca Nut Crop Based on Weather Parameters [10] this study uses GRUs and LSTMs with optimizers like Adam and RMSprop to predict fruit rot disease in areca nut using 50 years of weather data. Min-max scaling was applied, and disease scores were generated via a rule-based classifier. The GRU model with Adam achieved high accuracy (MSE of 0.0009), but the Adagrad optimizer performed poorly, limiting effectiveness. Areca Nut Disease Dataset Creation and Validation using Machine Learning Techniques based on Weather Parameters [1] this paper used weather data and machine learning models like random forest regression (RFR) to predict areca nut fruit rot disease. Early prediction helps farmers take preventive measures, which is the main advantage. However, the dataset's regional focus limits broader applicability. Detection and classification of areca nuts with machine vision [2] this paper presents a machine vision system to detect and classify areca nuts using image processing techniques and a backpropagation neural network (BPNN). By extracting features like color, geometry and defect area, the system classifies nuts into Excellent, Good, and Bad grades with an impressive accuracy of 90.9, significantly improving sorting efficiency. However, a key limitation is its inability to inspect obscured regions of the nuts, which restricts its capability for quality assessment.

# III. METHODOLOGY

This research focuses on developing an efficient and accurate system for detecting areca nut diseases using deep learning. The methodology involves key steps, including preprocessing and augmenting images, leveraging the ResNet-50 model for feature extraction, and classifying diseases into predefined categories. This approach ensures reliable detection and facilitates early intervention for disease management in areca nut farming.

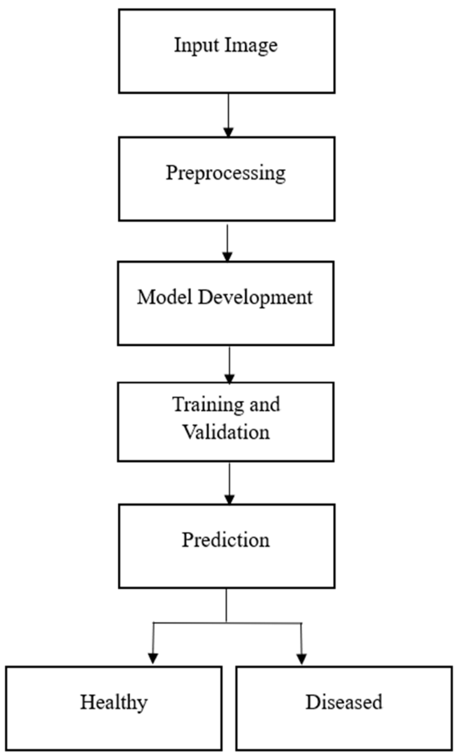



**Fig.1: Work Flow Diagram of Areca nut Disease Detection**

**1.Dataset Collection**

The dataset used in our paper was source from Kaggle and contains images of Healthy and diseased areca nuts, leaves and trunk. The dataset used for this study comprises images in JPEG format with an RGB color mode. The sample images include a resolution of 209*241 pixels. This dataset, referenced in the Disease Detection paper, focuses on detecting diseases in areca nuts.

**2.Data Preprocessing**

In the Areca Nut Disease Detection paper, a comprehensive preprocessing and augmentation strategy was implemented for all images, including those of leaves, stems, and areca nuts, to ensure they were well-suited for the pre-trained ResNet model. The preprocessing began with resizing all images to 224*224 pixels to match the input dimensions required by the ResNet architecture.

Subsequently, normalization was performed by scaling the pixel values to a range between 0 and 1. This step was important for maintaining consistency with the ResNet model’s requirements and improving training efficiency by accelerating convergence.

To remedy the challenge of limited dataset size and mitigate the risk of overfitting, data augmentation techniques were utilized. These methods enhanced the diversity of the dataset and improved the model’s classification performance and generalization capacity. The augmentation techniques included random rotation, translation, zooming, and horizontal flipping, applied uniformly across all image types.

