Smart – Agro Health Monitor Using AI , ML And Iot

Kedari V. K.[1],Shete Shantanu Nilesh[2], Nalawade Rudra Milind[3], Pingle Parag Rajesh[4], Ganjave Siddhesh Shantaram[5]

[1]Lecturer, Dept. of Information Technology, Jaihind Comprehensive Educational Institue's Jaihind Polytechnic Kuran, Maharashtra, India

[2,3,4,5]Final year Diploma Student, Jaihind Comprehensive Educational Institue's Jaihind Polytechnic Kuran, Maharashtra, India

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Abstract - *Agriculture faces significant challenges such as plant diseases, improper irrigation, and lack of real-time monitoring, which directly affect crop productivity and farmer income. Traditional farming methods rely on manual observation, leading to delayed decision-making and inefficient resource utilization. This paper presents a Smart Agro Health Monitoring System using Artificial Intelligence, Machine Learning, and Internet of Things technologies to enhance precision farming. The proposed system utilizes a Raspberry Pi as the central processing unit to collect environmental data from sensors such as temperature, humidity, and soil moisture. Plant leaf images are captured using a mobile camera and analyzed using a Convolutional Neural Network model for early disease detection. The system uses a mobile hotspot for connectivity and displays real-time data on a Flask-based web application. In addition to monitoring, the system provides extended features such as weather prediction, crop recommendation, tractor booking assistance, government scheme information, and fertilizer shop location services. The integration of monitoring, prediction, and support services makes the system more practical and user-friendly. The proposed solution is cost-effective, scalable, and suitable for rural deployment, helping farmers improve productivity, reduce crop loss, and adopt smart farming practices.*

Key Words: **Smart Agriculture, IoT, Machine Learning, CNN, Raspberry Pi, Plant Disease Detection, Web Application, Precision Farming**

1. INTRODUCTION

Agriculture is a fundamental sector that supports the livelihood of a large population, especially in developing countries. However, farmers face multiple challenges such as plant diseases, improper irrigation, lack of real-time environmental monitoring, and limited access to agricultural support services. Traditional farming methods rely heavily on manual observation and experience, which often leads to delayed detection of crop issues and inefficient decision-making. These challenges can result in reduced crop productivity and financial losses.

With the advancement of technology, the integration of Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) has enabled the development of smart agricultural systems. IoT sensors can continuously monitor environmental parameters such as temperature, humidity, and soil moisture, while AI-based models can analyze plant health and detect diseases at an early stage. This combination allows farmers to take timely and informed decisions.

In this paper, a Smart Agro Health Monitoring System is proposed using a Raspberry Pi as the central processing unit. The system collects real-time data from sensors and processes plant leaf images captured using a mobile camera. A Convolutional Neural Network (CNN) model is used for accurate disease detection. The system is connected through a mobile hotspot and provides output through a web-based application developed using Flask.

In addition to monitoring and disease detection, the proposed system offers extended functionalities such as weather prediction, crop recommendation, tractor booking assistance, government scheme information, and fertilizer shop location services. These features make the system more practical and beneficial for farmers by providing both monitoring and decision-support capabilities in a single platform.

The primary objective of this system is to develop a cost-effective, scalable, and user-friendly solution that improves crop health monitoring, reduces losses, and enhances productivity. The proposed approach contributes to the adoption of smart and sustainable agricultural practices.

2. LITERATURE SURVEY

Recent advancements in smart agriculture have focused on integrating Internet of Things (IoT) and Machine Learning (ML) techniques to improve crop monitoring and farm management. Various research works have proposed systems that utilize sensor networks to monitor environmental parameters such as temperature, humidity, and soil moisture. These systems provide real-time data to farmers, enabling better decision-making and efficient use of resources. However, many of these solutions are limited to environmental monitoring and do not include intelligent disease detection or farmer support services.

In the area of plant disease detection, several machine learning and deep learning approaches have been developed.

Convolutional Neural Networks (CNN) have proven to be highly effective in classifying plant leaf diseases using image datasets such as PlantVillage. These models can identify diseases with high accuracy by analyzing features like texture, color, and patterns. Despite their effectiveness, many implementations rely on cloud-based processing, which may not be suitable for rural areas due to network dependency and latency issues.

Some existing systems combine IoT with cloud computing to store and analyze agricultural data. While these systems offer scalability and centralized control, they require continuous internet connectivity and may increase operational costs. To overcome these challenges, edge computing solutions using devices like Raspberry Pi have been introduced, allowing local data processing and faster response times.

