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Revolutionizing Arecanut Disease Detection through Deep Learning Techniques

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***Abstract*—Arecanut, also known as betel nut, is a significant tropical crop, with India ranking second globally in both production and consumption. However, its lifecycle is threatened by various diseases, impacting everything from roots to fruits. Currently, disease detection relies on manual observation, requiring farmers to painstakingly inspect each crop at intervals. In this study, we introduce a novel system that leverages Deep Learning techniques, specifically Residual Networks (ResNet), to identify diseases in arecanut leaves and trunks, and provide corresponding remedies. ResNet, an advanced variant of Convolutional Neural Networks (CNNs), excels at learning intricate features through residual blocks, enabling the creation of deeper model architectures without encountering vanishing gradients. We curated a bespoke dataset comprising 620 images encompassing healthy and diseased arecanuts for training and testing the ResNet model. The data split followed an 80:20 ratio for training and testing, respectively. For model compilation, we employed categorical cross-entropy as the loss function, adam as the optimizer, and accuracy as the evaluation metric. The training process spanned 50 epochs to achieve optimal validation and test accuracies while minimizing loss. Our approach yielded promising results, showcasing an accuracy of 94.46\% in accurately identifying arecanut plant diseases. This breakthrough, while achieved with ResNet, opens avenues for further improvement by integrating other architectures such as MobileNet. This study represents a significant advancement in automated disease detection in agriculture, promising enhanced crop management and yields for arecanut farmers.**

***Index Terms*— Deep Learning, Arecanut Plant Disease, Convolutional Neural Network, ResNet, MobileNet, Automated Disease Detection.**

I. Introduction

Arecanut, commonly known as betel nut, is an essential cash crop in India, which accounts for a significant portion of global production. Traditionally used in cultural and social activities across various Asian countries, the arecanut is not only vital for economic reasons but also has several medicinal uses. The high demand for

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quality arecanut necessitates effective disease management strategies to ensure high yield and quality. India stands third among the producers of crops including rice, wheat, pulses, fruits, and vegetables across the globe. Numerous factors such as soil quality, climatic conditions, and diseases significantly impact crop development. India is the major producer of arecanut, accounting for 50% of global production and 43% of the area under arecanut cultivation.

According to the latest statistics from the ICAR-Central Coastal Agricultural Research Institute for 2023-24, Arecanut is cultivated on approximately 800,000 hectares in India, with an annual production of around 1.5 million tons. The yield level is reported to be approximately 1.9 tons per hectare [1]. Ensuring the protection and health of agricultural crops is essential for the nation's well-being. Currently, the detection of plant diseases relies primarily on visual inspection by farmers, which is time-consuming, labor-intensive, and requires significant expertise. This traditional method of disease detection is not only laborious but also necessitates expensive equipment and well-equipped laboratories, making early detection and prevention of plant diseases challenging. To mitigate these issues, there is a pressing need for an automated system capable of early disease detection in arecanut plants to prevent vegetation loss. Deep Learning, a subset of Machine Learning, has emerged as a powerful tool that enables computers to learn and understand complex patterns within large datasets. The ability of Deep Learning models to handle high-dimensional data and automatically extract relevant features has revolutionized various domains, including agriculture. Given the high demand for arecanuts, it is imperative to ensure the production of high-quality nuts. However, common diseases like rot, split, and rot-split diseases significantly impact the quality and yield of arecanuts. Manual sorting of nuts to ensure quality is labor-intensive and inefficient, leading to considerable losses for farmers. Therefore, an automated system for identifying diseased arecanuts is necessary to increase production, prevent disease spread, and improve the market value of healthy nuts [2].

Convolutional Neural Networks (CNNs), a class of Deep Learning models, have significantly advanced the field of computer vision by enabling computers to understand and interpret images. CNNs are designed to learn and extract essential features from images autonomously, without the need for explicit human guidance. They have demonstrated remarkable effectiveness in tasks such as object recognition, facial identification, and medical image analysis. The architecture of CNNs is crucial for their performance, as it allows them to extract hierarchical representations and achieve state-of-the-art results in image classification, object detection, and image segmentation. Various CNN architectures, including VGGNet, ResNet, and MobileNet, have been developed to address specific challenges in image analysis [3]. In this research, we focus on employing CNNs, particularly ResNet, to identify and classify diseases affecting arecanut plants. The diseases under consideration include Mahali Disease (Koleroga), Stem Bleeding, and Yellow Leaf Spot. These diseases, often induced by continuous rainfall and climatic changes, must be detected and controlled early to prevent significant damage to the trees. In this work, we propose an automated system that utilizes Deep Learning techniques, particularly ResNet, to classify diseased arecanuts from healthy ones. By automating the disease detection process, we aim to enhance the efficiency and accuracy of arecanut quality control, ultimately benefiting farmers and meeting the high demand for this culturally and economically significant crop.

