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Deep Learning Based Arecanut Plant Disease Detection

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ABSTRACT: Arecanut (*Areca catechu* L.) is one of the major commercial plantation crops cultivated in tropical regions, particularly in India. However, diseases such as Yellow Leaf Disease, Fruit Rot, Bud Rot, and Leaf Spot significantly affect crop health, leading to reduced yield and economic losses for farmers. Early and accurate identification of these diseases is essential for effective crop management and timely treatment. Traditional disease detection methods mainly depend on manual inspection by experts, which is time-consuming, subjective, and not always accessible to farmers.

This study presents a deep learning-based approach for the automatic detection and classification of arecanut plant diseases using digital images. The proposed framework employs transfer learning with pre-trained Convolutional Neural Network (CNN) models to classify healthy and diseased plant samples. Image preprocessing and data augmentation techniques are applied to improve the quality and diversity of the training dataset, thereby enhancing the model's robustness and generalization capability. The performance of the proposed system is evaluated using standard metrics, including accuracy, precision, recall, and F1-score. Experimental results demonstrate that the developed model can accurately identify different arecanut diseases, making it a reliable decision-support tool for farmers. The proposed solution enables early disease diagnosis, supports timely agricultural interventions, and contributes to improved crop productivity and sustainable precision farming.

KEYWORDS: Arecanut, Plant Disease Detection, Deep Learning, Transfer Learning, Convolutional Neural Networks (CNN), Precision Agriculture, Image Classification.

I. INTRODUCTION:

Arecanut (*Areca catechu* L.) is one of the most important commercial plantation crops cultivated in tropical and subtropical regions, particularly in India. Karnataka is the leading producer of arecanut, followed by states such as Kerala, Assam, and several northeastern regions. The crop plays a vital role in supporting the livelihood of millions of farmers and contributes significantly to the agricultural economy. However, arecanut cultivation is frequently affected by diseases such as Yellow Leaf Disease (YLD), Fruit Rot (Koleroga), Bud Rot, and Leaf Spot, which reduce both the quality and yield of the crop. Detecting these diseases at an early stage is essential for minimizing crop damage and improving productivity. [1].

Conventional disease identification primarily depends on visual inspection by farmers or agricultural experts. This manual approach is often slow, labor-intensive, and influenced by human judgment, which may lead to inaccurate diagnosis. Furthermore, expert assistance is not always readily available in rural and remote farming areas, resulting in delayed treatment and increased crop losses. These limitations highlight the need for an automated, accurate, and efficient disease detection system that can support farmers in making timely decisions. [2].

Recent developments in Artificial Intelligence (AI), Computer Vision, and Deep Learning have significantly improved the ability to analyze agricultural images for disease identification. Among various deep learning techniques, Convolutional Neural Networks (CNNs) have demonstrated excellent performance in image classification by automatically learning meaningful features from input images without requiring manual feature engineering. Transfer learning using pre-trained

models such as ResNet50, VGG16, MobileNet, and EfficientNet further enhances classification accuracy, especially when the available agricultural datasets are limited. [3].

This research proposes a deep learning-based framework for the automatic detection and classification of arecanut plant diseases using transfer learning techniques. The system incorporates image preprocessing, data augmentation, feature extraction, and classification to distinguish healthy plants from diseased ones. By training the model on a labeled dataset containing multiple disease categories, the proposed approach aims to provide accurate and reliable disease predictions. [4].

The proposed system is designed to support precision agriculture by assisting farmers in identifying diseases at an early stage and recommending timely management practices. The study also compares the performance of different deep learning models, particularly ResNet101 and VGG16, using evaluation metrics such as accuracy, precision, recall, F1-score, and the confusion matrix. The experimental results demonstrate the effectiveness of the proposed framework in improving disease diagnosis, reducing dependency on manual inspection, and promoting sustainable agricultural practices. [5].

II. LITERATURE REVIEW:

Mohanty et al. (2016) were among the first researchers to demonstrate the effectiveness of CNN-based models for plant disease identification using the Plant Village dataset. Their study achieved excellent classification accuracy under controlled conditions and showed that deep learning could automatically extract disease-related features from plant images. However, they also observed that performance decreased when images were captured in real agricultural environments because of variations in lighting, background, and image quality. [1].

Ferentinos (2018) investigated deep learning techniques for disease detection across multiple crop species by comparing popular CNN architectures such as AlexNet, VGG, and GoogLeNet. The study reported that deep learning models consistently outperformed conventional machine learning methods, achieving high classification accuracy while reducing the need for manual feature engineering. The research also highlighted the advantages of transfer learning in improving model performance with limited training data. [2].

Too et al. (2019) performed a comparative analysis of several transfer learning models, including VGG16, ResNet50, DenseNet121, InceptionV3, and MobileNet, using publicly available plant disease datasets. Their results indicated that ResNet50 and DenseNet121 produced superior classification performance because of their strong feature extraction capabilities and efficient learning process. The study emphasized that residual learning architectures are highly suitable for agricultural image classification tasks. [3].