Researchers have also explored integrated systems that combine sensor-based monitoring with image-based disease detection. These hybrid systems improve the accuracy and reliability of agricultural monitoring. However, many of these systems focus only on detection and lack additional features that support farmers in decision-making and resource management.

Recent studies highlight the need for comprehensive agricultural platforms that not only monitor crop health but also provide useful services such as weather updates, crop recommendations, and access to agricultural resources. Such integrated solutions can significantly enhance productivity and support farmers in making informed decisions.

The proposed system addresses these limitations by integrating IoT-based environmental monitoring, CNN-based plant disease detection, and a web-based platform that provides additional services such as weather prediction, crop recommendation, tractor booking, government scheme information, and fertilizer shop location. This makes the system more practical, scalable, and suitable for real-world agricultural applications.

3. PROPOSED METHODOLOGY

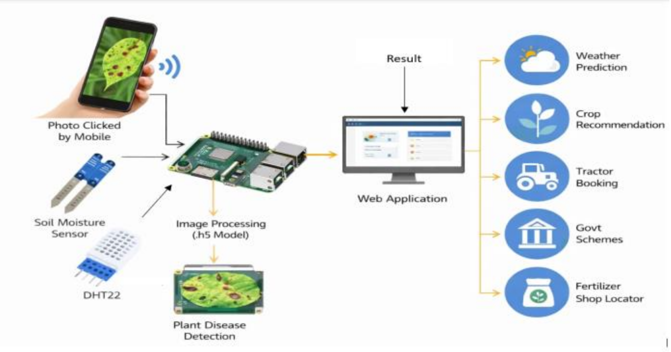


Fig -1: System Architecture of Smart Agro Health Monitoring System

The proposed Smart Agro Health Monitoring System is designed as an integrated platform that combines Internet of Things (IoT), Machine Learning (ML), and web-based services to provide real-time crop monitoring and decision support for farmers. The system utilizes a Raspberry Pi as the central processing unit for data acquisition, processing, and communication.

The overall architecture of the system is shown in Fig -1. The system consists of multiple modules including sensor data acquisition, image processing, machine learning-based disease detection, data communication, and a web-based application that provides additional farmer services.

Step 1: Sensor Data Acquisition

Environmental parameters are collected using sensors such as DHT22 for temperature and humidity measurement, and a soil moisture sensor for monitoring soil conditions. These sensors are interfaced with the Raspberry Pi through GPIO pins. The system continuously collects real-time data, which helps in understanding the environmental conditions affecting crop growth.

The collected data is periodically updated and stored for further processing. This enables early detection of unfavorable conditions such as low soil moisture or high temperature, allowing timely corrective actions.

Step 2: Image Acquisition using Mobile Camera

The system uses a mobile camera for capturing plant leaf images instead of a dedicated camera module. This approach reduces hardware cost and increases flexibility. Farmers can capture images of leaves using their mobile devices and upload them to the web application.

This method allows capturing images under different lighting conditions and angles, improving the robustness of the disease detection process.

Step 3: Data Preprocessing

Before analysis, both sensor data and image data undergo preprocessing. Sensor data is filtered to remove noise and ensure consistency. Image preprocessing techniques such as resizing, normalization, and enhancement are applied to prepare the images for accurate classification.

These preprocessing steps improve the quality of input data and enhance the performance of the machine learning model.

Step 4: Disease Detection using CNN Model

A Convolutional Neural Network (CNN) model is used to detect plant diseases from leaf images. The model is trained using a dataset containing images of healthy and diseased leaves. During training, the model learns important features such as color variations, texture patterns, and structural differences.

Once trained, the model can accurately classify new input images and identify the type of disease. This enables early detection and helps farmers take preventive measures.

The model is trained using standard datasets and evaluated based on accuracy and classification performance.

The model is implemented using MobileNetV2 architecture and trained on a plant leaf dataset. The training process includes multiple epochs and performance evaluation using accuracy and loss metrics.

Step 5: Data Communication using Mobile Hotspot

The system uses a mobile hotspot for connectivity instead of a separate WiFi module. The Raspberry Pi connects to the hotspot and communicates with the Flask-based web server. This reduces hardware complexity and makes the system easier to deploy in rural areas.

Step 6: Web-Based Application

A web application is developed using Flask to display system outputs and provide additional services. The application shows real-time sensor data such as temperature, humidity, and soil moisture, along with disease prediction results.