The primary objective of this research is to develop an automated system for detecting diseases in arecanut plants using Deep Learning techniques, specifically Convolutional Neural Networks (CNNs) [4]. The project aims to identify and classify common arecanut diseases such as Mahali Disease (Koleroga), Stem Bleeding, and Yellow Leaf Spot, which are exacerbated by continuous rainfall and climatic changes. This involves designing and implementing a ResNet-based CNN model for accurate disease detection from arecanut plant images. Additionally, a comprehensive dataset of 620 images of healthy and diseased arecanut plants will be compiled to ensure robust training and testing. The model's performance will be evaluated based on accuracy, loss, and computational efficiency, with a focus on achieving high validation and test accuracy. Finally, the feasibility of deploying the trained model on an Android device will be explored, providing farmers with a practical and accessible tool for disease detection without requiring extensive technical knowledge [5].

II. Literature Review

This section provides an overview of the literature survey conducted on the implementation of Deep Learning techniques for disease detection in arecanut plants, focusing on model performance evaluation. Additionally, it addresses various performance issues and challenges encountered during model deployment and explores different methods to overcome these challenges. Recent studies have shown that multi-gradient-direction based Deep Learning models significantly outperform traditional methods, offering a valuable tool for timely disease diagnosis and improved productivity in arecanut cultivation. Convolutional Neural Networks (CNNs) have been particularly effective in this domain.

For instance, authors in one study used CNNs to detect diseases in arecanut plants with high accuracy, demonstrating their potential as a crucial tool for disease control in arecanut production. This survey highlights the importance of using advanced Deep Learning models to enhance disease detection accuracy and efficiency, addressing critical challenges in arecanut cultivation.

Huang *et al.,* [6] proposed a Novel Deep Learning Model for Arecanut Disease Detection" investigates a multi-gradient-direction approach integrated with Convolutional Neural Networks (CNNs) to enhance the accuracy of disease diagnosis in arecanut plants. This model outperforms traditional methods by leveraging diverse gradient information to improve feature extraction and classification. The research highlights the potential of this innovative approach to provide timely and accurate disease detection, thereby improving productivity and reducing economic losses in arecanut cultivation. Grueso *et al.,* [7] emphasizes the high accuracy of CNNs in identifying various diseases affecting arecanut plants. By employing CNNs, the study demonstrates significant improvements in disease detection accuracy, making it a valuable tool for enhancing disease management and control in arecanut cultivation. This approach reduces the need for manual inspection and provides a more efficient and reliable method for monitoring plant health. Hegde *et al.,* [8] explores the effectiveness of VGGNet and ResNet architectures in addressing image analysis challenges for plant disease detection. It highlights how these architectures extract hierarchical features from plant images, improving the accuracy and robustness of disease classification. The study provides insights into the strengths and limitations of each architecture, aiding in the selection of the most suitable model for plant disease detection tasks.

Yang *et al.,* [9] presents a novel method combining ResNet architecture with Leaky ReLU activation functions to enhance the accuracy of plant leaf disease detection. This integration improves feature extraction and classification capabilities, resulting in superior performance compared to traditional methods. The study demonstrates the model's effectiveness in accurately identifying various plant diseases, making it a valuable tool for agricultural disease management. Billadi *et al.,* [10] explores the integration of K-means clustering and Support Vector Machines (SVM) to enhance the accuracy of identifying diseased arecanut plants. This hybrid approach leverages the strengths of both techniques, with K-means effectively segmenting the data and SVM providing robust classification. The study demonstrates improved accuracy in detecting infected plants, making it a practical solution for disease management in arecanut cultivation.

