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INTELLIGENT PESTICIDE SPRINKLING SYSTEM DETERMINED BY THE INFECTION LEVEL OF THE PLANT

Manohar BR, Prajwalkumar MP, Sharath G, Nithesh, Prof. Divyashree N
Student, Student, Student, Student, Assistant Professor
School of Computing and Information Technology
Reva University Bengaluru, India

Abstract: Precision agriculture aims to optimize resource usage while improving crop productivity and sustainability. Traditional pesticide spraying methods often result in excessive chemical usage due to lack of real-time monitoring of plant health. This paper proposes an intelligent pesticide sprinkling system that determines spraying requirements based on plant infection levels. The system integrates an Arduino-based embedded controller, environmental sensors, and automated spraying mechanisms to enable real-time decisionmaking. Sensor data is continuously monitored and processed using threshold-based logic to detect infection conditions. When infection is identified, the system activates a pump and solenoid valve to perform targeted spraying. The proposed system reduces pesticide usage, minimizes environmental impact, and improves crop yield. Experimental observations indicate improved efficiency and reduced manual intervention, demonstrating the effectiveness of the proposed solution for small-scale and precision farming applications.

Keywords: smart agriculture, LoRaWAN, edge computing, precision irrigation, terrain-aware systems, Internet of Things (IoT).

I. Introduction

Agriculture is a fundamental sector that supports global food production and economic stability. However, traditional agricultural practices often rely on manual methods and uniform application of resources such as water, fertilizers, and pesticides. In particular, pesticide spraying is commonly performed without considering the actual health condition of plants, leading to excessive chemical usage, increased costs, and adverse environmental effects. Overuse of pesticides not only contaminates soil and water resources but also affects beneficial organisms and human health. With the rapid growth of population and increasing demand for food, there is a pressing need for efficient and sustainable agricultural practices. Precision agriculture has emerged as a promising approach that utilizes modern technologies such as sensors, embedded systems, and data-driven decisionmaking to optimize resource utilization. By monitoring environmental conditions and plant health in real time, precision agriculture enables targeted interventions that improve productivity while minimizing waste. Recent advancements in Internet of Things (IoT) and embedded systems have enabled the development of smart farming solutions. Microcontrollers such as Arduino provide a low-cost platform for integrating sensors and actuators, making them suitable for small-scale farmers. These systems can continuously monitor parameters such as temperature, humidity, and plant conditions, and automate agricultural operations based on predefined logic. In addition, machine learning techniques, part icularly Convolutional Neural Networks (CNN), have shown significant potential in plant disease detection using imagebased analysis. These techniques can identify disease patterns with high accuracy, enabling early detection and timely intervention. However, most existing solutions focus only on disease detection and lack integration with automated pesticide spraying systems. To address these limitations, this paper proposes an intelligent pesticide sprinkling system that determines spraying requirements based on plant infection levels. The system integrates sensor-based monitoring with an Arduinobased control unit to enable automated decision-making and targeted pesticide application. By applying pesticides only when required, the system reduces chemical usage, lowers operational costs, and promotes environmentally sustainable farming practices. The main contributions of this work are as follows: • Design of a low-cost embedded system for automated pesticide spraying • Implementation of sensor-based infection detection and decision-making • Development of an efficient spraying mechanism for targeted application • Proposal of a scalable system that can be extended with IoT and AI technologies Overall, the proposed system aims to enhance precision agriculture by combining automation, efficiency, and sustainability, making it suitable for real-world deployment in small and medium-scale farms.

II. Literature Review

A. Smart Agriculture Systems Smart agriculture has gained significant attention due to its ability to improve productivity and resource efficiency through automation and data-driven decision-making. IoTbased systems enable real-time monitoring of environmental parameters such as temperature, humidity, soil conditions, and plant health. These systems use distributed sensors and wireless communication technologies to collect and transmit data for analysis. Studies have shown that such systems can enhance crop yield and reduce resource wastage by enabling precise agricultural operations. Most existing smart farming systems focus on irrigation management, where soil moisture sensors are used to automate water supply. While these systems improve water efficiency, they often do not address pesticide management, which remains largely manual and inefficient.

B. IoT and Embedded Systems in Agriculture Embedded systems such as Arduino and ESP32 have been widely used in agricultural automation due to their low cost, flexibility, and ease of implementation. These systems can interface with multiple sensors and control actuators such as pumps and valves. IoT integration allows remote monitoring and control of agricultural operations through cloud platforms and mobile applications. Technologies such as WiFi, GSM, and LoRa enable communication between field devices and centralized systems. However, in many rural and remote areas, network connectivity remains a challenge, limiting the effectiveness of fully cloud-based systems.

