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Plant Monitoring System

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Abstract – Farmers face several key issues in Arecanut farming during irrigation, to prevent stress caused by excess or shortage of water which in turn affects the yield and its quality. This main purpose of this paperis to solve these issues with technology. This paper develops and implements a very effective solution which also aims to reduce costs through IoT based system to monitor and maintain moisture levels in soil during cultivation. This system makes utilize of a network of sensors which are deployed across the entire field of cultivation which assists the farmers to make perfect decisions on irrigation, to prevent water stress and optimize water usage to improve plant health and yield of Arecanut. This smart watering system assures timely watering by relying on real-time soil conditions quite than guessing. Automating water supply reduces waste and supports sustainable farming practices. Finally, the strategy enables farmers to increase output while lowering input expenditures.

Key Words: DeepLearning, ML, Moisture Sensor.

1.INTRODUCTION

Agriculture which is the backbone of the Indian economy is plagued by various problems which affect the palnt and yield. To improve the quality of the yield and arecanut produced, there needs to be efficient way of monitoring the crops. In the old school methods of agriculture these include observation through labor who can sometimes be prone to lack of knowledge and expertise in this regard, even then this process is time consuming, very intense and inaccurate. To solve these issues modern methods and techniques like sensors, Internet of things, data analysis can be employed and engaged to develop a Plant communication along with Monitoring System.The paper is formulated by taking Arecanut plant as an example to develop an automated plant monitoring system. This plant, commonly cultivated in costal and Malnad regions of India, is very sensitive and requires highest care in terns of soil moisture, disease prevention and timely watering, These things need to be monitored to help farmers decide to ensure healthy plant growth and reduce loss of crops and yield. The suggested system uses modern sensors to constantly monitor soil moisture, temperature, and the humidity levels around the plant.By integrating Internet of Things (IoT) machine, sensor data can be broadcast in the real time to farmers' mobile phones or dashboards.This guarantees that farmers are immediately warned when soil moisture levels drop down the required level or disease symptoms are identified.The use of data analysis aids in anticipating plant health trends and addressing future problems before they worsen.Automation eliminates the need for manual labor and minimizes human errors in observation and decision-making.The technique also promotes timely irrigation, which prevents both water scarcity stress and overwatering of the arecanut crop. Farmers can rely on the system to keep their plants healthy, which leads to increased productivity and higher-quality harvest.

Such technology-based solutions help to promote sustainable farming practices and efficient resource utilization. The monitoring system serves as a virtual communication channel between plants and farmers, conveying crops' true demands.Overall, this technique assures that agriculture becomes wiser, more cost-effective, and more dependable in meeting the problems of arecanut cultivation.

2. LITERATURE SURVEY

Dohare et al. [1] proposes a system to integrate IoT sensors and ML models to observe plant health and predict diseases. This approach aims to move beyond simple monitoring to provide predictive analytics for preemptive agricultural interventions.

Devi et al. [2] analyzes techniques to reduce power consumption in 45nm 6T SRAM cells, a critical component of high-performance computing. This work focuses on optimizing design parameters to minimize leakage power and improve overall energy efficiency.

Tarigan et al. [3] presents an IoT system to monitor environmental parameters in hydroponic setups, automating data collection for soilless agriculture. Their work focuses on the practically implementing sensors and connectivity to maintain optimal growth conditions.

Son et al. [4] critically evaluates the evidence for plant acoustic communication, concluding that while plants emit stress-induced sounds, these are likely inaudible to other plants. They argue that most observed "responses" are to substrate vibration, not airborne sound, and find no conclusive proof of information exchange via acoustics.

Ang el al. [5] reviews biosensors which are nondestructive for diagnosing plant health through detection of internal metabolites. This paper highlights the potential of these tools for enabling precision agriculture and early stress detection in plants.

Barhate et al. [6] presents automated plant watering and monitoring of soil conditions through IoT-based system. The paper emphasizes the practically integrating sensors and cloud computing for remote control and real time data access.

D. Roja et al. [7] details an IoT framework and utilize sensors to observe key factors of plant health like soil moisture and temperature in real-time. The system is formulated to transmit data to a cloud platform for analysis and provide actionable insights to farmers.

