Soil Based Crop Diseases Early Warning System

Ankita Anand Dhawle
Electronics and communication
Usha Mittal Institute of Technology
Mumbai, India

Sandhya Bablu Gupta
Electronics and Communication
Usha Mittal Institute of Technology
Mumbai, India

Srushti Machindra Jarad
Electronics and Communication
Usha Mittal Institute of Technology
Mumbai, India

Prof./Dr.Kavita Mhatre
Usha Mittal Institute of Technology
Mumbai, India

Prof.Neha Athavale Mhalgi
Usha Mittal Institute of Technology
Mumbai, India

Abstract—The Soil-Based Crop Disease Early Warning System utilizes IoT, AI, and Machine Learning to monitor soil and environmental conditions for early disease detection. Sensors measure temperature, humidity, and soil moisture, while a camera module captures plant images. A Convolutional Neural Network (CNN) analyses images to detect plant diseases, and AI processes sensor data for predictive insights. The system provides real-time alerts on an LCD and enables remote monitoring via wireless communication. This cost-effective solution helps farmers mitigate crop losses and improve agricultural productivity. By integrating smart technologies, the system enhances precision farming and sustainable agriculture.

Keyword- Machine Learning, CNN, Plant Disease Detection, Soil Monitoring, Early Warning System, Smart Agriculture, Wireless Communication

INTRODUCTION

Agriculture is vital for food production, employment, and raw materials, but crop diseases reduce yield and cause financial losses. To tackle this issue, a Soil-Based Crop Disease Early Warning System is proposed, utilizing IoT, sensors, and data analysis for real-time soil monitoring. By measuring moisture, temperature, pH, and nutrient levels, the system detects disease risks early. It sends alerts and predicts potential diseases, enabling farmers to take preventive measures. The technology includes soil sensors, microcontrollers, and wireless devices, while machine learning analyses the collected data. This approach helps prevent crop diseases, reduces pesticide use, improves soil health, and increases productivity.The study aims to develop an IoTbased system for real-time data collection, processing, and remote monitoring. It focuses on analysing soil parameters to identify conditions favourable for crop diseases. Predictive algorithms will generate early warning alerts, helping farmers take timely action. The objective is to enhance precision agriculture, reduce crop losses, and promote sustainability. By enabling proactive interventions, the system supports data-driven decisionmaking for better farm management. This report is organized into multiple chapters, with Chapter 1 introducing the concept and motivations behind this study.

