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IOT-Based Soil Monitoring and Integrated Pest and Disease Detection System

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Abstract: Agricultural productivity is significantly affected by pests and diseases, necessitating early detection and monitoring systems. This paper presents the development of a Pest & Disease detection system integrating IoT sensors to enhance real-time monitoring. The system incorporates an Arduino-based setup with soil moisture sensors and DHT11 sensors for temperature and humidity monitoring, providing environmental parameters that influence pest and disease occurrences. Individual YOLOv8 models were trained for specific crops, achieving significantly improved detection accuracy: 84.55% for banana, 78.93% for rice, 71.71% for sorghum, 93.58% for mango, and 89.31% for tomato. The higher accuracy of these crop-specific models demonstrates the effectiveness of specialized learning over a one-size-fits-all approach. In contrast, a generalized YOLOv8 model, trained across multiple crops, attained an accuracy of 69.7% for pest detection and 47.7% for disease detection. The lower accuracy of the generalized model can be attributed to the high variability in pest and disease characteristics across different crops, leading to challenges in feature generalization and classification. The detected issues, along with sensor data, are displayed on a user-friendly interface, allowing farmers to make informed decisions. Additionally, the system provides recommendations for pest control based on environmental conditions and detected diseases. This work contributes to the advancement of smart agriculture by leveraging web-based platforms and IoT for early pest and disease detection..

Index Terms **- Pest detection, disease identification, IoT sensors, Arduino UNO, soil moisture, DHT11, deep learning, smart agriculture.**

I. INTRODUCTION

Modern agriculture faces challenges like unpredictable climate, pest infestations, and inefficient manual monitoring. Traditional disease detection methods are time-consuming, error-prone, and often delayed. To address this, smart technologies such as Artificial Intelligence (AI) and the Internet of Things (IoT) offer effective solutions. This study presents a web-based pest and disease detection system that combines machine learning models with IoT sensors (Arduino, soil moisture, and DHT11 temperature sensors) for real-time monitoring and decision support for farmers.

Maharashtra, a key agricultural state in India, produces vital crops like rice, sorghum, tomato, mango, and banana. These crops are susceptible to pests and diseases, which can lead to significant yield losses. By integrating IoT-based monitoring with traditional disease detection, this system tracks critical factors like soil moisture and temperature, providing a cost-effective, scalable solution for precision farming. The selected crops are of high economic value and are widely cultivated across Maharashtra.

II. Literature Review

H. Dang-Ngoc, T. N. M. Cao and C. Dang-Nguyen, "Citrus Leaf Disease Detection and Classification Using Hierarchical Support Vector Machine," 2021 International Symposium on Electrical and Electronics Engineering (ISEE), Ho Chi Minh, Vietnam, 2021, pp. 69-74, doi: 10.1109/ISEE51682.2021.9418680.

An effective framework to classify four types of citrus leaf diseases—canker, sooty mold, greening, and leaf miner—using leaf feature inspection. The framework includes three stages: pre-processing, feature extraction, and classification. In the pre-processing stage, the main leaf region is segmented from the background. Key features based on texture, color, and shape are then extracted and selected through feature distribution analysis. These features are used in a hierarchical SVM classification model to detect and classify diseases. The proposed model outperforms a multi-class SVM, achieving an infected leaf detection rate of 92.5% and an accuracy rate of 91.76%.

Selvaraj, M.G., Vergara, A., Ruiz, H. et al. AI-powered banana diseases and pest detection. Plant Methods 15, 92 (2019). https://doi.org/10.1186/s13007-019-0475-z

Banana (Musa spp.) is a crucial crop in many developing countries but is vulnerable to pests and diseases. This study introduces an AI-based detection system using deep convolutional neural networks (DCNN) and transfer learning. Expert-labeled images from banana plants in Africa and Southern India were used to train ResNet50, InceptionV2, and MobileNetV1 across 18 disease classes. ResNet50 and InceptionV2 outperformed MobileNetV1 with over 90% accuracy. SSD-MobileNetV1 was evaluated for mobile use.