Afif, S. et al. [8] designed smart monitoring system using plant bioelectrical signals as a novel, real-time indicator of health status in indoor farming. Their system employs silver-wire electrodes and signal processing to detect stress; this method is more responsive and alternative to spectral imaging. The work lays the base for using machine learning on electrophysiological data for early stress detection.

Tarigan et al. [9] presents an IoT system to monitor environmental parameters in hydroponic setups, automating data collection for soilless agriculture. Their work focuses on the practically implementing sensors and connectivity to maintain optimal growth conditions.

Dalal [10] explores the evidence of plants emitting and responding to acoustic signals as a form of communication and stress response. This review synthesizes research and suggests sound influences processes like germination, growth, and defense mechanisms.

3.METHODOLOGY

A. Workflow Diagram

Deep learning-based image classification approach is used in Arecanut Disease Prediction System to automatically detect and classify diseases in arecanut plants. A preprocessed dataset of arecanut leaf images—categorized into healthy and diseased classes is used to train a Convolutional Neural Network (CNN) model—using data augmentation to improve generalization. The system includes a user-friendly GUI built with Tkinter which allows farmers to upload images, view predictions, and hear results via text-to-speech. Input images are resized, normalized and are fed to trained CNN to give output class probabilities, which are designed to be displayed both visually and audibly for easy interpretation by non-technical users. The model achieved high accuracy in identifying multiple disease classes, ensuring reliable performance even with diverse image samples. This system can serve as an effective decision-support tool for early disease management and sustainable arecanut cultivation.

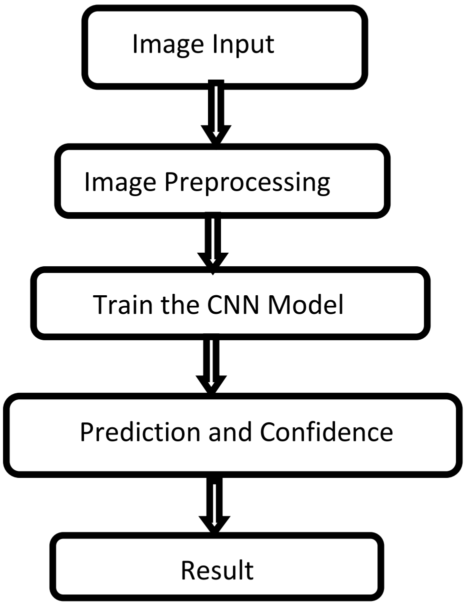

Fig.1: Workflow Diagram

Image Input: The process is started when a user uploads a digital image of an arecanut plant or leaf through a simple button in the graphical interface. The interface is built using Tkinter, which makes it easy for anyone, including farmers without technical skills, to select and submit an image from their device easily for analysis.

Image Preprocessing: Before the image is analyzed, it must be prepared for the model. The system automatically resize the image to aa standard dimension of 150x150 pixels. It also converts the pixel values into a numeric format and normalizes them, which is simply nothing but scaling the numbers down to a range between 0 and 1. This step ensures the image is simply nothing but scaling the numbers down to a range between 0 and 1. This step ensures the image in this format the trained the model expects for accurate prediction.

Trained CNN Model: The preprocessing image is fed into a pre-trained CNN model.

Prediction and Confidence: The CNN model processes the image feature and probability for each possible disease category.

Result: Ultimatly the result is presented to farmers in multiple ways.

B. Dataset Description

A dataset is the collection of linked data, typically organized in a table format that used as the analysis, training ML models.

Table 1: Dataset Description

Category	Explanation
Healthy_Leaf	Images of the disease free arecanut plants leaves used as the served a healthy leaf.
Healthy_Nut	Images of this nuts with the no mould infestation, defect.
Healthy_Trunk	Trunks is in the good condition, with the no cracks lesions
Stem_bleeding	Steam Bleeding disease has caused black lesions and gum exudation on the trunks.
Normal	Normal plant images with a no problems are not further classified.

