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RESEARCH ARTICLE

# IoT-Based Smart Coconut Farm Monitoring and Disease Prediction System using CNN

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**ABSTRACT**

Coconut farming is an important crop in the tropics and plays a large role in food production and rural livelihoods in these areas. But the changes in environment, nutrient deficiencies, inadequate irrigation, and disease attacks frequently affect productivity and cause loss of yield and income from the crop. To overcome these issues, a novel system has been proposed which is based on IoT, cloud computing, and CNN for smart monitoring system of coconut plantation for plant disease prediction and precision agriculture. The system involves the use of sensors connected to the Internet of Things (IoT) to track various important parameters in the farm, such as soil moisture, soil temperature, soil humidity, soil pH, nutrient levels (NPK) and rainfall, on a continuous basis. The sensors are then linked to microcontrollers like ESP32 and NodeMCU, allowing for effective data collection and transmission to a cloud-based system where they can be stored, displayed, and analyzed. Besides environmental monitoring, the images of the leaves are taken by the camera module and then analyzed with a CNN-based disease prediction model to know the condition of the plant health. The data set consists of readings from the environmental sensors, old farm records and images of the coconut leaves with three classes: Healthy, Nutrient/Environmental Stress and Diseased. CNN-based discriminative feature extraction and automatic disease classification of leaf images is used to classify the diseases like bud rot, leaf spot, stem bleeding and root wilt. By combining data from IoT devices with deep learning algorithms for image analysis, farmers can detect signs of crop stress and disease early, allowing for prompt action and decision-making. The results of the experiments show that the proposed system is effective in improving the accuracy of disease prediction, optimizes resource utilization, and improves the performance of the entire farm. The developed framework is scalable and cost-effective approach for sustainable coconut farming and smart agricultural management.

***Keywords:*** *Internet of Things (IoT), Smart Coconut Farm Monitoring, Convolutional Neural Network (CNN), Disease Prediction, Precision Agriculture.*

## INTRODUCTION

Agriculture is one of the most important economic sectors, contributing to the economic development, food security and rural livelihoods in the world. Coconut is an important crop in India, especially in the south Indian states like Tamil Nadu, Kerala, Karnataka and Andhra Pradesh (Domingues, T., et al., 2022; Patel, V., et al., 2024). Coconut palms have diverse products such as food, oil, fibre and raw materials used for industries that make them a good cash crop for farmers. But various environ-

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mental fluctuations, water shortage, nutrient deficiency, pest infestation, and plant disease can negatively impact crop health and productivity, posing challenges to coconut production.

The monitoring of the condition of crops and diseases is largely based on manual field inspection and the experience of the farmers, which are traditional farming methods. These are time-consuming, labour intensive and are generally poorly effective in detecting the early signs of stress and disease. Thus losses in yield and management costs may be considerable due to late diagnosis. With the advent of the IoT and AI technologies, smart and data-driven agriculture is a new possibility to the traditional farming field.

Smart agriculture with IoT allows for the continuous monitoring of environmental and soil parameters, thanks to the interconnectedness of sensors and communication technologies. With real-time soil moisture, temperature, humidity, pH, nutrient level and precipitation information, farmers can make better decisions about when to irrigate, fertilize and take care of their crops (Yani, N. A., et al., 2024; Kurian, N., et al., 2024). At the same time, deep learning has achieved incredible results in plant disease detection and classification using images. Concurrently, innovations in deep learning—especially CNNs have proven to be highly effective for imaging-based plant disease detection and classification.

This study aims to create an IoT-Based Smart Coconut Farm Monitoring and Disease Prediction System using CNN for the enhancement of crop health monitoring and disease diagnosis. The system consists of IoT sensors, cloud data processing, and CNN image analysis to help track the condition of the farm and categorize coconut plant health as either Healthy, Nutrient/Environmental Stress, or Diseased. Images of leafs are taken from the coconut plantation and environment attributes are collected from Thanjavur district, Tamil Nadu, and the proposed framework is developed, tested, and evaluated using such images and attributes. The ultimate goal is to offer the farmers an intelligent and real-time decision support system that will enable them to detect diseases at an early stage, utilise resources more efficiently and improve productivity (Adivarekar, P. P., et al., 2023; Kathavate, P. N., & Mahant, M. A. 2025; Sowmya Sundari, L.K., et al., 2026).

The proposed system will further support the development of precision agriculture by integrating the use of sensors and deep learning algorithms, which will support sustainable farming practices for growing coconuts and minimizing economic losses due to environmental stress and diseases. The following are objectives of the proposed research:

- To create a smart monitoring system with continuous real-time data collection and analysis of environmental and soil parameters (soil moisture, soil temperature, soil humidity, soil pH, soil NPK, and rainfall) from coconut farms using IoT.
- To develop a CNN disease prediction model to accurately classify healthy, nutrient stressed and diseased coconut plants based on image of leaves.
- To combine IoT sensing and deep learning into a holistic decision support system to detect crop stress, nutrient deficiency and disease early so that appropriate response can be taken.
- To optimize irrigation, fertilizer usage and disease management practices in the coconut fields with smart monitoring and predictive analytics, to increase the productivity and sustainability of the coconut farms.