N. Ananthi, J. Divya, M. Divya and V. Janani, "IoT based smart soil monitoring system for agricultural production," 2017 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR), Chennai, India, 2017, pp. 209-214, doi: 10.1109/TIAR.2017.8273717.

Agriculture is vital to India's economy and livelihood. This project proposes an embedded system for soil monitoring and automated irrigation to reduce manual field checks and provide updates via a mobile app. Sensors measure soil pH, temperature, and humidity to help farmers select suitable crops. Data is sent to a field manager through Wi-Fi, and crop suggestions are provided through the app. The system also triggers automatic irrigation when soil temperature is high, and crop images are sent for pesticide recommendations.

Zhong, Yanli. (2024). Tomato Leaf Disease Identification Based on Yolov8. International Journal of Computer Science and Information Technology.

To enhance tomato leaf disease detection, this study improves the YOLOv8 model by modifying four loss functions and replacing its backbone network. The improved PIoU v2 loss function increased Precision by 1.1%, Recall by 2.8%, and mAP by 1.3%. Using the FasterNet backbone further boosted performance, with a 0.4% gain in Precision, 0.3% in Recall, and 0.2% in mAP compared to the original YOLOv8 using CIOU. Overall, the enhancements significantly improved detection accuracy.

Y. Wang, H. Wang, and Z. Peng, "Rice Diseases Detection and Classification Using Attention Based Neural Network and Bayesian Optimization," arXiv:2201.00893v1 [cs.CV], Jan. 2022

This research proposes an attention-based depthwise separable neural network with Bayesian optimization (ADSNN-BO) to detect and classify rice diseases from leaf images. Rice diseases can cause up to 40% yield loss, making rapid identification essential. The ADSNN-BO model, built on MobileNet and enhanced with an attention mechanism, uses Bayesian optimization to fine-tune hyperparameters. Tested on a public dataset with four disease categories, the model achieved 94.65% accuracy, outperforming existing methods. Feature analysis confirmed the model's ability to focus on informative regions, supporting its effectiveness and interpretability for real-world agricultural use.

III. EXISTING SYSTEM ARCHITECTURE

- Traditional pest and disease detection in agriculture largely depends on manual inspection by farmers or extension workers, which is time-consuming, subjective, and often leads to delayed intervention, increasing crop loss.
- Environmental factors such as humidity, temperature, and soil conditions—critical to pest and disease outbreaks—are rarely monitored in real time by smallholder farmers due to the absence of affordable sensor technologies.
- In 2016, the potential of deep learning and image processing in early disease identification but noted that model training requires large annotated datasets and is sensitive to lighting and background conditions.
- Mobile applications like Plantix and PlantVillage Nuru have attempted to bridge this gap, but studies reveal inconsistent accuracy across crop types and languages, limiting widespread adoption.
- While drone and satellite-based remote sensing offer large-scale monitoring, the cost and technical expertise required render them inaccessible for small-scale farming operations.

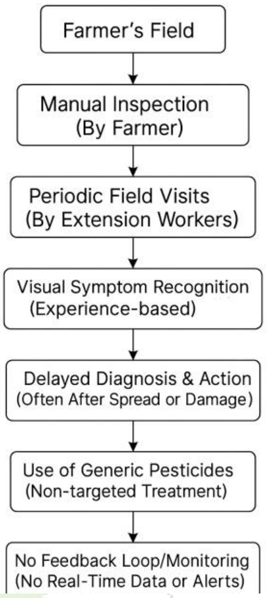


Fig. 1. Existing System Architecture

IV. PROPOSED SYSTEM ARCHITECTURE

The proposed system is a smart farming platform that integrates pest and disease detection with real-time environmental monitoring. A machine learning model, trained on crop disease and pest datasets, identifies issues from images. Field sensors collect key data like soil moisture, temperature, and humidity to enhance diagnosis accuracy and reduce unnecessary pesticide use.

