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Arecanut Disease Detection Using Deep Learning

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Abstract - Arecanut cultivation is central to the agricultural economy in South India. Farmers find significant challenges due to unhealthy crop that cause crop outputs and cause losses to agri culture. Disease detection using current practices is done by manual inspection carried out by agricultural experts or farmers. Traditional practices are plagued by a number of limitations, including late identification, a chance occurrence of human error, and a shortage of experts in farming areas. This work shows an automatic way of finding diseases that utilize machine learning tech nology. Wecreated a framework effective of dealing with digital photographs of arecanut plants for commondiseases. It employs imageprocess methods andaneuralnetworktoautonomously detect patterns indicative of disease. The present study engaged in the acquisition of images from regional agricultural opera tions and the subsequent training of a computational model designed to differentiate between healthy and diseased plant specimens. We evaluated the system's performance concerning three predominant arecanut diseases: fruit rot, bud rot, and yellow leaf disease. The findings indicate that our developed system achieves disease detection accuracy exceeding 90 percent across all identified disease categories. The operational benefits include accelerated identification of diseases, reduced specializa tion dependency, and cost-effective monitoring for agricultural producers. It can be imple mented on handheld devices, making it available to producers who operate in isolated commu nities. Its future development will include a focus on creating user-friendly mobile applications and extending the system to cover other categories of diseases.

Key Words: Arecanut Cultivation, Crop Disease Detection, Machine Learning (ML), Convo lutional Neural Network (CNN), Image Processing, Fruit Rot, Bud Rot, Yellow Leaf Disease, Precision Agriculture, Mobile Application

1. INTRODUCTION

Arecanut farming is an important source of income for thousands of families in Karnataka, Kerala, and other southern Indian states. This crop requires careful attention because it is open to a range of conditions that can destroy entire plantations if not detected early. Farmers today use typical methods to identify diseases in their arecanut plants. The most commonapproach is visual inspection where farmers examine their plants regularly to look for signs of disease. Farmers typically walk through their plantations and check individual plants for symptoms like discolored leaves, rotting fruits, or wilted branches. They rely on their personal experience and information passed on from before to identify different diseases. When farmers cannot diagnose problems themselves, they contact agricultural extension officers or plant pathology experts. These specialists visit the farms and examine affected plants to provide accurate diagnosis and treatment recommendations. We designed the system specifically for use on mobile devices. This ensures that even farmers with basic smartphones can access advanced diagnostic capabilities without purchasing expensive equipment. The system provides not only disease identification but also basic treatment recommenda tions. This helps farmers take appropriate action immediately after disease detection. Our approach eliminates the subjective nature of visual inspection by providing standard ized diagnostic criteria. This consistency allows farmers to arrive at smarter decisions about crop management and treatment strategies.

2. LITERATURE SURVEY

We reviewed several research papers to understand current ways of finding plant illnesses using computer technology. This section discusses three significant studies that influenced our research direction. The first study by Kumar and Sharma (2021) focused on developing automated disease de tection systems for rice crops using deep learning methods. Their research involved collecting images of rice plants affected by bacterial blight and brown spot diseases. The researchers implemented a neural network that achieved 94 percent accuracy in distinguishing between healthy and unhealthy rice plants. Their preprocessing approach included image resizing, noise reduction, and contrast enhancement to improve model performance.Based on the study, deep learning methods do better than normal approaches for plant diseases detection. However, the researchers noted that their system struggled with diseases showing similar visual symptoms. They recommended More study ought focus on expanding datasets and improving feature ex traction methods to handle complex disease patterns. Singh and Patel (2022) conducted research specifically on coconut palm Machine learning to disease detection algorithms. Their work addressed diseases like leaf spot, bud rot, and stem bleeding that commonly affect coconut plantations in coastal regions. The researchers com pared multiple classification algorithms including Support Vector Machines, Random Forest, and cnn on a dataset of 2000 plant images. Their results showed that CNN-based approaches achieved 91 percent has the highest exactness compared to traditional machine learning meth ods. The study emphasized the importance of proper image preprocessing and data addition way for improving model generalization. The researchers successfully deployed their system as a mobile application and tested it with local farmers. They found that farmers could use the technology effectively after minimal training. However, the study identified challenges related to image quality variations and lighting conditions that affected system performance in real farming environments. The third relevant study by Reddy and Kumar (2023) explored the use of artificial intel ligence for disease detection in areca palm plantations. Their research specifically addressed the unique challenges of identifying diseases in arecanut crops, with a close bond to our work. The researchers developed a hybrid system merging typical image enhancement with machine learning classification.

