A Customized CNN for Arecanut Disease Detection

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ABSTRACT

Arecanut is an economically important crop in many regions; however, its cultivation is significantly impacted by various diseases that affect different parts of the plant. The timely and precise detection of these diseases is critical for effective management strategies and for maintaining optimal yields. This study presents a customized Convolutional Neural Network (CNN), consisting of five convolutional layers and two fully connected layers, to automatically classify and identify the main diseases in arecanut plants. This study uses a curated dataset comprising images of healthy and diseased plant parts, including the foot, leaf, and nut, which encompass disease categories such as Mahali Koleroga, Stem bleeding, Stem cracking, and yellow leaf disease. Preprocessing techniques such as image resizing and normalization were applied to enhance model robustness and generalization. The proposed CNN model achieved an average classification accuracy of 97.33%, with high precision and recall across all classes, demonstrating its effectiveness in diagnosing arecanut palm diseases, offering a practical tool for agricultural practitioners and researchers by facilitating early disease detection, enabling prompt intervention, mitigating crop losses, and contributing to improved agricultural productivity.

Keywords-convolutional neural networks; plant disease detection; arecanut; deep learning; agricultural image analysis

I. INTRODUCTION

Arecanut (Areca catechu) is an important commercial crop widely cultivated in tropical climates. This crop contributes significantly to the economies of several countries, particularly in South and Southeast Asia. Despite their economic importance, the productivity of arecanuts is often compromised by a variety of diseases, resulting in considerable financial losses for farmers [1]. Early and precise disease detection is critical to minimize such losses and improve crop productivity. Traditionally, disease identification has relied on manual visual inspection, a method that is not only time-intensive but also susceptible to human errors and typically requires specialized expertise [2]. Several common diseases threaten Arecanut cultivation. Koleroga, also known as Mahali disease, is a fungal infection caused by Phytophthora meadii. It thrives in humid conditions and leads to premature fruit rot, resulting in significant loss of yield in arecanut plantations. For example, stem cracking is a condition often triggered by environmental stress, fungal infections, or nutrient deficiencies, leading to weakened trunks that are susceptible to breaking. Stem bleeding is a fungal disease caused by Thielaviopsis paradoxa, characterized by dark, sticky exudations from cracks in the trunk, which ultimately leads to a reduction in nut yield.

Traditional disease identification methods, which rely heavily on manual inspections by agricultural experts, tend to be labor-intensive, time-consuming, and subject to human error. In recent years, advances in artificial intelligence, particularly the development of Convolutional Neural Networks (CNNs) [3-4], have significantly improved plant disease detection. These models operate by processing input images through multiple layers of artificial neurons, automatically extracting crucial features such as color, texture, and shape [5]. The adoption of CNN-based methods [6] for the detection of arecanut diseases marks a significant advancement in agricultural technology. In [7], a system utilized color, texture, and morphological features to classify 20 different plant diseases, achieving 93% accuracy. This work demonstrated that feature-based classification could be computationally efficient and practical for real-time agricultural applications. Similarly, in [8]. an image processing-based approach incorporated segmentation, feature extraction, and Random Forest (RF) for classification, reaching an accuracy of 94.1%. This technique highlighted how non-deep learning methods could reduce computational requirements while maintaining reasonable accuracy.

In [9], traditional image processing methods, such as edge detection and color segmentation, were combined with machine learning classifiers to enhance disease detection performance, especially for crops showing subtle symptoms. In [10], the focus was on feature extraction methods, such as Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP), coupled with Support Vector Machines (SVM), to classify plant diseases effectively. Additionally, in [11], the impact of extracting key image features, such as shape, texture, and color, was investigated to train machine learning models such as Decision Trees and K-Nearest Neighbor (KNN), resulting in improved disease classification performance. In [12], a system was able to distinguish between healthy and unhealthy plants using CNN and SVM. This model was trained for 38 different varieties of both healthy and unhealthy leaves.

