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Agrisentinel Rover: An IoT-Integrated Ml System for Crop Detection and Plant Disease Analysis

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Abstract- Agriculture plays a fundamental role in global food production; however, plant diseases, climate variability, and delayed monitoring significantly reduce crop yield and quality. Traditional manual inspection methods are labor-intensive, time-consuming, and prone to human error, particularly in large-scale agricultural environments. This paper proposes the AgriSentinel Rover, an autonomous IoT-integrated robotic system designed for real-time crop detection and plant disease analysis using deep learning techniques. The system integrates environmental sensors, high-resolution image acquisition, Convolutional Neural Network (CNN)-based classification, and cloud-based monitoring to enable predictive and precision agriculture. The rover autonomously navigates agricultural fields, captures crop leaf images, collects environmental parameters such as soil moisture, temperature, humidity, and light intensity, and processes the data using a trained MobileNetV2-based model. The processed information is transmitted to a cloud dashboard, providing real-time alerts and analytical insights to farmers. Experimental evaluation demonstrates high disease classification accuracy and efficient environmental monitoring, thereby improving early detection and reducing crop loss.

Keywords— IoT, Precision Agriculture, Convolutional Neural Network, MobileNetV2, Raspberry Pi, Plant Disease Detection, Autonomous Rover.

I. INTRODUCTION

Agricultural productivity is increasingly affected by plant diseases, pest infestations, and environmental stress conditions. Early detection of crop diseases is essential to prevent large-scale yield loss and economic damage. Conventional farming techniques rely heavily on manual inspection, which is inefficient and unreliable for extensive agricultural fields. The emergence of Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), and embedded robotics has enabled the transformation of conventional agriculture into precision agriculture.

The AgriSentinel Rover is designed as an integrated intelligent system capable of autonomous navigation, environmental sensing, and real-time plant disease classification. The system combines hardware and software modules to provide predictive insights rather than reactive monitoring. By integrating CNN-based image classification with IoT-based environmental monitoring, the system offers a comprehensive solution for smart agriculture.

II. EXISTING SYSTEM

The existing agricultural monitoring systems primarily fall into three categories: manual inspection, standalone IoT-based monitoring, and aerial drone surveys. Manual inspection involves periodic field visits by farmers or agricultural experts to visually assess crop health. This approach is time-consuming, labor-intensive, and prone to human error, particularly when early-stage disease symptoms are subtle. In many cases, diseases are detected only after significant crop damage has occurred, reducing yield and increasing treatment costs.

Standalone IoT monitoring systems utilize sensors to measure environmental parameters such as soil moisture and temperature. While these systems provide useful data regarding irrigation and climatic conditions, they lack the capability to perform intelligent disease analysis. Drone-based monitoring offers aerial imaging of large fields but involves high operational costs and requires skilled personnel. Moreover, most existing systems operate independently without integrating environmental data and disease prediction models into a centralized decision-support framework. These limitations highlight the need for a comprehensive and autonomous agricultural monitoring solution.

III. PROPOSED SYSTEM

The AgriSentinel Rover is designed as an integrated smart agricultural system combining robotics, IoT sensing, and deep learning-based image classification. The rover autonomously navigates through agricultural fields using a motor-driven chassis and obstacle detection sensors. A high-resolution camera captures images of crop leaves, which are processed using a lightweight CNN model deployed on an embedded processor. Simultaneously, environmental sensors collect real-time data on soil moisture, temperature, humidity, and light intensity.

The captured image data undergoes preprocessing and classification using a trained MobileNetV2 model, enabling early detection of plant diseases such as blight, rust, and mildew. Environmental data is transmitted through Wi-Fi communication to a cloud-based dashboard for visualization and analytics. If abnormal environmental conditions or disease patterns are detected, the system generates alerts for farmers through the dashboard. This integrated approach enhances predictive monitoring, reduces manual effort, and supports sustainable farming practices by enabling timely intervention.

IV. SYSTEM ARCHITECTURE AND BLOCK DIAGRAM

The proposed system consists of four major components: autonomous rover platform, IoT sensor module, machine learning inference engine, and cloud-based monitoring dashboard.

The rover platform is built using a four-wheel chassis integrated with DC motors and controlled through an embedded processing unit. A Raspberry Pi 4 Model B acts as the central processing unit responsible for executing image preprocessing and CNN inference. An ESP32 microcontroller handles sensor interfacing and IoT communication. Sensors such as soil moisture sensor, DHT22 temperature and humidity sensor, ultrasonic sensor for obstacle detection, and light intensity sensor are integrated to provide environmental awareness.