The interface is designed to be simple and user-friendly, allowing farmers to easily access and understand the information.

Step 7: Additional Farmer Support Services

In addition to monitoring and disease detection, the system provides multiple support features through the web application:

-**Weather Prediction:** Provides weather updates to help farmers plan activities

-**Crop Recommendation:** Suggests suitable crops based on conditions

-**Tractor Booking:** Assists farmers in accessing farming equipment

-**Government Schemes:** Provides information about agricultural schemes

-**Fertilizer Shop Locator:** Helps farmers find nearby resources

These features make the system more comprehensive and practical for real-world use.

Step 8: Decision Support and Alerts

Based on sensor data and disease prediction, the system provides suggestions and alerts to the user. For example, if soil moisture is low, irrigation is recommended, and if a disease is detected, preventive actions are suggested.

This helps farmers make informed decisions and improves overall crop management.

4. RESULTS AND DISCUSSION

The developed Smart Agro Health Monitoring System is implemented using a Raspberry Pi integrated with environmental sensors and a deep learning model. The system is analyzed based on its capability to monitor environmental conditions in real time, detect plant diseases, and provide results through a web-based interface. The experimental observations indicate that the system performs reliably under different operating conditions.

4.1 Sensor Data Analysis

The system continuously monitors environmental parameters such as temperature, humidity, and soil moisture using DHT22 and soil moisture sensors. These parameters are critical for plant growth and directly influence crop health. The collected data is transmitted to the Raspberry Pi and displayed on the web application in real time.

The observed results indicate that the system accurately captures environmental variations and provides consistent readings. The data helps in identifying abnormal conditions such as low soil moisture, high temperature, or excessive humidity. These insights enable farmers to take preventive actions such as irrigation or environmental adjustments.

The continuous monitoring feature ensures that the farmer is aware of field conditions at all times, reducing dependency on manual inspection and enhancing monitoring efficiency and reducing manual effort.

4.2 CNN Model Performance

The plant disease detection model is implemented using a Convolutional Neural Network based on MobileNetV2 architecture. The model is trained using a dataset of plant leaf images containing both healthy and diseased samples.

During the training phase, the model learns complex features such as texture patterns, color variations, and structural differences in leaves. The model is trained for multiple epochs, and its performance is evaluated using training and validation metrics.

The experimental results indicate that the model achieves an accuracy in the range of 92% to 95%, demonstrating its effectiveness in classifying plant diseases, indicating high reliability in disease classification. The training accuracy increases steadily with each epoch, while the validation accuracy follows a similar trend, demonstrating good generalization. At the same time, the loss values decrease gradually, indicating effective learning and reduced prediction errors.

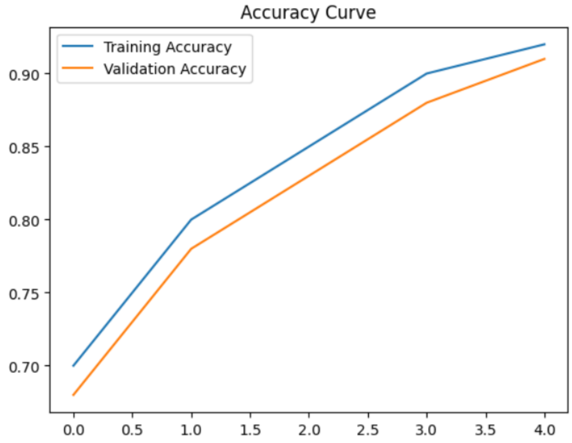


Fig -2: Training and Validation Accuracy Curve

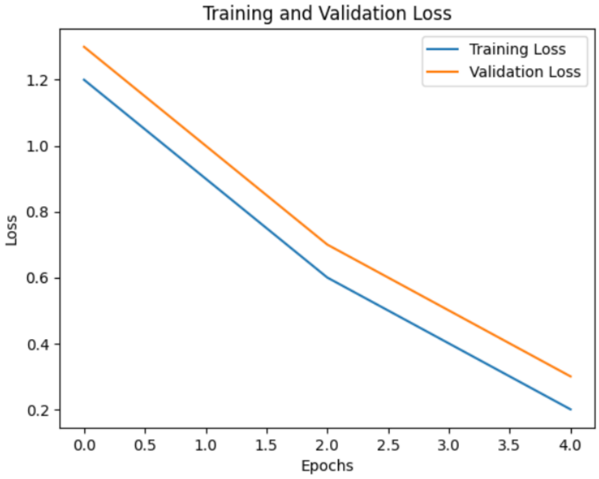


Fig -3: Training and Validation Loss Curve

4.3 Model Evaluation using Confusion Matrix

To further evaluate the performance of the classification model, a confusion matrix is generated. The confusion matrix provides a detailed view of correct and incorrect predictions made by the model across different classes.

