A Unified Approach to Smart Coconut Farming with IoT and Deep Learning for Recommendation of Pesticides and Fertilizers

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Abstract. Coconut production has a significant impact on the livelihoods of many farmers worldwide, serving as a primary source of income. However, recent observations have revealed a concerning decline in tree health and leaf condition, attributed to prevalent diseases and soil nutrition deficiencies. This deterioration poses a direct threat to productivity, gradually weakening coconut trees' strength, nutrient absorption capacity, and yield production. Recognizing the urgency of this issue, this paper proposes an innovative approach leveraging Deep Learning, specifically Convolutional Neural Networks (CNNs), and the interconnected network of physical devices commonly referred to as the Internet of Things (IoT). The primary objective of this project is to develop a comprehensive web application for early coconut disease detection using CNN. Advanced technologies, including classification and image processing are integrated to assess tree health, identify disease symptoms, and detect pest infestations. Beyond disease detection, the project incorporates a recommendation system for pesticides to effectively cure identified diseases. Additionally, Internet of Things (IoT) technology is employed to analyze soil conditions, providing insights that inform personalized fertilizer recommendations. This proactive system not only mitigates current challenges faced by coconut farmers but also establishes a sustainable framework for optimizing productivity. The overall performance of this architecture is validated with an impressive accuracy measure of 97.2%.

Keywords: CNN · Image Processing · Classification · Internet of Things

1 Introduction

Coconut farming stands as a cornerstone of agricultural economies across the globe, supporting the livelihoods of millions of farmers and serving as a primary source of income [1]. The versatility of the coconut tree, with its myriad uses ranging from food and oil production to construction materials and cosmetics [2], underscores its economic

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importance. However, despite its significance, coconut cultivation faces numerous challenges that threaten its sustainability and productivity [3]. It is widely grown across tropical regions around the world, particularly in countries with coastal areas and warm climates, such as the Philippines, Indonesia, India, Sri Lanka, and Brazil [4]. Coconut palms thrive in sandy soils and are highly valued for their ability to grow in diverse ecological conditions. The coconut industry not only contributes substantially to the national economy but also serves as a vital source of foreign exchange. Coconut trees are known for their resilience and ability to withstand harsh environmental conditions like strong winds and salty soils, making them an essential crop for coastal communities. They have significant cultural, economic, and nutritional importance, providing food, shelter, and livelihoods for millions of people worldwide.

One of the most pressing concerns in coconut farming is the declining health of coconut trees and the consequent reduction in yield. Observations in recent years have highlighted a troubling trend characterized by deteriorating tree health and diminishing leaf condition. Factors such as prevalent diseases and soil nutrient deficiencies have been identified as primary contributors to this decline. Diseases such as lethal yellowing, stem bleeding, and bud rot, coupled with inadequate soil nutrition, have severely compromised the vigor and productivity of coconut trees [5, 6]. The ramifications of this decline in tree health are profound, posing significant economic and social implications for coconut-dependent communities. Reduced yields directly impact the income and livelihoods of farmers, exacerbating poverty and food insecurity in affected regions. Moreover, the ecological balance and resilience of coconut ecosystems are jeopardized, further worsening the susceptibility of agricultural systems to environmental stresses and climate variability. Tackling the obstacles encountered by coconut farming requires innovative approaches that integrate advanced technologies with traditional agricultural practices. In this context, leveraging Deep Learning, specifically Convolutional Neural Networks (CNN), and the Internet of Things (IoT) presents a promising avenue for enhancing coconut tree health monitoring and management [7]. By harnessing the power of data analytics and real-time monitoring, this research aims to empower farmers with timely insights and actionable information to mitigate disease outbreaks, optimize soil nutrition, and improve overall productivity. So, there is an urgency to resolve these issues. One method to protect the crop is through early disease detection, followed by the timely application of suitable pesticides. Additionally, monitoring soil conditions allows for the selection and application of the correct fertilizers to optimize crop growth. This protects the crop from severe disease attacks to increase coconut cultivation and get more cost-effective benefits. Considering the challenges inherent in coconut farming, our objective is to integrate Convolutional Neural Networks (CNN) and IoT technologies. Our project prioritizes the utilization of CNN and image processing techniques to accurately detect diseases and recommend appropriate pesticides for treatment. Additionally, we employ IoT sensors to gather soil data, enabling us to recommend the most suitable fertilizers for optimal crop growth. By integrating this advanced technology, which includes CNN for disease detection and IoT for soil data collection, we envision a reduction in disease-related issues, enabling farmers to address concerns promptly and enhance overall coconut tree productivity. This innovative approach signifies a step forward in revolutionizing coconut farming practices, promoting a more sustainable and productive agricultural landscape.