C. Plant Disease Detection Techniques Plant disease detection is a critical aspect of precision agriculture. Traditional methods rely on manual inspection by farmers, which is time-consuming and prone to human error. To overcome this limitation, image processing and machine learning techniques have been introduced. Convolutional Neural Networks (CNN) have been extensively used for plant disease classification due to their high accuracy in image recognition tasks. CNN models can detect disease symptoms such as leaf discoloration, spots, and texture variations. These systems enable early detection of plant diseases, allowing timely intervention. Despite their effectiveness, most CNN-based systems are limited to detection and do not integrate automated response mechanisms such as pesticide spraying.

D. Automated Spraying Systems Automation in pesticide spraying has been explored using robotic systems, drones, and sensor-based mechanisms. Some systems use GPS-based navigation to perform fieldwide spraying, while others rely on predefined schedules. Although these approaches reduce manual labor, they often lack real-time adaptability and still apply pesticides uniformly. This leads to unnecessary chemical usage and increased operational costs. There is a need for intelligent systems that can perform targeted spraying based on actual plant conditions.

E. Research Gap From the literature, it is evident that significant progress has been made in smart agriculture, IoT-based monitoring, and plant disease detection. However, there are several limitations in existing systems: • Most systems focus on irrigation rather than pesticide optimization • Limited integration between disease detection and automated spraying • Dependence on manual intervention for pesticide application • Lack of low-cost solutions suitable for small-scale farmers To address these gaps, this project proposes an intelligent pesticide sprinkling system that integrates sensor-based monitoring, embedded control, and automated spraying. The system aims to provide a cost-effective and efficient solution for precision agriculture by applying pesticides only when required.

Research Gap

Despite significant advancements in smart agriculture, several limitations still exist in current systems related to pesticide management and automation. Most existing solutions primarily focus on irrigation optimization using IoT and sensor-based monitoring, while pesticide spraying remains largely manual and non-adaptive. This leads to excessive chemical usage, increased costs, and environmental damage.

Additionally, many plant disease detection systems based on machine learning and CNN models are limited to classification tasks and do not integrate with real-time actuation mechanisms such as automated spraying. Another major limitation is the lack of integration between sensing, decision-making, and action within a single system. Existing approaches often require human intervention after disease detection, reducing efficiency and delaying response time. Furthermore, several advanced systems rely on high-cost hardware, drones, or cloud-based infrastructure, making them unsuitable for small-scale farmers, especially in developing regions. There is also a gap in low-cost, embedded solutions that can operate independently without continuous internet connectivity. Many systems assume stable network availability, which is not always feasible in rural agricultural environments. To address these challenges, this project proposes a lowcost, Arduino-based intelligent pesticide sprinkling system that integrates sensor-based monitoring, automated decision-making, and real-time spraying. The system focuses on targeted pesticide application based on infection levels, reducing chemical usage and improving efficiency. It also provides a scalable framework that can be extended with IoT and AI technologies in future implementations.

III. System Architecture The proposed intelligent pesticide sprinkling system is designed as an integrated embedded and autonomous platform that combines sensing, processing, communication, and actuation. The architecture consists of multiple modules working together to enable real-time plant disease detection, decision-making, and targeted pesticide spraying.

A. User Control and Manual Mode The system supports both automatic and manual operation modes. In manual mode, the farmer interacts with the system using a smartphone application. Commands are transmitted via Bluetooth to the ESP32 microcontroller, allowing the user to control robot movement and spraying operations directly. This feature is particularly useful during system testing, emergency conditions, or when precise human intervention is required.

B. ESP32 Microcontroller (Central Processing Unit) The ESP32 microcontroller acts as the central control unit of the system. It is responsible for coordinating all system components and executing decision logic. The controller receives input data from multiple sources, including: • CNN-based disease detection module • UV sensor for obstacle detection • Smartphone interface for manual commands Based on the received inputs, the ESP32 processes the data and generates appropriate control signals. These signals are sent to the motor driver for navigation control and to the sprayer unit for pesticide application. The use of ESP32 ensures efficient processing due to its dual-core architecture and integrated wireless capabilities.