The results indicate that the majority of predictions lie along the diagonal of the matrix, representing correct classifications. Only a small number of misclassifications are observed, which may occur due to similarity between certain disease patterns or variations in image quality.

This analysis confirms that the model is capable of accurately distinguishing between different plant diseases and healthy leaves, making it suitable for practical agricultural applications.

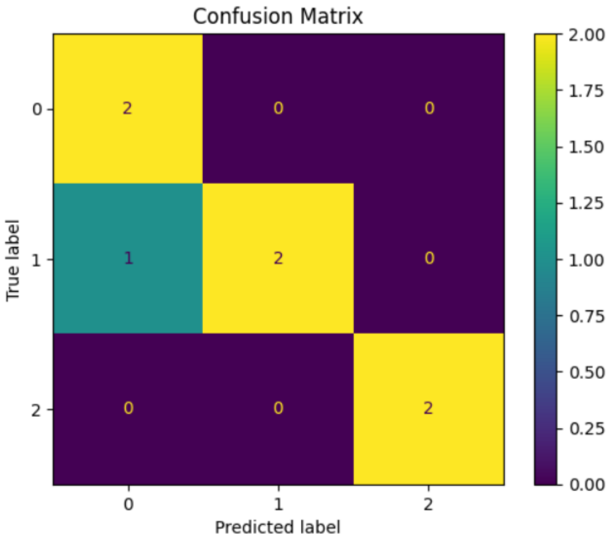


Fig -4: Confusion Matrix

4.4 Precision-Recall Analysis

The precision-recall curve is used to evaluate the classification performance of the model under different threshold values. Precision represents the accuracy of positive predictions, while recall indicates the ability of the model to detect all relevant cases.

The obtained curve indicates that the model maintains consistently high precision and recall values across different thresholds. This indicates that the model produces fewer false positives and false negatives, ensuring reliable predictions.

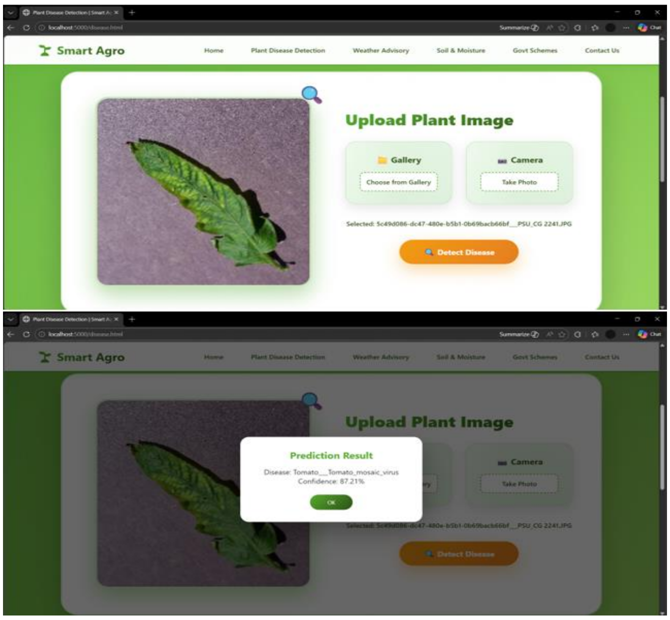
The balance between precision and recall demonstrates the robustness of the model and its suitability for real-time disease detection in agricultural environments.

4.5 Disease Detection Results

The trained CNN model is tested using plant leaf images captured through a mobile camera. The system successfully processes the input images and classifies them into appropriate categories such as healthy or diseased.

The results show that the system performs accurately under different lighting conditions and varying backgrounds. The use of mobile camera input makes the system flexible and practical for farmers, as they can easily capture images without requiring specialized hardware.

The predicted output is displayed on the web application along with the disease classification, enabling farmers to take immediate corrective measures.