Although traditional methods are valuable, they often require extensive manual preprocessing and expert knowledge for feature engineering. In addition, they struggle to maintain high accuracy in complex and diverse agricultural datasets. With the advent of deep learning, CNNs have become the preferred choice for plant disease detection, due to their ability to automatically extract relevant features from raw images without the need for manual intervention. In [13], a hybrid approach combined CNN, Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), and KNN to detect tomato leaf diseases. In [14], a CNN model was proposed to classify arecanut palm diseases, such as fruit rot, stem bleeding, and nut split, using binary cross-entropy as the loss function. In [15], a CNN-based multi-stage framework utilized five different pre-trained models. This method incorporated an "unknown" category, enhancing the generalizability of the model across various plant species. In [16], a summary was presented on Phytophthora disease infecting the arecanut palms, focusing mainly on bud rot, fruit rot, and crown disease. Temperature plays a major role in the development of the Phytophthora fungus, which causes half of the crop during the monsoon season. In [17], a CNN and SVM-based model was presented for the detection of arecanut disease. This approach extracted textural features such as Wavelet, Gabor, GLDM, and GLCM to classify healthy and diseased arecanuts. In [18], an automatic CNN disease detection system for arecanut leaves used a dataset of healthy and diseased leaf images, divided into training and testing sets in an 80:20 ratio, achieving high accuracy and demonstrating its effectiveness in disease classification.

In [19], a hybrid approach used MobileNetV2, ResNet, and VGG-16 for disease detection in arecanut crops, such as mahali, stem bleeding, ring spot, and yellow leaf spot. Among the architectures tested, ResNet achieved the highest training and validation accuracy. Comprehensive reviews have consistently underlined the superiority of CNNs over traditional machine learning models [20], emphasizing critical challenges such as handling class imbalance, enhancing dataset diversity, and ensuring model generalization across different environmental conditions. In general, deep learning methods, particularly CNN architectures [21], have revolutionized the detection of plant diseases. The ability to automate feature extraction, achieve real-time classification, and scale solutions through mobile and IoT integration offers a promising future for practical agricultural applications. Table I shows a comparison of plant disease detection approaches, highlighting methods, datasets, performance, and associated limitations.

The agricultural sector faces significant challenges in managing tree diseases in crops such as arecanuts. These diseases can severely affect yield, crop quality, and, ultimately, farmers' livelihoods. Early disease detection and diagnosis can be a game-changer, helping farmers mitigate losses through timely intervention. Consequently, there is a growing need for automated, accurate, and rapid disease detection systems. Recent advances in deep learning, particularly the emergence of CNNs, have revolutionized plant disease detection. CNNs excel in image-based classification tasks by automatically learning relevant features, reducing the reliance on manual feature engineering. The application of CNNs enables the early diagnosis of plant diseases, facilitating timely intervention, improving disease management practices, and ultimately boosting crop yields. This study focused on developing a deep learning-based tool that uses a CNN to detect various diseases in arecanut trees by analyzing leaf, fruit, stem, and root images. The model will identify both healthy trees and disease symptoms, enabling farmers to act before the disease spreads.