## LITERATURE SURVEY

The literature review outlines the latest developments in smart agriculture and deep learning in monitoring crops and identifying diseases in the context of IoT. It explores the different machine learning and CNN models proposed for coconut disease detection, plant health surveillance, and precision agriculture. The survey reveals the pros and cons of the current approaches in terms of accuracy, scalability and real-time deployment. Moreover, it points out future research directions that inspire the creation of IoT Based Smart Coconut Farm Monitoring and Disease Prediction System utilizing CNN.

Chaitra Bai, J., et al., (2026) introduces a detailed discussion on IoT and Machine Learning (ML) based Smart and Sustainable Agriculture (SSA) Systems and its relevance in the modern farming. The authors highlight the need for integrating IoT equipment to gather environmental and crop-related data in real-time such as temperature, humidity, soil moisture, light intensity and ultraviolet radiation. The sensor data are then processed through the application of ML techniques to aid decision-making and enhance agricultural productivity. The study also presents a CNN and LightGBM-based crop recommendation system to boost the efficiency and sustainability of farming.

The coconut tree disease detection (Anitha, B., & Santhi, S. 2023) uses CNNs to detect coconut diseases with accuracy from the leaf image of a coconut tree. To improve the quality of the images prior to classification, image pre-processing techniques are integrated in the framework such as resizing, normalization, and noise removal. Using a web interface, farmers can upload leaf images, and the trained CNN model can analyze the images and provide a classification of healthy or diseased leaves. The system gives fast and accurate prediction with suitable remedial actions which helps to take immediate action to minimize crop losses. The proposed approach shows the potential of artificial intelligence in smart and precision agriculture, by reducing the need for agricultural experts and enabling timely detection of diseases.

Saleem, M., et al., (2025) emphasize the importance of early detection of coconut leaf diseases to ensure the health of the crop and thereby increase the productivity of the farmers. This research aims to develop an automatic disease recognition system from the coconut leaf image classification using the DenseNet-121 deep learning architecture. A hand picked dataset of 526 images of leaves from healthy and diseased coconut plants was used for training and evaluation of the model. The DenseNet-121 model performed around 99% accuracy, which is better than the other methods, as it has been able to successfully overcome the vanishing gradient problem and enhance the propagation of features with dense connections. The proposed system is cost effective and automatic disease identification system which minimizes the dependency on expert agriculture personnel. The study points to the possibility of deep learning methods in smart agriculture and stresses that the collection of disease images throughout the infected stages is still a key challenge to develop and validate models.

Priya, S. N., & Ramesh, D. (2024) highlights the significant impact of plant diseases on global agricultural productivity and emphasizes the importance of early and accurate disease detection to minimize crop losses. The authors argue that the symptoms of the disease are mainly observed on leaves and thus the use of image processing and computational intelligence techniques as effective alternatives to the traditional manual inspection, which demands a lot of knowledge, is discussed. The paper summarizes various feature extraction techniques applicable to plant disease detection systems with particular emphasis placed on those features related to color, texture and shape of images. In addition, it examines the pros and cons of different feature extraction methods and its efficiency in detecting different plant diseases. The review highlights the urgent need for feature extraction to boost the accuracy of disease classification and assist in creating intelligent and automatic systems for agricultural monitoring.

To overcome the drawbacks of conventional manual diagnosis of coconut tree diseases, which are labour intensive and hard to scale, Daga, M., et al., (2025) have introduced DeepSeqCoco, a deep learning-based framework for automatic and accurate identification of coconut tree diseases. Different optimization methods (SGD, Adam, hybrid) were tried to optimize for classification accuracy, minimization of loss and computational complexity. The experimental results showed that DeepSeqCoco has an impressive accuracy of 99.5% compared to the best results of the available models, which were up to 5% below. The hybrid optimizer SGD-Adam achieved the best validation loss of 2.81%, and it also decreased the training time up to 18% and prediction time up to 85%. The results demonstrate the model's effectiveness, scalability, and potential for use in precision agriculture applications, where AI models can facilitate efficient disease monitoring and better management practices for crops.

Abade, A. D., et al., (2020) provides an extensive systematic review about Plant Disease Identification and Classification using CNNs. The authors review 121 research articles from the last decade with regard to various techniques used to detect diseases, properties of the datasets, crop types and pathogen classification. The review points out the increasing usage of CNN-based models because of their excellent performance for the automatic extraction of features and for the recognition of diseases from the plant images. Moreover, it highlights future research directions, innovations and the efficacy of deep learning approaches for agricultural disease detection. In addition, the current challenges and research gaps are discussed, offering insights and future research directions for the evolution of more powerful, scalable, and efficient CNN based plant disease detection systems in precision agriculture.

