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Wire Trail Crop Monitor

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***Abstract*—The Wire Trail Crop Monitor is a smart automated farming system, agricultural automation solution designed for active crop health management and efficient resource utilization. The system operates on two coordinated ESP32 microcontrollers and a dual monitoring principle. First, an ESP32-CAM module is mounted on a mobile platform controlled by DC motors and boundary-defining IR sensors. This unit continuously captures real-time video and image data as it moves along a fixed wire, allowing remote crop inspection. This visual data is wirelessly transmitted to a central unit for image processing and deep learning analysis to identify the type and location of plant diseases. Second, a secondary ESP32 module monitors ambient conditions via a DHT11 sensor (temperature and humidity) conditions. The system then correlates the detected disease with a database to determine the correct single pesticide required for treatment. Functioning as the Pesticide Dispenser and Control Unit, this secondary ESP32 precisely controls the preparation: it activates only one of the three valves/pumps to release the specific *pesticide* (or solution) and controls a water pump to add water to the mixture. For delivery, a servo motor precisely aligns the mixture output pipe with the mobile unit's container intake port for refilling. The loaded mobile unit then traverses back to the zone and dispenses the solution the affected area. Telegram integration provides farmers with real-time alerts regarding disease detection, recommendations and data. This integrated, dual-controller approach ensures efficient monitoring, automated disease management, reduced water and chemical wastage, and minimal manual labour, improving overall productivity and sustainability in smart agriculture**

I. Introduction

Agriculture remains a fundamental pillar of economic stability and food security worldwide. However, modern farming faces escalating challenges due to rapid population growth, increasing global food demand, climate variability, water scarcity, soil degradation, and rising labor costs. Traditional agricultural practices, which rely heavily on manual inspection and uniform pesticide application, are becoming inefficient and unsustainable under these pressures. Delayed detection of crop diseases and pest infestations often leads to significant yield losses, excessive chemical usage, and environmental degradation. These limitations necessitate the adoption of intelligent, automated, and resource-efficient agricultural technologies capable of improving productivity while minimizing ecological impact.

In recent years, Smart Agriculture has emerged as a transformative solution through the integration of Internet of Things (IoT), embedded systems, wireless communication, and artificial intelligence. Advanced sensing and automation technologies enable real-time crop monitoring, early disease detection, and data-driven decision-making. However, many existing monitoring systems are either static, limited in field coverage, or dependent on manual intervention for pesticide application. Such approaches reduce scalability and restrict the ability to provide continuous and comprehensive surveillance in agricultural fields. Therefore, there is a growing need for a mobile, intelligent system capable of dynamic monitoring and automated precision spraying.

To address these challenges, this paper presents the Wire Trail Crop Monitor, an integrated crop surveillance and precision pesticide dispensing system designed to shift agricultural management from reactive to proactive operation. The core innovation of the proposed system lies in its wire-guided mobile surveillance mechanism. An ESP32-CAM module is mounted on a mechanical frame that traverses along a fixed wire path using DC motors controlled through a motor driver circuit. Infrared (IR) sensors positioned at the endpoints ensure accurate boundary detection and automatic bidirectional motion, enabling continuous back-and-forth scanning of the crop field. Unlike stationary camera setups, this mobile platform provides diverse viewing angles and comprehensive canopy coverage, significantly improving the probability of early anomaly detection.

As the camera module moves across the field, it captures real-time images and transmits them wirelessly for advanced processing. The acquired visual data undergo deep learning-based analysis using a trained object detection model capable of identifying and localizing diseased regions within plant leaves. By leveraging modern advancements in computer vision and convolutional neural network architectures, the system not only classifies disease types but also determines their spatial coordinates within the captured frame. This localization capability enables precise intervention rather than indiscriminate spraying. The detection results are forwarded to a secondary control unit responsible for executing targeted pesticide application.