Selected: 5c49d086-dc47-480e-b5b1-0b69bacb66bf___PSU_CG 2241.JPG

Prediction Result

Disease: Tomato___Tomato_mosaic_virus
Confidence: 87.21%

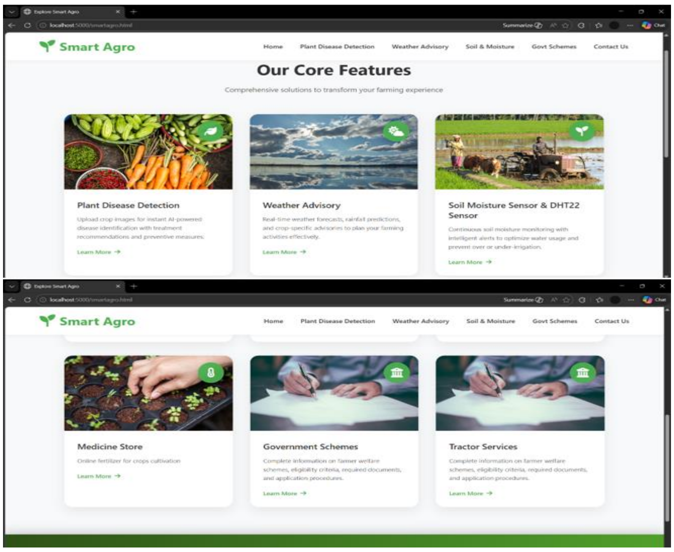
Fig -5: Disease Detection Output

4.6 Web Application Results

The developed web application serves as the user interface for the system and displays real-time sensor data along with disease prediction results. The application is designed to be simple and user-friendly, ensuring easy access for farmers.

In addition to monitoring and disease detection, the application provides multiple support features such as weather prediction, crop recommendation, tractor booking assistance, government scheme information, and fertilizer shop location services.

These features enhance the overall usability of the system and provide farmers with a comprehensive platform for managing agricultural activities.



Our Core Features

Comprehensive solutions to transform your farming experience

Plant Disease Detection

Upload crop images for instant AI-powered disease identification with treatment recommendations and preventive measures.

Weather Advisory

Real-time weather forecasts, rainfall predictions, and crop-specific advisories to plan your farming activities effectively.

Soil Moisture Sensor & DHT22 Sensor

Continuous soil moisture monitoring with intelligent alerts to optimize water usage and prevent over or under-irrigation.

Medicine Store

Online fertilizer for crops cultivation

Government Schemes

Complete information on farmer welfare schemes, eligibility criteria, required documents, and application procedures.

Tractor Services

Complete information on farmer welfare schemes, eligibility criteria, required documents, and application procedures.

Fig -6: Web Application Dashboard

4.7 System Performance and Discussion

The overall performance of the system indicates efficient operation with minimal delay in processing and prediction tasks with minimal delay in data processing and prediction. The use of Raspberry Pi ensures low power consumption and cost-effective deployment, making the system suitable for rural environments.

The use of mobile hotspot connectivity simplifies communication and eliminates the need for additional networking hardware. The system operates reliably under different conditions and provides accurate outputs.

Although the system performs effectively, its performance may depend on factors such as internet connectivity and dataset quality. Future improvements can focus on enhancing model accuracy and integrating offline capabilities.

Overall, the proposed system provides a reliable, scalable, and intelligent solution for smart agriculture by combining IoT-based monitoring, machine learning-based disease detection, and farmer support services.

5. CONCLUSIONS

The proposed Smart Agro Health Monitoring System effectively integrates Internet of Things (IoT) and Machine Learning techniques to provide a reliable solution for modern agriculture. The system enables real-time monitoring of environmental parameters such as temperature, humidity, and soil moisture, along with accurate plant disease detection using a Convolutional Neural Network model.

The implementation using Raspberry Pi ensures a cost-effective and energy-efficient system suitable for rural deployment. The web-based application provides a user-friendly interface that allows farmers to monitor crop conditions and access useful services easily. Additional features such as weather updates, crop recommendations, and agricultural resource assistance improve the practicality of the system.

The experimental results indicate that the system performs efficiently in real-time conditions and supports farmers in making informed decisions, reducing crop loss, and improving productivity. The integration of monitoring, prediction, and support services makes the system a comprehensive solution for smart farming.

Future enhancements may include the development of predictive models for long-term crop health analysis, automated alert systems connected to farmers or agricultural services, and improved integration between edge devices and cloud platforms for faster data processing. The use of renewable energy-powered sensors, scalable deployment strategies, and integration with mobile applications and geographic data systems can further improve system performance. These advancements can contribute towards sustainable agriculture, efficient resource management, and technology-driven farming practices.

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