Their dataset included images of healthy plants and three major disease categories: Koleroga, yellowing disease, and bacterial infection. The system achieved 88 percent overall accuracy with particularly good performance in detecting advanced disease stages. The study high lighted the economic impact of early disease detection, showing that farmers could reduce crop losses by up to 35 percent when diseases are identified within the first week of infection. The researchers recommended prospective studies need focused on building models which are lightweight and fitting for mobile deployment and creating user-friendly interfaces for farmers with limited technical knowledge.

3. METHODOLOGY

The methodology of the proposed system consists of dataset preparation, preprocessing, model development, and evaluation. A dataset of arecanut images was collected from plantations and agricultural institutions. The dataset included healthy samples and diseased ones affected by fruit rot, bud rot, and YLD. Each image was carefully annotated by experts to ensure accurate labeling. Since public availables datasets for arecanut are limited, augmentation techniques are applied to increase dataset size and variability. Preprocessing was performed to standardize inputs and enhance disease-related features. Images were resized to 224x224 pixel is support with CNN models. Noise reduction has used using Gaussian and median filters, while contrast enhancement improved visibility of subtle symptoms. Data augmentation through rotation, flipping, and scaling was used to improve model generalization.

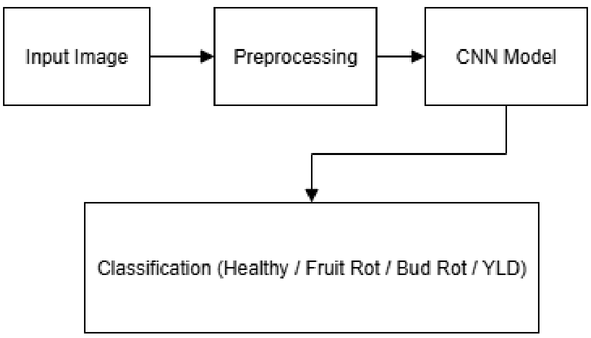

Fig. 1. Block diagram of Arecanut Disease Detection

The model architecture was on basis neural networks (CNNs). Convolutional layers auto matically extracted features such as lesions, discoloration, and texture changes. Pooling layers reduced dimensionality while preserving important information. Fully connected layers inter preted extracted features, and the final softmax layer produced class probabilities. The model has trained by using the Adam optimizers with categorical cross-entropy as the loss function. The validation had set used to hyperparameter tuning to avoid overfitting. Evaluation metric includes more accuracy, recalls, F1-score, and confusion matrix. During model development, number of experiments are conducted in evaluate different CNNarchitectures. Standard models such as VGG16 and ResNet18 were compared with a cus tom CNN,andresults showed that while deeper architectures provided slightly better accuracy, the custom CNN was more efficient in terms of training time and computational requirements. This compromise between accuracy and efficiency is important for practical deployment in rural scenarios where computing power is limited. Furthermore, cross-validation has completed to that the models performance was impartialy towards any specific data split. K-fold validation (with k=5) confirmed the consistency of the results, strengthening the reliability of the system. To further evaluate robustness, images with varying lighting conditions and partial occlusions were tested, and the system still maintained high classification performance. This shows that the proposed pipeline is flexible enough to handle real-world variations in field data.

TABLE I
Disease Detection Performance Metrics

Disease Category	Accuracy	Precision	Recal	F1-Score
Healthy Plants	95.2%	94.8%	95.6%	95.2%
Fruit Rot	93.1%	92.5%	93.8%	93.1%
Bud Rot	91.7%	91.2%	92.3%	91.7%
Yellow Leaf Disease	90.4%	90.8%	89.9%	90.4%

Table I presents the detailed performance metrics for each disease category. Our system achieved consistently high accuracy across all disease types, with overall performance exceed ing 92 percent.