2 Related Work

Recently, research has been conducted on incorporating deep learning and image processing technologies for the prediction of coconut diseases [8]. The researchers focused on detecting pest attacks and nutrient deficiencies in coconut leaves and analyzing diseases. They monitored the coconut leaves after the application of pesticides and fertilizer, utilizing machine learning and image processing techniques [9]. In this study, they developed an Android app designed to recognize pests by analyzing their feeding patterns, prevalent diseases, and symptoms of nutritional deficiencies, particularly within coconut trees. They utilized SVM and CNN as their primary classifiers, achieving accuracies of 93.54% and 93.72%, respectively. Despite these achievements, the research exhibited several limitations. Firstly, the development of an Android application for pest identification and disease analysis might have inadvertently restricted accessibility, potentially excluding farmers with limited access to Android devices. Secondly, the research solely focuses on pest detection and disease classification, lacking integration with critical aspects of crop management, such as soil condition analysis. Innovatively, our project addresses the limitations of prior research efforts while introducing groundbreaking features to revolutionize coconut disease prediction and management. We developed a web application primarily focusing on detecting coconut diseases using image processing techniques and recommending pesticides for disease mitigation. Unlike previous research, our web application can be accessed through any internet-enabled device, including desktop computers and tablets, making it more inclusive for farmers with varying technological resources. Additionally, we integrated our model with IoT sensors capable of analyzing soil conditions and suggesting appropriate fertilizers. This integration enables a comprehensive approach to crop management, addressing both above-ground disease threats and soil nutrient deficiencies. By providing actionable insights into both pest management and soil health, our project offers a holistic solution to enhance crop yield and sustainability. Through this initiative, we aim to detect diseases at an early stage, ultimately enhancing crop yield and providing valuable support to farmers while also ensuring accessibility and inclusivity in technology adoption.

3 Architectures

The architecture of the Coconut Disease Prediction System is built upon a Convolutional Neural Network (CNN) model. The CNN model comprises of five layers meticulously designed to derive distinctive characteristics from input visuals effectively. Initially, the model itself is structured with convolutional layers employing rectified linear unit (ReLU) activation functions, which facilitate the discernment of spiral characteristics from the input images. Following this, max-pooling layers are integrated to down sample the feature maps, reducing computational complexity while retaining essential features. This down sampling mechanism aids in achieving translation invariance, allowing the model to detect features regardless of their position within the input image. Additionally, the CNN architecture includes fully connected dense layers that incorporate the spatial characteristics acquired through convolutional layers, leading to high-level feature representation. Ultimately, a SoftMax activation function is employed at the output layer to generate probability distributions across disease classes, enabling the model to make accurate predictions. Overall, the CNN architecture leverages hierarchical feature extraction to robustly classify coconut diseases based on input image data.

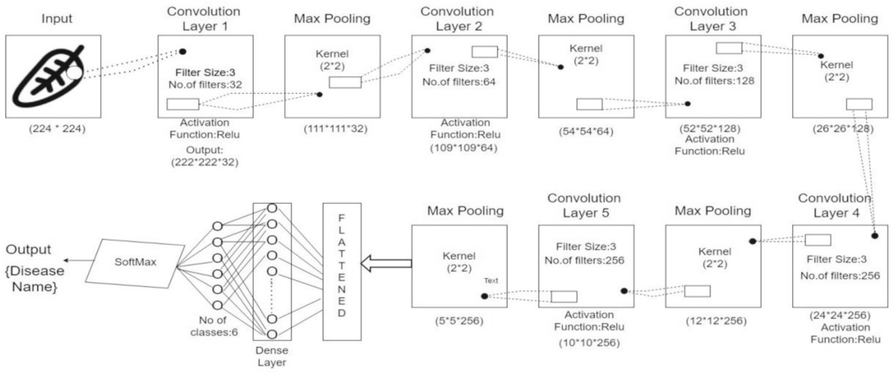


Fig. 1. Architecture of Coconut disease detection using Convolutional Neural Network