PLANT LEAF DISEASES CLASSIFICATION SYSTEM

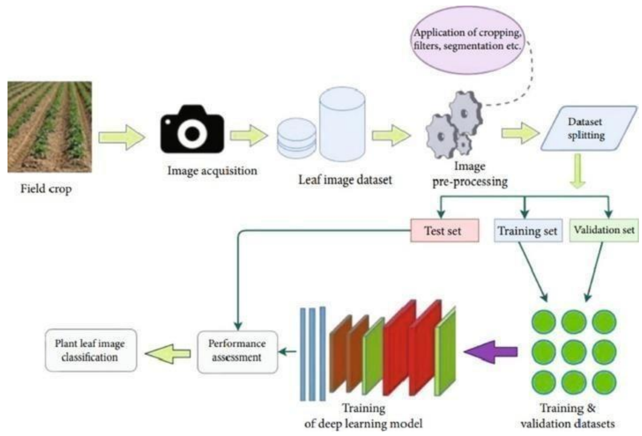

Fig 1. PLANT LEAF DISEASES CLASSIFICATION SYSTEM

What are plant leaf diseases classification system*?*

This image represents a deep learning-based plant leaf disease classification system that utilizes image processing and machine learning techniques. The process begins with image acquisition, where a camera module captures images of field crops, specifically focusing on their leaves. These images are then stored in a dataset, which serves as the foundation for training and testing the machine learning model. Before feeding the images into the model, preprocessing is performed, which includes techniques such as cropping, filtering, and segmentation to enhance the quality of the images and remove unnecessary elements. Once pre-processing is complete, the dataset is split into three subsets: training, validation, and test sets. The training set is used to train the deep learning model, typically a Convolutional Neural Network (CNN), which learns to distinguish between healthy and diseased plant leaves. The validation set helps fine-tune the model's hyperparameters to improve accuracy, while the test set is used to assess the model's overall performance. The deep learning model undergoes training using the training and validation datasets, learning the distinct features of different plant diseases. After training, the model is evaluated using the test dataset, where its accuracy, precision, recall, and other performance metrics are analysed.The final step involves the classification of plant leaf images, where the trained model can classify new images as either healthy or exhibiting a specific disease.

This automated classification system aids in early disease detection and can be integrated into IoT- based agricultural monitoring solutions. Such a system has significant applications in precision agriculture, as it enables real-time plant health monitoring, reducing dependency on manual inspections. By combining IoT sensors with machine learning, farmers can receive automated alerts regarding plant health, improving crop yield and reducing losses due to diseases. This pipeline aligns with your Soil- Based Crop Disease Early Warning System, where IoT sensors monitor environmental conditions while a CNN model classifies plant diseases based on leaf images. Let me know if you need assistance with the technical implementation.

LITERAATURES SURVEY

This study presents an IoT-based agricultural system designed for crop prediction and automated irrigation control.[1] It integrates real-time environmental monitoring using IoT sensors to measure soil moisture, temperature, and humidity. Machine learning models are employed to predict optimal crop selection based on soil conditions, while an automated irrigation system ensures efficient water usage. The system enhances precision farming, reduces water wastage, and improves crop yield through data driven decision-making. [2] In that Intelligence (AI) in agriculture, emphasizing advancements in plant disease detection and management. It discusses various AI techniques such as Machine Learning (ML), Deep Learning (DL), and Computer Vision to analyse soil health, plant diseases, and environmental factors affecting crop growth. [3] The research highlights the integration of AI-driven models with IoT sensors for real-time monitoring and early disease prediction, improving agricultural productivity and reducing crop losses. This study introduces an IoT and AI-powered system for crop recommendation and disease [4] prediction, aiming to enhance agricultural productivity. It employs real-time IoT sensors to monitor soil properties, temperature, humidity, and moisture levels, while AI models analyse this data to recommend the bestsuited crops and predict potential diseases. Machine learning and deep learning algorithms are used for accurate disease [5] detection and classification, enabling farmers to take timely preventive measures. IoT-based crop disease detection system using machine learning algorithms like CNNs, SVMs, and RFC to RFC to analyze sensor data and crop images for early disease detection. Traditional methods are timeconsuming and error-prone, whereas this system provides accurate predictions and management recommendations web [6]-based interface. Results show RFC offers high accuracy, reducing overfitting. Future improvements include scalability, real-time weather integration, deep learning models, and drone-based monitoring for enhanced precision agriculture. This study presents an [7] IoT- enabled system for real-time crop monitoring and disease detection, integrating smart sensors to track temperature, humidity, soil moisture, and other environmental parameters. The collected data is processed using machine learning algorithms [8] to identify early signs of plant diseases. The system provides real-time alerts to farmers, enabling timely intervention and reducing crop losses. The study highlights the effectiveness of AI-driven predictive models in improving precision agriculture.

METHEDOLOGY

A. Proposed system methodology

The research methodology for the Soil-Based Crop Disease Early Warning System follows a step-by-step approach that combines IoT, AI, and Machine Learning to detect plant diseases early. The system has three main parts: sensor-based data collection, image-based disease detection, and cloud-based monitoring with alerts. First, a Raspberry Pi or Arduino Uno is used to collect data from different sensors, such as soil moisture, temperature, and humidity sensors, along with a camera module to capture plant images. This data is sent to an online storage platform like Firebase or ThingSpeak using Wi-Fi or Bluetooth. The camera images are processed by resizing, removing noise, and enhancing details to make them suitable for analysis.For disease detection, a machine learning model (CNN) is trained to recognize signs of plant diseases by analysing healthy and unhealthy plant images. The model works by learning patterns in images and predicting if a plant is infected. To improve accuracy, techniques like image adjustments, data balancing, and optimizing model learning are used. The system then displays results on an LCD screen and a web dashboard built with Flask, allowing farmers to monitor crop conditions easily. Additionally, Twilio or Telegram notifications are sent to farmers when a potential disease is detected, so they can take action quickly.