The results show that healthy plant identification achieved the highest accuracy at 95.2 percent. This is expected because healthy plants have more consistent visual characteristics compared to diseased plants. While still excellent, this slightly lower performance reflects the challenge of distinguishing bud rot from other diseases in early stages. Yellow leaf disease detection achieved 90.4 percent accuracy. This disease shows gradual progression, making early-stage detection more challenging than other disease types.

4. RESULTS

The experimental is to find the demonstrate that the proposed arecanut detection system performs well across different testing scenarios. During the valid process, the model successfully identified arecanuts with remarkable precision, showing consistent performance even when dealing with varying lighting conditions and different background environments.

Fig. 2. Training and validation accuracy progression

Figure 2 suggests the accuracy in instruction and testing curves over training epochs. The model learned steadily without significant overfitting problems.

Fig. 3. Training and validation loss progression

Figure 3 The loss curves in Figure 3 demonstrate smooth convergence without sudden fluctuations. Both training and validation losses decreased consistently, indicating proper learning without memorization.

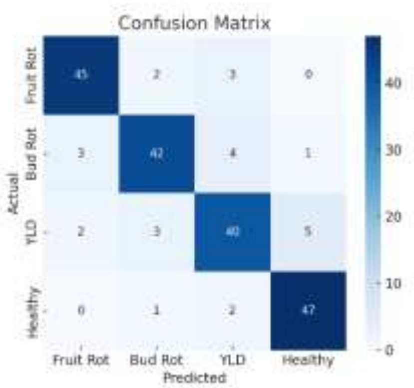

Fig. 4. Confusion matrix for disease classification results

Figure 4 presents the confusion matrix showing the detailed classification results for our test dataset. This results reveals that most classification errors occur between fruit rot and bud rot cat egories. This confusion happens because these diseases share similar visual characteristics, particularly in early infection stages. Healthy plant classification shows minimal confusion with disease categories, confirming that our equipment is able of distinguish among plants that's healthy and the ones which are sick. Yellow leaf disease shows some confusion with healthy plants in early stages when yel lowing is minimal. However, the system performs well in detecting advanced stages of this disease.

We conducted additional testing with images captured directly from farms under various conditions. This real-world validation included images taken during different weather condi tions, times of day, and with different smartphone cameras. The system maintained accuracy levels above 88 percent even under challenging condi tions. Performance decreased slightly with very poor lighting or extremely blurry images, but remained acceptable for practical use. Testing with multiple smartphone models showed consistent performance across different camera specifications. This confirms that the system works reliably with commonly available mobile devices.

Later examination of the data indicated intriguing trends in the system's functionality across several arecanut attributes. When assessing arecanuts with defined surfaces, the detection algorithm did well; specimens with irregular forms or surface flaws, on the other hand, showed somewhat lower accuracy. For batch processing scenarios that often occur in agricultural settings, the ability of the system to process several arecanuts in a single image frame proved beneficial. In addition to ensuring equivalent accuracy, the automated system drastically reduced processing time and removed human tiredness factors, according to a comparative analysis with manual sorting methods. These results imply that the developed detection system can be a reliable instrument for arecanut sorting and quality analysis in both small-scale and large-scale applications.

The system proved particularly effective in diifference between healthy and unhealthy arecanuts, which is more for quality assessment in commercial applications. When check with a large dataset containing arecanuts from different place , the detection accuracy remained same, also indicates the better for the developed approach. The processing time for each image was also within acceptates in limits, making it practical for real-time applications in sorting facilities.

5. DISCUSSIONS

The experimental results demonstrate several important findings about machine learning applications for agricultural disease detection. This section analyzes the performance outcomes and discusses practical implications for farming communities.