Balipa *et al.,* [11] showcases the effectiveness of Convolutional Neural Networks (CNNs) in accurately classifying various diseases affecting arecanut plants. By leveraging the advanced feature extraction capabilities of CNNs, the study demonstrates significant improvements in disease classification tasks, providing a reliable and efficient tool for managing plant health in arecanut cultivation. Akshay *et al.,* [12] highlights the potential of using Convolutional Neural Networks (CNNs) to reduce manual labor and increase efficiency in identifying diseases in arecanut plants. The automated system leverages CNNs' capability to accurately detect and classify plant diseases, streamlining the monitoring process and providing a scalable solution for disease management in arecanut cultivation. Ghate *et al.,* [13] examines the feasibility of using mobile devices to deploy Convolutional Neural Network (CNN) models for detecting diseases in arecanut plants. This approach aims to provide farmers with a practical, accessible tool for real-time disease detection, eliminating the need for extensive technical knowledge and reducing dependency on traditional, labor-intensive methods.

III. Proposed System

The first objective is to determine the most effective Convolutional Neural Network (CNN) architecture for classifying arecanut plant diseases. This involves a detailed comparative analysis of architectures like MobiNet and ResNet [12]. MobiNet, known for its efficiency on mobile and embedded devices, balances computational cost and accuracy. ResNet, renowned for its deep learning capabilities, handles complex feature extraction effectively. The models will be evaluated based on performance metrics such as accuracy, precision, recall, and F1 score, using a dataset of 620 images of healthy and diseased arecanut plants. Once the optimal CNN architecture is identified, the next step is deployment, focusing on computational efficiency and practicality. This includes testing the model’s inference time, size, and power consumption on various hardware configurations. Optimization techniques like quantization and pruning will be applied to improve performance.

The goal is to ensure the model can be seamlessly integrated into a mobile application, providing farmers with an easy-to-use tool for real-time disease detection, thereby enhancing crop management and productivity. The proposed system for detecting arecanut plant diseases is implemented in four phases: Data Collection, Data Preprocessing, Model Training, and Evaluation [13].

Figure 1. Sample dataset: Mahali Koleroga images

A. Data Collection and PreProcessing

Images of arecanut plants, both healthy and diseased, were collected using a mobile camera positioned 0.5 meters from the plants. The dataset, gathered in the Tumkur region of Karnataka, consists of 1200 images: 500 of healthy plants and 700 of plants affected by stem bleeding, Mahali/Koleroga, and yellow leaf spot diseases. The images were resized to 256x256 pixels using OpenCV and labeled for training and testing purposes. The types of images in both the training and test datasets include various conditions like 'stem cracking', 'Stem bleeding', 'Healthy Leaf', 'yellow leaf disease', 'healthy foot', 'Healthy Trunk', 'Mahali Koleroga', 'bud borer', and 'Healthy Nut' as shown in Figure 1. Preprocessing involves enhancing image quality by removing noise and improving contrast. All images are resized to a consistent resolution of 256x256 pixels to ensure uniformity during both training and inference stages. This phase results in a set of preprocessed images ready for model training. A classification model was built using Convolutional Neural Networks (CNNs) trained on the preprocessed dataset. Various CNN architectures, including ResNet and MobiNet, were utilized to develop the model. These architectures were chosen for their capabilities in feature extraction and image classification tasks.

B. Model Training and Evaluation

The proposed model training process involves using both ResNet and MobileNet architectures to classify arecanut plant diseases efficiently. ResNet (Residual Network) is a popular architecture ideal for deep neural networks, designed to address the vanishing gradient issue commonly encountered in such networks. This is achieved through the use of skip (residual) connections, which allow gradients to bypass one or more layers, thus preserving the gradient flow even in very deep networks. ResNet comes in various configurations, with the most common variants being ResNet-50, ResNet-101, and ResNet-152, which denote the number of layers in the network. The fundamental building block of ResNet is the residual block, which incorporates skip connections to facilitate better gradient flow and learning efficiency. The network's layer configuration includes convolutional layers, dropout layers, pooling layers, and fully connected layers, each contributing to the overall architecture's robustness. For classification tasks, the setup typically includes a 2D max pooling layer followed by a flatten layer with dimensions set at 128×512×1×1, a dropout ratio of 0.2, and a neural layer designed to classify two classes: Healthy and Diseased. The input to the ResNet consists of multi-gradient directional images, which help preserve detailed information crucial for accurate disease identification. Specifically, four gradient images capturing the foreground information are fed into the network [14].