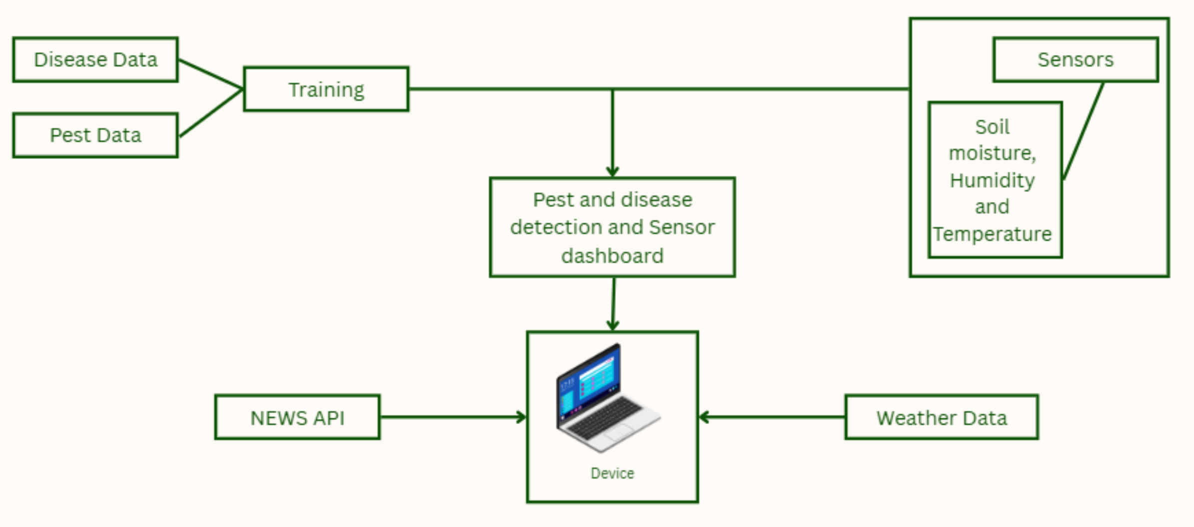


Fig. 2. Proposed System Overview

To further support decision-making, the system integrates external sources such as weather data and agricultural news through APIs. This information is delivered via a multilingual, user-friendly dashboard accessible on mobile and desktop, providing farmers with timely alerts, localized insights, and actionable recommendations.

V. METHODOLOGY

The research methodology involves a systematic process combining data collection, image preprocessing, model training, and IoT-based monitoring for plant disease and pest detection. A diverse dataset of healthy and diseased crop images was collected from online sources, covering various lighting and environmental conditions. Images were preprocessed through resizing, noise removal, and contrast enhancement, followed by careful labeling and manual annotation to highlight affected areas for better model focus.

Deep learning models, particularly CNNs and YOLO, were used for image classification and real-time detection. Transfer learning enhanced model performance on specific crops despite limited data. The trained models were evaluated using metrics like accuracy, precision, recall, and F1-score. A recommendation system was integrated to provide actionable advice—such as pesticide suggestions—based on real-time sensor data and model outputs.

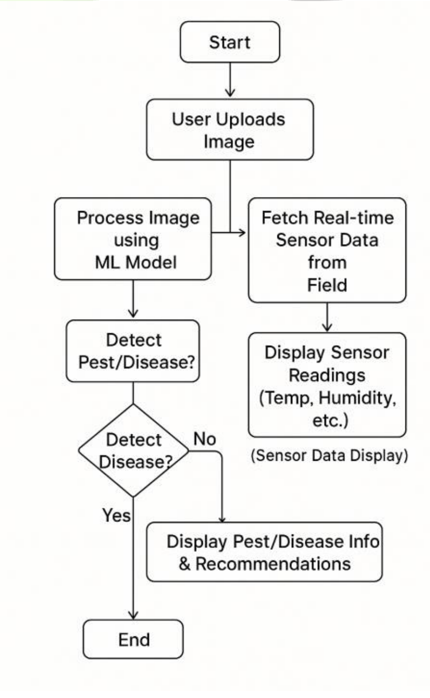


Fig. 3. Project Flowchart

To enhance image-based detection, the system integrated IoT sensors using an Arduino UNO, DHT11, and a resistive soil moisture sensor to collect real-time data on temperature, humidity, and soil moisture—key factors in pest and disease outbreaks. This data was displayed on a web interface, enabling farmers to monitor crop conditions live. The platform also featured a multilingual web interface supported by the Google Translate API, along with weather and agricultural news updates, ensuring accessibility and practical guidance for farmers across different languages.