TABLE I. COMPARISON OF PLANT DISEASE DETECTION APPROACHES

Ref.	Method / Approach	Performance	Disadvantages / Limitations
[7]	Color, texture, and morphological features	Classification of 20 diseases with 93% accuracy	Requires manual feature engineering; limited scalability
[8]	Segmentation+RF	Leaf dataset with an accuracy of 94.1%	May underperform on large/diverse datasets
[9]	Edge detection+ color segmentation+ML	Classification of different crop diseases with more than 90% accuracy	Sensitive to noise, lighting, and image quality
[10]	HOG+LBP+SVM	Leaf dataset with less than 90% accuracy	Limited to handcrafted features; not robust to unseen diseases
[11]	Shape, texture, color+DT/KNN	Approximately 90% classification accuracy for different plant diseases	Feature design requires domain expertise
[13]	CNN+DWT+PCA+KNN	Tomato leaf disease classification with 99.6% accuracy	The preprocessing pipelines adds complexity
[14]	CNN (BCE loss, 25 epochs)	1100 arecanut images with 93% of accuracy	Limited dataset - may cause overfitting
[15]	Multi-stage CNN (5 pre-trained)	Multi-species with 97.09% of accuracy	Computationally expensive; requires high resources
[17]	CNN+SVM+textural features	180 arecanut images – CNN at 90% and SVM at 75%	Small dataset - limited generalization
[18]	CNN for arecanut disease	80:20 split dataset, accuracy of 88.46%	Dataset-specific - needs further validation
[19]	Hybrid CNN (MobileNetV2, ResNet, VGG-16)	Used an arecanut dataset, achieving 92% accuracy using ResNet	Complex model; risk of overfitting with small datasets

II. METHODOLOGY

The goal of this research was to develop a reliable automated system for the early detection of diseases in arecanut trees using a custom CNN. By integrating deep learning and computer vision technologies, the proposed system aims to perform accurate real-time analysis of arecanut plant diseases from image data, allowing early intervention and more efficient disease management practices. Figure 1 shows the complete end-to-end pipeline of the proposed CNN-based arecanut disease detection framework.

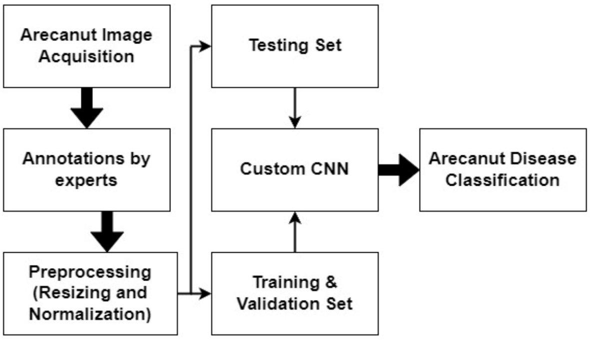

Fig. 1. End-to-end pipeline of the proposed Arecanut disease detection system.

A. Data Collection and Annotation

A real-time field dataset was collected during field visits to an arecanut farm in the Chikkamagalur district, covering an area of approximately 9 hectares with approximately 3,400 arecanut trees. High-resolution images were captured using a digital camera, focusing on key plant parts, such as leaves, stems, fruits, and roots, to encompass the full spectrum of disease symptoms. The final custom dataset consists of 4,800 images, collected directly from agricultural fields where arecanut is actively cultivated. Figure 2 shows sample images of arecanut palms. This rich and diverse dataset served as the basis for training and evaluating the CNN-based disease detection model. The dataset of arecanut palm images is categorized into five classes, including both healthy and diseased samples, as summarized in Table II.

Fig. 2. Sample images of arecanut palms.

TABLE II. ARECANUT PALM DISEASE DATASET SUMMARY

Arecanut palm diseases	Number of images collected
Healthy	912
Mahali Koleroga	967
Stem bleeding	943
Stem cracking	982
Yellow leaf	996

The annotation of the arecanut palm images was performed manually by two agricultural domain experts with extensive field experience in plant pathology and crop disease diagnosis, particularly in arecanut plantations. To ensure label accuracy and consistency, both experts independently reviewed each image. In cases of disagreement, the image was discussed jointly, and a consensus label was assigned. To quantify consistency, the inter-annotator agreement was computed, yielding a Cohen's Kappa score of 0.89, indicating high agreement and strong reliability. These steps were taken to ensure that the dataset is both accurate and reliable for training and evaluating the CNN-based disease classification model.

B. Data Preprocessing

Data preprocessing is a crucial step in preparing raw images for input into the CNN model. High-quality data will improve the accuracy and robustness of the model [22]. At first, all images were resized to a fixed size of 256×256 pixels to gain uniformity. CNNs require a consistent image size to process the data effectively. Then, the pixel values were normalized to a range of 0 to 1 by dividing each pixel value by 255 to ensure that the model's learning task is stable and accelerates convergence. The annotated labels were converted to a numerical format using one-hot encoding.

