Grenze International Journal of Engineering and Technology, June Issue

ArecaSafe: An Intelligent Sentinel for Arecanut Crop Health

John Prakash Veigas[1], Pratheeksha R Puthran[2], Rohith R[3], Thrisha Thokottu[4] and Pavan M C[5]
[1-5]AJ Institute of Engineering and Technology, Mangaluru, India
Email: john.veigas@ajiet.edu.in, pratheekshaputhran22@gmail.com, rohithrohithkulal@gmail.com, thrishavinay1@gmail.com, pavanmc0009@gmail.com

***Abstract*— ArecaSafe is an intelligent framework powered by the Internet of Things (IoT) and Artificial Intelligence (AI) that is designed to help monitor Arecanut (Areca catechu) plantations ahead of time and find Fruit Rot disease early. The system uses real-time environmental monitoring, machine learning to anticipate climate risk, and deep learning to analyze images to give accurate and rapid illness assessments. The climate prediction module uses a Random Forest (RF) classifier that has been trained on 10 years' worth of weather data (2014–2024) from the Zonal Agricultural and Horticultural Research Station (ZAHRS) in Brahmavara. The image-based illness detection system also uses a Convolutional Neural Network (CNN) driven by EfficientNetB0 and transfer learning to tell the difference between healthy and unhealthy arecanut fruits. An ESP32-based IoT node with BME280 (temperature and humidity), BH1750 (light intensity), and rainfall sensors collects environmental data. This data is then sent through a FastAPI–Supabase cloud infrastructure. Experimental results reveal that the system can properly classify several levels of disease severity—Low, Moderate, and High—and also performs well in identifying visual symptoms through picture analysis. In general, ArecaSafe is a useful, cheap, and data-driven solution for precision agriculture. It helps farmers take prompt steps to prevent crop loss and keep yields stable over the long run.**

***Index Terms*— Areca catechu, Internet of Things (IoT), Convolutional Neural Network (CNN), Random Forest (RF), Disease Prediction, Supabase, FastAPI, Fruit Rot.**

I. INTRODUCTION

Arecanut (Areca catechu) is an important commercial plantation crop that is cultivated all across India, but especially in Karnataka, Kerala, and Tamil Nadu. It is an important crop that supports the livelihoods of many small- and medium-sized farmers. However, it is often threatened by fungal diseases, the most serious of which is fruit rot, caused by Phytophthora palmivora. If this disease is not detected and treated early, it can lead to severe crop loss and long-term damage to plantations. [1]. Farmers have always relied on physical inspection, visual examinations, and chemical treatments from time to time to keep illnesses at bay. These procedures take a long time, are based on personal opinion, and usually only find illnesses after they have already spread. These kinds of delays make it more likely that there will be a lot of harm. The situation gets worse since there isn't enough ongoing and accurate monitoring of the environment. This is because climate conditions have a big effect on fungus development. With the Internet of Things (IoT) and artificial intelligence (AI) moving quickly forward, agriculture may now move from reactive methods to automated, proactive, and data-driven disease control [2].

Grenze ID: 01.GIJET.12.2.150_21

IoT sensors that constantly monitor important environmental elements like temperature, humidity, light levels, and rainfall are very important for understanding and controlling fungal infections. The integration of Artificial Intelligence (AI) with machine learning models provides a reliable way to predict disease occurrence by examining long-term climatic and environmental observations. These predictive capabilities help farmers receive timely warnings, enabling them to respond proactively to potential crop outbreaks. In addition, computer vision (CV) techniques—especially Convolutional Neural Networks (CNNs)—are highly effective in detecting visible symptoms of disease on arecanut fruits through automated image analysis. This enables more precise assessment of disease severity and supports early measures to avoid further proliferation of disease. The ArecaSafe framework integrates multiple technologies into a single, data-driven and decision support system. It provides real-time disease prediction and constantly monitors environmental conditions for possible crop outbreaks. This, in turn, supports informed decision-making and improves farmers to take appropriate measures to protect their crops from environmental changes. By overcoming the limitations of traditional manual methods, the approach offers a scalable and sustainable solution for modern arecanut cultivation.