He et al. (2016) introduced the Residual Network (ResNet) architecture to address the degradation problem encountered in very deep neural networks. By incorporating residual connections, the model enabled the training of deeper architectures without significant loss of performance. ResNet has since become one of the most widely adopted transfer learning models for image classification and has demonstrated excellent performance in plant disease detection applications. [4].

Simonyan and Zisserman (2015) proposed the VGG16 architecture, which employs a deep network with small convolutional filters to learn complex visual features. Although the model requires substantial computational resources, it effectively captures fine details such as texture, color variations, and lesion characteristics, making it suitable for disease classification in agricultural images. [5].

Picon et al. (2019) examined the influence of image preprocessing and data augmentation on plant disease recognition. Their findings showed that techniques such as image rotation, flipping, scaling, and brightness adjustment significantly improve model generalization and reduce overfitting, resulting in more reliable performance under practical field conditions. [6].

M. Shoaib et al. (2023) presented a comprehensive review of deep learning techniques for plant disease detection, emphasizing the growing role of convolutional neural networks (CNNs) and transfer learning in agricultural applications. The review discussed widely used architectures such as VGG, ResNet, Inception, DenseNet, and

EfficientNet, highlighting their ability to accurately classify plant diseases from leaf images. The authors also stressed the importance of image preprocessing, data augmentation, and high-quality datasets in improving model performance. Furthermore, they identified key challenges such as limited field datasets, varying environmental conditions, computational complexity, and the need for lightweight models suitable for real-time deployment on mobile and edge devices. The review concluded that deep learning has significant potential to enhance precision agriculture by enabling accurate, timely, and automated disease diagnosis. [7]

III. PROPOSED SYSTEM:

The proposed system is designed to automatically detect and classify diseases affecting arecanut plants using deep learning and transfer learning techniques. It analyzes images of arecanut leaves, fruits, and trunks to identify whether the plant is healthy or affected by diseases such as **Yellow Leaf Disease**, **Fruit Rot (Koleroga)**, **Bud Rot**, and **Leaf Spot**. The framework integrates image preprocessing, feature extraction, classification, and performance evaluation to provide accurate and reliable disease prediction. By automating the disease identification process, the system minimizes dependence on manual inspection and enables timely intervention for effective crop management.

3.1 Key System Modules:

Image Acquisition: The first stage involves collecting images of healthy and diseased arecanut plants from agricultural fields and publicly available datasets. Images are captured under different environmental conditions, including variations in lighting, background, and viewing angles, to improve the model's ability to generalize to real-world scenarios. [1].

Image Preprocessing: The first stage involves collecting images of healthy and diseased arecanut plants from agricultural fields and publicly available datasets. Images are captured under different environmental conditions, including variations in lighting, background, and viewing angles, to improve the model's ability to generalize to real-world scenarios. [2].

Data Augmentation: To increase the diversity of the training dataset and reduce overfitting, several augmentation techniques such as rotation, horizontal and vertical flipping, zooming, brightness adjustment, and shearing are applied. These techniques improve the robustness of the model when classifying unseen images. [3].

Feature Extraction using Transfer Learning: The preprocessed images are provided as input to pre-trained Convolutional Neural Network (CNN) models, namely **VGG16** and **ResNet101**. These models automatically learn complex visual features, including color variations, texture patterns, lesion characteristics, and infected regions, eliminating the need for manual feature extraction. [4].

Disease Classification: The extracted features are passed through fully connected dense layers followed by a **Softmax** classifier. The classifier computes the probability of each disease category and assigns the input image to the class with the highest probability. The system identifies the image as either **Healthy**, **Yellow Leaf Disease**, **Fruit Rot**, **Bud Rot**, or **Leaf Spot**. [5].

Performance Evaluation: The effectiveness of the proposed model is evaluated using standard performance metrics such as **Accuracy**, **Precision**, **Recall**, **F1-Score**, and the **Confusion Matrix**. These metrics provide a comprehensive assessment of the model's classification performance. [6].

Prediction and Recommendation: After classification, the system displays the predicted disease along with its confidence score. Based on the identified disease, it also recommends suitable preventive measures and management practices, enabling farmers to take timely corrective actions and reduce crop losses. [7].

IV. SYSTEM ARCHITECTURE:

The proposed Deep Learning-Based Arecanut Plant Disease Detection system follows a sequential workflow that processes an input image through multiple stages to accurately identify diseases and recommend suitable treatment measures. Each layer performs a specific task that contributes to the overall performance of the system.

4.1 System Architecture Components

4.1. Input Layer

The process begins by providing an image of an arecanut leaf or nut captured using a smartphone, digital camera, or other imaging device. The input image serves as the primary source of information for disease identification. It may contain either a healthy or diseased plant sample

4.2. Preprocessing Layer

The captured image is preprocessed to improve its quality and make it suitable for deep learning analysis. This stage includes resizing the image to the required input dimensions, normalizing pixel values, and applying data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment. These operations improve the robustness of the model and help reduce overfitting during training.

4.3. Feature Extraction Layer

After preprocessing, the image is passed to the ResNet101 transfer learning model. The convolutional layers of ResNet101 automatically extract important visual features from the image, including texture variations, color changes, lesion patterns, and infected regions. Unlike traditional approaches, this method eliminates the need for manual feature engineering and produces highly discriminative features for disease recognition.