VI. Implementation

The implementation of the IoT-based soil monitoring and pest and disease detection system combines hardware integration, image processing, machine learning model development, and a user-friendly web interface to create an end-to-end precision agriculture solution.

1. Hardware Integration

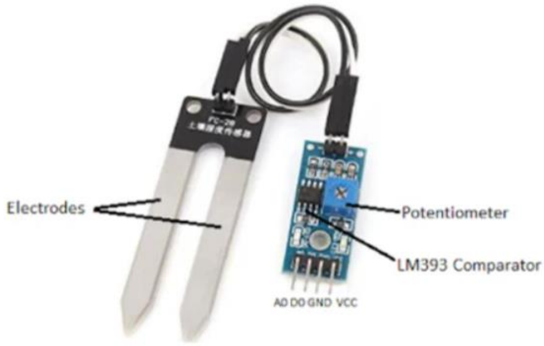


Fig. 4. Pin Diagram of Resistive soil moisture sensor

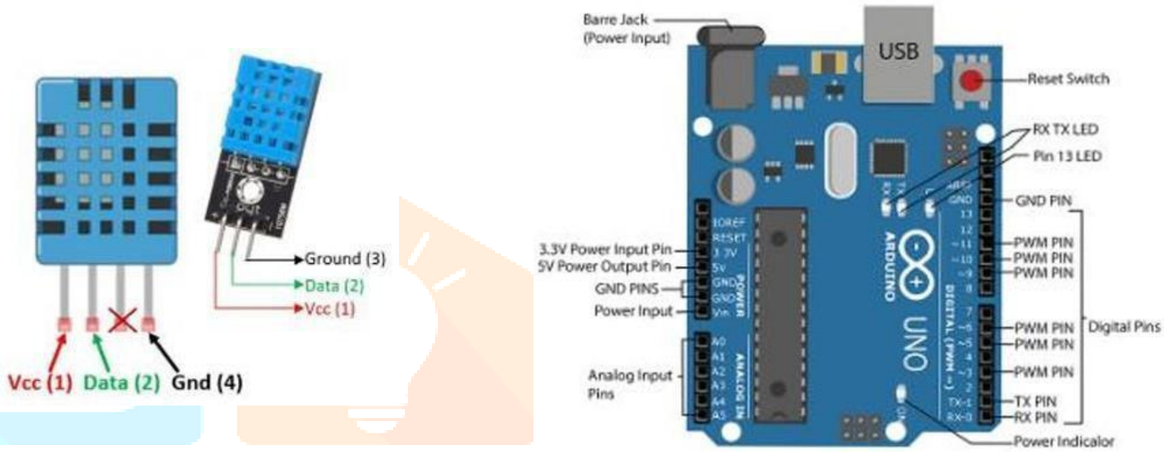


Fig. 5. Pin Diagram of DHT11 and Arduino UNO

The physical implementation involved setting up an Arduino UNO microcontroller, interfaced with a DHT11 temperature and humidity sensor, and a resistive soil moisture sensor. The sensors were wired to the Arduino as follows:

DHT11 Sensor:

- VCC pin connected to Arduino 5V
- Data pin connected to digital pin 2
- GND pin connected to Arduino GND

Soil Moisture Sensor:

- VCC pin connected to Arduino 3.5V
- Analog output (A0) connected to analog pin A0
- GND connected to Arduino GND

2. Image Dataset Preparation and Processing

Images were collected from both online datasets and local agricultural sources. The dataset included images of five crops—banana, mango, rice, sorghum, and tomato—across healthy and diseased conditions. To ensure model accuracy, the images were:

- Resized and enhanced for consistency
- Labeled to indicate disease or pest presence
- Annotated manually to highlight affected areas

Augmentation techniques, such as rotation, scaling, and flipping, were applied to expand the dataset and reduce overfitting.