C. Algorithm

The CNN processes images in the sequence of these structured steps. The input layer starts with the pixel picture. The convolution layer then uses filters to extract key features, including the edges, textures, and patterns. These collected characteristics are processed using the ReLU activation function, which incorporates nonlinearity to increase the model's learning ability. These pooling layer decreases the extent of the feature maps while keeping important facts. The fallowing that the flatting phase reduces the 2D feature maps to 1D vector exact for the Classification. This flattened vector is then fed into the fully linked layers, where high-level reasoning is used. The final output layer assigns the image to the appropriate categories using a softmax function.Thus, these successive processes enable the CNN to effectively turn raw input images into meaningful predictions.

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1. Input Layer- The image data is to fed in the network
2. Convolution Layer- Filters are used to extract key elements such as the edges, textures, and the patterns.
3. Activation Function- Introduces nonlinearity to enhance learning capability.
4. Pooling Layer- Reduce the size of the feature maps while essential information.
5. Flattening- Convert the feature maps into the vector.
6. Fully Connected Layer- Learns the complex classifies features.
7. Output Layer- Produces the probability scores for each of disease class

D. Model Training Process

The model training process involves the feeding a dataset into the ML model, which learns patterns and relationships. Preprocessing data, training algorithms, and the modifying parameters to improved prediction accuracy.

Fig.2: Model Training

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Epoch 1/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 369ms/step - accuracy: 0.1331 - loss: 2.1237
27/27 ━━━━━━━━━━━━━━━━━━━━ 14s 483ms/step - accuracy: 0.1331 - loss: 2.122
Epoch 2/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 336ms/step - accuracy: 0.1964 - loss: 2.0390
27/27 ━━━━━━━━━━━━━━━━━━━━ 12s 427ms/step - accuracy: 0.1967 - loss: 2.038
Epoch 3/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 330ms/step - accuracy: 0.2232 - loss: 1.9412
27/27 ━━━━━━━━━━━━━━━━━━━━ 12s 433ms/step - accuracy: 0.2244 - loss: 1.940
Epoch 4/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 352ms/step - accuracy: 0.3307 - loss: 1.7218
27/27 ━━━━━━━━━━━━━━━━━━━━ 12s 444ms/step - accuracy: 0.3305 - loss: 1.722
Epoch 5/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 337ms/step - accuracy: 0.4005 - loss: 1.5813
27/27 ━━━━━━━━━━━━━━━━━━━━ 12s 431ms/step - accuracy: 0.4008 - loss: 1.581
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Fig.2: Model Training Process

4.Results and Discussion

The Developed CNN model successfully identified arecanut disease across classes with strong prediction accuracy. The findings accentuate its potential for reliable early detection and practical use in precision agriculture. The model achieved consistent performance during testing, showing robustness against variations in images samples. Such accuracy can help farmers timely preventive measures and improve crop productivity.

A.Precision-recall Curve

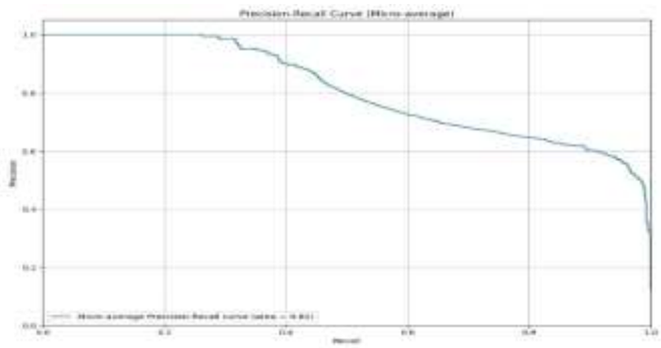

Fig 3: precision recall-curve

The Precision-Recall curve illustrates the balance between precision and recall achieved by the CNN model in classifying arecanut diseases. As shown in the graph, the model maintains high precision at lower recall values, with a gradual decline as recall increases. The area under the curve (AUC) is 0.81, indicating good predictive performance and the model's ability to distinguish between different disease classes. This result confirms that the system is effective in handling imbalanced datasets and can provide reliable predictions in practical agricultural scenarios.