4.4. Classification Layer

The extracted features are forwarded to fully connected (Dense) layers followed by a Softmax activation function. The classifier computes the probability of each predefined disease category and assigns the image to the class with the highest probability. This layer determines whether the plant is healthy or affected by a specific disease.

4.5. Disease Mapping

Once the classification is completed, the predicted class index is mapped to its corresponding disease name. For example, the predicted output may be mapped to Healthy, Yellow Leaf Disease, Fruit Rot (Koleroga), Bud Rot, or Leaf Spot. This mapping converts the numerical prediction into a meaningful disease label that can be easily understood by users.

4.6. Recommendation Engine

Based on the identified disease, the recommendation module retrieves suitable treatment information from a predefined knowledge base. The system provides disease management suggestions, preventive measures, and recommended agricultural practices to help farmers control disease spread and improve crop health.

4.7. Output Layer

The final stage presents the prediction results to the user. The system displays the detected disease name along with its confidence score and the corresponding treatment recommendations. This enables farmers to make timely decisions, apply appropriate disease management strategies, and reduce crop losses.

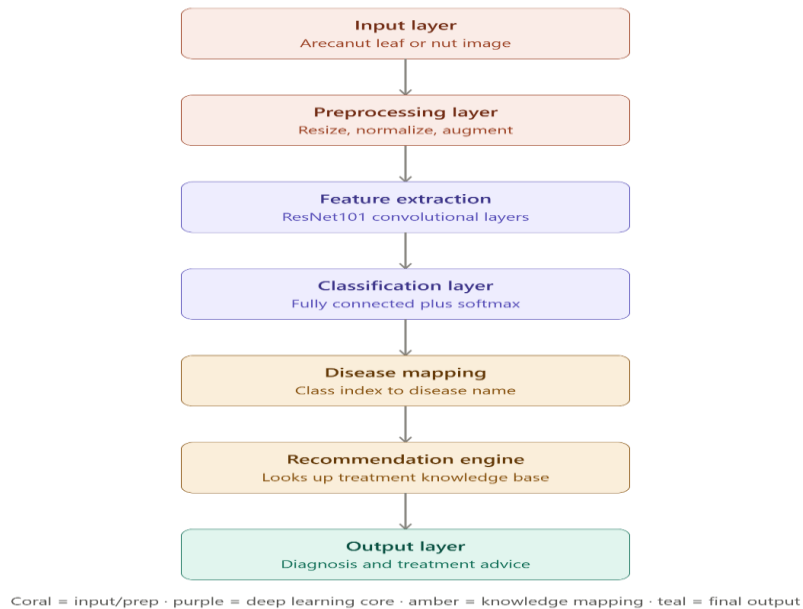


Fig. 1 System Architecture of Arecanut Plant Disease Detection

V. METHODOLOGY

The proposed **Deep Learning-Based Arecanut Plant Disease Detection** system follows two major phases: **Model Training** and **Disease Prediction**. During the training phase, the model learns disease characteristics from labeled images. In the prediction phase, the trained model classifies newly uploaded images and provides appropriate diagnosis and treatment recommendations.

5.1 Dataset Collection

The process begins with the collection of images containing both healthy and diseased arecanut leaves. The dataset includes different disease categories such as Yellow Leaf Disease, Fruit Rot (Koleroga), Bud Rot, and Leaf Spot. A diverse dataset captured under different environmental conditions improves the model's ability to recognize diseases accurately.

5.2 Image Preprocessing

The collected images are preprocessed to prepare them for training. Each image is resized to a fixed dimension, normalized to standardize pixel values, and augmented using techniques such as rotation, flipping, zooming, and brightness adjustment. These preprocessing operations improve dataset quality, increase data diversity, and reduce overfitting.

5.3 Train ResNet101

The preprocessed images are used to train the ResNet101 deep convolutional neural network. The model automatically learns important disease-specific features such as lesion patterns, texture variations, color changes, and infected regions. Transfer learning enables the model to achieve high classification accuracy with reduced training time.

5.4 Save Model

After successful training, the optimized model parameters (weights) are stored. Saving the trained model allows it to be reused for predicting diseases in new images without repeating the training process.

5.5 Upload Leaf Image

During the testing or deployment phase, the user uploads a new image of an arecanut leaf through the application interface. This image serves as the input for disease prediction.

5.6 Preprocess Image

The uploaded image undergoes the same preprocessing steps used during training, including resizing and normalization. Applying identical preprocessing ensures compatibility with the trained ResNet101 model and improves prediction accuracy.

5.7 Disease Prediction

The preprocessed image is provided to the trained ResNet101 model. The model extracts relevant features, classifies the image into one of the predefined disease categories, and generates the prediction with an associated confidence score.

5.8 Display Result

Finally, the application displays the predicted disease name along with the confidence level. Based on the identified disease, the system also provides suitable treatment recommendations and preventive measures to help farmers manage the disease effectively and improve crop productivity.