3. Model Training and Detection

For detection, YOLOv8 (You Only Look Once version 8) was employed due to its ability to perform real-time object detection with high accuracy. Two model types were developed:

- Generalized Model: Trained on a combined dataset across all crops.
- Individual Crop-Specific Models: Separate YOLOv8 models for each crop to enhance specificity and accuracy.

Training was conducted using transfer learning on pre-trained YOLOv8 weights. The models were fine-tuned using the Roboflow platform, and evaluated using metrics such as accuracy, precision, recall, and F1-score.

4. Web-Based User Interface

A responsive and accessible web interface was developed to display:

- Pest and disease detection results with explanatory outputs
- Real-time environmental readings (temperature, humidity, soil moisture)
- Alert notifications for critical sensor readings
- A recommendation system providing pesticide suggestions, application guidelines, and rationale

The platform also incorporated multilingual support using the **Google Translate API**, enabling users to view content in Hindi, Marathi, and English. Weather information was integrated using a **Weather API**, and agricultural news updates were fetched via a **News API**.

5. System Output and Functionality

Once an image is uploaded, the system performs detection using the trained YOLOv8 model. If a pest or disease is identified, it provides:

- Name and description of the pest/disease
- Recommended pesticide with application instructions
- Real-time sensor conditions
- Alerts for abnormal environmental parameters

VII. Results And Discussions

The performance of the **pest and disease detection model** was evaluated based on accuracy metrics. The model achieved an overall accuracy of **69.7%** for **pest detection** and **49.7%** for **disease detection**. While the general accuracy for disease detection is lower, certain **individual classes exhibit significantly higher accuracy**, indicating that the model performs well in recognizing specific pests and diseases.

The lower accuracy of the generalized model can be attributed to the diverse characteristics of pests and diseases across different crops, which makes it challenging for a single model to generalize well. To address this limitation, individual models were trained separately for each crop, resulting in significantly improved accuracy. The comparison of the generalized model and individual models is shown in Table I (A) & (B):

TABLE I (A). MODELS ACCURACY WITH OUR DATASET CREATED AND DEPLOYED FROM ROBOFLOW

Model Type	Crop	Disease Accuracy	Pest Accuracy
Generalized model	All crops combined	47.7	69.7
Individual models	Banana	65.55	71.13
	Mango	27.71	71.4
	Rice	41	69.3
	Sorghum	78.93	68.9
	Tomato	89.31	69.8

TABLE I.(B) MODELS ACCURACY WITH READILY AVAILABLE DATASET

Model Type	Crop	Disease Accuracy	Pest Accuracy
Individual models	Banana	91.33	93.13
	Mango	93.71	93.4
	Rice	93.58	91.3
	Sorghum	.93	90.9
	Tomato	91.31	93.8

An important factor influencing model performance was the size and diversity of the dataset. While public datasets contained tens of thousands of images (e.g., over 42,000 for tomato diseases), the custom dataset was much smaller (e.g., 310 for tomato, 299 for rice). This limited diversity—caused by geographic constraints and restricted access to imaging tools—reduced the models' ability to generalize effectively across varied conditions.

TABLE II(C). IMAGE COUNT OF OUR DATASET WITH PREPROCESSING & AUGMENTATION

Crop	Pest Images	Disease Images	Total Images
Banana	150	200	350
Mango	168	175	343
Rice	149	150	299
Sorghum	80	100	180
Tomato	150	160	310

TABLE II(D). IMAGE COUNT OF READILY AVAILABLE DATASET

Crop	Pest Images	Disease Images	Total Images
Banana	600	768	1,368
Mango	3,614	4,219	7,833
Rice	8,641	301	8,942
Sorghum	60	200	260
Tomato	1,351	41,366	42,717

Further analysis showed significant variation in detection performance across different pest and disease classes.