Montero, C. D., et al., (2023) explore the use of deep learning and computer vision for the automated identification of diseases and pests in coconut trees. The authors designed a 2D CNN model that resulted in the classification of five categories of coconut leaf conditions: caterpillar infestation, leaflet damage, drying leaflets, flaccidity and yellowing. The CNN model performed extremely well in classification tasks, with an accuracy rate of 99%

for the yellowing detection and 100% for other classes. The findings show the capability of CNN image analysis to precisely diagnose coconut plant health problems and attacks from pests. The proposed framework provides a sturdy and effective diagnostic tool for helping disease management and precision farming practices, and can be incorporated into current coconut farming disease monitoring systems to improve the health management and productivity of the crop.

## PROPOSED WORK

The proposed CNN architecture seeks to improve coconut crop management by monitoring and identifying coconut disease intelligently in real time. The system is designed to use IoT sensors to gather the information about the environment and soil, and CNN model to analyze the image of leaves and determine the condition of the plants. The framework incorporates deep learning methods and sensor-based monitoring, allowing for early detection of diseases and prompt decision-making (Bommineni, K.R., et al., 2026). This strategy ensures precision agriculture, leading to better crop yields, resource use, and sustainable farming. The Figure 1 shows the workflow of the proposed work.

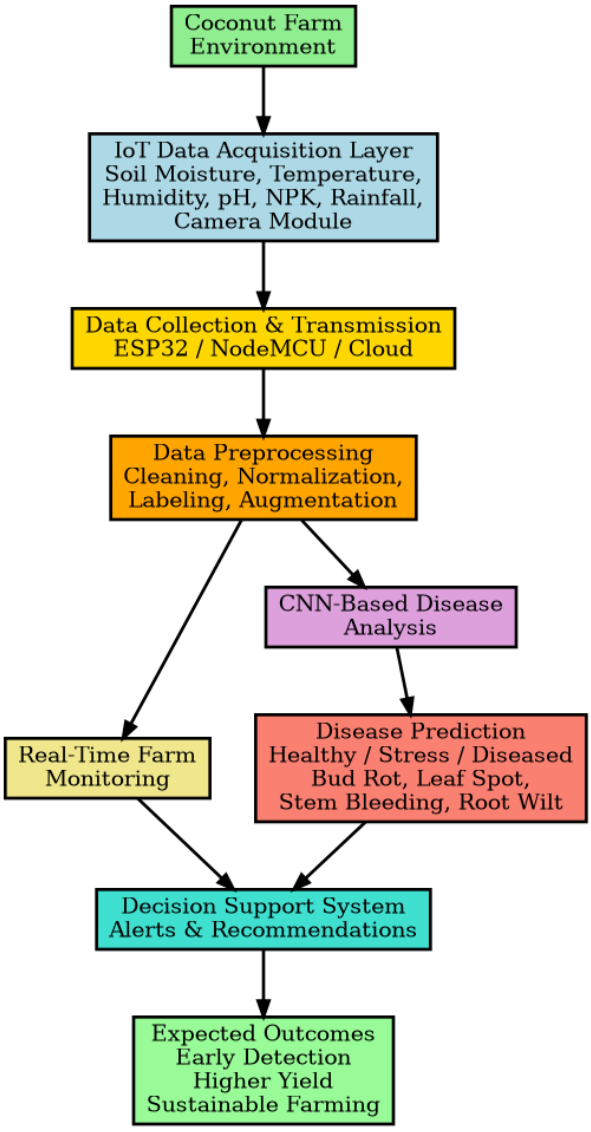



**Figure 1: Proposed flowchart**

### *Data Collection*

Data collection for the proposed IoT-based smart coconut farm system involves gathering real-time environmental, soil, and plant health data using sensors, cameras, and field observations. Soil moisture, temperature, humidity, pH, NPK levels, rainfall, and leaf images are collected using IoT devices such as Soil Moisture Sensor (e.g., Capacitive Soil Moisture Sensor v1.2), Temperature and Humidity Sensor (DHT11), Soil pH Sensor, NPK Sensor Module, Rain Sensor Module (YL-83/YL-69), and a Camera Module (ESP32-CAM or Raspberry Pi Camera). These sensors are connected to microcontrollers like ESP32, NodeMCU, or Arduino Uno, which collect and transmit the data to the cloud for further analysis. In addition, historical data such as irrigation schedules, fertilizer usage, and yield records are included. The collected data is cleaned, labeled, and organized to form a structured dataset that supports both real-time monitoring and machine learning-based analysis.

The dataset for this study was collected from coconut farms located in the Tanjore (Thanjavur) district of Tamil Nadu, India, during the period from June 2025 to may 2026. Primary data was obtained through IoT sensor deployment directly in selected farm fields, while plant leaf images were captured using camera modules and farmer mobile devices. Secondary data, including past yield records and fertilizer usage, was collected through farmer interviews and local agricultural records. Regular field visits were conducted to ensure data accuracy and proper labeling of plant conditions.

