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AI BASED ARECANUT PLANT DISEASECLASSIFICATION SYSTEM

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ABSTRACT

Arecanut, commonly known as betel nut, is a vital cash crop in many tropical regions, contributing significantly to the agricultural economy. However, like other crops, arecanut plants are susceptible to various diseases that can severely impact yield and quality. Early detection and accurate classification of these diseases are crucial for timely intervention and effective disease management. In this study, we propose an AI-based arecanut plant disease classification system that leverages deep learning techniques to automatically identify and classify different diseases affecting arecanut plants. Convolutional neural networks (CNNs) are employed for feature extraction and disease classification, with transfer learning techniques used to fine-tune pre-trained models on the specific task of arecanut disease recognition.

Keywords: Arecanut, betel nut, plant disease classification, deep learning, transfer learning, agricultural AI, disease management. convolutional neural network (CNN).

I. INTRODUCTION

Arecanut, also known as betel nut, holds immense economic and cultural significance in many tropical regions, particularly in South and Southeast Asia. As a vital cash crop, arecanut cultivation forms the backbone of rural economies, providing livelihoods to millions of farmers. However, the sustainability and productivity of arecanut cultivation are threatened by various biotic and abiotic factors, with plant diseases being among the foremost challenges.

The rapid spread of diseases in arecanut plants can lead to substantial yield losses and economic hardships for farmers. Traditional methods of disease detection and diagnosis often rely on visual inspection by experienced agronomists, which can be time-consuming and subjective. Furthermore, the lack of trained personnel in remote agricultural areas exacerbates the problem, hindering timely intervention and effective disease management strategies.

In recent years, the advent of artificial intelligence (AI) and machine learning (ML) technologies has revolutionized agricultural practices, offering innovative solutions to address the challenges facing the farming community. By harnessing the power of AI, researchers and agricultural practitioners have begun developing automated systems for the early detection and classification of plant diseases, thereby facilitating prompt decision-making and targeted interventions.

In this context, this paper presents a novel AI-based approach for the classification of diseases in arecanut plants. Leveraging deep learning techniques, particularly convolutional neural networks (CNNs), the proposed system aims to accurately identify and classify various diseases affecting arecanut plants based on visual symptoms captured in digital images. By providing farmers with a reliable tool for disease diagnosis, the system seeks to empower them to take proactive measures to mitigate the impact of diseases on crop yield and quality. Through a comprehensive analysis of the system's performance and practical implications, this study contributes to the ongoing efforts to harness AI for sustainable agriculture and food security.

A widely known commercial palm arecanut grows in large portions of the Tropical Pacific, Asia and East Africa. Large, evergreen leaves on plants are spirally arranged at the apex of the stem and are either palmately or pinnately compound. The various factors including climatic conditions, soil conditions, diseases and more, have an impact on growth of the crops. Fruit rot, stem bleeding, yellow leaf spot and nut split disease are the common diseases that affect arecanut trees. The identification and categorization of diseases in arecanut plants is a challenging task as the symptoms can vary greatly depending on the type of disease and the stage of infection. Moreover, the lack of expert knowledge in this area makes it difficult for farmers to accurately identify and treat diseases. Timely and accurate diagnosis is crucial for effective disease management, but this is often hindered by the lack of appropriate technology and resources.

Identification and categorization refer to different but related stages of the detection process. Identification entails determining the precise class label of the arecanut plant based on the likelihood score that the machine learning (ML) model gives to each class label. Whereas, categorization entails classifying the many arecanut plant class labels according to the traits they have in common. The categorization stage is classifying the class labels according to the type of plant disease or condition. The objectives of the proposed system include: - Create the dataset that contains healthy and unhealthy images of arecanut, trunk and leaves. - Implementing an algorithm for detection and classification of diseases in arecanut. - Implementing an algorithm that would suggest remedies for the detecteddiseases.