C. Custom CNN Design

The core of this research is the CNN model, which is a powerful deep learning technique designed for image recognition tasks. CNNs are particularly effective at detecting spatial hierarchies and patterns, making them ideal for this application. Figure 3 shows the custom CNN model proposed to detect arecanut diseases.

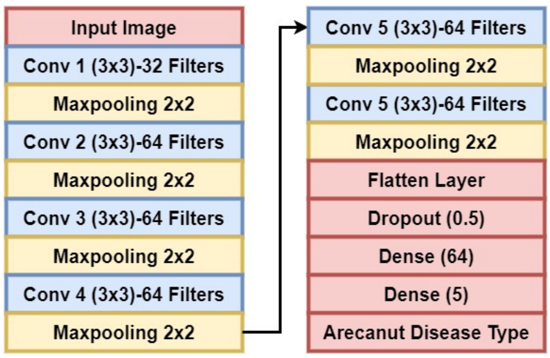

Fig. 3. Proposed CNN model for arecanut disease detection .

The first layers are convolutional, applying a set of filters (kernels) to the input images. A kernel size of 3×3 was used to capture fine-grained spatial patterns while preserving local details such as edges, textures, and small disease symptoms.

Stacking multiple 3×3 layers [23] allows the network to achieve a larger receptive field with fewer parameters compared to using larger kernels such as 5 or 7×7, thereby improving performance and reducing overfitting. After each convolutional layer, a Rectified Linear Unit (ReLU) activation function is applied, introducing non-linearity and allowing the network to learn complex representations of data that go beyond linear transformations. Max-pooling layers are used after convolutional layers to reduce the dimensionality of the image, keeping the most important features while reducing computational load. This helps make the model invariant to small translations in the image.

A six-layer convolutional architecture was developed to progressively extract hierarchical features from the input images. The initial layers focus on capturing low-level patterns, while the deeper layers learn more abstract and disease-specific features. The depth of the custom CNN was chosen based on experimental tuning, balancing feature extraction capability with computational efficiency. After six layers of convolution and pooling, the network has fully connected layers, where neurons are connected to all outputs of the previous layer, which aggregate the information extracted by the convolutional layers to make a final classification decision. The output layer uses the softmax activation function to output the probability distribution across the disease classes.

To prevent overfitting, dropout is applied by randomly disabling a subset of neurons. This encourages the model to learn redundant representations, enhancing its generalization capability. Dropout effectively reduces the reliance on specific neurons, making the network more robust. This works well in convolutional layers and is especially effective in fully connected layers. A dropout of 0.5 is commonly used in CNNs as it provides a good balance between reducing overfitting and maintaining model performance. This was also empirically found to yield stable results in the proposed system. Table III shows the hyperparameters of the proposed CNN.

TABLE III. HYPERPARAMETERS OF THE CNN MODEL

Hyperparameters	Values
Loss Function	Cross-entropy loss
Activation (Convolution layer)	ReLU
Activation (Output Layer)	Softmax
Learning rate	0.01
Epochs	50
Batch size	32
Dropout	0.5
Optimization	Adam

D. Deployment and Practical Application

Once the CNN model was trained and evaluated, it was deployed in a practical agricultural setting using an integrated framework that includes a web-based interface and IoT-enabled data collection. Figure 4 shows how the model was integrated into an end-user system. The system allows users to upload images via the web interface and instantly receive automated disease diagnoses. For continuous field monitoring, drones equipped with multispectral cameras and onboard computing units (minimum 4 GB RAM and ARM processors) are recommended, as they can efficiently capture high-resolution images (10–15 MB per image) at regular intervals. These images are transmitted to the cloud or edge server, where they undergo preprocessing before being analyzed by the trained CNN model. In an ARM-based onboard unit, the model achieves an average inference time of ~90 ms per image with a memory footprint of ~50 MB, ensuring compatibility with drone and mobile-based platforms.