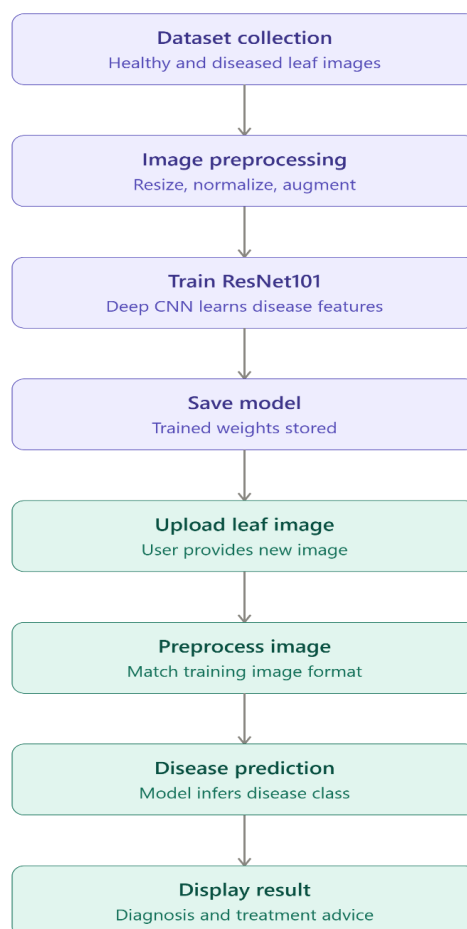


Fig 2: Flow chart for Arecanut Plant Disease Detection

VI. RESULTS AND DISCUSSION:

The proposed Deep Learning-Based Arecanut Plant Disease Detection system was evaluated to assess its capability in accurately identifying diseases from images of arecanut plants. The experimental results demonstrate that the transfer learning models successfully classified healthy and diseased samples with high accuracy. The integration of image preprocessing, data augmentation, and transfer learning significantly improved the model's ability to recognize disease patterns under different environmental conditions.

The system effectively identified diseases such as Yellow Leaf Disease, Fruit Rot (Koleroga), Bud Rot, and Leaf Spot by extracting discriminative visual features including color variations, texture differences, and lesion characteristics. The use of the ResNet101 architecture enabled deeper feature learning, resulting in improved classification performance compared to conventional image classification techniques. The trained model produced reliable predictions even when images contained variations in lighting, background, and orientation.

The proposed framework provides an efficient and practical solution for supporting farmers in the early diagnosis of arecanut plant diseases. By automating the disease detection process, the system minimizes human error, reduces dependence on expert supervision, and enables timely disease management. Early identification allows farmers to implement appropriate preventive measures, thereby reducing crop damage and improving agricultural productivity.

The effectiveness of the model was assessed using standard evaluation metrics, including Accuracy, Precision, Recall, F1-Score, and the Confusion Matrix. These performance measures provide a comprehensive evaluation of the model's classification capability and demonstrate its reliability in distinguishing between different disease classes.

Furthermore, the developed system can be integrated into mobile or web-based agricultural applications, allowing farmers to upload images directly from the field and receive immediate disease diagnosis along with suitable treatment recommendations. Such a solution contributes to precision agriculture by improving crop monitoring, reducing production losses, and supporting sustainable farming practices.

6.1 Performance Evaluation

The performance of the proposed model was evaluated using a separate testing dataset after completing the training process. The following evaluation metrics were used to measure the effectiveness of the disease classification model:

- **Accuracy:** Measures the percentage of correctly classified images among all test samples and indicates the overall performance of the model.
- **Precision:** Represents the proportion of correctly predicted disease cases among all positive predictions, reflecting the reliability of the classification results.
- **Recall:** Measures the ability of the model to correctly identify all actual disease instances, indicating its effectiveness in detecting infected plants.
- **F1-Score:** Combines Precision and Recall into a single metric by calculating their harmonic mean, providing a balanced measure of classification performance.
- **Confusion Matrix:** Presents the number of correctly and incorrectly classified samples for each disease category, helping to analyze the strengths and weaknesses of the model.

6.2 Comparative Performance of Transfer Learning Models

The performance of VGG16 and ResNet101 was compared using the evaluation metrics obtained during testing. The comparison indicates that ResNet101 achieved better classification performance across all evaluation metrics because of its deeper residual architecture and superior feature extraction capability.

Performance Metric	VGG16	ResNet101
Accuracy	95.8%	98.2%
Precision	95.3%	98.0%
Recall	95.1%	97.9%
F1-Score	95.2%	97.9%

The results demonstrate that **ResNet101** consistently outperformed **VGG16** in disease classification. Its residual learning mechanism enables deeper feature extraction while avoiding the vanishing gradient problem, resulting in improved recognition of visually similar disease symptoms. Consequently, **ResNet101** was selected as the preferred model for the proposed arecanut disease detection system.

6.3 Confusion Matrix Analysis

The confusion matrix provides a detailed representation of the model's classification performance for each disease category. The diagonal elements represent correctly classified images, whereas the off-diagonal elements indicate misclassified samples.