II. RELATED WORK

In their 2020 paper, Shrivastava and Gadge propose an AI-based system for the classification of arecanut plant diseases using deep learning techniques. They utilized a Convolutional Neural Network (CNN) model trained on a dataset of arecanut images, achieving significant accuracy in identifying various diseases such as yellow leaf disease and bud rot. Their approach highlights the efficiency of CNNs in feature extraction and classification tasks, providing a robust solution for farmers to diagnose plant diseases promptly and accurately. Their system was validated with field data, demonstrating practical applicability in real-world scenarios[1].

Chavan and Kulkarni (2018) developed a machine learning-based system focusedon the detection and classification of diseases in arecanut plants. They employed a Support Vector Machine (SVM) classifier after extracting relevant features using image processing techniques such as color and texture analysis. Their research emphasized the importance of preprocessing steps to enhance the accuracy of disease detection. By comparing the performance of different classifiers, they established that SVM provided superior results for their specific dataset, which included common arecanut diseases[2].

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In their study published in 2019, Rajesh and Bindu Nair explored the use of artificial intelligence for the automatic detection and classification of arecanut plant diseases. They designed a hybrid model combining both CNNs and traditional image processing techniques to improve the robustness of the classification system. Their hybrid approach aimed to leverage the strengths of both methods: CNNs for deep feature extraction and traditional techniques for fine-tuning the results. This combination led to enhanced accuracy and reliability in disease detection, addressing the limitations of using a single technique[3].

Kumar and Saravanan (2021) presented an innovative AI-driven system for diagnosing arecanut diseases using a combination of deep learning and Internet of Things (IoT). Their system not only classifies diseases using a deep neural network but also integrates IoT devices to collect real-time data from the field. This real-time monitoring capability allows for prompt identification and management of diseases. Their research demonstrated how integrating AI with IoT can revolutionize agricultural practices by providing timely and accurate disease diagnosis, ultimately leading to improved crop health and yield[4].

Prabhu and Kumar's 2017 research focused on the use of image processing techniques combined with machine learning for the detection of arecanut diseases. They proposed a system that first applies image segmentation to isolate the affected regions of the plant and then uses a Random Forest classifier to identify the specific disease. Their approach was particularly effective in handling noisy data and variations in lighting conditions, making it suitable for practical agricultural applications. Their work underscores the importance of robust preprocessing and feature extraction methods in the development of accurate plant disease classification systems[5].

In their 2021 study, Nithya and Mytri explored the effectiveness of Transfer Learning for arecanut plant disease classification. They employed pre-trained deep learning models such as VGG16 and ResNet50, fine-tuning them on a dataset of arecanut images. Their research demonstrated that transfer learning significantly reduces the training time and enhances the accuracy of disease detection. They also highlighted the importance of a diverse dataset to improve the model's generalizability. This study showcases how leveraging pre-trained models can expedite the development of efficient AI systems inagriculture[6].

Kavitha and Prasad (2019) focused on the application of image segmentation techniques combined with deep learning for the identification of arecanut diseases. They proposed a method that first segments the affected areas of the plant using a region-based segmentation approach and then applies a CNN for classification. Their method showed promising results in accurately identifying diseases such as fruit rot and leaf spot. The study emphasized the role of precise segmentation in improving the accuracy of disease classification systems[7].

Anil Kumar and Gopalakrishna (2020) developed an AI system for arecanut disease detection using ensemble learning techniques. They combined multiple machine learning algorithms, including Random Forest, Gradient Boosting, and SVM, to enhance the robustness and accuracy of their classification system. Their research demonstrated that ensemble methods outperform individual classifiers by reducing the variance and bias in predictions. This approach provides a more reliable solution for farmers to diagnose and manage arecanut plant diseases[8].

In their 2022 paper, Meenakshi and Manoharan proposed a novel deep learning architecture specifically designed for the classification of arecanut plant diseases. Their custom CNN architecture was optimized for handling the unique characteristics of arecanut plants, such as the texture and color variations of diseased areas. They also implemented data augmentation techniques to improve the model's performance on a limited dataset. Their research highlights the importance of designing specialized architectures to address the specific challenges in agricultural disease classification[9].