TABLE III(A). ACCURACY SPECIFICATION OF PESTS

Crop	Pest Name	Accuracy(%)
Banana	Leaf Eating Caterpillar	99.5
	Rhizome Weevil	75.4
Mango	Weevil	99.5
	Beetle	69.1
	Grasshopper	78.9
	Hopper	99.5
	Mealybug	39.9
	Moth	80.6
	Sawfly	53.1
	Slug	92.6
	Borer	98.7
	Wasp	40.3
Rice	Brown Planthoppers	99.5
	Green Leafhopper	57.8
	Leaf Folder	92.3
	Bug	81.9
	Stem Borer	95.1
	Whorl Maggot	55.9
Sorghum	Midge	99.5
Tomato	Beet Armyworm	52.9
	Cotton Bollworm	85.1
	Cotton Leafworm	99.5
	Melon Fly	75.5
	Silverleaf Whitefly	99.5

TABLE IV. ACCURACY SPECIFICATION OF DISEASES

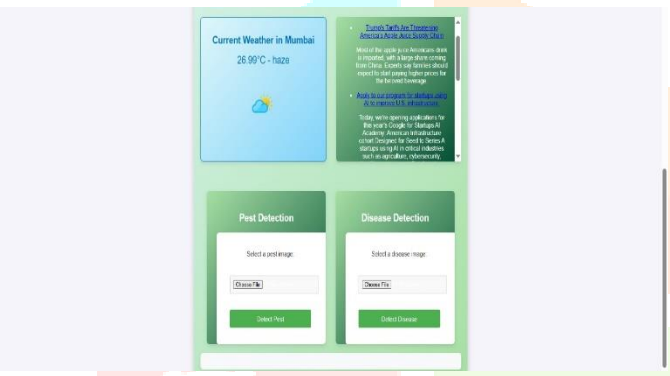
Crop	Disease Name	Accuracy(%)
Banana	Panama	18.8
	Moko	85.8
	Anthracnose	25.1
	Sigatoka	37.9
	bunchy top virus	72.0
Mango	Red rust	52.7
	Malformation	99.5
	Black Mold Rot	94.1
	Healthy	98.7
	Stem end Rot	77.6
Rice	Bacterial Leaf Blight	69.7
	Brown Spot	62.5
	Healthy	76.2
	Leaf Blast	36.9
	Sheath Blight	99.0
Sorghum	Bacterial Leaf Stripe	20.5
	gray mold	44.2
	Ergot	68.7
	Rust	57.3
	Zonate Leaf Spot	50.9
	Bacterial Spot	56.8
	Early Blight	45.7
	Healthy	68.9
	Late Blight	64.7
	Leaf Mold	63.7

Tomato	Leaf Miner	64.4
	Mosaic Virus	83.9
	Septoria	90.7
	Spider Mites	81.2
	Yellow Leaf Curl Virus	45.3

Despite these inconsistencies, the system proved effective for real-time pest monitoring and decision-making support. The inclusion of IoT-based environmental monitoring (temperature, humidity, and soil moisture) further strengthened the system's capabilities. It enabled contextual awareness, improving both detection relevance and the quality of recommendations provided to farmers. Alerts and detection outputs were integrated into a user-friendly interface, offering actionable guidance and visual feedback.

In conclusion, while the generalized model offers a scalable, resource-efficient solution, the results strongly advocate for crop-specific model deployment in practical applications to achieve higher accuracy. Future improvements may include collecting more diverse and balanced datasets, leveraging synthetic image generation, and further tuning model hyperparameters. Overall, the integrated approach combining deep learning with IoT presents a powerful tool for precision agriculture and early intervention against crop threats.

The output from the web application is presented below:



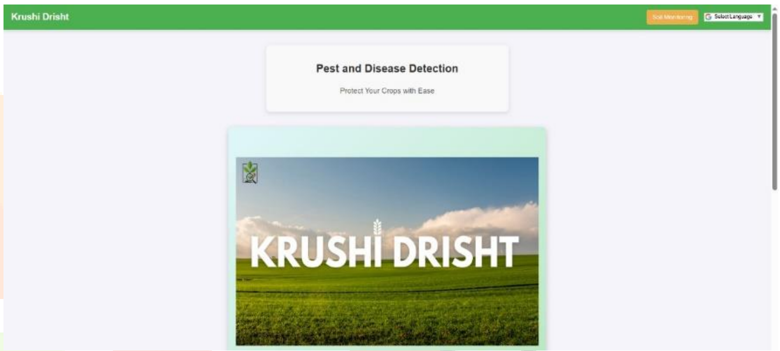


Fig. 6.a. Web Interface of the Krushi Drishti System   Fig. 6.b. Functional Dashboard