C. Image Processing and Disease Detection The system incorporates an image-based disease detection module for accurate identification of plant health conditions. A camera module captures real-time images of crop leaves, which are processed using a Convolutional Neural Network (CNN) model. The CNN model classifies plant conditions into four categories: • Healthy • Mild infection • Moderate infection • Severe infection Based on the classification output, the system determines the required spraying intensity. This enables precision pesticide application, ensuring that chemicals are used only where necessary and in appropriate quantities.

D. Navigation and Obstacle Detection

Autonomous navigation is achieved using a UV sensorbased obstacle detection system. The sensor continuously monitors the surroundings and detects obstacles in real time. When an obstacle is identified, the system adjusts the robot’s path to avoid collisions.
This capability allows the robot to operate efficiently in agricultural fields without manual guidance, improving safety and operational reliability.

E. Wireless Communication Module (HC-12)

The system uses an HC-12 RF communication module to enable long-range wireless communication between the ESP32 controller and the sprayer unit. The HC-12 module ensures reliable data transmission over extended distances, making the system suitable for large agricultural fields.
This communication mechanism allows the separation of control and spraying units, enhancing flexibility and scalability of the system.

F. Sprayer Unit

The sprayer unit is responsible for pesticide application and consists of:

- Pump
- Spray nozzles

The unit receives control signals from the ESP32 and activates spraying based on the detected infection level. The system ensures:

- Targeted spraying only on affected plants
- Controlled pesticide quantity based on severity

This approach significantly reduces chemical wastage and improves environmental sustainability.

G. Movement System

The movement of the robot is controlled using a motor driver interfaced with DC motors. The system supports:

- Forward and backward motion
- Turning and directional control
- Autonomous navigation based on sensor input

This enables efficient coverage of the agricultural field and ensures proper positioning for spraying operations.

H. Power Supply System

The entire system is powered using a rechargeable battery, which supplies energy to:

- ESP32 microcontroller
- Sensors and communication modules
- Motor driver and DC motors
- Sprayer system

The battery-powered design ensures portability and allows the system to operate in remote agricultural environments without dependency on external power sources.

IV. Methodology

The implementation of the proposed intelligent pesticide sprinkling system follows a **modular and systematic approach**, where individual subsystems are developed, tested, and integrated to form a complete functional system. The methodology includes hardware assembly, firmware development, CNN-based disease detection, communication protocols, and system integration.

A. Hardware Assembly

The hardware platform is built using a **robotic chassis constructed from aluminium extrusion profiles (20×20 mm)** forming a rectangular frame of dimensions 35 cm × 25 cm. DC geared motors are mounted at the four corners using aluminium brackets, enabling stable movement across agricultural terrain. Wheels with a diameter of 8 cm provide sufficient ground clearance (~4 cm) for navigating uneven soil surfaces.

A weatherproof **IP54-rated enclosure** houses all electronic components, including the ESP32 microcontroller, motor driver (L298N), HC-12 RF module, relay module, and power distribution system. A **12V rechargeable battery** supplies power to the entire system.

The pesticide spraying unit consists of a **2-litre tank, submersible pump, and nozzle assembly**, connected using silicone tubing. Additionally, the UV sensor and ESP32CAM module are mounted strategically to enable obstacle detection and image capture, respectively.

B. Firmware Implementation

The ESP32 firmware is implemented using the Arduino framework and follows a **finite state machine (FSM)** model with three states:

- **INITIALISATION** – System setup and configuration
- **MANUAL MODE** – User-controlled operation via Bluetooth
- **AUTO MODE** – Fully autonomous operation

During initialization, all GPIO pins, serial communication channels, Bluetooth interface, ADC inputs, PWM channels, and camera module are configured. PWM signals with a frequency of 1 kHz are used for motor speed control.

C. Motor Control and Navigation

Motor control is implemented using PWM-based speed regulation and directional control logic. The system supports:

- Forward and backward motion
- Left and right turning
- Stop functionality

In autonomous mode, the robot operates at a fixed speed (~60%), while manual mode allows dynamic speed control via Bluetooth commands.

Obstacle detection is achieved using a **UV sensor**, which continuously monitors the environment. A rolling average filter is applied to sensor readings to reduce noise. When an obstacle is detected within approximately 30 cm, the robot performs a reactive navigation sequence involving stopping, reversing, and turning to avoid collisions.

D. CNN-Based Disease Detection

The system employs a **Convolutional Neural Network (CNN)** model for plant disease detection. Images are captured using the ESP32-CAM module and processed using a TensorFlow Lite model on a companion processing unit.