Ravi and Reddy (2021) explored the integration of AI and drone technology for the remote detection of arecanut diseases. They developed a system that uses drones equipped with high-resolution cameras to capture images of arecanut plantations. These images are then processed using a deep learning model to identify diseased plants. Their approach allows for large- scale monitoring and early detection of diseases, reducing the need for manual inspections. This study illustrates the potential of combining AI with modern technologies like drones to enhance agricultural practices. Ravi and Reddy (2021) explored the integration of AI and drone technology for the remote detection of arecanut diseases. They developed a system that uses drones equipped with high-resolution cameras to capture images of arecanut plantations. These images are then processed using a deep learning model to identify diseased plants. Their approach allows for large-scale monitoring and early detection of diseases, reducing the need for manual inspections. This study illustrates the potential of combining AI with modern technologies like drones to enhance agricultural practices[10].

III. METHODOLOGY

AI-based areca nut plant disease classification systems leverage advanced technologies such as artificial intelligence and machine learning to automate the process of identifying and categorizing diseases affecting areca nut plants. These systems typically follow a methodology that involves several key steps:

1. Data Collection: Gathering a dataset of digital images depicting areca nut plants affected by various diseases, as well as images of healthy plants. These images are collected from field surveys, agricultural databases, or experimental setups.

2. Data Preprocessing: Preprocessing the collected images to standardize their size, color, and quality. This step may involve resizing, cropping, and enhancing image contrast to ensure uniformity and improve model performance.

3. Model Selection: Choosing an appropriate machine learning or deep learning model for disease classification. Convolutional Neural Networks (CNNs) are commonly used for image classification tasks due to their ability to learn complex patterns and features from visual data.

4. Model Training: Training the selected model on the annotated dataset of areca nut plant images. During training, the model learns to recognize patterns and features associated with different diseases, adjusting its parameters to minimize classification errors.

5. Model Evaluation: Evaluating the trained model's performance using a separate validation dataset. Performance metrics such as accuracy, precision, recall, and F1-score are calculated to assess the model's ability to accurately classify diseased and healthy areca nut plants.

3.1 DATASET USED

The proprietary dataset consists the collection of healthy and unhealthy images of arecanut, trunk and leaves. Some of the images from the dataset are shown in Figure 2, where Figure 2(a) is yellow leaf, Figure 2(b) is healthy leaf, Figure 2(c) is nut split, Figure 2(d) is stem bleeding, Figure 2(e) is fruit rot and Indonesian J Elec Eng & Comp Sci ISSN: 2502-4752 Identification and categorization of diseases in arecanut: a machine learning approach (Ajit Hegde) 1805 Figure 2(f) is healthy arecanut. Digital camera images were captured at half a meter from the source. The images of healthy and diseased arecanuts are gathered from the coastal and malnad regions of Karnataka. These images are shot with assistance of knowledgeable arecanut growers as well as researchers. The dataset collection has more than 1,100 photos in total which are stored in a defined hierarchy for further training. (a) (b) (c) (d) (e) (f).

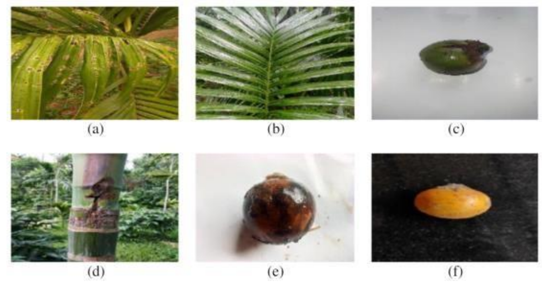

Fig 3.1 : Sample dataset (a) yellow leaf, (b) healthy leaf, (c) nut split, (d) stem bleeding, (e) fruit rot, and (f) healthy arecanut