## 3.Model development

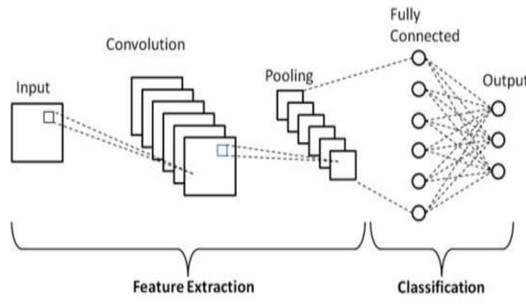



**Fig 2: Convolutional Neural Network**

A Convolutional Neural Network (CNN) is a deep learning model designed primarily for image preprocessing and classification mechanism. It consists of many layers that work together to extract features and make prediction.

**1. Input Layer:**

The input layer takes in raw image data represented as a grid of pixel values, serving as the starting point for processing within the CNN.

**2. Convolutional Layer:**

This layer uses small filters, known as kernels, to scan the input image and identify features such as edges, textures, and patterns. It generates a set of feature maps that highlight distinct characteristics of the image.

**3. Pooling/Down-Sampling Layer:**

Pooling decreases the spatial dimensions of the feature maps through methods such as Max Pooling or Average Pooling, preserving key features while minimizing computation and the risk of overfitting.

**4. Non-Linear Unit:**

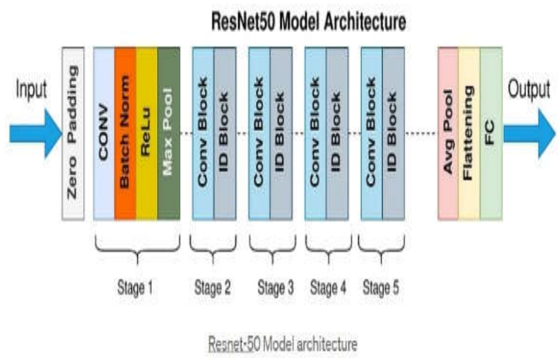
Non-linearity is introduced by making use of activation functions like ReLU (Rectified Linear Unit), which helps the network to learn complex relationships by transforming values into non-linear outputs.

**5. Fully Connected Layer:**

The feature maps are merged into a single vector, and this layer connects all the neurons to gather the extracted features, enabling the network to interpret relationships for decisions-making.

**6. Output Layer:**

The final layer produces the output, such as classification results. For multi-class problems, a SoftMax function is used to




assign probabilities to each label.

**Fig 3: ResNet-50 Model**

The image illustrates the architecture of the ResNet-50 model, which is a 50-layer deep residual network used for classify images and other computer vision tasks. Here's a breakdown of the architecture in layers:

**1. Input Stage:**

- Zero Padding: Adds padding around the input image to maintain the spatial dimensions for convolution.

**2. Stage 1:**

- Convolution (Conv): A 7x7 convolution is applied with a large receptive field to capture coarse features.

- Batch Normalization: Normalizes the outcome of the convolution layer to improve training stability.
- ReLU Activation: Introduces non-linearity.
- Max Pooling: Lessens the spatial dimensions to downsample the input and retain prominent features.

**3. Stage 2 (Conv Block + Identity Blocks):**

Conv Block:

- Contains three convolutional layers.
- Performs downsampling and increases the number of feature maps.
- Includes slip connections to introduce residual learning.

Identity Blocks:

- Stack multiple blocks with skip connections.
- Maintains the same spatial dimensions and number of channels.

**4. Stage 3 (Conv Block + Identity Blocks):**

- Similar to Stage 2 but with a larger number of filters and more identity blocks to capture deeper features.

**5. Stage 4 (Conv Block + Identity Blocks):**

- The number of filters increases and more identity blocks are stacked to process complex patterns.

**6. Stage 5 (Conv Block + Identity Blocks):**

- Final set of convolutional and identity blocks with the maximum number of filters to capture the most abstract features.

**7. Output Stage:**

- Average Pooling: Reduces each feature map to a single value, summarizing information globally.
- Flattening: Converts the 2D feature map into a 1D vector for the fully connected layer.
- Fully Connected Layer (FC): Performs classification based on the learned features.