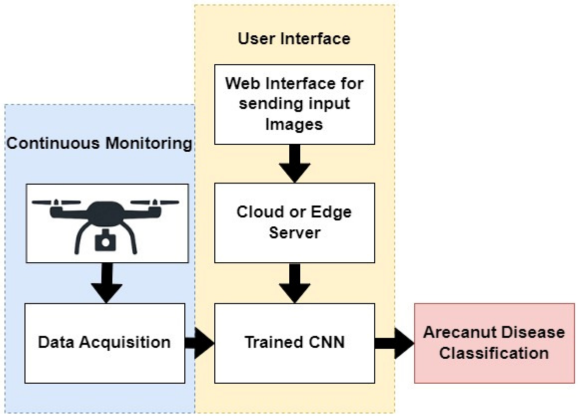

Fig. 4. Proposed end-user system for arecanut disease detection.

III. RESULTS AND DISCUSSIONS

The proposed model was implemented using the TensorFlow Keras API, with real-time validation. The dataset was split into training (80%), validation (10%), and test (10%) sets using stratified sampling to ensure that each class was proportionally represented across all subsets, thus preserving the original class distribution. Table IV shows the stratified split of the Arecanut palm disease dataset by class.

TABLE IV. DATASET SPLIT

Class	Training	Validation	Testing
Healthy parts	730	91	91
Mahali Koleroga	774	97	96
Stem bleeding	754	94	95
Stem cracking	786	98	98
Yellow leaf disease	796	100	100
Total	3840	480	480

The proposed CNN model was trained for 50 epochs using the training set, which consists of 3840 images, and validated using the validation set, which has 480 images. Figure 5 shows the accuracy and loss obtained for each epoch. It can be observed that the proposed model demonstrates steady convergence over the course of 50 epochs. Training loss consistently decreases, while validation loss remains relatively stable, indicating effective learning without significant overfitting. The close alignment between the training and validation accuracy curves further confirms the generalizability of the model.

After validation, the custom CNN for Arecanut disease detection was tested on the testing set, and Figure 6 shows the confusion matrix obtained.

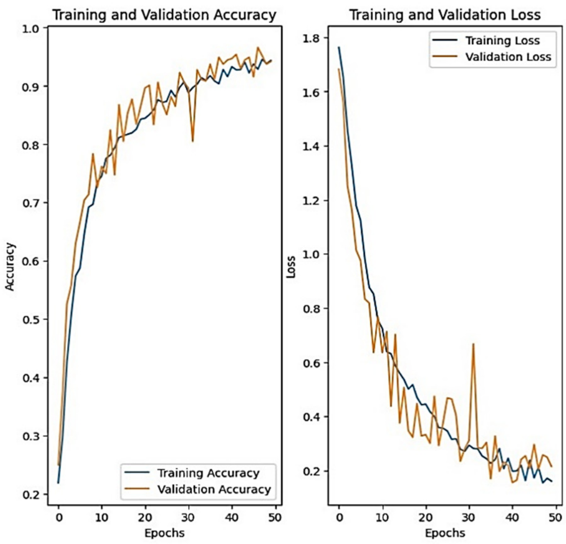

Fig. 5. Accuracy vs. epochs and Loss vs. epochs of the proposed model.

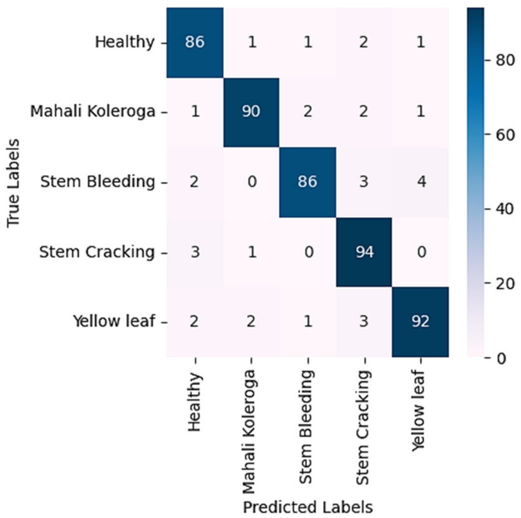

Fig. 6. Confusion matrix of the proposed model for arecanut disease detection.