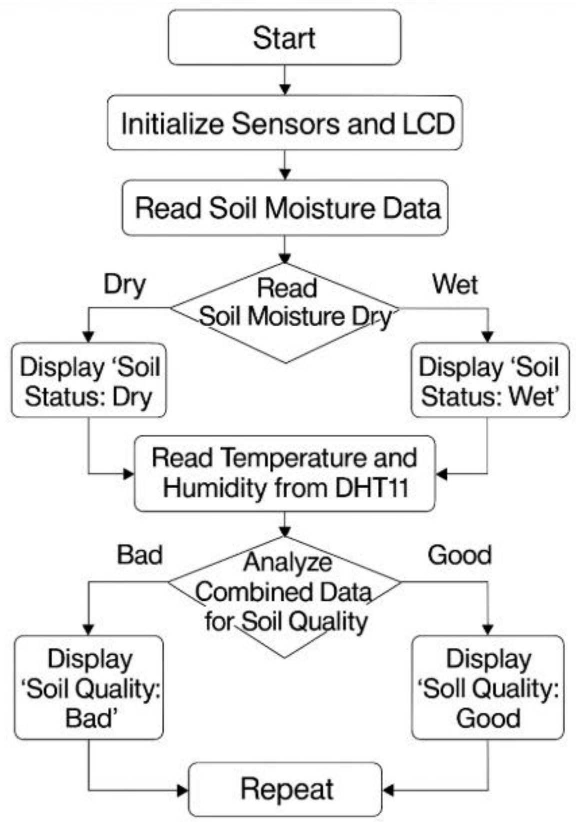

Fig 2. SOIL DISEASES DETECTION FLOW CHART

To check if the system works well, it is tested for accuracy, response time, and reliability. The CNN model's performance is measured using methods like accuracy scores and error analysis to ensure it correctly identifies diseases. The IoT system is also tested to make sure sensor readings are correct, alerts are sent quickly, and the system runs smoothly. Finally, the system is deployed in real farms for testing, where farmers use it to detect diseases in actual crops. The goal is to provide an affordable, easy-to-use, and effective system that helps farmers prevent crop losses and improve agricultural productivity.

B. Testing Arrangements

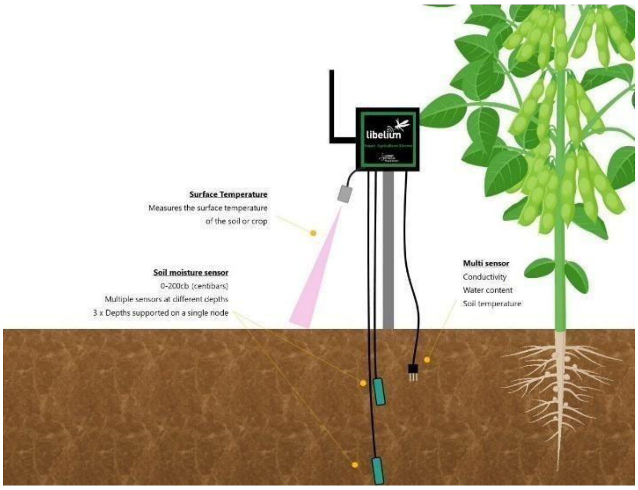

Fig 3. Soil-monitoring-with-iot-smart-agriculture

programming via Arduino IDE. Ideal for IoT and embedded system projects.