The ResNet-50 model, part of the Residual Network (ResNet) family, is a convolutional neural network designed for image analysis tasks. It is composed of 50 layers, including convolutional, pooling, and fully connected layers, and is structured to effectively learn complex patterns in image data. Unlike traditional convolutional networks, ResNet-50 incorporates skip connections, also known as shortcut connections, which enable gradients to flow through the network without diminishing during backpropagation. This design overcomes the vanishing gradient problem, facilitating the training of very deep neural architectures.

ResNet-50 is organized into five stages, each containing a series of convolutional layers and identity blocks. These blocks incorporate batch normalization and ReLU activation to improve stability and performance. In the first stage, the input image is processes through a convolutional layer and max-pooling layer to extract basic features like edges and textures. As the stages progress, the network refines feature extraction, capturing more complex representations such as shapes and patterns.

The final stage includes a global average pooling layer and a fully connected layer, where the model outputs class probabilities. For this work, the ResNet-50 architecture is fine-tuned using transfer learning. Pre-trained on the ImageNet dataset, the network’s weights are adapted to classify areca nut diseases, optimizing for disease specific patterns while maintain computational efficiency.

# IV. RESULTS

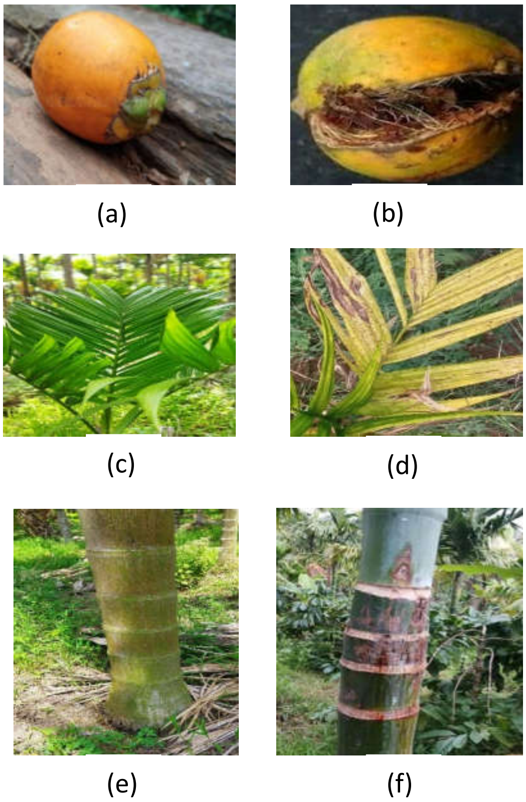



**Fig: a. Healthy nut, b. Mahali Koleroga, c. Healthy leaf, d. yellow leaf spot, e. Healthy Stem, f. Stem bleeding.**

The above figures show healthy and diseased images of different parts of an areca nut plant. As in the above images they have varying features like cracked and open nut, yellow spots in case of leaves and dripping stem.

**Model Evaluation**

The Areca Nut Disease Detection work evaluates ResNet using accuracy and loss on a validation dataset. It effectively identifies diseases like Mahali Koleroga, Yellow Leaf Spot, and Stem Bleeding, with metrics plotted over epochs to ensure optimal performance. Despite minor inaccuracies from image variations, the model shows strong accuracy in classifying diseases.

# V. CONCLUSION

The areca nut disease detection system presented in this work demonstrate the effective utilization of deep learning and image processing methods to identify and classify various diseases affecting areca nut crops by leveraging a pre-trained ResNet-50 model, the system achieves accurate predictions of diseases such as Mahali Koleroga, stem bleeding, and yellow leaf diseases as well as healthy states of leaves, nuts, and trunks.

The integration of preprocessing techniques like resizing, color conversion, deblurring, denoising and edge detection enhances performance. This approach ensures that the system is robust and adaptable to variations in image quality.

This system serves as a cast-effective and efficient tool for early disease detection, empowering farmers to take timely actions to protect their crops. With further refinement, including larger datasets and improved model generalization, the proposed solution has the potential to be deployed on mobile or IoT platforms for real-time detection, contributing to sustainable agricultural practices and enhanced productivity in the areca nut industry.

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