The precision pesticide dispensing subsystem is governed by a dedicated microcontroller that selects the appropriate chemical treatment based on the detected disease category. Multiple solenoid-controlled pesticide channels are integrated into the system, each corresponding to a specific disease type. Upon detection, only the required pesticide is actuated and mixed with water in controlled proportions. A servo-actuated directional mechanism ensures accurate alignment of the spray toward the infected region, thereby enabling highly localized application. This approach substantially reduces overall chemical consumption, operational costs, and environmental contamination compared to conventional blanket spraying techniques.

In addition to intelligent monitoring and precision actuation, the system incorporates wireless communication features to enhance usability and farmer accessibility. Real-time video streaming and system notifications are transmitted through a mobile communication interface, allowing farmers to remotely observe field conditions, receive disease alerts, and monitor spraying operations. LED indicators further provide on-site operational feedback regarding system status, detection events, and dispensing activity. By integrating mobile surveillance, deep learning-based diagnostics, automated control, and remote communication, the proposed Wire Trail Crop Monitor offers a scalable, cost-effective, and sustainable solution for next-generation precision agriculture. The system contributes toward improved crop health management, optimized resource utilization, reduced human intervention, and enhanced agricultural productivity.

II. Problem Statement

Modern agriculture faces critical challenges in early plant disease detection, excessive pesticide usage, inefficient resource management, and high dependency on manual labour. Traditional monitoring methods rely on periodic visual inspection by farmers, which is time-consuming, inconsistent, and often reactive rather than preventive. Moreover, conventional pesticide spraying techniques lack precision, leading to chemical overuse, environmental contamination, increased costs, and potential harm to crop yield and soil health. Existing IoT-based agricultural systems typically focus either on monitoring or automation, but rarely integrate real-time mobile surveillance, intelligent disease diagnosis, and localized precision dispensing into a unified architecture. Therefore, there is a need for an intelligent, automated, and resource-efficient crop monitoring system that combines real-time visual analysis, environmental sensing, and targeted pesticide application to enable proactive, sustainable, and scalable smart agriculture.

III. Literature Survey

The design and development of the WIRE TRAIL CROP MONITOR are fundamentally supported by contemporary research across three critical technological domains: Internet of Things (IoT) hardware integration, advanced computer vision, and scalable deep learning methodologies. This review synthesizes the findings of three recent IEEE Access publications to validate the project's core architectural and algorithmic choices, focusing specifically on robust disease detection, IoT implementation efficiency, and longterm model scalability.

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A. Enhancing Visual Accuracy in Field Imagery through Advanced Segmentation

Study: Moupojou, E., et al. (2024). Segment Anything Model and Fully Convolutional Data Description for Plant Multi-Disease Detection on Field Images. IEEE Access. This paper addresses the complexity of real-world agricultural image analysis, where background clutter, variable light, and occlusion compromise detection accuracy. The methodology leverages state-of-the-art segmentation to enhance the robustness of Neural Network models, a finding critical for the Mobile Surveillance Platform (ESP32-CAM). Key Contributions and Relevance to the Project:

- SAM for Noise Reduction: The research utilizes the Segment Anything Model (SAM) for zero-shot segmentation, isolating relevant plant regions (leaves/stems) from visual noise (soil, shadows, etc.). This validates the system's image analysis pipeline by ensuring that the movement and variable viewing angles of the ESP32-CAM do not compromise diagnostic accuracy. A cleaner image input maximizes the efficiency of the remote processing unit by focusing the Deep Learning model exclusively on disease features.

- FCDD for Multi-Label Detection: The study integrates a Fully Convolutional Data Description (FCDD) method, which is effective at multi-label pattern recognition— identifying multiple diseases existing on a single leaf. This capability is essential for the Wire Trail system's Precision Pesticide Protocol, ensuring the decision logic can accurately identify complex, simultaneous afflictions to select the correct chemical treatment.

- Field Deployment Feasibility: The authors demonstrated a notable increase in detection accuracy (exceeding 10%) through the integrated SAM-FCDD approach. This confirms the technical viability of deploying complex visual analysis techniques for the type of images collected by the mobile, field-deployed ESP32-CAM, guiding the project toward implementing similar segmentation principles for optimal disease localization.