1. LCD Display 16x - A 16x2 LCD (Liquid Crystal. Display) can show 16 characters per row across 2 rows. Uses an HD44780 controller and can be 2 rows. Uses an HD44780 controller and can be interfaced using I2C or parallel 4-bit/8-bit mode Displays data such as sensor readings or alerts.
2. Arduino Uno- A microcontroller board based on the at mega328P chip. Features 16 MHz clock speed, 2KB RAM,14 digital I/O pins, and 6 analog inputs Supports C/C++.
3. Soil Moisture Sensor - Measures the water content in the soil. Works on capacitive or resistive principles. Provides either analog or digital output. Helps automate irrigation systems.
4. DHT11 sensor - A temperature and humidity sensor. Provides digital output. Less accurate than DHT22, but cheaper and easier to use.
5. Jumper Wires -Used to connect components in circuits. Available in male and female types. Essential for prototyping.
6. USB Cable - Connects microcontrollers to a computer for power and programming. Enables code upload and communication.

CHALLENGES

High Initial Cost: Sensors, microcontrollers, and AI models require investment.
Technical Knowledge Requirement: Farmers need training to use the system effectively.
Connectivity Issues: Rural areas may lack stable internet for cloudbased monitoring.
Data Accuracy and Reliability: AI models require large datasets for precise predictions.
Sensor Calibration & Maintenance: Regular calibration is needed to ensure accurate readings.
Integration with Traditional Farming: Convincing farmers to adopt technology-based solutions can be challenging.
Climate and Soil Variability: Regional differences may affect sensor performance and AI predictions.