The remainder of this paper is organized as follows: the next section presents a brief review of related work, followed by a detailed explanation of the proposed methodology. The subsequent section discusses the results, and the paper concludes with key insights and potential avenues for future research.

II. Literature Survey

The following section provides the brief review of literature in Arecanut related disease detection approaches.

A. Climatic Data-based Disease Prediction

It is known that environmental conditions including temperature, relative humidity, rainfall, and amount of sunlight can affect the growth and spread of fungal infections in crops [3], [4]. Previous studies have thoroughly investigated the application of machine learning techniques—such as Random Forests, Support Vector Machines, and Decision Trees—to assess these intricate connections and forecast disease occurrences. A recent study proposed an IoT and machine learning-based model for predicting arecanut crop diseases, emphasizing how weather parameters directly affect disease severity [5]. Another study confirmed a clear relationship between the occurrence of Fruit Rot disease in arecanut and fluctuations in climatic conditions, emphasizing that factors such as temperature and humidity play a decisive role in its spread [6]. Among various predictive algorithms, the Random Forest method is particularly well-regarded in agricultural analytics.

The method handles complicated, non-linear connections between environmental factors well, lowers the chance of overfitting, and makes it easy to understand by using feature importance analysis [7]. This dependability makes it a strong choice for predicting illness risks based on weather conditions.

B. Image-based Disease Detection

Computer vision has been an effective and non-invasive way to find plant diseases in the last few years. Convolutional Neural Networks (CNNs) are an important part of this strategy [8] since they can learn hierarchical imagery on their own that show little indicators of infection. Transfer learning with pretrained models like EfficientNetB0 has become common to improve performance [9]. This method makes it easier to train models on little datasets and makes them better at generalizing across varied illness and illumination situations [10]. EfficientNetB0 is very efficient and very accurate, which makes it perfect for real-time agricultural image classification applications.

C. Internet of Things in Smart Agriculture

The IoT devices make it possible to keep a watch on environmental factors that are important for tracking the spread of disease in real time and all the time [11], [12]. Microcontrollers like the ESP32 work well with different sensors and can send data wirelessly to cloud services. The connectivity with powerful cloud databases like Supabase makes it easier to store and manage large amounts of data in one place. This feature makes it possible to analyze enormous amounts of data and helps farmers make quick, informed decisions based on that data [13]. Numerous studies have demonstrated that IoT-based monitoring systems greatly mitigate crop loss and enhance disease management approaches.

III. Methodology

Despite advancements in smart farming technologies, arecanut growers continue to encounter significant challenges in the management of crop diseases, particularly fruit rot, resulting in considerable annual yield losses. Conventional approaches rely extensively on manual observation and delayed visual detection, frequently recognizing issues only after substantial damage has taken place. Regular monitoring is essential due to the close relationship between the onset of fruit rot and climatic factors such as temperature, humidity, and rainfall. Collecting this data manually presents challenges, including slow processing times, inconsistency, and a high likelihood of errors. Prior research has investigated IoT-based environmental monitoring, machine learning for disease prediction, and computer vision for disease identification; however, these methods are typically examined in isolation [14], [15]. Predictive models that utilize weather data have demonstrated high accuracy in assessing disease risk. Concurrently, CNN-based image classifiers have proven to be effective in detecting early visual symptoms. When these technologies function in isolation, they result in fragmented systems that do not provide farmers with a cohesive decision-support solution. This gap underscores the necessity for a cohesive framework that integrates real-time sensing, predictive analytics, and image-based diagnosis.The ArecaSafe system effectively tackles this challenge by integrating IoT automation, machine learning, and deep-learning-based image analysis into a unified platform. The system utilizes BME280, LUX, and rain gauge sensors interfaced with an ESP32 microcontroller to collect real-time climatic data. This data is subsequently stored in a Supabase cloud database and accessed via FastAPI services.The Random Forest model is utilized for prediction by training on historical climatic parameters, including rainfall, temperature, humidity, and sunshine hours, to assess the probability of fruit rot occurrence. A CNN utilizing EfficientNetB0 concurrently analyzes arecanut fruit images to assess their health status. ArecaSafe integrates these components to provide climatic risk prediction and visual disease diagnosis, resulting in a cohesive, scalable, and proactive solution for crop health management. This integrated approach facilitates enhanced decision-making and assists farmers in managing diseases more efficiently, thereby promoting sustainable yield improvement.