For disease prediction, the dataset is categorized into three main classes: Healthy, Nutrient/Environmental Stress, and Diseased. A sample dataset may consist of a total of 1200 data samples, where the Healthy class contains 400 samples, the Nutrient/Environmental Stress class contains 350 samples (including conditions like nitrogen deficiency, potassium deficiency, and water stress), and the Diseased class contains 450 samples (including diseases such as bud rot, leaf spot, stem bleeding, and root wilt). This balanced distribution of data helps in effectively training the machine learning model for accurate classification and reliable prediction.

### *Data pre-processing*

Raw data from an IoT sensor can include variations in scale, noise, and missing data. Can use mean imputation for missing values:

$$X_{missing} = \frac{1}{n}\sum_{i=1}^{n} X_i \quad (1)$$

where $X_i$ is a valid sensor reading and n is the number of available records.

A moving average filter can be used to smooth out the readings from the sensor to reduce noise.

$$S_t = \frac{1}{k}\sum_{i=0}^{k-1} X_{t-i} \quad (2)$$

The values of $S_t$, $X_t$, and $k$ are respectively the smoothed value, the current value of the sensor, and the size of the window.

Min-Max normalization is used to normalize the sensor values within a common range. Using the Min-Max normalization technique the values of the sensor are then normalized in a common domain. The sensor values are then normalized in the same domain using the Min-Max normalization technique.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (3)$$

The images of the coconut leaves are scaled to a fixed size, e.g., 224 X 224, which conforms with the input size of CNN. Normalization is performed on pixels:

$$I' = \frac{I}{255} \quad (4)$$

where $I$ is the absolute value of a pixel and $I'$ is the normalized absolute value of a pixel.

The proposed preprocessing method helps to increase data quality, remove noise, normalize input features, and improve the performance of CNN model in accurately predicting coconut disease.

### *Segmentation*

The proposed segmentation method for the proposed work is segmentation of the Leaf area based segmentation using K means clustering with morphological processing. For segmentation of coconut leaf disease, k-means clustering is effective because there are visible color variations in the area of disease, which is in the form of yellowing, brown spots, black lesions, and pale spots (Cowlishaw, R., et al., 2025). The method is to divide the image of the coconut leaf into various parts according to color, which allows the CNN to focus primarily on the affected areas of the image.

The input coconut leaf image is first transformed to HSV or Lab color space, as both of these color spaces are better to separate the color and brightness information in the image. Next, K-means clustering technique classifies the pixels into similar classes like healthy green area, background, and diseased region.

The objective function of K-means clustering is calculated by defining:

$$J = \sum_{i=1}^{k} \sum_{x_j \in C_i} \left|\left|x_j - \mu_i\right|\right|^2 \quad (5)$$

Where,

$x_j$ is the pixel value i, $C_i$ represents the $i^{th}$ cluster, $\mu_i$ is the centroid of the cluster, and $k$ is the number of clusters.

Each pixel is assigned to the closest cluster based on:

$$C_i = \arg\min_i \left|\left|x_j - \mu_i\right|\right|^2 \quad (6)$$

Once the clusters are clustered, the affected cluster is picked according to the colour attribute such as Brown, Yellow or Dark area. A binary mask is created as:

$$M(x,y) = \begin{cases} 1, & if\ pixel\ belongs\ to\ diseased\ region \\ 0, & otherwise \end{cases} \quad (7)$$

Morphological operations like erosion and dilation are performed to mask out small noises and enhance the segmented region:

$$A \ominus B = \{z | B_z \subseteq A\} \quad (8)$$

$$A \oplus B = \{z | B_z \cap A \neq \emptyset\} \quad (9)$$

A is the binary image and $B$ is the structuring element.

Lastly, the segmented diseased area is derived by multiplying the original image and binary mask.

$$I_s(x,y) = I(x,y) X M(x,y) \quad (10)$$

Where, $I(x,y)$ is the original image and $I_s(x,y)$ is the segmented disease image. This segmentation technique decreases the need to include background areas and only marks the sick coconut leaf area, thus enhancing the prediction of the disease. It also speeds up the computing process and enables the CNN to extract more salient features. For this reason, K-means clustering with morphological processing is a simple, efficient and appropriate segmentation technique to be applied in the proposed smart farming system to detect the coconut leaf disease. For further elucidation, the original image and the segmented image analysis using K-means clustering with morphological processing is shown in the Figure 2.