The Fig. 1 describes Convolutional Neural Network (CNN) architecture proposed for disease detection in coconut plants. The model begins by taking the coconut image as the input image with a resolution of 224 * 224 pixels. It starts with a convolutional layer using a 3 * 3 filter and 32 filters, followed by Rectified Linear Unit (ReLU) activation, producing feature maps of size 222 * 222 * 32. A pooling layer with a 2 * 2 kernel halves the dimensions, resulting in feature maps of 111 * 111 * 32. Another convolutional layer with a 3 * 3 filter and 128 filters, followed by ReLU activation, generates feature maps of 109 * 109 * 64. Subsequently, another pooling layer reduces dimensions to 54 * 54 * 64. The next layer involves a convolutional operation with a 3 * 3 filter and 128 filters, leading to feature maps of size 52 * 52 * 128 with ReLU activation. Another pooling layer reduces dimensions to 26 * 26 * 128. The architecture then applies a convolutional layer with a 3 * 3 filter and 256 filters, followed by ReLU activation, producing feature maps of size 24 * 24 * 256. Another pooling operation halves the dimensions to 12 * 12 * 256. This is followed by another convolutional layer with a 3 * 3 filter and 256 filters, resulting in feature maps of size 10 * 10 * 256 with ReLU activation. Subsequently, a pooling layer further reduces dimensions to 5 * 5 * 256. Following this, a flattening layer prepares the data for input into a dense layer with ReLU activation. Finally, a dense layer with SoftMax activation is employed, with the number of classes corresponding to the detection of six diseases being the output objective in the project.

3.1 CNN Model

The Deep Convolutional Neural Network (CNN) architecture is a sophisticated advanced machine learning model tailored for examining grid-patterned data, such as images. Taking cues from the structural organization of the animal visual cortex, CNNs possess the capability to autonomously learn hierarchical spatial features, progressively from lower to higher levels of abstraction. Comprising three primary types of layers—convolution, pooling, and fully connected layers—CNNs are adept at feature extraction and classification tasks. Specifically, convolution and pooling layers play pivotal roles in feature extraction, while fully connected layers are responsible for mapping these features to produce final outputs, such as classification results. The convolution layer, a cornerstone of CNNs, employs mathematical operations, notably convolution, to efficiently derive the relevant features from the input data.

The Convolution Layer. The Deep Convolutional Neural Network (CNN) architecture is a sophisticated advanced machine learning model tailored for examining grid-patterned data, such as images. Taking cues from the structural organization of the animal visual cortex, CNNs possess the capability to autonomously learn hierarchical spatial features, progressively from lower to higher levels of abstraction. Comprising three primary types of layers—convolution, pooling, and fully connected layers—CNNs are adept at feature extraction and classification tasks. Specifically, convolution and pooling layers play pivotal roles in feature extraction, while fully connected layers are responsible for mapping these features to produce final outputs, such as classification results. The convolution layer, a cornerstone of CNNs, employs mathematical operations, notably convolution, to efficiently derive the relevant features from the input data.

The Pooling Layer. Following the Convolutional Layer, a Pooling Layer is frequently employes to shrink the dimensions of the resulting convolved feature map, reducing computational load. This layer works independently on each feature map, minimizing interlayer connections. Various Pooling operations exist, such as Max Pooling, which selects the largest element, and Mean Pooling, which computes the mean value of elements in a defined section. Positioned between the Convolutional Layer and the Fully Connected Layer, the Pooling Layer aids in generalizing features, reducing computational demands.