The ArecaSafe framework brings together IoT-based sensing, machine-learning-driven prediction, and deep-learning-based image analysis in a single architecture designed for real-time disease management in arecanut plantations. Figure 1 illustrates the overall system structure, showing how the IoT module, cloud backend, and predictive components interact.

A. IoT Sensor Module

The IoT sensor module is responsible for continuously collecting environmental parameters that influence fruit rot occurrence. It comprises a BME280 sensor for temperature and humidity measurement, a LUX sensor for light intensity detection, and a rain gauge for measuring precipitation. An ESP32 microcontroller acts as the core control unit, interfacing with the sensors and transmitting data to the cloud via Wi-Fi. The specifications of each sensor and component are summarized in Table I. Data collected by these sensors are transmitted to the cloud backend every 15 minutes, where they undergo pre-processing, analysis, and disease risk prediction.

TABLE I. SENSOR SPECIFICATION USED IN ARECASAFE IOT MODULE

Sensor	Measured Parameter	Unit	Interface
BME280	Temperature / Humidity	°C / % RH	I2C
LUX Sensor	Light Intensity	lx	Analog
Rain Gauge	Rainfall	mm	Digital Pulse
ESP32	Controller Unit	–	Wi-Fi

B. Predictive Modelling Framework

ArecaSafe uses two complementary models—a Random Forest (RF) classifier and a Convolutional Neural Network (CNN)—to handle climatic risk prediction and image-based disease classification. The Random Forest model utilizes ten years of historical climatic data (2014–2024), including rainfall, maximum and minimum temperature, relative humidity, sunshine hours, and wind parameters, to predict the likelihood of fruit rot disease. Each climatic feature is used as an input parameter, and the model produces a binary output indicating whether disease conditions are likely or not. The Random Forest classifier was trained using the scikit-learn implementation with 200 estimators and a fixed random seed to ensure reproducibility.For image-based classification, the CNN model is built on EfficientNetB0, selected for its strong accuracy and efficiency even when working with smaller datasets. Transfer learning with pretrained ImageNet weights was applied, and the final layers were fine-tuned to perform a binary classification of Healthy versus Diseased fruit images. Image augmentation techniques such as rotation, flipping, and brightness adjustment were applied during Training to improve robustness. The model was trained using categorical cross-entropy loss and Adam optimizer with an adaptive learning rate scheduler. A comparison of both models, highlighting their input features, objectives, and key performance considerations, is shown in Table II.