B. Architectural Validation of IoT-Based Detection Systems and Algorithm Selection

Study: Nyakuri, J. P., et al. (2024). State-of-the-Art Deep Learning Algorithms for Internet of Things-Based Detection of Crop Pests and Diseases: A Comprehensive Review. IEEE Access. This systematic review provides the architectural context for implementing the "smart" components of the Wire Trail Monitor, focusing on the efficient intersection of Deep Learning and IoT. It confirms the selection of the core AI algorithm and highlights practical constraints related to resource-constrained devices. Key Findings and Relevance to the Project:

- CNN Dominance and Resource Constraints: The review confirms that CNNs remain the state-of-the-art method for high-accuracy classification in agricultural image recognition. Crucially, the paper emphasizes the trade-off between accuracy and computational complexity in IoT applications. This validates the project's core design decision to use a CNN-based model and justifies the critical choice of offloading the heavy processing task from the resource-constrained ESP32-CAM to a dedicated Central Processing Unit (CPU) via a reliable Wi-Fi link.

- Importance of Multi-Modal Data Fusion: The review stresses that integrating image data with environmental parameters (temperature and humidity) significantly enhances reliability. This validates the Wire Trail's dual-monitoring principle, where the visual diagnosis is contextualized and confirmed by the environmental data collected by the DHT11 sensor connected to the Stationary ESP32-Control Unit. This combined data is 5 essential for ensuring reliable disease diagnosis and guiding the Precision Pesticide Dispensing Protocol.

C. Ensuring Scalability and Long-Term Model Viability via Self-Supervised Learning

Study: Mamun, A. A., et al. (2024). Plant Disease Detection Using Self-Supervised Learning: A Systematic Review. IEEE Access. This systematic review addresses the long-term challenge of massive manual dataset labelling in agricultural AI. The findings offer a powerful solution for ensuring the system's scalability and longevity without incurring prohibitive labelling costs. Key Findings and Relevance to the Project:

- Mitigation of Labelling Bottleneck via SSL: The paper details how Self-Supervised Learning (SSL) techniques enable models to learn meaningful feature representations from vast amounts of unlabelled or minimally labelled data via "pretext tasks." This is crucial for the Wire Trail system because the Mobile Surveillance Platform continuously generates a high volume of images under natural field conditions, allowing the project to leverage this dataset for model improvement without the prohibitive cost of human annotation.
- Superior Generalization and Robustness: SSL-trained models exhibit superior generalization capability compared to purely supervised models. By adopting SSL principles, the project ensures the diagnostic model remains accurate and relevant as new disease strains emerge, making the system future-proof and highly adaptable.

IV. Proposed System

A. System design

The proposed crop monitoring and intelligent pesticide spraying system is designed using a distributed embedded architecture comprising three functional subsystems: (i) Camera Scanning Unit, (ii) Image Processing and Decision Unit, and (iii) Pesticide Dispensing Unit. The camera scanning unit is built around a NodeMCU (ESP8266) microcontroller, which controls a DC motor via a motor driver IC to enable horizontal traversal of the imaging platform. Two infrared (IR) sensors are deployed at the terminal ends to detect positional limits and automatically reverse the direction of motion, thereby ensuring continuous bidirectional coverage of the crop field. An ESP32-CAM module is integrated for real-time image acquisition and wireless video streaming.

Captured image data are transmitted to the image processing and control unit, where a trained machine learning model performs disease classification. Upon detection of a specific crop disease, a control signal is forwarded to the pesticide dispensing subsystem, which is centered on an ESP32 microcontroller. This unit actuates one of three dedicated pesticide pumps corresponding to the detected disease class. A servo motor mechanism provides directional control to ensure localized transfer. Environmental parameters such as temperature and humidity are measured using a DHT11 sensor to assist in monitoring field conditions. The modular architecture ensures scalability, distributed processing, and precise actuation.