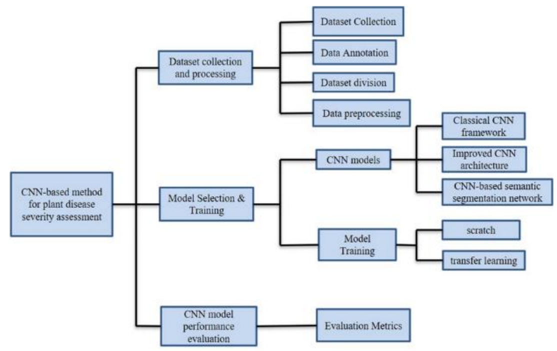

Figure 1. Block Diagram

The captured data is transmitted via Wi-Fi to a cloud server where it is visualized through a dashboard, enabling farmers to monitor crop health remotely.

V. METHODOLOGY

The methodology of the proposed system follows a structured approach beginning with dataset collection and model training. Leaf images representing healthy and diseased crops are collected and categorized into various classes. Image preprocessing techniques such as resizing, normalization, and augmentation are applied to enhance model robustness. Transfer learning is implemented using the MobileNetV2 architecture due to its efficiency and suitability for embedded deployment. The dataset is divided into training and validation sets to evaluate performance metrics including accuracy, precision, recall, and F1-score.

Once trained, the model is converted into TensorFlow Lite format and deployed on the Raspberry Pi for real-time inference. The rover continuously captures images and environmental data during field navigation. Sensor readings and classification results are transmitted to the cloud platform for storage and visualization. Unit testing, integration testing, and field validation are conducted to ensure reliability and operational efficiency under real-world conditions.

VI. HARDWARE IMPLEMENTATION

The hardware implementation of the AgriSentinel Rover is designed to ensure efficient edge-level processing, autonomous navigation, and reliable environmental data acquisition in agricultural fields. The system architecture follows a distributed processing model where computational tasks and sensor management are handled by dedicated embedded components to improve performance and reduce latency.

A. Raspberry Pi 4 Model B

Figure 2. Raspberry Pi 4 Model B

The Raspberry Pi 4 Model B acts as the central processing unit responsible for image acquisition, preprocessing, and deep learning inference. Its quad-core processor and adequate RAM enable real-time execution of the TensorFlow Lite model without significant computational delay. The Raspberry Pi interfaces directly with the camera module and communicates with the ESP32 microcontroller via serial communication or GPIO-based protocols.

B. ESP32 microcontroller

Figure 3. ESP32 microcontroller

The ESP32 microcontroller is employed for environmental sensor integration and IoT communication. It offers built-in Wi-Fi and Bluetooth capabilities, enabling seamless transmission of sensor data to cloud platforms. The ESP32 handles data acquisition from multiple sensors simultaneously and transmits structured JSON packets to the server for monitoring and storage.

C. Raspberry Pi Camera Module

The Raspberry Pi Camera Module captures high-resolution images of crop leaves. Image clarity is critical for accurate CNN classification; therefore, proper camera positioning and stable mounting are implemented to minimize motion blur. The module supports real-time frame capture and integration with OpenCV for preprocessing operations.

Figure 4. Raspberry Pi Camera Module

D. Soil Moisture Sensor

Figure 5. Soil Moisture Sensor

The Soil Moisture Sensor measures volumetric water content in the soil using electrical resistance or capacitive sensing principles. Accurate soil moisture monitoring helps optimize irrigation scheduling and prevents water stress conditions that may increase disease susceptibility.

E. DHT22 Temperature and Humidity Sensor

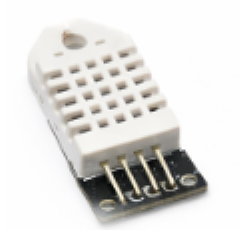

Figure 6. DHT2 Sensor

The DHT22 Temperature and Humidity Sensor monitors ambient climatic conditions. Since many plant diseases spread rapidly under specific humidity and temperature ranges, real-time monitoring enables predictive risk assessment.

F. Ultrasonic Sensor (HC-SR04)
The Ultrasonic Sensor (HC-SR04) ensures obstacle detection during rover navigation. It measures the distance to nearby objects using echo pulse timing, allowing the rover to avoid collisions and maintain safe field movement.

Figure 7. Ultrasonic Sensor (HC-SR04)

G. L298N Motor Driver Module

Figure 8. L298N Motor Driver Module

The L298N Motor Driver Module controls DC geared motors for rover locomotion. The driver allows bidirectional motor control and speed adjustment through PWM signals. This ensures smooth navigation across uneven agricultural terrain.