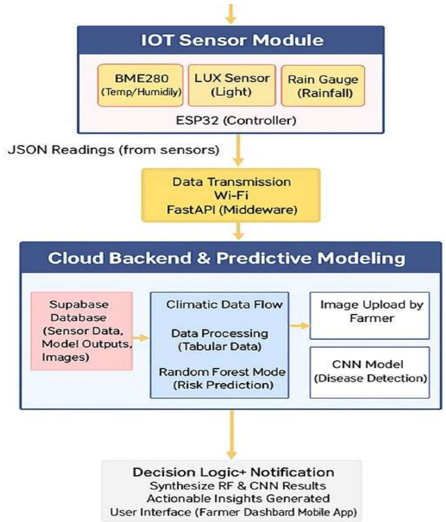

Fig. 1. High-level system architecture of the ArecaSafe platform

C. Backend Infrastructure

The backend system facilitates data storage, model inference, and farmer notifications. FastAPI serves as the middleware handling API requests from sensor modules and web or mobile interfaces. Supabase acts as a cloud-based database for storing all sensor readings, model outputs, and image metadata. The integration between FastAPI and Supabase ensures seamless data transfer between the IoT devices, predictive models, and user-facing applications. Upon receiving new sensor data, the Random Forest model performs real-time disease risk estimation. Simultaneously, if an image is uploaded by a farmer, the CNN model performs classification to determine disease presence. The combined results are synthesized and sent as actionable insights to the farmer's dashboard. This integrated design enables proactive, data-driven, and automated crop health management.

TABLE II: COMPARISON TABLE FOR RANDOM FOREST AND CNN

Feature	Models	
	Random Forest	CNN (EfficientNetB0)
Core Algorithm	Ensemble of Decision Trees	Image Data (RGB)
Primary Objective	Fruit Rot Risk Prediction	Image-Based Disease Detection
Key Parameters	Rainfall, Humidity, Temperature, Sunshine	Image-Based Disease Detection
Training Dataset	Training Dataset10-year Climatic Records (2014-2024)	Convolution Filters, Depth wise Separable Layers Labeled Arecanut Fruit Images
Advantage	Interpretability, Low Overfitting	High Accuracy, Feature Extraction
Limitations	Limited Spatial Insight	Requires High Quality Labeled Data

IV. RESULTS AND DISCUSSION

The following section describe about the dataset, experimentation and analysis of the result obtained.

A. Dataset and Experimentation

The datasets obtained from ZAHRS, Brahmavara, were essential for sensor calibration, improved data collection, and validating the disease prediction framework under local climatic conditions. Historical weather data (2014–2024) — including rainfall, temperature, humidity, sunshine hours, and cloud cover along with Fruit Rot incidence observations from farmers and experts, provided the basis for modeling disease behavior in real field environments. Ten climatic CSV files, containing 143 records and 25 different attributes, were merged and cleaned to form a single consolidated dataset. Redundant columns were removed, and key predictors such as rainfall, rainy days, temperature, humidity, cloud cover, sunshine hours, wind, and evaporation were retained. Preprocessing confirmed that the dataset had no missing or duplicate values. The final processed dataset (df_final) was used to train a Random Forest Classifier with an 80:20 train–test split. With 200 estimators, the model effectively identified climatic conditions favorable for Fruit Rot, with humidity-related variables and rainfall emerging as the most influential features.

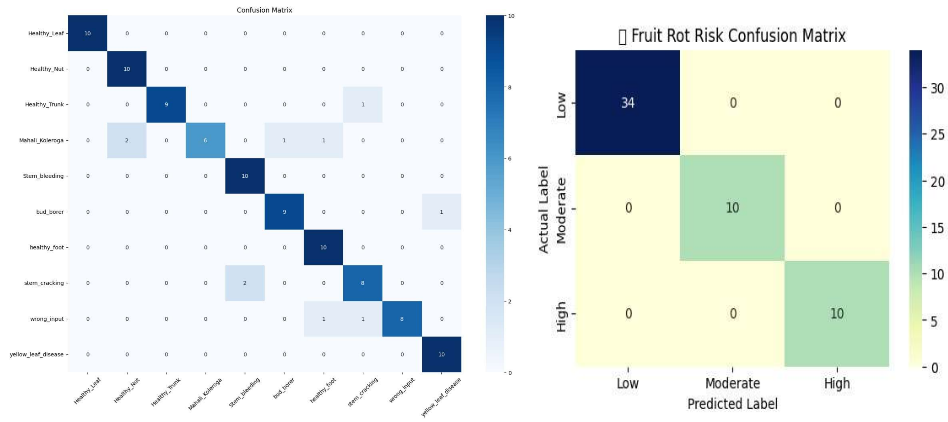

Fig 2. Confusion Matrix of the Convolutional Neural Network Climatic Risk Prediction and Random Forest