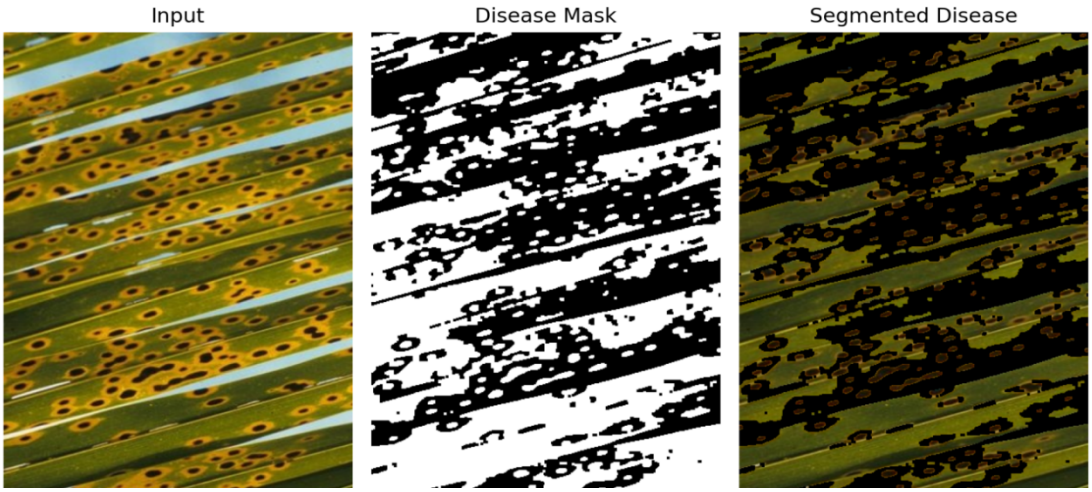



**Figure 2: Original Vs segmented image**

### *Feature Extraction*

The image of the segmented leaf is supplied to the CNN which learns features associated with disease on each layer (Soni, K., & Chandra Gangwar, R. 2025). The CNN first captures low level features like edges, boundaries, color shifts and small spot patterns. These features enable us to detect visible changes in healthy green leaf areas and diseased areas.

The CNN is able to identify features like circular lesions, brown spots, yellow patches, irregular disease regions, rough surface patterns, and vein discoloration in the middle layers. These features are significant in the diagnosis of leaf spot, nutrient deficiency and environmental stresses in coconut.

The CNN is used to extract high-level disease features, including general disease pattern, severity of infection, location of spots, and similarity between infected samples, in the deeper layers. The features

are used to classify the image into Healthy, Nutrient/Environmental Stress, or Diseased classes. This convolution is written as:

$$F(i,j) = \sum_m \sum_n I(i+m, j+n) X\ K(m,n) + b \quad (11)$$

where $I$ is the input image, $K$ is the filter, $b$ is bias, and $F(i,j)$ is the extracted feature map.

### *Feature Selection*

Feature selection is performed automatically through convolution, ReLU, pooling, and dense layers. The ReLU layer removes less useful negative values:

$$ReLU(x) = \max(0, x) \quad (12)$$

The max-pooling layer selects the most dominant features from each region:

$$P(i,j) = \max(F(i,j)) \quad (13)$$

This keeps strong disease features such as dark lesions and yellow spots while reducing irrelevant background information. The dense layer further selects the most important extracted features for classification. Finally, the Softmax layer assigns the image to the correct class based on selected features.

### *Sensor Based Feature*

In addition to image features, IoT sensors offer additional characteristics like soil moisture, temperature, humidity, pH, NPK values, and rainfall. These helps determine if disease symptoms are associated with nutrient deficiency, water stress or changes in the environment. The proposed system thus extracts and selects the visual disease and environmental features to increase the accuracy of prediction of coconut disease. An extracted and selected feature are shown in Table 1.

**Table 1: Extracted and selected features**

| Feature Level | Extracted Features | Description | Features for Classification |
|---|---|---|---|
| Low Level | Edges | Boundary information between normal and abnormal areas | Strong edges around lesions (diseases) |
| | Color Variations | Changes in green, yellow, brown, black colors | Changes related to disease |
| | Leaf Vein Patterns | Structural vein information | Abnormal vein discoloration |
| | Spot Boundaries | Detection of disease spots | Clear Spots Outlines |
| Mid-Level Features | Lesion Shape | Circular, oval, or irregular disease spots | Dominant lesion shapes |
| | Texture Features | Roughness or smoothness and irregularities of surface texture due to infection | Infection-related Texture Features |
| | Spot Density | Number of disease spots per unit area | High-density infected regions |
| | Spot Distribution | Spatial arrangement of lesions | Clustered disease regions |
| | Yellowing Regions | Chlorosis caused by nutrient deficiency | Significant yellow patches |
| High-Level Features | Disease Pattern | Overall infection appearance | Characteristic disease signatures |
| | Severity Level | Percentage of infected leaf area | Highly affected regions |
| | Disease Region Area | Total infected area | Largest disease clusters |
| | Shape Complexity | Complexity of disease boundaries | Distinct disease structures |
| | Disease Class Representation | Learned disease-specific features | Features with highest CNN weights |
| Environmental Features (IoT Sensors) | Soil Moisture | Water availability in soil | Critical moisture levels |
| | Temperature | Ambient temperature conditions | Temperature anomalies |
| | Humidity | Relative humidity | Disease-conducive humidity levels |
| | Soil pH | Soil acidity/alkalinity | Abnormal pH values |
| | NPK Levels | Nitrogen, Phosphorus, Potassium content | Nutrient deficiency indicators |
| | Rainfall | Rainfall intensity and frequency | Excess or insufficient rainfall |