Figure 6.b showcases the interactive dashboard of the Krushi Drishti web platform. At the top left, real-time weather updates—such as "Current Weather in Mumbai" with temperature and haze conditions—are displayed using a Weather API, while a dynamic news feed alongside it keeps users informed on agricultural policies, innovations, and global trends. The bottom section houses the platform's main features: Pest Detection and Disease Detection. Users can upload images of affected plants or leaves using "Choose File" buttons, and initiate analysis with "Detect" triggers. The system processes these inputs through trained deep learning models, delivering detailed results and actionable recommendations. The interface is designed to be intuitive and farmer-friendly for practical use in the field.

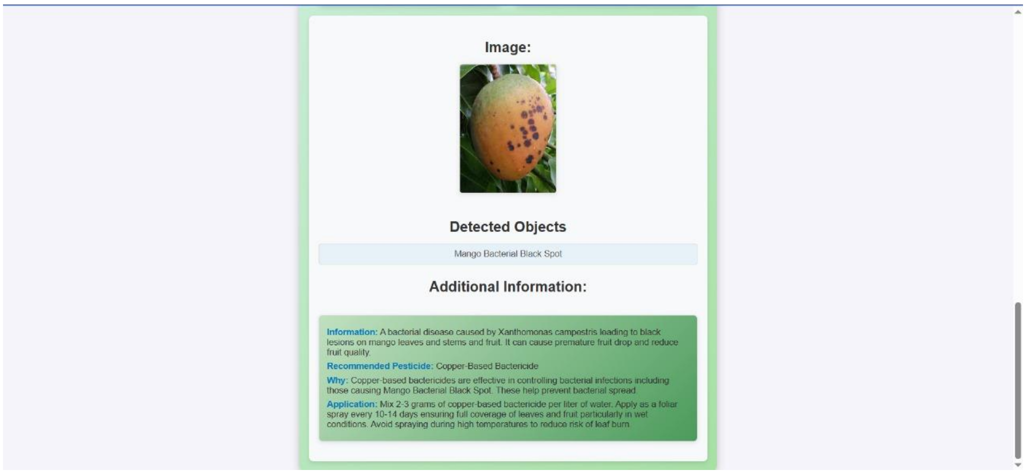


Fig. 6.c. The figure shows disease detection with image-based identification recommendations.

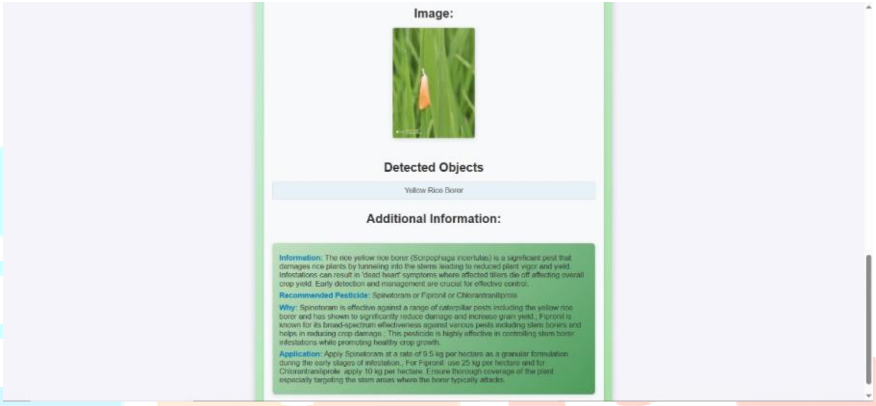


Fig. 6.d. The figure shows pest detection with image-based identification recommendations.