The Dense Layer. In a Dense Layer each neuron obtains input from every neuron in the preceding layer. Neurons within the Dense Layer perform matrix-vector multiplication operations. This involves aligning the row vector representing the output generated by previous layers with the column vector of the Dense Layer. It's essential to note that according to the principles of matrix-vector multiplication, the row vector's number of columns must match the dimension of the column vector.

The Fully Connected Layer. The Fully Connected (FC) layer is comprised of weights, biases, and neurons, enabling connections between neurons across layers. Usually positioned before the output layer, FC layers represent the concluding stages of a CNN Architecture. Input images are flattened from preceding layers and transmitted to the FC layer. Then, the compressed vector progresses through extra fully connected layers where mathematical computations commonly occur initiating classification. Utilizing multiple connected layers improves performance compared to a single connected layer. These layers in CNNs help in decreasing the requirement for human oversight.

3.2 Activation Function

The activation function is a crucial aspect of CNN models, determining which information should be activated during forward propagation. It introduces non-linearity, enabling the network to capture complex patterns in data. Common activation functions include ReLU, SoftMax, tan, and Sigmoid. For binary classification, Sigmoid and SoftMax activation functions are preferred, while SoftMax activation function is used for multi-class classification. Activation functions guide the network in making predictions by determining neuron activation. Hidden layers, situated between input and output layers, process data through weighted connections and activation functions. They capture intricate patterns in the data through non-linear transformations. Tuning the number of layers and neurons is crucial for optimal model performance. Despite their complexity, hidden layers enable neural networks to learn and generalize effectively.

ReLU (Rectified Linear Activation Unit). ReLU has become the dominant activation function in global deep learning systems owing to its simplicity and effectiveness. Both its function and derivative are monotonic, which aids in training convergence. However, ReLU suffers from the "dying ReLU" issue, where negative inputs are immediately mapped to zero, diminishing the model's capability to learn from negative values. ReLU function, denoted as f(x) = max (0, x) outputs zero for negative inputs (x) and the input value itself otherwise. This abrupt transforming negative values to zero can distort the representation of negative values in the final graph.

The ReLU function is determined through the following computation:

$$\mathrm{f(x)} = \max\ (0,\ \mathrm{x}) \tag{1}$$

This indicates that if the input value (x) is negative, the function returns.0; otherwise, it returns the input value.

SoftMax. The SoftMax function transforms an array of K real values into another array of K real values, ensuring that the resulting values sum up to 1. This function transforms input values, which may range from negative to positive, including zero, and scales them to fall within the interval from 0 to 1, making them interpretable as probabilities. When an input is diminutive or negative, SoftMax allocates it a relatively low probability; if it's large, it assigns a relatively higher probability, yet always ensuring it falls within the range of 0 to 1.

SoftMax is determined by the following calculation:

$$\sigma(Z)i = \frac{e^{zi}}{\sum_{j=1}^{k} e^{zj}} \tag{2}$$

where:

z is a vector of real numbers,

zi is the ith element of z,

K is the number of elements in z, and

σ (z)i is the ith element of the resulting SoftMax vector.

3.3 IOT: 7 in 1 Soil Sensor

The “7-in-1 soil sensor” refers to a multifunctional device designed to provide comprehensive information about soil conditions. Typically used in agriculture, gardening, or environmental monitoring, these sensors offer various measurements crucial for plant growth and soil health assessment. While features may vary between different models, a typical 7-in-1 soil sensor might include the following capabilities:

Soil Moisture. Measures the moisture content of the soil, indicating whether it is too dry or too wet for optimal plant growth.

Soil pH. Determines the acidity or alkalinity of the soil, which is essential for understanding nutrient availability and plant health.

Soil Temperature. Monitors the temperature of the soil, which influences biological processes such as seed germination, nutrient uptake, and microbial activity.

Light Intensity. Measures the amount of light reaching the soil surface, aiding in assessing sunlight exposure for plants and determining optimal planting locations.

Nutrient Levels. Some models may include sensors for essential nutrients like nitrogen (N), phosphorus (P), and potassium (K), providing insights into soil fertility and nutrient management.

Environmental Humidity. Tracks the humidity levels in the surrounding environment, which can influence soil moisture retention and plant transpiration.