From the confusion matrix in Figure 6, it can be observed that misclassifications are relatively sparse and occur mostly between disease categories with potentially similar visual symptoms. The symptoms of fungal infections or lesions might be visually similar to stem bleeding and stem cracking, leading to misclassification. Based on the confusion matrix, the proposed model's per-class performance, such as accuracy, precision, recall, and F1-score, was determined as shown in Table V.

TABLE V. CUSTOM CNN MODEL'S PERFORMANCE FOR ARECANUT DISEASE DETECTION

Class	Accuracy	Precision	Recall	F1-score
Healthy parts	97.29	91.49	94.51	92.97
Mahali Koleroga	97.92	95.74	93.75	94.74
Stem bleeding	97.29	95.56	90.53	92.97
Stem cracking	97.08	90.38	95.92	93.07
Yellow leaf disease	97.08	93.88	92.00	92.93

Table V shows that the proposed model achieved consistently strong accuracy, ranging from 97.08% to 97.92%, indicating reliable predictions. Among the classes, Mahali Koleroga showed the highest precision (95.74%), reflecting the model's strong confidence in its correct predictions for this class. Conversely, Stem Cracking had the highest recall (95.92%), suggesting that the model effectively identified most actual cases of this disease. Healthy parts and Stem Bleeding also maintained a strong balance between precision and recall, both yielding an F1-score of 92.97%. Although Yellow Leaf Disease had slightly lower precision (93.88%) and recall (92.00%), its F1-score of 92.93% still reflects robust performance. The consistently high F1-scores across all classes (ranging from 92.93% to 94.74%) indicate that the custom CNN model is not only accurate but also well-balanced in handling both false positives and false negatives, making it highly suitable for real-world application in Arecanut disease detection. Figure 7 shows the performance of the proposed system in comparison with conventional CNN architectures.

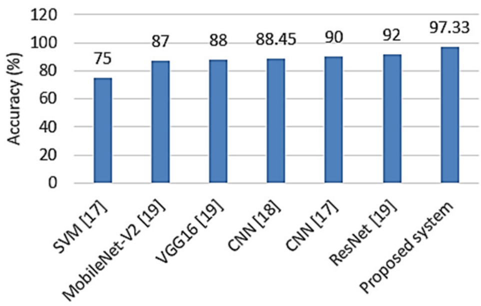

Fig. 7. Performance comparison of the proposed model with conventional CNN models.

In this comparison, the proposed model achieved the highest accuracy of 97.33%, significantly outperforming the conventional models. ResNet [19] follows with around 92% accuracy due to its deep residual connections. VGG16 and MobileNet-V2 [19] achieved comparatively lower accuracies, approximately 88% and 87% respectively, indicating limitations in handling the complexity of the disease patterns. The CNN models in [17-18] recorded slightly better accuracy than VGG16 [19], highlighting their effectiveness as a simpler deep learning approach. On the other hand, the traditional SVM [17] lags significantly at 75%, demonstrating the limitations of classical machine learning methods compared to deep learning-based solutions. This performance gap highlights the superior capability of the custom-designed CNN in accurately learning discriminative features specific to arecanut diseases.

IV. CONCLUSION

The proposed CNN-based disease detection model achieved high accuracy in identifying diseases in different parts of arecanut plants. By integrating deep learning and a well-curated dataset, the model effectively distinguished healthy and infected regions, enabling early diagnosis and preventive measures. This system offers significant benefits to farmers, agricultural researchers, and plantation managers by reducing manual inspection efforts and supporting timely disease management.