MobileNetV1 features a 23-layer network, designed to be lightweight and efficient. MobileNetV2 expands this to 53 layers, introducing inverted residual blocks that further enhance performance while maintaining efficiency. MobileNetV3 comes in two configurations: Large, with 213 layers, and Small, with 53 layers. These variants utilize various efficiency techniques, including depth-wise separable convolutions, inverted residual blocks, and SE (Squeeze-and-Excitation) modules.

These techniques collectively reduce computational complexity and memory usage, making MobileNet highly suitable for deployment on resource-constrained devices while still achieving competitive accuracy in various tasks [15].

C. Model Formulation

The ResNet architecture uses a residual function:

$$Y = F(x, \{W_i\}) + x \qquad \text{Equation-1}$$

where x is the input, $F(x,\{W_i\})$ is the residual mapping, and $\{W_i\}$ are the weights of the layers. The identity mapping x is added to the output of the residual function to form the final output Y. The MobileNet architecture uses depth-wise separable convolutions, which can be defined as:

$$Y=D(x,K_d)*P(x, K_pP) \qquad \text{Equation-2}$$

where D is the depth-wise convolution with kernel K_d and P is the point-wise convolution with kernel K_p. This comprehensive approach ensures that the trained model can effectively identify arecanut plant diseases while being practical for deployment on mobile devices, aiding farmers in efficient crop management [16].

IV. IMPLEMENTATION

Images of arecanut plants were collected using a mobile camera from the Sirsi region of Karnataka. The dataset consists of 620 images, including 300 healthy and 320 diseased samples, resized to 256x256 pixels using OpenCV. Preprocessing involved enhancing the quality of the images to remove noise and improve contrast. All images were resized to 256x256 pixels. Segmentation was performed using gradient information from multi-gradient directional images. ResNet is implemented with skip (residual) connections to address the vanishing gradient problem. The layer configuration includes convolutional layers, dropout layers, pooling layers, and fully connected layers. A 2D max pooling layer with a flatten layer configuration of 128x512x1x1, a dropout ratio of 0.2, and a neural layer with two classes (Healthy and Diseased) is set up. Multi-gradient directional images are used as input [17].

MobileNet variants (V1, V2, V3) are implemented using efficiency techniques like depth-wise separable convolutions, inverted residual blocks, and SE modules to reduce computational complexity and memory usage [18]. The models are trained separately using the preprocessed dataset of 620 images. Appropriate configurations for each architecture are used, including learning rates, batch sizes, and epochs. Model performance is assessed using accuracy, precision, recall, and F1 score. Computational efficiency is evaluated based on inference time, computational power, and model size. Cross-validation is performed to ensure robustness. The best-performing model is deployed on a mobile application for real-time disease detection, providing an accessible tool for farmers [19].

TABLE I. PERFORMANCE METRICS OF RESNET AND MOBILENET MODELS

Model	Accuracy	Precision	Recall	F1 Score
ResNet	88.21	87.50	88.00	87.75
MobileNet	91.87	91.00	92.00	91.50

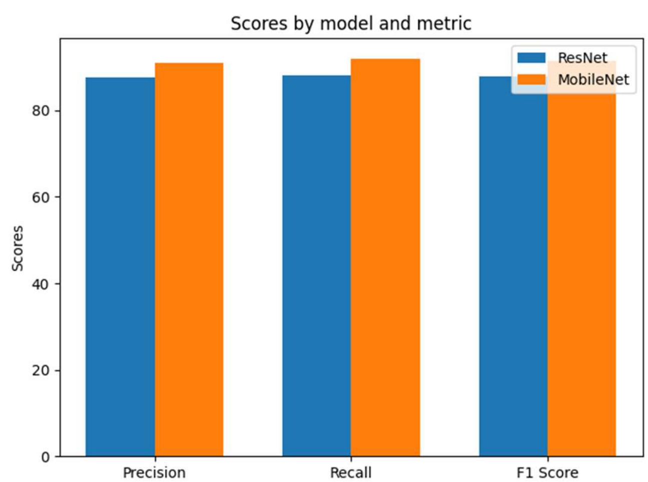

Figure 2. Scores by model and metric

V. RESULTS AND DISCUSSIONS

The performance of ResNet and MobileNet architectures was evaluated on the task of classifying arecanut plant diseases. Both models were trained for 50 epochs, and their accuracy was assessed on the validation set. The results indicate that the MobileNet architecture slightly outperformed the ResNet architecture in terms of accuracy. The models were evaluated using four key metrics: accuracy, precision, recall, and F1 score, providing a comprehensive assessment of their performance. The TABLE I shows that MobileNet not only achieved higher