B. Confusion Matrix of CNN Disease Classification

The CNN confusion matrix (Fig 2) exhibits clear diagonal Dominance here reflects strong true-positive rates. Misclassifications were minimal, occurring mainly between Mahali Koleroga and Stem Cracking. These two diseases often display similar fungal symptoms—such as brown lesions, uneven textures, and discoloration—which makes them naturally harder to distinguish. Similar patterns of confusion have been reported in earlier plant pathology studies, where visually comparable diseases tend to overlap in deep-learning models. Overall, the EfficientNetB0-based CNN shows strong generalization across healthy, diseased, and irregular classes, making it suitable for practical, real-world deployment.

C. Confusion Matrix of Random Forest Climatic Risk Prediction

The Random Forest confusion matrix (Fig. 2) indicates that the model successfully captured the overall climatic risk categories. Some overlap was observed between the “low-risk” and “medium-risk” classes, mainly because these categories can share similar weather conditions—such as temporary humidity spikes or slight rainfall variations. This behavior is common in climate-driven models, where closely related features naturally blur category boundaries. Even so, the RF model remains a dependable tool for interpreting climatic trends. The image dataset used for training was created from field-captured arecanut leaf images supplemented with reference materials. Images were resized to 224 × 224, normalized, and augmented through rotation, flipping, zooming, and brightness changes. EfficientNetB0, trained with transfer learning, was used for multi-class classification. Cross-entropy loss, adaptive learning-rate scheduling, and early stopping ensured stable model convergence. The model achieved a validation accuracy of 99.98%. Testing on a balanced dataset (10 images per class) resulted in 90% accuracy, with an average precision of 0.91, recall of 0.90, and F1-score of 0.90. Several classes—Healthy Leaf, Healthy Nut, Yellow Leaf Disease, Stem Bleeding, and Healthy Foot—achieved perfect recall (1.00). The wrong input class reached a precision of 1.00 and an F1-score of 0.89, showing the model’s ability to reject non-arecanut images effectively.

D. Integration of IoT Deployment and Hybrid Interpretation

The ArecaSafe integrates both climatic and image-based insights, creating a hybrid, multi-level understanding of disease progression in arecanut plantations. A single IoT sensing node—consisting of an ESP32 microcontroller, rainfall sensor (I2C), BH1750 light sensor, BME280 temperature and humidity sensor, and a power bank—is used for continuous field monitoring. Each node costs approximately ₹7,000, making the system affordable for small and medium-scale farms. Larger plantations can deploy multiple nodes to capture spatial variations and improve predictive reliability. The climatic risk assessment module, powered by the Random Forest model, identifies broad environmental triggers such as humidity shifts, rainfall intensity, and temperature fluctuations. At the same time, the EfficientNetB0-based CNN focuses on fine-grained, micro-level visual disease symptoms. Together, these models form a strong, complementary decision-support system. However, a few real-world constraints still exist. CNN accuracy may be influenced by image lighting or quality, while the climatic model may struggle with extreme weather patterns not represented in the training data. IoT connectivity issues in rural regions can also lead to occasional data interruptions. Despite these challenges, field evaluations show that

ArecaSafe performs reliably under diverse conditions, offering high adaptability and strong potential for farmer-focused, real-time disease management.

VI. Conclusion

ArecaSafe brings together IoT-based sensing, climatic analysis using Random Forest, and image-based diagnosis through an EfficientNetB0-CNN to deliver a proactive solution for detecting Fruit Rot in arecanut plantations. Field tests confirmed the system's reliability and practical usability. With future improvements—such as multi-disease detection, real-time edge inference, and expanded environmental sensing—ArecaSafe has strong potential to evolve into a complete decision-support tool for sustainable and modern arecanut cultivation. Future enhancements aim to expand ArecaSafe into a broader crop-health platform. Key directions include extending the CNN model to detect multiple arecanut diseases, integrating Edge AI for on-device, real-time processing, and adding more sensors for soil moisture, nutrient content, and leaf-wetness monitoring. Additional plans involve refining the hardware for lower-cost deployment and developing a scalable analytics dashboard with support for multi-farm management.