Atmospheric Pressure. Measures atmospheric pressure, which indirectly affects soil moisture levels and plant growth by influencing precipitation patterns and water movement in the soil.

Overall, a 7-in-1 soil sensor offers a comprehensive suite of measurements to help users make informed decisions about irrigation, fertilization, and overall soil management practices to optimize plant health and productivity.

4 Experimental Setup

4.1 Dataset Used

The Convolutional Neural Network (CNN) model was trained and tested using a comprehensive dataset comprising coconut disease images sourced from two reputable platforms: Kaggle and Mendeley.

Kaggle Coconut Leaf Dataset for Pest Identification. This dataset, obtained from Kaggle, contributes a significant portion of the images used in the research.

Mendeley Coconut Tree Disease Dataset. Images from Mendeley were also incorporated into the dataset, enriching it with additional samples and enhancing its diversity.

From the combined datasets, six major coconut diseases were selected based on their significant impact on production. These diseases were carefully chosen to provide a focused study on prevalent issues affecting coconut cultivation. Selected diseases are Bud Root Dropping, Bud Rot, Caterpillars, Flaccidity, Yellowing of Leaves and Stem Bleeding. Our comprehensive data set contains a total of 5160 images across six distinct disease classes. Each class consists of more than 300 images. Our dataset was meticulously split into three subsets to facilitate the training, validation, and testing phases of the Convolutional Neural Network model. Specifically, 70% of the dataset was allocated for training the model, 15% of the dataset for validation, and the remaining 15% for testing the model (see Fig. 2).

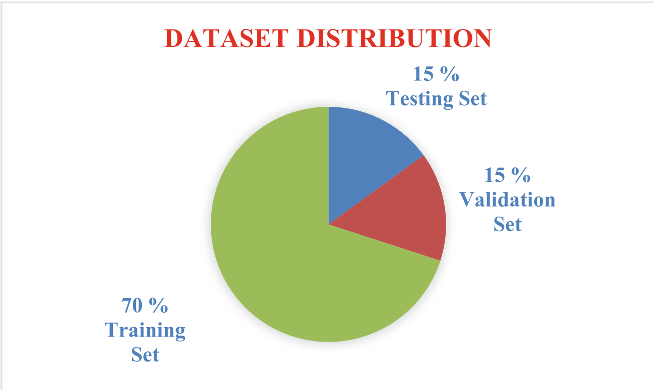


Fig. 2. Pie chart representing the distribution of the dataset

Prior to model application, thorough data preprocessing was conducted. Images were resized to 224 × 224 dimensions, and horizontal flipping transformations were applied to augment the dataset. Additionally, image pixel values were rescaled using "rescale = 1/255" to normalize them within the [0, 1] range, enhancing model performance. The experimental framework involved developing a structural Convolutional Neural Network (CNN) architecture with numerous convolutional and max-pooling layers, followed by dense layers for multi-class classification using SoftMax activation. The Adam optimization algorithm was utilized alongside the categorical cross-entropy loss function during model training, employing 10 epochs [10, 11]. The performance of the model was evaluated using categorical cross-entropy loss [12]:

$$CE = -\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{C} t_{ij}\log(p_{ij}) \tag{3}$$

where, n stands for number of samples

C denotes total number of classes

t_{ij} represents an indicator function denoting the truth class.

p_{ij} represents the predicted probability of class j

Subsequently, the trained model is saved for future utilization under the filename 'model.h5'. Furthermore, to demonstrate the practical applicability of our research, we have developed a user-friendly web application. This application allows users to upload coconut leaf images for disease classification. Upon image submission, our system preprocesses the image and employs our trained Convolutional Neural Network (CNN) model to predict the disease class. Subsequently, based on the predicted disease class, the application retrieves corresponding cure recommendations from a curated dictionary. Additionally, our web application integrates an Internet of Things (IoT) setup, enabling real-time monitoring of crucial soil conditions such as pH level, NPK (Nitrogen, Phosphorus, Potassium) levels, temperature, moisture content, and electrical conductivity. Using these soil values, the IoT system suggests appropriate fertilizers tailored to the specific needs of the soil, thereby providing farmers with comprehensive insights into both disease management and soil health optimization [13]. This comprehensive solution not only facilitates accurate disease classification and actionable cure suggestions but also enhances disease management strategies and soil fertility management in coconut farming through accessible and user-friendly technology.