H. Rechargeable Lithium-Ion Battery
A Rechargeable Lithium-Ion Battery powers the entire system. A voltage regulator ensures stable 5V and 3.3V outputs for different modules, preventing voltage fluctuation damage. The hardware design emphasizes energy efficiency, durability, and field adaptability.

VII. SOFTWARE IMPLEMENTATION

The software framework of the AgriSentinel Rover integrates image processing, machine learning inference, sensor data management, and cloud communication into a modular architecture. Python serves as the primary programming language due to its extensive library support and compatibility with embedded platforms.

Image acquisition is handled using the OpenCV library, which captures frames from the camera module and performs preprocessing operations such as resizing, normalization, and noise reduction. Preprocessed images are then passed to the TensorFlow Lite interpreter running on the Raspberry Pi for real-time inference. The MobileNetV2-based model classifies images into predefined categories such as healthy leaf, blight, rust, or mildew.

The ESP32 firmware is developed using embedded C within the Arduino IDE framework. It continuously reads sensor data and formats the output into structured packets for transmission via Wi-Fi. Communication protocols such as HTTP or MQTT are implemented to ensure reliable cloud connectivity.

The cloud platform (e.g., Firebase or ThingsBoard) stores environmental readings and disease classification results. A web-based dashboard developed using HTML, CSS, and JavaScript provides graphical visualization of temperature trends, humidity levels, soil moisture variations, and detected disease alerts. The system also integrates automated notifications that trigger alerts when abnormal conditions are detected.

The modular software design allows independent updates to the ML model, sensor firmware, or cloud interface without affecting the overall system functionality. Error handling mechanisms ensure stable operation during connectivity interruptions or sensor malfunctions.

VIII. RESULTS AND DISCUSSION

The experimental evaluation of the AgriSentinel Rover demonstrates promising results in real-time disease detection and environmental monitoring. The MobileNetV2-based CNN model achieved classification accuracy exceeding 90% on validation datasets. Real-time inference latency remained within acceptable thresholds for field deployment, confirming the feasibility of edge-based AI execution on the Raspberry Pi platform.

Environmental sensor readings provided consistent and accurate data across varying field conditions. Integration testing confirmed smooth data transmission from ESP32 to the cloud server without significant packet loss. The dashboard interface effectively visualized real-time parameters, enabling intuitive interpretation by users.

Compared to manual inspection methods, the system significantly reduces monitoring time and increases detection reliability. The autonomous mobility of the rover ensures continuous field coverage without human intervention. However, classification accuracy may vary under extreme lighting conditions or when leaf images contain occlusions. Future incorporation of advanced image enhancement or multispectral imaging could address these limitations.

The integration of robotics, IoT, and deep learning establishes a scalable foundation for precision agriculture. The predictive capability of the system enables early disease intervention, minimizing crop loss and optimizing resource usage.

IX. FUTURE WORK

Future improvements can significantly enhance the functionality and scalability of the AgriSentinel Rover. One major enhancement involves integrating multispectral or hyperspectral cameras to capture non-visible spectrum data, improving disease detection accuracy under diverse lighting conditions. Advanced image segmentation algorithms can further isolate infected leaf regions to enhance classification reliability.

The system can also incorporate automated pesticide spraying mechanisms triggered by disease detection results. This would enable targeted treatment, reducing chemical overuse and environmental impact. Integration with reinforcement learning algorithms may optimize rover navigation paths for efficient field coverage.

Another potential enhancement involves implementing predictive analytics models for yield estimation based on environmental trends and disease progression data. Drone-rover collaboration systems could provide comprehensive coverage of large agricultural lands. Additionally, a mobile application interface can improve farmer accessibility, providing real-time notifications and actionable recommendations.

Scalability can be improved through cloud-based distributed processing, allowing multiple rovers to operate in coordinated networks. Integration with blockchain technology may enhance agricultural data transparency and traceability for supply chain applications.

X. CONCLUSION

The AgriSentinel Rover represents a comprehensive intelligent agricultural monitoring system that integrates robotics, IoT sensing, and deep learning-based disease detection into a unified platform. By enabling autonomous navigation, real-time environmental monitoring, and predictive disease analysis, the system addresses major limitations of traditional agricultural practices. The edge-based deployment of a lightweight CNN model ensures efficient real-time classification, while IoT connectivity facilitates remote monitoring and data-driven decision-making.

The proposed solution enhances crop productivity, reduces labor dependency, and promotes sustainable farming practices. Its modular and scalable architecture makes it suitable for large-scale

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agricultural deployment. With further enhancements such as multispectral imaging and automated treatment mechanisms, the system has strong potential to revolutionize precision agriculture and contribute to global food security.

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