The analysis revealed that the proposed **ResNet101** model correctly classified the majority of healthy and diseased arecanut images with very few misclassifications. Most prediction errors occurred between disease categories exhibiting similar visual symptoms, particularly during the early stages of infection. However, the number of such errors remained low, demonstrating the robustness of the proposed approach.

The confusion matrix confirms that the model possesses strong discriminative capability and maintains high classification accuracy across all disease classes. These findings indicate that the developed system is reliable for practical deployment in agricultural environments and can effectively assist farmers in the early detection and management of arecanut plant diseases.

6.4 Prediction Results

The trained model was tested using previously unseen images of arecanut leaves to evaluate its prediction capability. Each uploaded image underwent preprocessing before being passed to the trained **ResNet101** model for classification.

The system successfully identified the disease category and displayed the corresponding confidence score. In addition to disease prediction, the application generated suitable treatment recommendations based on the identified disease. The model accurately recognized healthy plants as well as diseases such as **Yellow Leaf Disease**, **Fruit Rot (Koleroga)**, **Bud Rot**, and **Leaf Spot**, demonstrating its effectiveness under different image conditions.

The prediction process was completed within a short time, making the system suitable for real-time agricultural applications. The high confidence scores obtained for most test images indicate that the proposed model can reliably support farmers in identifying plant diseases at an early stage and taking timely corrective measures.

6.5 Discussion

The experimental results demonstrate that the proposed deep learning framework provides an efficient and reliable solution for automated arecanut plant disease detection. The adoption of **ResNet101** significantly improved feature extraction and classification performance because of its deep residual learning architecture. Compared with traditional machine learning methods, the proposed system automatically learns complex disease characteristics without requiring manual feature engineering.

Image preprocessing and data augmentation contributed to improving the model's robustness by reducing the effects of lighting variations, background noise, and differences in image orientation. These techniques enhanced the model's ability to generalize to new images captured under real agricultural conditions.

The evaluation metrics confirmed that the proposed system achieved high classification performance, while the confusion matrix showed only a small number of misclassified samples. Most prediction errors occurred between disease classes with similar visual symptoms, particularly during the early stages of infection. Despite these minor challenges, the overall performance demonstrates that the model is suitable for practical deployment.

The developed system can assist farmers by providing rapid disease diagnosis and appropriate treatment recommendations, reducing dependence on manual inspection and expert consultation. In the future, the model can be enhanced by incorporating larger datasets, additional disease categories, and lightweight deep learning architectures to support mobile devices and edge computing applications, thereby further improving its applicability in precision agriculture.