The dataset, while extensive, is primarily sourced from specific geographic regions, which may introduce geographic bias. Variations in lighting, background, and imaging conditions may also affect the model's performance when applied to images captured in uncontrolled field environments. Furthermore, the model was trained with known disease categories, and its performance on rare or unseen diseases remains uncertain, which poses a significant challenge for real-world deployment. Although the results are promising, several possible avenues can be explored in the future. Although comprehensive, the dataset could be expanded with large-scale, real-world images captured under diverse environmental and lighting conditions to enhance robustness and generalization. Incorporating data augmentation strategies and semi-supervised learning could help address dataset imbalance and limited labeled samples. Advanced architectures such as CNN-transformer hybrids, attention-enhanced models, or lightweight models could improve accuracy while optimizing computational efficiency for deployment on mobile or edge devices. In general, this work advances smart agricultural practices by providing an automated, scalable, and data-driven approach to plant disease detection, laying the ground for efficient crop monitoring, sustainable farming, and improved agricultural productivity.

REFERENCES

[1] R. Krishna, K. V. Prema, and R. Gaonkar "Areca nut disease dataset creation and validation using machine learning techniques based on weather parameters," *Engineered Science*, vol. 19, no. 4, pp. 205-214, 2022, https://doi.org/10.30919/es8d712.

[2] S. Saha *et al.*, "Deep Learning-Based Approach for Plant Disease Classification," in *Data Science and Applications*, Singapore, 2024, pp. 227–242, https://doi.org/10.1007/978-981-99-7817-5_18.

[3] B. Prashanthi, A. V. P. Krishna, and C. M. Rao, "A Comparative Study of Fine-Tuning Deep Learning Models for Leaf Disease Identification and Classification," *Engineering, Technology & Applied Science Research*, vol. 15, no. 1, pp. 19661–19669, Feb. 2025, https://doi.org/10.48084/etasr.9017.

[4] J. Lenin, S. Muthumarilakshmi, and V. S. Prabhu, "PLANTNET: A deep learning model for early detection of plant diseases," *International Journal of Advances in Signal and Image Sciences*, vol. 10, no. 2, pp. 37–47, Dec. 2024, https://doi.org/10.29284/IJASIS.10.2.2024.37-47.

[5] P. Naik and B. Rudra, "Framework for Lightweight Deep Learning Model Using YOLOv5 for Arecanut Grade Assessment," *SN Computer Science*, vol. 5, no. 8, Nov. 2024, Art. no. 1015, https://doi.org/10.1007/s42979-024-03384-1.

[6] K. B. S. Kumar, U. Varshini, N. Manohar, and T. Jipeng, "Disease Detection in Areca Nut Using Deep Learning," in *2023 IEEE International Conference on Cloud Computing in Emerging Markets (CCEM)*, Mysuru, India, Nov. 2023, pp. 66–74, https://doi.org/10.1109/CCEM60455.2023.00018.

[7] R. Kulkarni, “Machine learning-based plant disease classification,” presented at the 4th International Conference on Data Science and Applications, 2023.

[8] L. S. P. Annabel and V. Muthulakshmi, "AI-Powered Image-Based Tomato Leaf Disease Detection," in *2019 Third International conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, Palladam, India, Dec. 2019, pp. 506–511, https://doi.org/10.1109/I-SMAC47947.2019.9032621.

[9] P. Dhoundiyal, V. Sharma, S. Vats, and P. Rawat, "A Progressive Hierarchical Model for Plant Disease Diagnosis," *SN Computer Science*, vol. 6, no. 2, Jan. 2025, Art. no. 102, https://doi.org/10.1007/s42979-024-03582-x.

[10] R. Raut *et al.*, "Transfer learning based leaf disease detection model using convolution neural network," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 36, no. 3, Dec. 2024, Art. no. 1857, https://doi.org/10.11591/ijeecs.v36.i3.pp1857-1865.