5 Results

After using our trained model, we have built the web application using Flask (see Fig. 4). The accuracy stands at 9.72%. The plots (see Fig. 3) showcase the CNN model's training progress over epochs. The left subplot tracks the decreasing trend in loss, while the right subplot displays the increasing accuracy, indicating the model's improving performance over time.

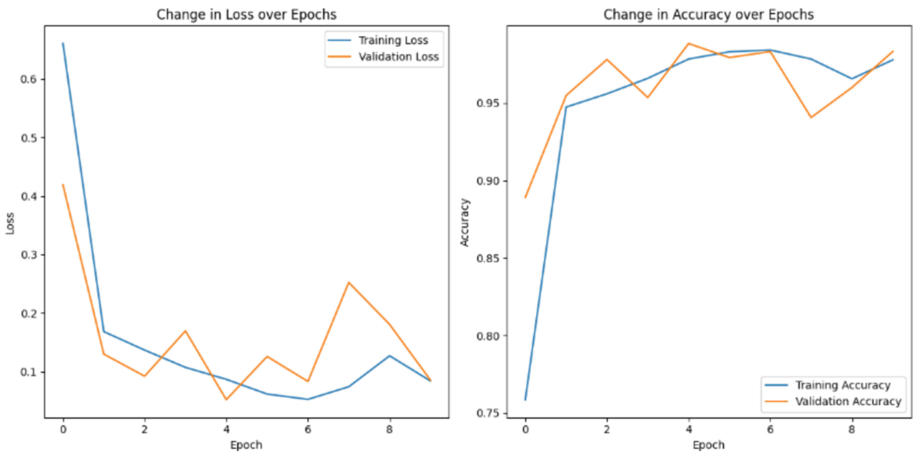
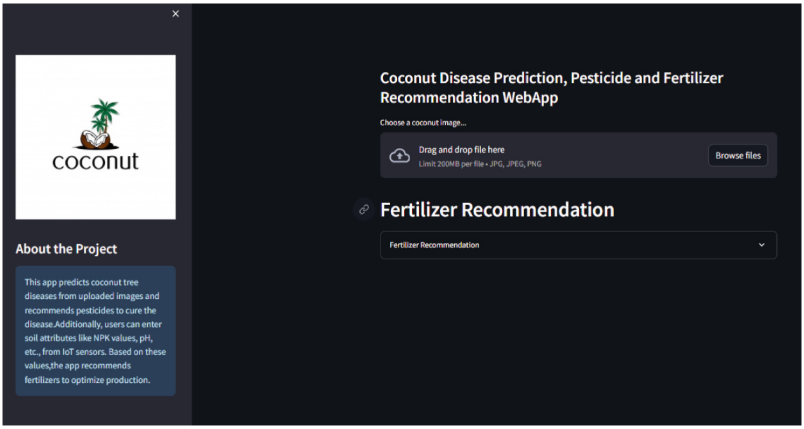


Fig. 3. Graph showing the Change in Training and Validation Accuracy across Epochs

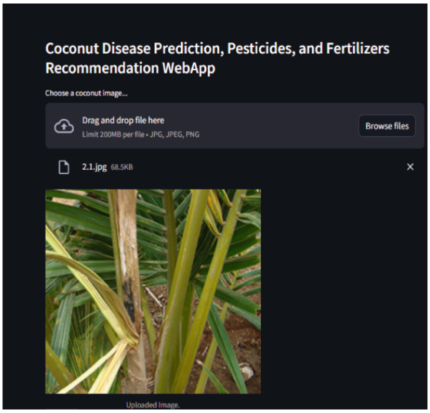
In our project, we utilized a Convolutional Neural Network (CNN) for its effectiveness in image tasks. Data preprocessing techniques such as resizing, normalization, and augmentation were employed [14]. The model was optimized with Adam optimizer and cross-entropy loss [15]. Multiple convolutional and pooling layers were utilized for feature extraction and dimensionality reduction. Rigorous hyperparameter tuning and validation ensured model performance. The achieved accuracy of 97.2% reflects our methodological rigor (Table 1).