### *CNN Architecture for Feature extraction and Selection*

In the proposed IoT Based Smart Coconut Farm Monitoring and disease Prediction System, a CNN

is employed to extract and select the important features of the disease automatically in segmented coconut leaf images. First of all, the dimension of the input image is converted to 224x224x3, where 224x224 is the height and width of the image, and 3 is the number of color channels (RGB).

$$I \in R^{224 \times 224 \times 3} \quad (14)$$

In this system, the whole coconut leaf image is preprocessed and segmented, and then given as input to the CNN. Very first convolutional layers recognize the fundamental visual patterns that are the edges, color contrast and small disease spots. The middle layers pick up more subtle features like lesion shape, yellowing, black patches and texture irregularities. The deeper layers are able to combine such features to perceive entire disease patterns. Lastly, the Softmax layer is used to determine whether the coconut leaf image is Healthy, Nutrient/Environmental Stress or Diseased.

The CNN architecture consists of the following layers:

*Input Layer*

The preprocessed image of the coconut leaf is fed to the CNN. Typically, the picture is resized to the size of:

$$224\ X\ 224\ X3 \quad (15)$$

Where, 224×224 is the image dimensions and 3 is the number of RGB channels.

*Convolution Layer*

Convolutional layer is used to detect features like edges, spots, textures, and patterns of lesions, by passing filters over the image.

$$F(i,j) = \sum_m \sum_n I(i+m, j+n) X\ K(m,n) + b \quad (16)$$

where $I$ is the input image, $K$ is the kernel, $b$ is the bias, and $F(i,j)$ is the feature map.

*ReLU Activation Layer*

ReLU is used to introduce non-linearity and to eliminate negative values.

$$ReLU(x) = \max(0, x) \quad (17)$$

This will enable the CNN to learn the complex pattern of the disease, e.g. irregular leaf spots and discoloration.

*Pooling Layer*

Max pooling decreases the dimensions of feature maps but does not delete significant features.

$$P(i,j) = \max(F(i,j)) \quad (18)$$

This minimises calculation and helps to maintain dominant disease characteristics like dark lesions and yellow patches.

*Feature Extraction*

CNN extracts different features at different levels are shown in Table 2. The pooling and dense layers choose features that are best for classification.

**Table 2: Feature extraction**

| Layer Level | Extracted Features |
|---|---|
| Initial layers | CNN extracts features of various levels |
| Middle Layers | Edges, changes in colors, boundaries of lessions |
| Deep layers | Symptoms of the disease, their severity, and distribution of infected area |

*Flatten and Fully Connected Layer*

The extracted feature maps are turned into a one-dimensional feature vector:

$$FV = [f_1, f_2, \ldots\ldots f_n] \quad (19)$$

These features are combined into single features in the dense layer using the following:

$$Y = WV + b \quad (20)$$

where $W$ is weight, $V$ is the feature vector, and $b$ is bias.

*Softmax Classification Layer*

The Softmax layer is used to make predictions on the probability of each class.

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{c} e^{z_i}} \quad (21)$$

The probability of class $i$ is $P(y_i)$, the output score is $z_i$ and the number of classes is $c$.

***Classification Algorithm***

A CNN model that is used for the prediction of Coconut Leaf Disease.CNN Based Coconut Leaf Disease Prediction.

***Input:*** The image data set of the coconut leaf
***Output:*** The model provides a prediction of the class, either Healthy, Stress or Diseased.
Step 1: Gather coconut leaf pictures from farms.
Step 2: Resize all images to 224 × 224 pixels.
Step 3: Normalize the pixel values from 0 to 1.

Step 4: Enhance the image using image augmentation (rotation, flipping, zoom).
Step 5: Segment regions affected by disease from an image.
Step 6: Input segmented picture into the CNN model.
Step 7: Apply convolution filters to obtain disease features.
Step 8: Use ReLU to Learn non-linear patterns.
Step 9: Use max pooling to extract prominent features.
Step 10: flatten the extracted feature maps: flatten the extracted feature maps to a feature vector.
Step 11: Pass on the feature vector to fully connected layers.
Step 12: Use Softmax classifier to predict the final disease class.
Step 13: Display the prediction result and the confidence score.

## RESULT AND DISCUSSION

The proposed work was tested with a data set obtained from the coconut farms in Thanjavur district of Tamil Nadu, which includes the environmental sensor data and coconut leaf images. The main goal was to track the health of the coconut plant in real-time and to accurately classify the health of the coconut plant into three categories: Healthy, Nutrient/Environmental Stress, and Diseased. The accuracy, precision, recall, F1-score, and confusion matrix analysis were employed to evaluate the performance of the CNN model.

## PERFORMANCE EVALUATION METRICS

The CNN model performance was assessed on the following measures:

### *Accuracy*

The overall correctness of the classification model, as measured using accuracy. It is the percentage of cases that have been classified correctly out of the total number of cases in the dataset.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (22)$$

where:

- TP (True Positive): Diseased leaves correctly classified as diseased.
- TN (True Negative): Healthy leaves correctly identified as healthy.
- FP (False Positive): Leaves that are not diseased but are marked as such.
- FN (False Negative): Leaves that are considered normal when they are diseased.