B. Snapshots

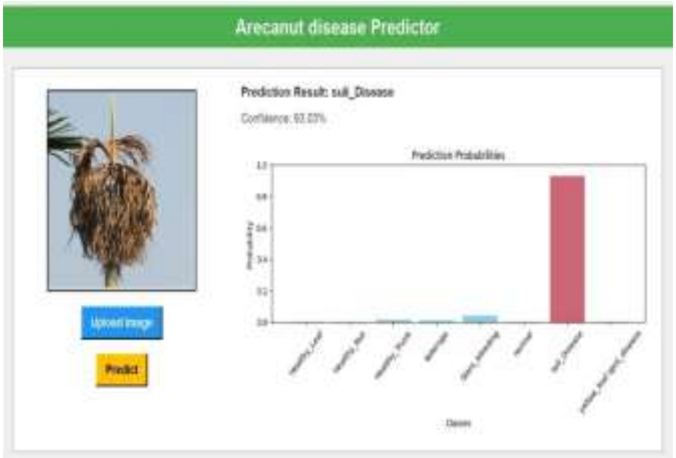

Fig.4: Arecanut Disease

The output of the Arecanut Disease Predictor demonstrates the detection of Suli_Disease with a confidence level of 93.03%. The uploaded image of the arecanut plant was processed by the CNN model, and the prediction probabilities graph clearly indicates that the highest probability corresponds to the Suli_Disease class, while other classes show very minimal values. This high confidence score highlights the reliability of the trained model in distinguishing between healthy and diseased conditions, proving its effectiveness in supporting farmers with accurate disease diagnosis.

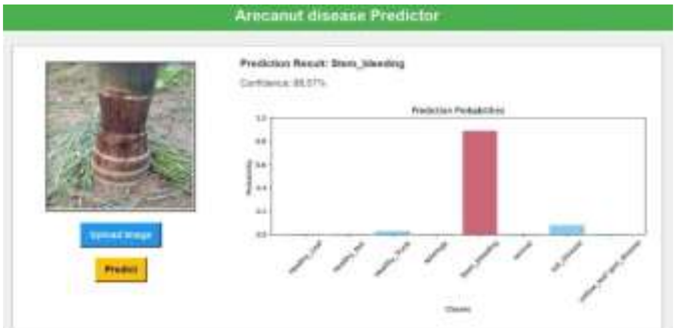

Fig.5: Stem bleeding disease detection

The above diagram shows how the Arecanut Disease Predictor system works. The user inputs an image of the arecanut tree trunk, which is analyzed by the deep learning model has been trained to detect potential diseases. Here, the disease has been predicted by the system as Stem Bleeding at a confidence value of 88.57%. The graph of the probability distribution clearly indicates that the highest prediction value is associated with the Stem Bleeding class and very low values for the other classes like Healthy Leaf, Healthy Nut, Healthy Trunk, Kole Roga, Suli Disease, and Yellow Leaf Spot Disease. This means that the model has correctly classified the image. Stem Bleeding is a severe arecanut fungal disease, showing reddish-brown exudate from the trunk, which ultimately lowers the plant's strength and yield. The prediction system allows farmers to identify such diseases at the initial stage, thus initiating timely management and preventive actions to ensure crop health.

3. CONCLUSIONS

The designed Plant Monitoring System for Arecanut plants successfully illustrates the use of this deep learning and IoT-based techniques for effective plant disease detection. By using the Convolutional Neural Network (CNN) model, the system can accurately classify plant images into healthy or disease-affected categories while also showing confidence probability. The addition of additional functions like the probability distribution graphs and a text-to-speech (TTS) module makes it more user-friendly and practical for farmers without much technical skills. Experimental results shows that the model can reliably identify diseases like Suli Disease, Stem Bleeding, and Yellow Leaf Spot Disease, while also recognizing healthy plant conditions. This system helps in reducing manual monitoring efforts, ensures early detection of diseases, and supports timely intervention, thereby improving crop yield of this productivity.
This method can be enhanced in the later by including more datasets, increasing model accuracy, and expanding its application to other crops.

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