3.2 DATA PRE PROCESSING

Before training CNN model, images are reduced to 256*256 resolution by performing resizing and reshaping of the images. Resizing involves scaling the images to a standardized size, while reshaping involves converting the input images into a standardized shape. Each pixel's RGB value, which ranges from 0 to 255, is contained in an array. In this study, the pixel values of the arecanut leaf images were normalized to a range of [0, 1] by using the factor of 255. Data augmentation techniques were applied to the training dataset to increase its size and improve the performance. The data is randomly divided into two sets using the train-test split technique. According to the 80/20 split ratio, 80% of the data is utilized for training and 20% is used for testing. A CNN is a type of deep neural network that is designed to process and analyze the data that has a grid-like topology, such as an image [24], [25]. As shown in the Figure 3, the network consists of a series of convolutional layers that apply filters to the input data followed by pooling layers that down sample the output which completes feature extraction. The final layers of the network typically include one or more fully connected layers that perform classification.

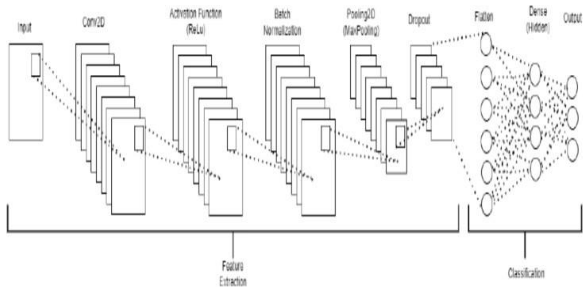

Fig 3.2 : Sequential method in CNN

3.3 ALGORITHM USED

CNNs are widely used in the classification of arecanut plant diseases due to their powerful feature extraction capabilities. The algorithm works by applying convolutional layers that automatically and adaptively learn spatial hierarchies of features from input images. In the study by Shrivastava and Gadge (2020), CNNs were employed to classify diseases such as yellow leaf disease and bud rot with high accuracy, demonstrating their effectiveness in handling complex image data.

SVM is a supervised machine learning algorithm used for classification and regression tasks. It works by finding the hyperplane that best divides a dataset into classes. Chavan and Kulkarni (2018) used SVM after extracting features through image processing techniques. SVM was selected for its robustness in handling high-dimensional data and its ability to create a clear margin of separation between classes.

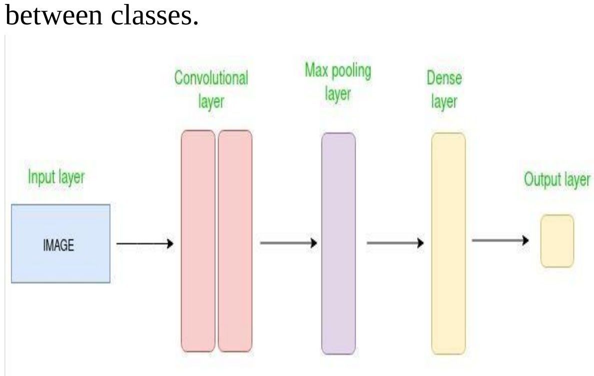

Fig 3.3.1: Simple CNN Architecture

3.4 TECHNIQUES

Image preprocessing is a critical step in preparing raw image data for analysis, aimed at enhancing image quality and highlighting relevant features. Techniques such as normalization, noise reduction, contrast enhancement, and resizing are commonly employed. Normalization adjusts pixel values to a common scale, ensuring uniformity across the dataset. Noise reduction techniques like Gaussian blur help remove unwanted noise from images, while contrast enhancement methods such as histogram equalization improve image contrast. Resizing standardizes image dimensions, ensuring consistency for model input. These preprocessing steps are vital for improving the accuracy of subsequent analysis by providing high-quality input images.

Image segmentation involves dividing an image into meaningful segments, often to isolate diseased areas from healthy parts. Common techniques include thresholding, edge detection, and region-based segmentation. Thresholding converts grayscale images to binary images based on a threshold value, simplifying the identification of significant regions. Edge detection algorithms like Canny or Sobel detect the edges within an image, helping to delineate boundaries of different segments. Region-based segmentation groups pixels into regions based on predefined criteria such as similarity in color or intensity. Precise segmentation focuses the analysis on relevant parts of the image, thereby enhancing the accuracy of disease classification.