### *Precision*

Precision is the accuracy of the positive predictions of the classification model. It indicates how many of the samples predicted as a particular class are actually correct. Precision in the proposed coconut disease prediction system is the proportion of correctly predicted coconut leaves that are diseased.

$$Precision = \frac{TP}{TP+FP} \quad (23)$$

### *Recall*

Recall (also called Sensitivity or True Positive Rate) indicates how well the model can detect all the true positive samples. In the proposed system, recall shows the efficiency of the CNN to identify diseased coconut leaves among all the diseased leaves in the dataset.

$$Recall = \frac{TP}{TP+FN} \quad (24)$$

### *F1-Score*

F1-Score is the harmonic mean of Precision and Recall. It has a balanced index of classification performance particularly in case of an imbalanced data set. The advantage of the F1 score is that it takes into account both false positives and false negatives.

$$F1\ Score = 2X\frac{Precision\ X\ Recall}{Precision+Recall} \quad (25)$$

The evaluation results of the system presented in Table 3 and Figure 3 prove the effectiveness of the proposed system. The model performed significantly well for all three classes with a high value of Accuracy, Precision, Recall and F1-Score, thereby demonstrating high classification capability of coconut leaf health conditions. The Diseased category had the highest performance, with an accuracy of 98.7%, precision of 98.5%, recall of 98.8%, and F1-score of 98.6%, demonstrating that under this category, the CNN had captured disease-specific features like lesion shape, spot distribution, discoloration and texture variations. The model also showed very good performance on the Healthy class with an accuracy of 98.0%, as it had few misclassifications of Healthy leaves. The performance of the Nutrient/Environmental Stress class was slightly lower, but was still above 96.9% for all metrics, likely due to the similar appearance of nutrient deficiency and early signs of disease infestation.

**Table 3: Performance analysis**

| Class | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| Healthy | 98 | 97.8 | 98.2 | 98 |
| Nutrient/Environmental Stress | 97.2 | 96.9 | 97.1 | 97 |
| Diseased | 98.7 | 98.5 | 98.8 | 98.6 |

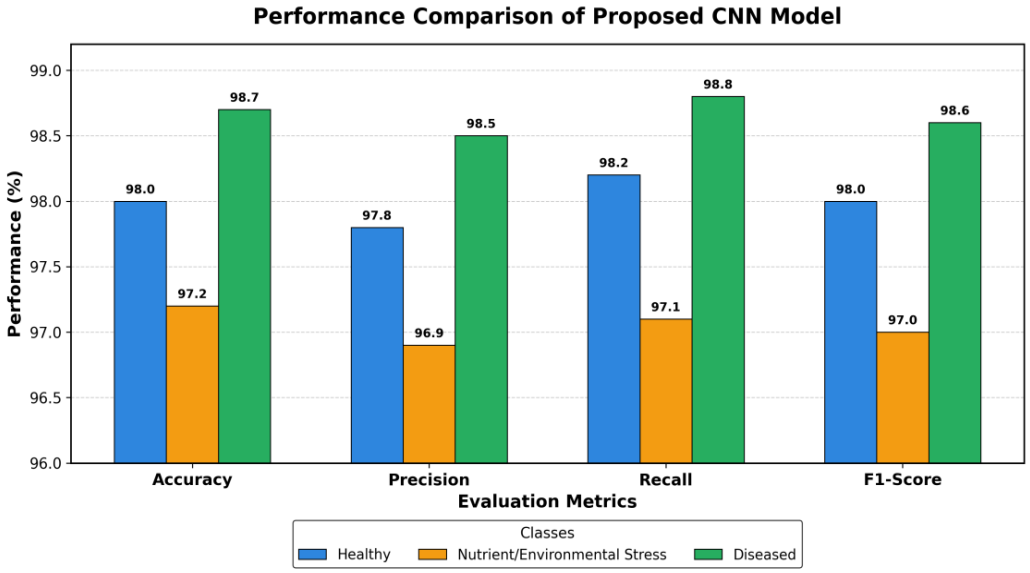



**Figure 3: Performance comparison**

The comparison graph in Figure 4 shows that all evaluation metrics are more or less grouped together, which demonstrates the robustness, reliability and generalization capabilities of the proposed CNN model. In addition, the balanced performance of all classes suggests that there is not considerable bias towards any class. Hence, the findings demonstrate the effectiveness of image preprocessing, segmentation, CNN feature extraction and classification techniques in detecting coconut diseases at an early stage and monitoring the smart farm, which ultimately helps the farmers in the real-time implementation of precision agriculture and enhances the productivity of the crops.