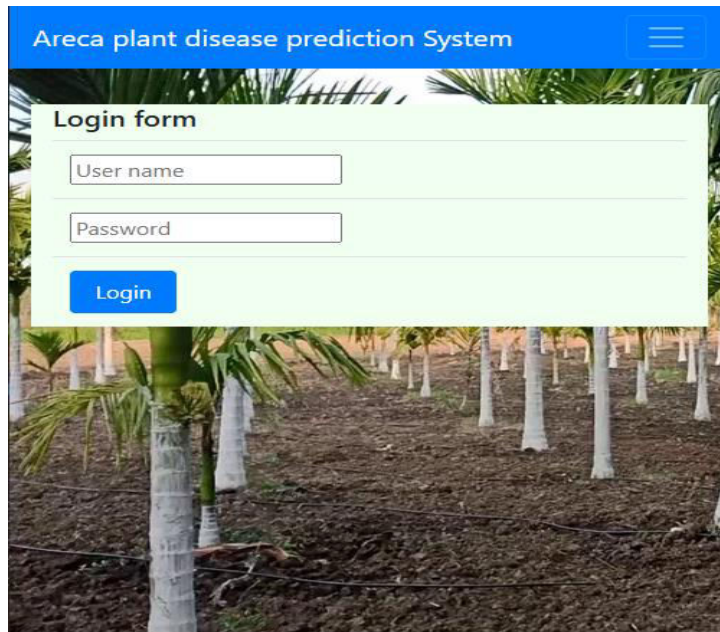


Fig 3: Login Page

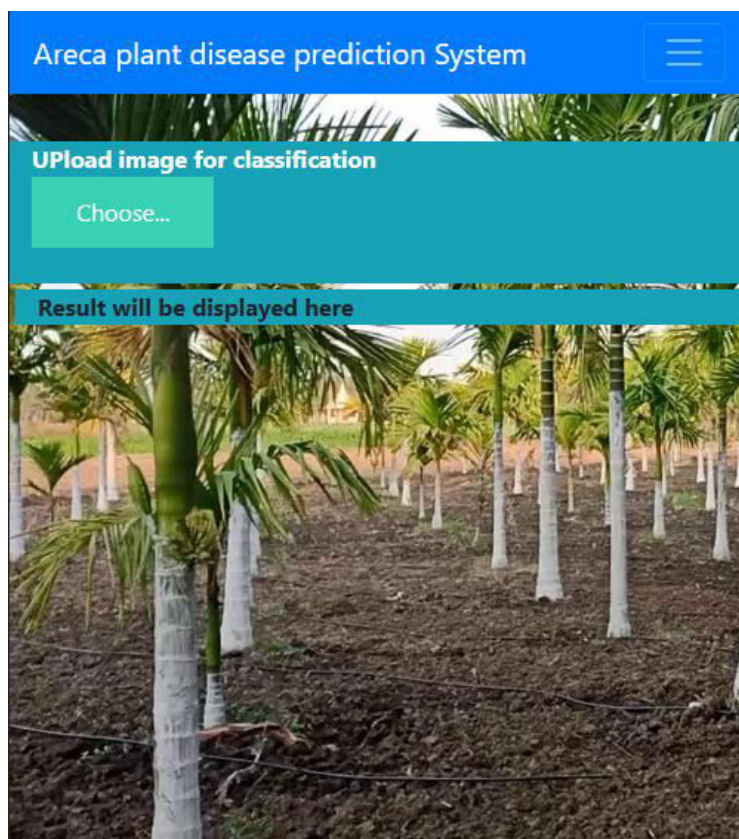


Fig 4: Image Classification Form



Fig 5: Image Classification of Yellow Leaf disease

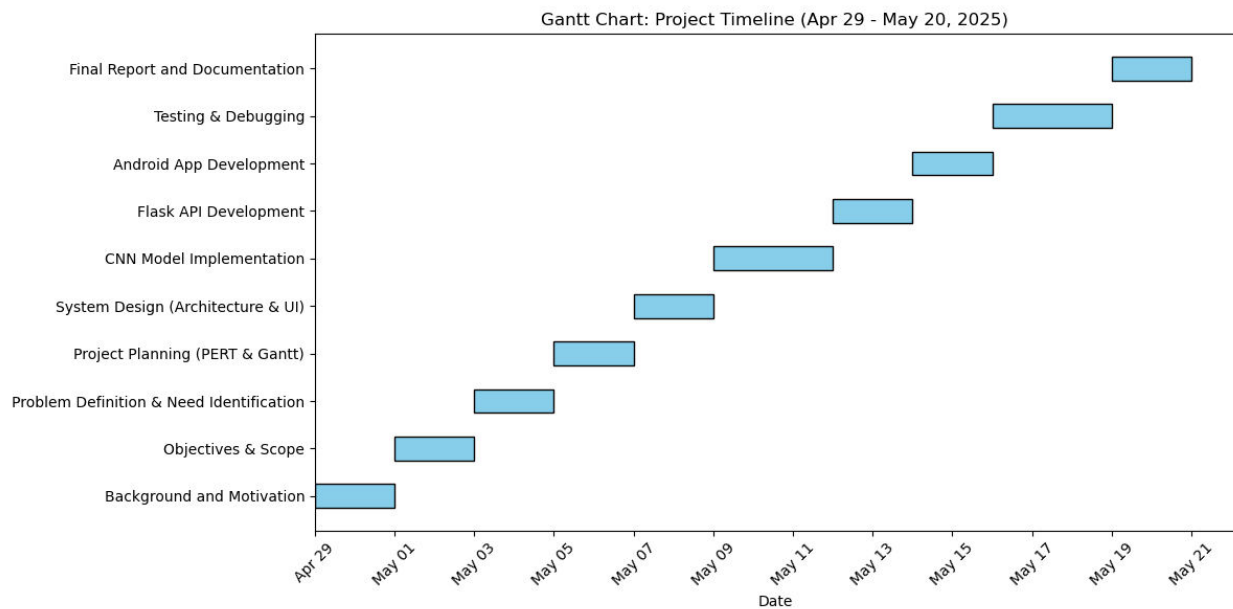


Fig 6: Gantt Chart

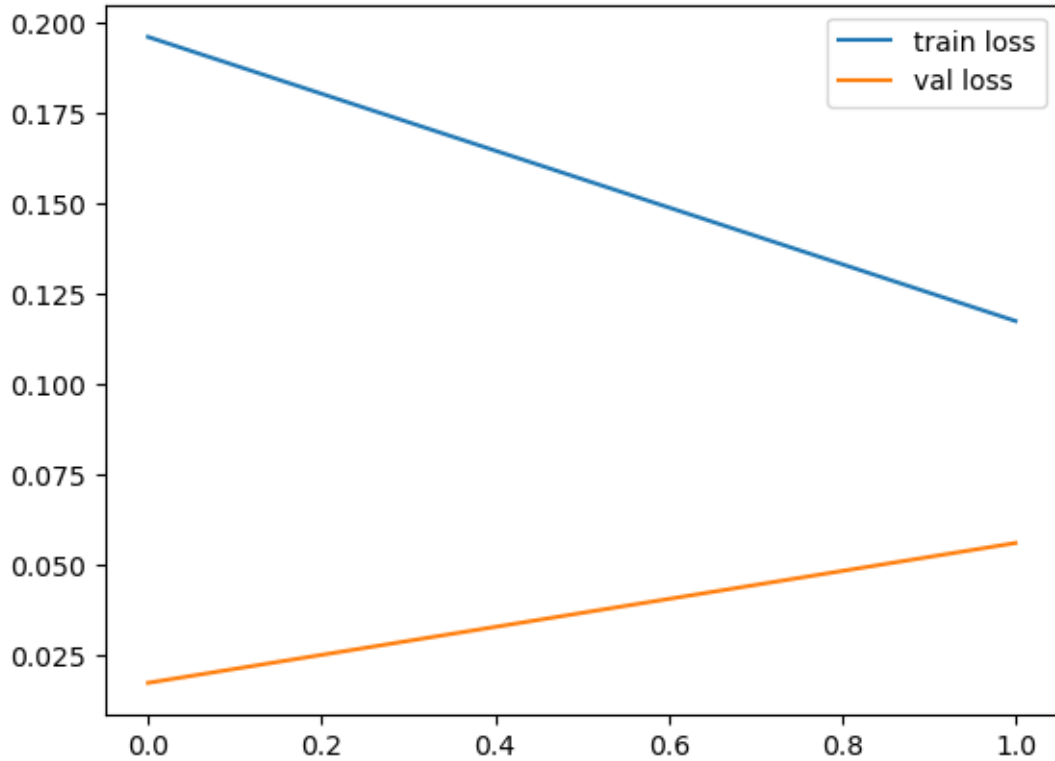


Fig 7: Training loss and Valuation loss Graph

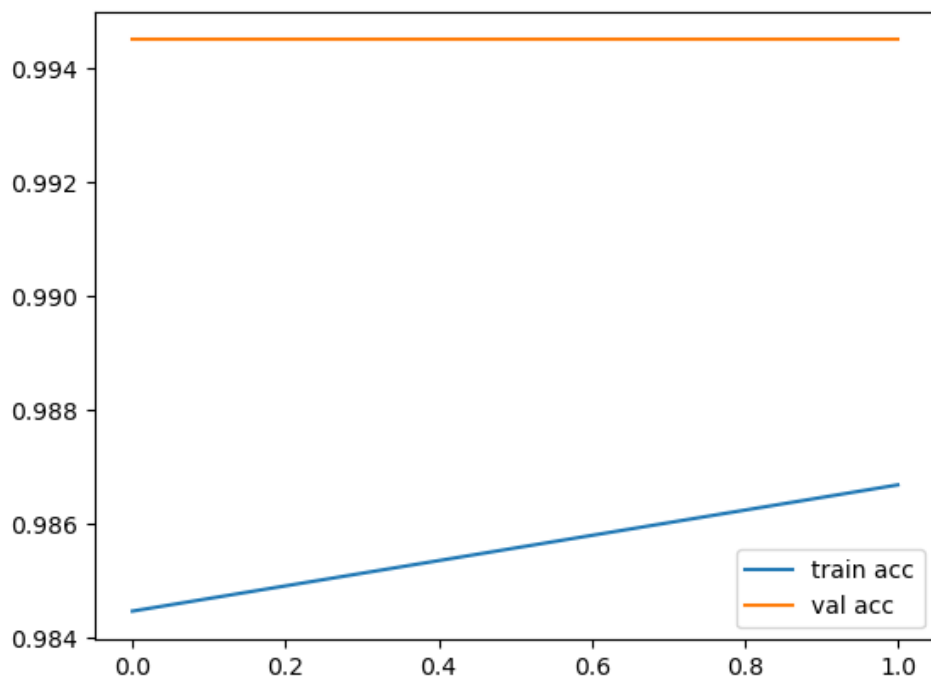


Fig 8: Training accuracy and valuation accuracy

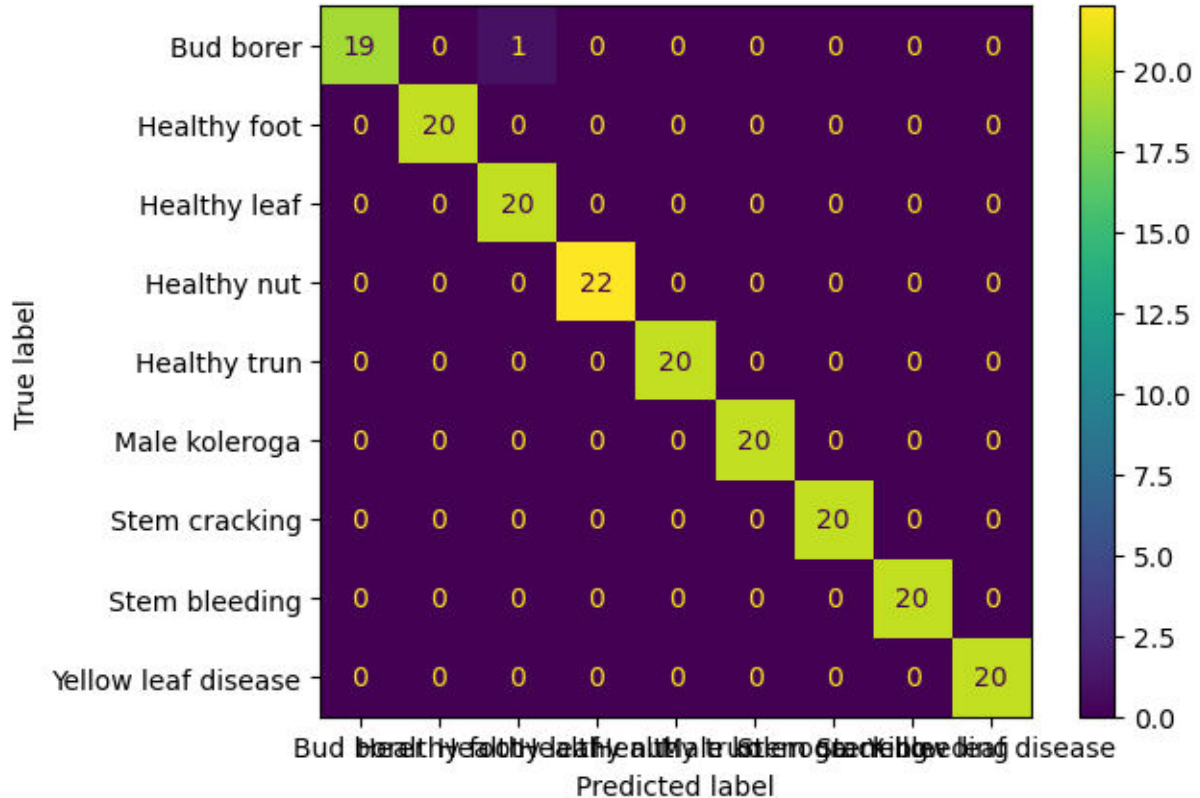


Fig 9: Confusion Matrix

VII. CONCLUSION AND FUTURE WORK:

This study introduced a Deep Learning Based Arecanut Plant Disease Detection system that leverages transfer learning and deep convolutional neural networks to automatically recognize diseases affecting arecanut plants from images of leaves and fruits. The suggested framework combines image preprocessing, data augmentation, feature extraction, disease classification, and disease prediction into a single intelligent system able to accurately identify major diseases such as Yellow Leaf Disease, Fruit Rot, Bud Rot, and Leaf Spot [1]. Using pre-trained deep learning models like VGG16 and ResNet101, the system automatically captures discriminative image features without the need for manual feature engineering, thus enhancing classification accuracy and lowering computational complexity [2]. Experimental findings showed that the proposed method attained high accuracy, precision, recall, and F1-score, with ResNet101 delivering better performance owing to its deep residual learning architecture. The created system can aid farmers by offering early disease