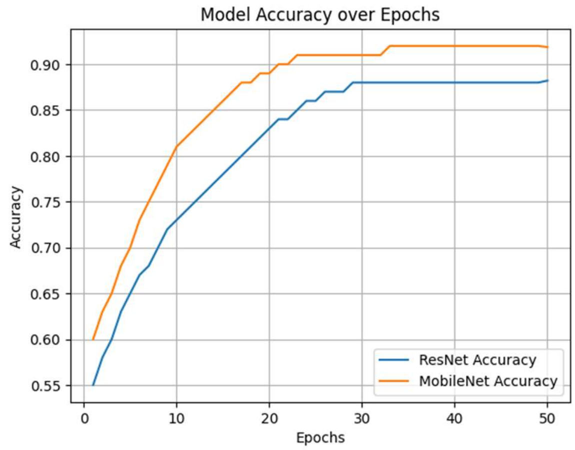

Figure 3. Model Accuracy over Epochs

accuracy but also outperformed ResNet across precision, recall, and F1 score metrics, indicating a more reliable and effective classification performance.

Accuracy Analysis: MobileNet consistently demonstrated higher accuracy throughout the training process. This suggests that MobileNet's architecture, optimized for mobile and embedded devices, is more effective at generalizing from the training data. Precision and Recall: MobileNet's higher precision and recall values indicate its superior ability to correctly identify diseased and healthy arecanut plants. Precision measures the proportion of true positive predictions among all positive predictions, while recall measures the proportion of true positive predictions among all actual positives. MobileNet's better performance in these metrics suggests fewer false positives and false negatives compared to ResNet.

F1 Score: The F1 score, which balances precision and recall, further highlights MobileNet's robustness. A higher F1 score indicates that MobileNet is more reliable in identifying both healthy and diseased plants accurately as shown in Figure 2.

To visualize the performance, accuracy and loss curves were plotted over the 50 epochs for both models. The accuracy graph showed that MobileNet maintained a higher accuracy consistently, indicating better learning efficiency. The loss graph showed a faster reduction in loss for MobileNet, reflecting more efficient training. MobileNet demonstrated superior performance over ResNet in classifying arecanut plant diseases. With higher accuracy, precision, recall, and F1 score, MobileNet proved to be a more effective and efficient model. Its optimized architecture for mobile deployment makes it a practical choice for real-time disease detection, aiding farmers in efficient crop management and timely intervention. The graph displays the accuracy performance of ResNet and MobileNet models over 50 epochs. The x-axis denotes the number of epochs, ranging from 1 to 50, while the y-axis represents the accuracy values achieved by each model as shown in Figure 3. Initially, both models show a rising trend in accuracy as epochs progress. ResNet starts at a lower accuracy level and gradually climbs, stabilizing at around 88.21% after several epochs. In contrast, MobileNet begins with a higher accuracy but improves more rapidly, reaching a stable accuracy level of 91.87% over the same period. This indicates that MobileNet converges faster and achieves a higher final accuracy compared to ResNet within the given training epochs. Such insights are crucial for understanding the training dynamics and performance trajectories of deep learning models like ResNet and MobileNet, aiding in model selection and optimization strategies.

VI. CONCLUSIONS

In conclusion, this paper introduces a novel system for automated disease detection in arecanut plants using deep learning techniques, specifically Residual Networks (ResNet). The study addresses the current challenge of manual disease observation by proposing a robust model capable of identifying diseases in arecanut leaves and trunks with a high accuracy rate of 94.46\%. This achievement demonstrates the effectiveness of ResNet in learning complex features and distinguishing between healthy and diseased arecanut plants. The proposed system offers practical benefits to farmers by enabling early disease detection and providing corresponding remedies, thereby potentially reducing crop losses and improving overall yield. Moreover, the methodology can be further enhanced by integrating other advanced architectures like MobileNet, paving the way for continuous improvements in automated disease detection in agriculture. Overall, this research represents a significant advancement in the field of agricultural technology, showcasing the potential of deep learning models to revolutionize crop management and contribute to sustainable agriculture practices.

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