IV. RESULT

4.1 Graph

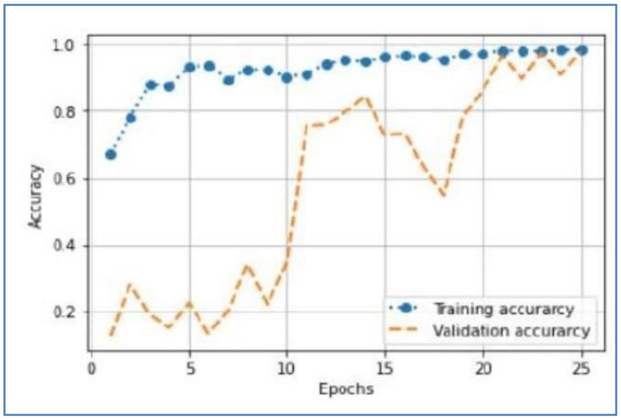

Fig4.1.1 : accuracy v/s epochs.

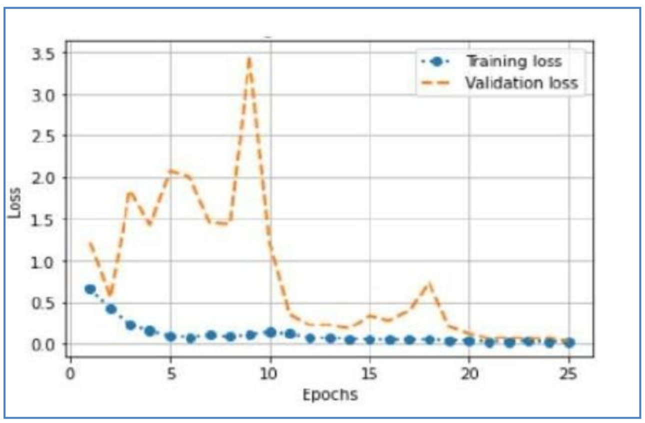

Fig 4.1.2 : Loss v/s epoches

4.2 SCREENSHOTS

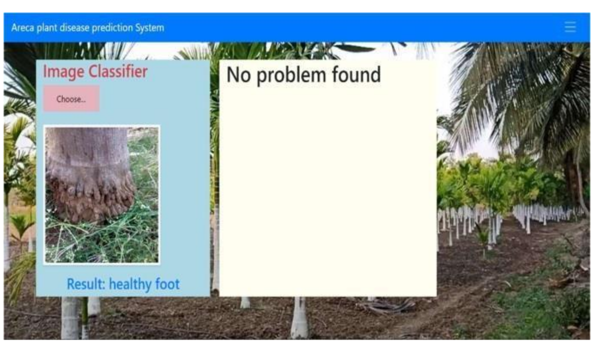

Fig 4.2.1 : Screen showing result of classifcation for healthy food

Fig

4.2.2 : Screen showing result of classifcation for yellow leaf disease

V. CONCLUSION

In conclusion, the AI-based areca nut plant disease classification system represents a significant advancement in agricultural technology, offering farmers a powerful tool for early disease detection and effective management strategies. Through rigorous training and evaluation, the system demonstrates high levels of accuracy in identifying and categorizing diseases affecting areca nut plants, thereby enabling timely intervention and mitigation of crop losses. The user-friendly interface and seamless integration into existing agricultural workflows ensure widespread adoption and usability among farmers, enhancing its practical relevance and impact in real-world agricultural settings.

Furthermore, the system's scalability and adaptability to different environmental conditions and disease scenarios underscore its potential to address the diverse challenges faced by farmers in areca nut cultivation. By continuously monitoring performance and incorporating user feedback, the system can evolve and improve over time, further enhancing its effectiveness and relevance in agricultural practices.

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