The dataset is derived from the PlantVillage dataset along with custom field images, categorized into four classes:

- Healthy
- Mild infection
- Moderate infection
- Severe infection

The CNN model is based on **MobileNetV2 with transfer learning**, achieving a test accuracy of approximately **91.7%**. Images are preprocessed by resizing to 224×224 pixels and normalizing pixel values.

A confidence threshold of 0.70 is applied to ensure reliable predictions. If the classification confidence is below the threshold, the result is ignored to prevent false spraying.

E. Communication System (HC-12 RF Module)

Wireless communication between the detection unit and spraying unit is established using the **HC-12 RF module** operating at 433.4 MHz. The system uses a simple packetbased protocol:

- Start byte (0xAA)
- Severity level (0–3)
- Checksum (XOR-based validation)

This ensures reliable long-range communication with minimal data loss.

F. Spraying Mechanism

The spraying mechanism is controlled using a relay module connected to a 12V pump. The spraying duration is determined based on the detected infection level:

- Healthy → No spraying
- Mild → 2 seconds
- Moderate → 5 seconds
- Severe → 10 seconds

This approach ensures **controlled pesticide application**, reducing chemical wastage and improving efficiency. A delay mechanism is included to prevent continuous activation and mechanical wear.

G. Bluetooth-Based Manual Control

The system supports manual operation using Bluetooth communication. Commands are transmitted from a smartphone application using simple ASCII-based protocols:

- Movement: F, B, L, R, S
- Mode control: A (Auto), M (Manual)
- Speed control: 0–9

The system achieves low latency (<100 ms), ensuring responsive control.

H. System Integration and Workflow

The complete system is integrated in multiple phases, including motor control, sensor integration, CNN processing, communication, and user interface.

The overall workflow is as follows:

Image Capture → CNN Processing → Disease Classification → Decision Making → Communication → Spraying Action

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V. Conclusion and Future Work

This paper successfully demonstrates the design, implementation, and validation of an intelligent autonomous pesticide spraying system for precision agriculture applications. The proposed system integrates an ESP32 microcontroller, UV sensor-based obstacle detection, CNNbased leaf disease severity classification, HC-12 RF wireless communication, DC motor-driven navigation, and Bluetooth-based manual control into a unified and functional platform. The modular architecture ensures efficient interaction between sensing, processing, and actuation components, enabling real-time decision-making and automated pesticide application. The experimental results validate the effectiveness of the system. The CNN model, based on a MobileNetV2 transfer learning framework, achieves a test accuracy of 91.7% across four disease severity categories, exceeding the predefined performance target. The UV sensor-based navigation system demonstrates reliable obstacle avoidance with zero collision occurrences during testing. Additionally, the HC-12 RF communication module maintains a packet delivery rate of approximately 99% over distances up to 200 meters, ensuring robust wireless control. The system also achieves a battery life of approximately 2.4 hours, meeting operational requirements for field deployment.

A key contribution of this work is the significant reduction in pesticide consumption achieved through targeted spraying. Experimental analysis shows that the proposed system reduces pesticide usage by approximately 61.8% compared to conventional blanket spraying methods. This reduction not only lowers input costs for farmers but also minimizes environmental impact by reducing chemical runoff, soil contamination, and harm to non-target organisms such as pollinators. Furthermore, the use of low-cost embedded hardware and open-source machine learning frameworks demonstrates the feasibility of developing affordable precision agriculture solutions suitable for small and medium-scale farmers.

Despite its effectiveness, the system has certain limitations, including constraints in navigation coverage efficiency and battery life for large-scale agricultural fields. These limitations can be addressed through further enhancements in system design and optimization techniques. **Future Work**

The proposed system establishes a strong foundation for future advancements in intelligent agricultural automation. The following enhancements are identified as key areas for improvement:

- Integration of advanced AI models for more accurate disease detection and classification
- Implementation of fully onboard CNN inference to eliminate dependency on external processing units • Enhancement of navigation using GPS or vision-based path planning for large-scale field coverage
- Development of IoT-based cloud integration for real-time monitoring and data analytics
- Improvement in battery capacity and energy management for extended operational duration
- Integration of multi-sensor fusion for improved environmental awareness and decision-making

Overall, the proposed system demonstrates a viable and scalable approach toward precision agriculture, offering a cost-effective alternative to high-end solutions such as drones and GPS-based systems. The integration of intelligent sensing, automation, and targeted pesticide application contributes significantly to sustainable and efficient agricultural practices.

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