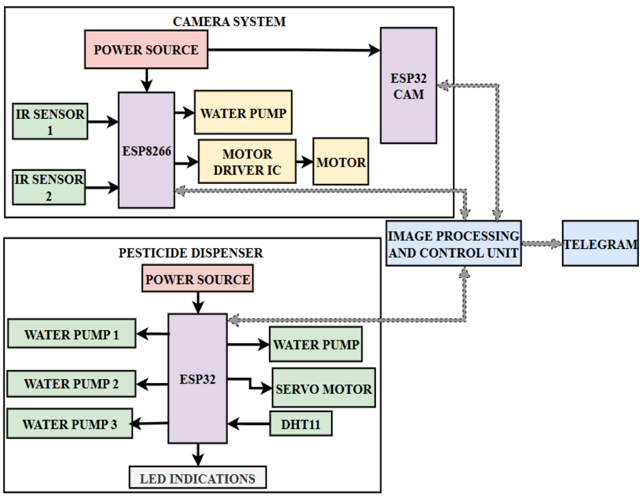

Fig 1: Block Diagram

V. Methodology

The proposed crop monitoring and intelligent pesticide spraying system was developed using a structured hardware–software co-design methodology integrating embedded systems and deep learning-based object detection. The design process began with requirement analysis focusing on automated disease detection, real-time monitoring, and selective pesticide application. Based on these objectives, the system was divided into two primary subsystems: the camera-based monitoring unit and the pesticide dispensing unit, enabling modular implementation and improved system reliability.

A. Hardware Development

The monitoring unit was designed around a NodeMCU (ESP8266) microcontroller responsible for motion control of the scanning mechanism. A DC motor interfaced through a motor driver circuit enabled horizontal traversal of the imaging platform. Two IR sensors were deployed at the boundary limits of the track to detect end positions and automatically reverse the direction of motion, ensuring continuous bidirectional field coverage. Image acquisition and streaming were handled by an ESP32-CAM, which captured real-time crop images during movement.

The pesticide dispensing subsystem was implemented using an ESP32, selected for its higher processing capability and multiple GPIO interfaces. Three independent pesticide pumps, each assigned to a specific disease class, were connected through driver circuits, along with an additional mixing pump. A servo motor was incorporated to provide directional control for targeted spraying. Environmental parameters were monitored using a DHT11 temperature and humidity sensor. Regulated power supply units were used to ensure stable operation of microcontrollers and actuators.

B. Software and Deep Learning Implementation

The software development phase consisted of embedded firmware programming, communication setup, and deep learning model deployment. The ESP8266 firmware was programmed to manage IR sensor input processing, motor direction control, and auxiliary pump logic. The ESP32-CAM was configured to stream live video and transmit image frames for disease analysis. A Telegram bot interface was integrated to provide remote field monitoring access to the farmer.

For disease detection, the YOLOv8 (You Only Look Once Version 8) deep learning framework was employed. A labeled dataset of crop images containing healthy and diseased leaves was collected and annotated. The dataset was preprocessed through resizing, normalization, and augmentation to improve robustness. The YOLOv8 model was trained to perform real-time object detection and classification of plant diseases by identifying infected regions within image frames. Unlike traditional classification models, YOLOv8 performs simultaneous localization and classification, enabling the system to determine both the disease type and its spatial position in the image.

During operation, captured image frames were passed to the trained YOLOv8 model for inference. Upon detection of a disease instance, the model output provided bounding box coordinates and class labels. A decision-mapping algorithm translated the detected class label into a corresponding pesticide pump activation signal. The ESP32 in the dispensing unit received this signal wirelessly and activated the appropriate pump for a predefined duration. Simultaneously, the servo motor was positioned based on bounding box alignment to ensure targeted spraying toward the infected plant region.

C. System Architecture Overview

The system operates on a distributed architecture utilizing two ESP32 microcontrollers. The ESP32-CAM forms the mobile front-end, responsible for data capture and movement control, and uniquely includes the integrated chemical payload container. The secondary ESP32 serves as the fixed back-end, managing all physical actuation (pumps, valves, servo) and environmental sensing. Communication between the mobile platform and the stationary control unit, as well as the external Telegram interface, is handled via Wi-Fi.

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