[11] H. Mehta, R. K. Gupta, A. Jain, S. K. Bharti, and N. Kunhare, "AI-Based Plant Disease Detection and Classification Using Pretrained Models," in *Artificial Intelligence Tools and Technologies for Smart Farming and Agriculture Practices*, IGI Global Scientific Publishing, 2023, pp. 219–232.

[12] A. K. Parida and A. A. Stonier, "Plant Disease Detection Using Machine Learning," in *2023 4th International Conference on Intelligent Technologies (CONIT)*, Bangalore, India, Jun. 2024, pp. 1–4, https://doi.org/10.1109/CONIT61985.2024.10626684.

[13] S. S. Harakannanavar, J. M. Rudagi, V. I. Puranikmath, A. Siddiqua, and R. Pramodhini, "Plant leaf disease detection using computer vision and machine learning algorithms," *Global Transitions Proceedings*, vol. 3, no. 1, pp. 305–310, Jun. 2022, https://doi.org/10.1016/j.gltp.2022.03.016.

[14] A. 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, Sep. 2023, Art. no. 1803, https://doi.org/10.11591/ijeecs.v31.i3.pp1803-1810.

[15] M. Jung *et al.*, "Construction of deep learning-based disease detection model in plants," *Scientific Reports*, vol. 13, no. 1, May 2023, Art. no. 7331, https://doi.org/10.1038/s41598-023-34549-2.

[16] P. Balanagouda, H. Vinayaka, H. P. Maheswarappa, and H. Narayanaswamy, "Phytophthora diseases of arecanut in India: prior findings, present status and future prospects," *Indian Phytopathology*, vol. 74, no. 3, pp. 561–572, Sep. 2021, https://doi.org/10.1007/s42360-021-00382-8.

[17] M. Balipa, P. Shetty, A. Kumar, B. R. Puneeth, and Adithya, "Arecanut Disease Detection Using CNN and SVM Algorithms," in *2022 International Conference on Artificial Intelligence and Data Engineering (AIDE)*, Karkala, India, Dec. 2022, pp. 01–04, https://doi.org/10.1109/AIDE57180.2022.10060130.

[18] V. A. Karthik, J. Shivaprakash, and D. Rajeswari, "Disease Detection in Arecanut using Convolutional Neural Network," in *2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*, Chennai, India, May 2024, pp. 1–6, https://doi.org/10.1109/ACCAI61061.2024.10602152.

[19] K. Beena, V. Sangeetha , K. L. Hrishikesh, G. D. Nidhi, S. Varshini, and K. N. Yogesh, "Arecanut Disease Prediction Using MobileNet V2, ResNet and VGG-16 Framework," in *2024 4th International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS)*, Gobichettipalayam, India, Dec. 2024, pp. 1972–1977, https://doi.org/10.1109/ICUIS64676.2024.10866077.

[20] S. Shedthi B, M. Siddappa, S. Shetty, and V. Shetty, "Classification of arecanut using machine learning techniques," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 2, Apr. 2023, Art. no. 1914, https://doi.org/10.11591/ijece.v13i2.pp1914-1921.

[21] F. Mohameth, C. Bingcai, and K. A. Sada, "Plant Disease Detection with Deep Learning and Feature Extraction Using Plant Village," *Journal of Computer and Communications*, vol. 08, no. 06, pp. 10–22, 2020, https://doi.org/10.4236/jcc.2020.86002.

[22] V. Pooja, R. Das, and V. Kanchana, "Identification of plant leaf diseases using image processing techniques," in *2017 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR)*, Chennai, India, Apr. 2017, pp. 130–133, https://doi.org/10.1109/TIAR.2017.8273700.

[23] M. Sardogan, A. Tuncer, and Y. Ozen, "Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm," in *2018 3rd International Conference on Computer Science and Engineering (UBMK)*, Sarajevo, Bosnia and Herzegovina, Sep. 2018, pp. 382–385, https://doi.org/10.1109/UBMK.2018.8566635.