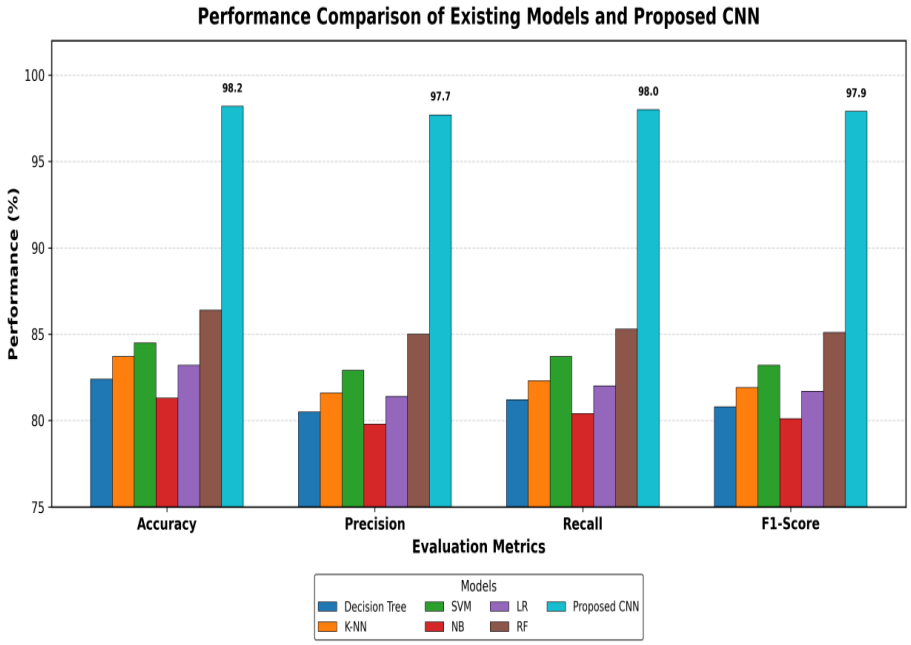



**Figure 4: Performance comparison existing Vs proposed**

## OVERALL COMPARISON

The Performance of proposed work is widely compared with the existing methods given in this section. The performance results as shown in Table 4 and compared by graph in Figure 4 also show the effectiveness of the proposed model compared to the conventional ML classifiers such as DT, KNN, SVM, NB, LR and RF. The best results were obtained by the Random Forest with the accuracy of 86.4%, precision of 85.0%, recall of 85.3%, and F1-score 85.1%, among the present methods. But the proposed CNN performed much better than all the baseline models with an accuracy of 98.2%, Precision of 97.7%, Recall of 98.0% and F1 score of 97.9%.

**Table 4: Performance comparison of proposed Vs existing**

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Decision Tree | 82.4 | 80.5 | 81.2 | 80.8 |
| K-NN | 83.7 | 81.6 | 82.3 | 81.9 |
| SVM | 84.5 | 82.9 | 83.7 | 83.2 |
| NB | 81.3 | 79.8 | 80.4 | 80.1 |
| LR | 83.2 | 81.4 | 82 | 81.7 |
| RF | 86.4 | 85 | 85.3 | 85.1 |
| Proposed (CNN) | 98.2 | 97.7 | 98 | 97.9 |

This significant improvement is also visually presented in the comparison graph, where the bars of the proposed CNN are significantly higher than the traditional classifiers in all the evaluation metrics. This enhanced performance is due to CNN's capability of learning discriminative features directly from the coconut leaf images, such as the shape of the lesion, changes in its colour, its texture patterns, and the severity of the disease, which are not so heavily dependent on conventional machine learning algorithms for feature extraction. The high recall rate suggests that the proposed model correctly classifies diseased samples with relatively few misclassifications (few false negatives), whereas the high precision indicates that the few misclassifications made are relatively few false positives. Moreover, the balanced F1-score illustrates the reliability and robustness of the model in real-world classification applications. The overall results confirm that the proposed CNN architecture is an efficient and effective approach for detecting coconut leaf disease and monitoring a smart farm, thus suggesting that it can be used for precision agriculture applications.

## CONCLUSION

The design of IoT-Based Smart Coconut Farm Monitoring and Disease Prediction system by CNN effectively combines the IoT sensing technologies and deep learning techniques to provide real-time monitoring and prediction of diseases in coconut farms. Continuous monitoring of soil moisture, temperature, humidity, PH, NPK level, rain fall using IoT sensors and capturing of coconut leaf images for analysis of disease. The disease affected areas were segmented using image preprocessing and K-Means segmentation technique, and a CNN was applied to detect and classify coconut leaves as Healthy, Nutrient/Environmental Stress and Diseased classes, respectively. This comprehensive solution provides timely irrigation, fertilization and disease management decisions.

The proposed framework was evaluated experimentally with 1200 samples collected from the coconut farms in Thanjavur district and results showed that the framework is effective. The CNN model achieved an overall accuracy of 98.2%, precision of 97.7%, recall of 98.0% and F1-score of 97.9% which outperforms the conventional machine learning algorithms like DT, K-NN, SVM, NB, LR and RF. The findings indicate a system that reliably, scalably, and economically enables early disease detection and enhanced crop productivity as well as sustainable precision agriculture. Enhancements in the future will include advanced deep learning models, integration with meteorological forecasts, yield prediction, and mobile deployment for real-time applications in the field.

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