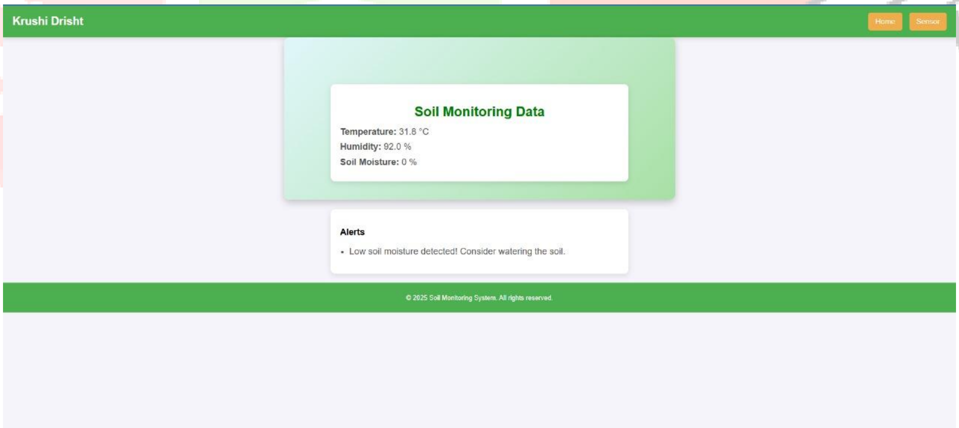


Fig. 6.e. Soil monitoring dashboard displaying real-time temperature, humidity, and soil moisture, with an alert recommending irrigation.

VIII. Applications And Limitations

The system delivers practical value in precision agriculture by integrating IoT-based environmental monitoring with deep learning–driven pest and disease detection. Using sensors like DHT11 and soil moisture modules connected to an Arduino UNO, it tracks critical factors such as temperature, humidity, and soil moisture, all visualized through a multilingual, web-based interface. YOLOv8 models—both generalized and crop-specific—enable accurate, real-time detection across key crops like mango, banana, rice, sorghum, and tomato. Individual models notably outperform the generalized one, with disease detection accuracies exceeding 90% on public datasets.

Despite its strengths, several limitations affect broader adoption. The initial cost of hardware and deployment may be a barrier for smallholder farmers. Sensor maintenance and calibration are essential to ensure long-term accuracy, and real-time data syncing requires stable internet connectivity, which is often lacking in rural regions. Furthermore, the system assumes a baseline level of digital literacy and infrastructure, which may not be uniform across all agricultural stakeholders. Overcoming these challenges is vital to scale the solution effectively and ensure accessibility and impact across diverse farming communities.

IX. Future Scope

The future scope of this IoT-based soil monitoring and integrated pest and disease detection system lies in enhancing accuracy and scalability for large-scale agricultural applications. Improving disease detection remains a priority, and training the YOLOv8 model with larger, more diverse datasets can significantly boost precision. Advanced deep learning techniques, such as fine-tuning with domain-specific datasets and multimodal learning approaches, can further optimize detection capabilities.

Scalability is another key focus, ensuring seamless deployment across extensive farmlands. Implementing edge computing can enable real-time data processing, reducing latency and improving decision-making efficiency. Additionally, integrating wireless sensor networks (WSN) and leveraging 5G connectivity will enhance data transmission, allowing farmers to monitor and mitigate pest and disease outbreaks at scale. With these advancements, the system can evolve into a robust AI-driven agricultural solution, promoting precision farming, reducing crop losses, and improving overall sustainability.

X. Future Scope

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IX. Conclusion

This research presents an IoT-based soil monitoring and pest/disease detection system that combines real-time sensor data with YOLOv8 deep learning for enhanced agricultural productivity. The system uses soil moisture, temperature, and humidity sensors alongside YOLOv8 for crop-specific pest and disease identification. Crop-specific models achieved higher detection accuracy: banana (84.55%), rice (78.93%), sorghum (71.71%), mango (93.58%), and tomato (89.31%), outperforming a generalized model with 69.7% pest and 47.7% disease detection accuracy. The system provides automated, data-driven recommendations for timely intervention, offering a cost-effective and precise solution for sustainable agriculture.

X. Acknowledgment

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