RESULTS

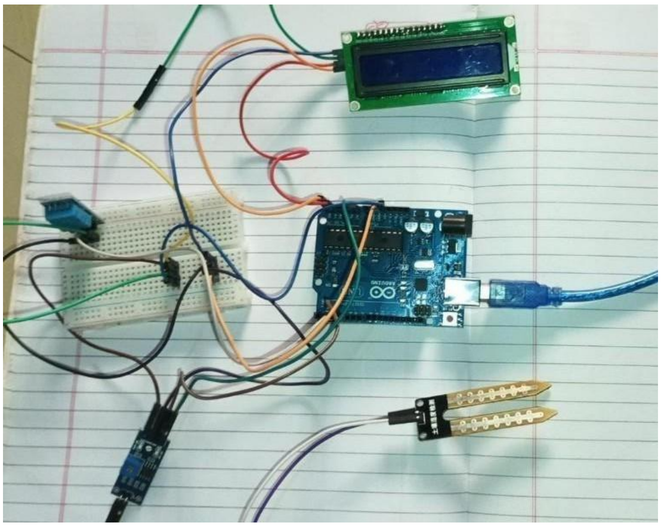

Fig 4. Hardware Setup of the Soil Health Monitoring System

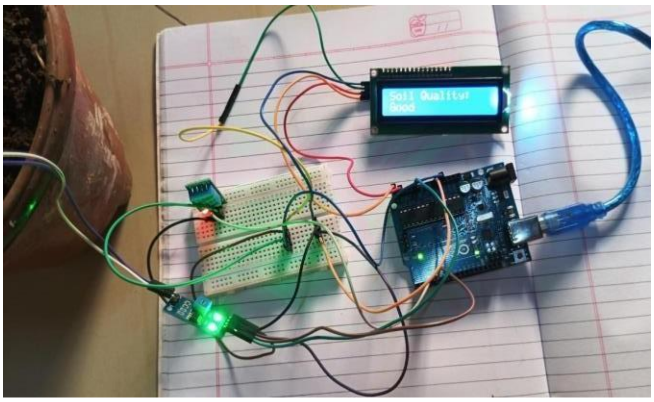

Fig 5. Soil Quality Detection and Display Output

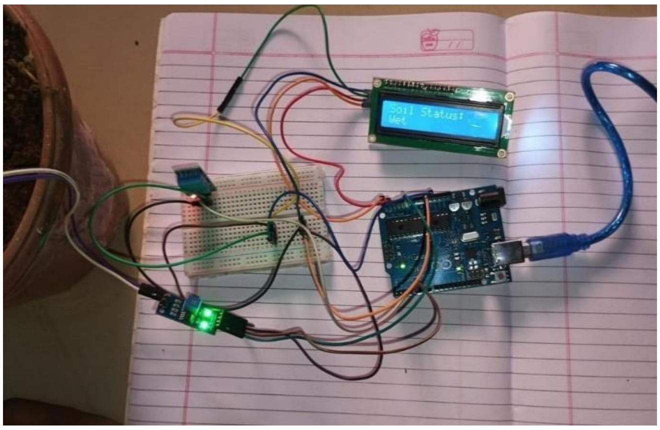

Fig 6. Soil Condition Analysis and Predictive Indication

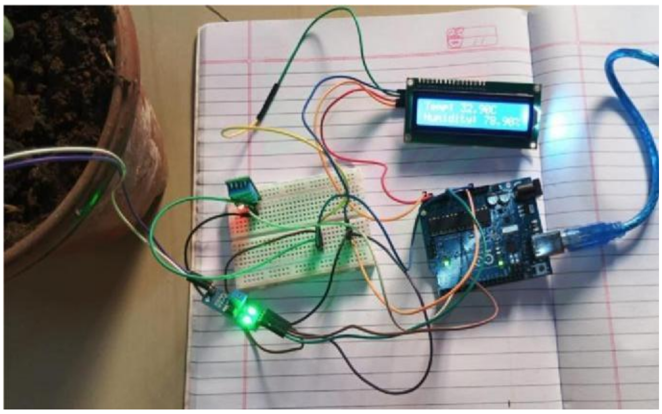

Fig 7. Real-Time Temperature and Humidity Monitoring

An interactive platform, "Smart Crop Health Monitoring System using Arduino," designed to monitor crop health by detecting early signs of disease, was developed using a rose plant as the test subject. The system integrates both hardware and software components, namely DHT11 and soil moisture sensors interfaced with an Arduino Uno and a 16x2 LCD module, to continuously assess environmental and soil conditions. As shown in Fig. 4 (Circuit Connection), the components were connected on a breadboard for real-time data acquisition. Sensor data—specifically temperature, humidity, and soil moisture—were acquired in real time and displayed clearly on the LCD module. This allows for intuitive monitoring, enabling early detection of conditions favorable to disease development. Recorded sample values as shown in Fig. 7 (Real-time Temperature and Humidity) indicate a temperature of 33.9°C and humidity of 74.0%, determining a high-moisture environment that may contribute to fungal risks such as powdery mildew in roses. The soil quality feedback ("Good"), displayed as shown in Fig. 5 (Soil Quality Indication), reflected real-time moisture levels and was validated through physical soil inspection. Furthermore, the prediction of soil conditions and plant health, illustrated in Fig. 6 (Condition of Soil and Prediction), was achieved using threshold-based logic, enabling the device to classify soil quality effectively and suggest potential plant health conditions. The modular nature of the system makes it simple to expand or integrate with additional IoT components for remote access or machine learning models. The clear visualization, stable readings, and smooth response contribute to its suitability for early disease detection, educational use, and precision agriculture practices. This system has the potential to evolve into a more comprehensive platform by incorporating image processing for leaf disease detection and cloud connectivity for historical data analysis. With proper scaling, it can be applied in larger gardens, greenhouses, or farms to reduce yield loss due to disease outbreaks.

CONCLUSION

The Soil-Based Crop Disease Early Warning System plays a crucial role in modern precision agriculture by enabling early detection and prevention of soil-borne crop diseases. By leveraging sensors, IoT technology, and machine learning algorithms, the system provides real-time monitoring of soil parameters such as moisture, temperature, pH, and nutrient levels. The integration of predictive algorithms. enhances disease detection accuracy, allowing farmers to take preventive measures before diseases spread, thereby reducing crop losses and improving yield quality. Through simulation-based testing, the system demonstrates its feasibility and effectiveness in identifying disease-prone conditions, even in the absence of physical hardware implementation. Future enhancements could include realtime cloud integration, automated decision-making, and wider adaptation of AIdriven disease prediction models. Ultimately, this system contributes to sustainable agriculture by minimizing chemical usage, optimizing resource management, and promoting early intervention strategies, making it a valuable tool for modern farming.