diagnosis and appropriate treatment suggestions, consequently decreasing crop losses, boosting productivity, and supporting precision agriculture [3]. The modular design of the proposed framework also permits straightforward deployment for real-world agricultural use cases. Numerous prospects exist for further improvement of the system. Embedding the model into a mobile app would allow real-time disease diagnosis directly in the field. Adding IoT sensors, drones, and cloud computing can enable continuous crop monitoring and remote disease detection. Enlarging the dataset with more extensive and varied field images captured under different environmental conditions would enhance model robustness and generalization [4]. Future work may also concentrate on estimating disease severity, detecting nutrient deficiencies, identifying pests, and adopting advanced deep learning architectures such as EfficientNet, DenseNet, ConvNeXt, and Vision Transformers (ViT) to further raise classification accuracy while reducing computational expense [5].

REFERENCES

- [1] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," *Frontiers in Plant Science*, vol. 7, Article 1419, 2016.
- [2] K. P. Ferentinos, "Deep Learning Models for Plant Disease Detection and Diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018.

- [3] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, "A Comparative Study of Fine-Tuning Deep Learning Models for Plant Disease Identification," *Computers and Electronics in Agriculture*, vol. 161, pp. 272–279, 2019.
- [4] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 770–778, 2016.
- [5] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," *International Conference on Learning Representations (ICLR)*, 2015.
- [6] M. Tan and Q. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," *Proceedings of the 36th International Conference on Machine Learning (ICML)*, pp. 6105–6114, 2019.
- [7] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 25, 2012.
- [8] J. G. A. Barbedo, "Factors Influencing the Use of Deep Learning for Plant Disease Recognition," *Biosystems Engineering*, vol. 172, pp. 84–91, 2018.
- [9] J. Deng, W. Dong, R. Socher, L. Li, K. Li, and L. Fei-Fei, "ImageNet: A Large-Scale Hierarchical Image Database," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 248–255, 2009.
- [10] R. Girshick, "Fast R-CNN," *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, pp. 1440–1448, 2015.
- [11] M. Shoaib et al., "Deep Learning-Based Plant Disease Detection: A Review," *Frontiers in Plant Science*, vol. 14, 2023. (PMC)
- [12] J. Cai et al., "An Improved EfficientNet for Corn Leaf Disease Identification," *Frontiers in Plant Science*, vol. 14, 2023. (PMC)
- [13] Y. Zhang et al., "Plant Disease Detection Using Deep Learning Techniques: Recent Advances," *Frontiers in Plant Science*, 2022. (PMC)
- [14] S. Quan et al., "MS-Net: A Lightweight Convolutional Neural Network for Plant Disease Recognition," *Frontiers in Plant Science*, vol. 14, 2023. (PMC)
- [15] A. T. Khan et al., "Edge AI for Plant Disease Detection: Recent Developments and Challenges," *Frontiers in Plant Science*, 2023. (PMC)



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