Table 1. The below table representing the Epoch-wise Loss and Accuracy Summary

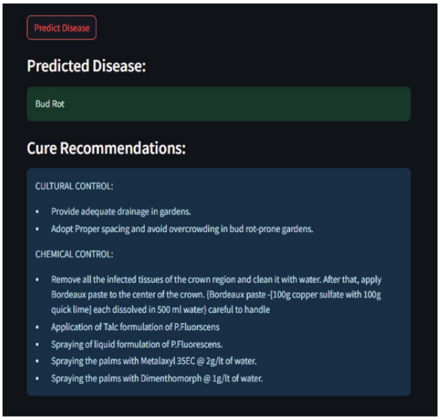
Epochs	Loss	Accuracy	Optimizer	Validation loss	Validation Accuracy
1	0.8248	66.05%	Adam	0.2911	88.00%
2	0.3165	89.41%	Adam	0.1210	96.13%
3	0.2147	93.40%	Adam	0.1887	92.26%
4	0.1326	95.70%	Adam	0.0790	96.90%
5	0.1310	95.84%	Adam	0.1068	96.00%
6	0.1315	95.70%	Adam	0.1617	94.06%
7	0.0805	97.70%	Adam	0.0291	98.71%
8	0.0628	98.09%	Adam	0.1773	93.55%
9	0.0736	97.59%	Adam	0.1485	95.10%
10	0.0652	97.87%	Adam	0.0938	96.00%



a. This is the Official Website appearance of our Web application using Streamlit"

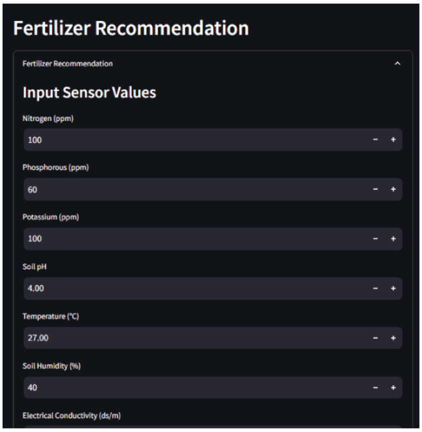


b. Farmers will upload the diseased coconut images in the Application

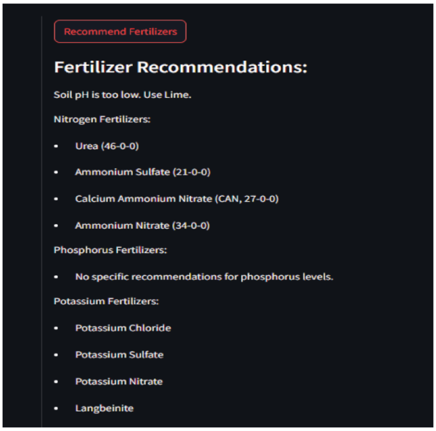


c. After uploading, the app will predict the disease name and suggest pesticides to cure that disease.

Fig. 4. The images (a, b, c, d, e) will illustrate our developed coconut web application



d. We will incorporate the IoT 7 in 1 soil sensor in the soil and enter the values obtained from the sensor in our web application.



e. Based on the soil attributes the app will recommend the fertilizers used to maintain good soil health and achieve good production.

Fig. 4. (*continued*)

6 Conclusion and Future Scope

In conclusion, our study leverages Convolutional Neural Networks (CNNs) to effectively identify six distinct coconut tree diseases [16] and recommend suitable pesticides based on disease classification and recommend fertilizers from soil attributes acquired through IoT sensors. Achieving a commendable accuracy of 97.2%, our model showcases promising potential for practical agricultural applications. Moving forward, future research could focus on refining the model architecture, exploring additional features for improved disease detection, and enhancing the integration of IoT technology to develop a user-friendly web application for real-time disease diagnosis and soil management in agricultural contexts. Such advancements hold significant promise for enhancing crop yield, sustainability, and overall agricultural productivity.

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