FUTURE SCOPE

1. **Wireless Communication:** The system can be upgraded with wireless modules like the ESP8266 or ESP32, allowing it to connect to Wi-Fi and send sensor data to cloud platforms such as Thingspeak, Firebase, or Blynk. This would enable remote monitoring, allowing users to view real-time temperature, humidity, and soil moisture data through a mobile application or a web dashboard.
2. **Mobile Alerts:** By integrating messaging services such as Telegram or Twilio, the system can be programmed to send SMS or mobile alerts whenever certain thresholds are crossed—for example, if the soil becomes too dry or the temperature rises beyond a safe limit. These smart notifications can help farmers take timely actions, improving crop health and reducing manual monitoring.
3. **Crop Disease Prediction:** A camera module can be added to the system to capture images of plant leaves, which can then be analyzed using a Convolutional Neural Network (CNN) to detect early signs of crop diseases. By combining this with environmental data from sensors, the system can act as a complete early warning tool for disease prevention in crops.
4. **Automated Irrigation:** The project can be enhanced with a relay module and a water pump to automate irrigation. When the soil moisture level drops below a predefined threshold, the pump can be turned on automatically. This would create a closed-loop system where irrigation is fully automated based on real-time soil conditions, conserving water and reducing labour.
5. **Machine Learning for Prediction:** Machine learning models can be trained using historical data to predict optimal watering times or detect early signs of crop failure. These predictions can be enhanced further by integrating weather data, allowing for smarter and more precise irrigation planning.

REFERENCES

1. D. Hebri, R. Nuthakki, A. K. Digal, K. G. S. Venkatesan, S. Chawla, and C. Raghavendra Reddy, “Effective Facial Expression Recognition System Using Machine Learning”, EAI Endorsed Trans IoT, vol. 10, Mar. 2024.
2. M. D. Alshehri, F. K. Hussain, and O. K. Hussain, "Clusteringdriven intelligent trust management methodology for the internet of things (CITM-IoT)," Mobile Networks & Applications, vol. 23, no. 3, pp. 419-431, 2018
3. Y. X. Wei, "Study on the application of internet of things-based intelligent microscope in blood cell analysis," Journal of Computational and Theoretical Nanoscience, vol. 14, no. 2, 2017, pp. 1199-1203.
4. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, “Electron spectroscopy studies on magneto-optical media and plastic substrate interface,” IEEE Transl. J. Magn. Japan, vol. 2, pp. 740–741, August 2010.
5. T. Domingues, T. Brand˜ ao, and J. C. Ferreira, “Machine learning for detection and prediction of crop diseases and pests: A comprehensive survey, “Agriculture, vol. 12, no. 9, p. 1350, Sep. 2022.
6. "Critical Review of Deep Learning Algorithms for Plant Diseases by Leaf Recognition," Journal of Contemporary Issues in Business and Government, vol. 27, no. 05, p. 10, 2021.
7. Y. Zhao, Z. Chen, X. Gao, W. Song, Q. Xiong, J. Hu, and Z. Zhang, ‘‘Plant disease detection using generated leaves based on DoubleGAN,’’ IEEE/ACM Trans. Comput. Biol. Bioinf., vol. 19, no. 3, pp. 1817–1826, May 2022.
8. H. Jin, Y. Li, J. Qi, J. Feng, D. Tian, and W. Mu, ‘‘GrapeGAN: Unsupervised image enhancement for improved grape leaf disease recognition,’’ Comput. Electron. Agricult., vol. 198, Jul. 2022.