Acknowledgment

The authors would like to express their sincere gratitude to Zonal Agricultural and Horticultural Research Station (ZAHRS), Brahmavara, for their invaluable support and collaboration throughout this project. We also extend our thanks to the A.J. Institute of Engineering and Technology, Mangalore, for providing the necessary resources and encouragement that made this work possible.

References

[1] P. Phalke, S. Jadhav, A. Kulkarni, and V. Raut, "IoT-Based Smart Agriculture for Crop Disease Detection," Int. J. Eng. Res., vol. 9, no. 4, pp. 112–119, 2022.
[2] R. Buyya et al., "IoT-Enabled Smart Farming: Cloud Integration and Edge Processing," Future Generation Computer Systems, vol. 115, pp. 38–53, 2021.
[3] S. Sharma and R. Gupta, "Random Forest Model for Plant Disease Prediction," J. Agric. Informatics, vol. 14, no. 2, pp. 45–53, 2021.
[4] A. J. Dsouza and P. S. Rao, "Impact of Climatic Variables on the Sporulation and Spread of Phytophthora palmivora," Phytopathology Research, vol. 5, no. 1, 2020.
[5] K. R. Sharath Kumar, K. Mohan, and Nirisha, "Arecanut Crop Disease Prediction Using IoT and Machine Learning," J. Sci. & Technol., vol. 5, no. 3, pp. 160–165, 2020.
[6] K. Rajashree, K. Prema, G. Rajath, and S. Angad, "Prediction of Fruit Rot Disease Incidence in Arecanut Based on Weather Parameters," Estonian Univ. Life Sci., 2022.
[7] T. G. Sankar, B. S. Murthy, and L. R. Devi, "Predictive Modeling of Crop Disease Risk Using Ensemble Machine Learning Algorithms," Computers and Electronics in Agriculture, vol. 189, 106399, 2021.
[8] A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," Advances in Neural Information Processing Systems, vol. 25, pp. 1097–1105, 2012.
[9] M. Sandler, A. G. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR), 2018.
[10] C. V. S. Rao, G. B. Goud, and K. M. Krishna, "Fine-Tuning Convolutional Architectures for Disease Diagnosis on Arecanut Images," Int. J. Image Process. Vis. Comput., vol. 11, no. 4, pp. 112–125, 2024.
[11] V. S. Rajpoot, A. P. Singh, and M. P. Singh, "A Comprehensive Review on Arecanut Diseases and Their Management Strategies," J. Crop Protection, vol. 22, no. 1, pp. 15–24, 2023.
[12] K. P. Mohana, P. V. Hegde, and S. G. Prabhu, "IoT-Based Environmental Monitoring for Fungal Disease Management in Tropical Horticulture," IEEE Sensors J., vol. 23, no. 18, pp. 21000–21012, 2023.
[13] H. V. Ramesh and A. R. Kumar, "A Serverless Approach for Real-Time IoT Data Management in Agriculture Using Supabase and FastAPI," Int. J. Computing and Digital Systems, vol. 12, no. 3, pp. 401–415, 2022.
[14] J. R. Latha and M. S. Gowda, "Optimizing Wireless Data Transmission from BME280 Sensors for Agricultural Applications," Int. J. Sensor Technology and Applications, vol. 8, no. 2, pp. 89–101, 2021.
[15] G. S. Hegde and R. K. Shanbhag, "Review on the Application of Machine Learning in Precision Agriculture for Tropical Crops," Agricultural Systems, vol. 202, 103444, 2022.
[16] Zonal Agricultural and Horticultural Research Station (ZAHRS), Brahmavara, Karnataka, India, "Regional Arecanut Crop and Climatic Data Repository (2014–2024)."