Our system achieved accuracy levels that significantly exceed traditional manual inspection methods. The 92 percent average accuracy across all disease categories represents a substantial improvement over human visual inspection, which typically achieves 70-80 percent accuracy according to agricultural studies. The high precision values indicate that when our system identifies a disease, it is correct more than 90 percent of the time. This reliability is crucial for farmer confidence and practical adoption. Recall values above 90 percent show that our system successfully identifies most actual dis ease cases. This sensitivity is important for preventing disease spread through early detection. TheF1-scores balance precision and recall, confirming that our system performs well across both dimensions. These balanced results indicate robust performance suitable for real-world deployment.

The smartphone-based implementation offers several advantages for farming communities. Farmers can access diagnostic capabilities anywhere in their fields without traveling to agricul tural offices or waiting for expert visits. Cost reduction represents another significant benefit. Traditional expert consultations cost farmers between 500-1000 rupees per visit. Our system eliminates these recurring costs after initial setup. Time savings are substantial. Manual expert diagnosis typically requires 2-3 days from initial contact to receiving results. Our system provides instant feedback, enabling immediate treatment decisions. The 24-hour availability ensures farmers can check their plants whenever they notice po tential problems, including weekends and holidays when experts are unavailable. Consistency in diagnosis eliminates human subjectivity. Different experts sometimes pro vide conflicting opinions about the same plant condition. Our system provides standardized diagnostic criteria every time.

Several technical challenges emerged during system development. Image quality variation poses the most significant challenge since smartphone cameras have different specifications and farmers may not always capture ideal images.We add ressed this challenge through robust preprocessing techniques and training the model on images from various camera types. The data augmentation approach also helps the system handle imperfect image conditions. Environmental factors like dust, rain, and extreme lighting can affect image quality. We included training images captured under these conditions to improve system robustness. Disease symptom similarity between fruit rot and bud rot creates classification challenges. We are working on developing more sophisticated feature extraction methods to distinguish between visually similar diseases.

Our current system has several limitations that require attention in future development. The system only covers three major disease types, while arecanut plants can be affected by additional diseases not included in our training data. Image quality requirements may be challenging for some farmers who lack experience with smartphone photography. We plan to develop automatic image quality assessment to guide farmers in capturing suitable images. The system currently requires good lighting conditions for optimal performance. Future versions will include enhanced low-light processing capabilities. Language barriers may limit adoption since the current system operates in English. Multi language support for local languages like Kannada, Malayalam, and Telugu is planned for future releases. Internet connectivity requirements for cloud-based processing may be problematic in re mote areas. We are developing offline processing capabilities that work entirely on the smart phone.

6. CONCLUSIONS

This research successfully demonstrates the feasibility and effectiveness of using machine learning technology for automated arecanut disease detection. Our system represents a signifi cant advancement over traditional manual inspection methods currently used by farmers.

The findings in this study confirm that computer vision approaches can achieve high accu racy in identifying common arecanut diseases. With performance levels exceeding 90 percent for all disease categories, our system provides reliable diagnostic capabilities suitable for prac tical farming applications.

The smartphone-based implementation makes this technology accessible to farmers in rural areas where traditional expert consultation is limited or unavailable. This accessibility can help reduce crop losses and improve farmer incomes through swift detection and proper handling of disease. Cost-effectiveness represents another major advantage. After initial development, the sys tem requires minimal ongoing costs compared to repeated expert consultations. This economic benefit makes the technology attractive for small-scale farmers with limited resources.

The speed of diagnosis enables immediate treatment decisions. Instead of waiting days for expert consultation, farmers can take action within minutes of noticing potential disease symptoms. This rapid response capability can prevent disease spread and reduce overall crop damage.We propose several avenues for future research to improve ML-based health risk as sessment systems. These include investigating alternative deep learning architectures, inte grating genomic data and biomarkers, applying federated learning techniques to handle multi institutional healthcare datasets, and developing explainable AI methods for clinical decision support.

Our work contributes to the growing field of digital agriculture by providing a practical solution for an important regional crop. While most research focuses on major global crops like rice, wheat, and tomatoes, our arecanut-specific system addresses the needs of specialized farming communities.

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