Smart Agricultural System Using IoT for Optimized Irrigation and Pest Detection

[1]Saksham Gupta, [2]Sarthak Lakhotia, [3]Mohit Kumar Sahoo, [4]KB Ramesh

[1]Student, [2]Student, [3]Student, [4]Associate Professor
[1]Computer Science and Engineering,
[1]RV College of Engineering, Bengaluru, India
[1]sakshamgupta.cy23@rvce.edu.in, [2]sarthaklakhotia.cy23@rvce.edu.in, [3]mohitkumarsahoo.cy23@rvce.edu.in,
[4]rameshkb@rvce.edu.in

***Abstract*—T In recent years, the integration of Internet of Things (IoT) technologies into agriculture has enhanced crop monitoring and resource management. However, many existing systems rely on cloud computing and high-power microcontrollers, which increase cost, latency, and dependence on stable internet connectivity. This study presents a low-cost, standalone Smart Agriculture System built around the ARM7-based LPC2148 microcontroller. The system leverages built-in ADC channels to acquire real-time data from LM35 temperature sensors, a soil moisture sensor, and a POT-HG humidity sensor. A logistic regression model processes soil moisture and UART-based rainfall forecast input to determine irrigation need, while a rule-based thermal-humidity model detects pest risk using temperature fusion logic. Outputs are provided via a relay-driven water pump, an alert LED, and a 16x2 LCD. All computations are performed locally on-device, enabling offline decision-making with minimal hardware. The system was fully simulated using Proteus 8.13 and Keil µVision, and demonstrated timely irrigation activation and accurate pest alerts based on environmental conditions. These results confirm that low-power microcontrollers can enable intelligent agricultural automation without the need for cloud infrastructure, making the solution highly suitable for deployment in connectivity-limited rural areas.**

***Index Terms*— Smart Agriculture, LPC2148, ARM7 microcontroller, Embedded Systems, Pest Control, Smart Irrigation, Logistic Regression, Edge Computing, Proteus Simulation, UART forecast.**

I. Introduction

The global agricultural sector is undergoing a transformation driven by the integration of smart technologies that aim to increase yield, reduce water wastage, and improve overall resource management. Among these, the Internet of Things (IoT) has emerged as a promising enabler for precision farming, offering real-time monitoring and control through sensor networks and automated decision-making systems. Traditional IoT-based agricultural systems have shown considerable progress in monitoring environmental parameters and automating irrigation. However, a majority of these solutions are either cloud-dependent or focused solely on irrigation, thereby limiting their autonomy, increasing system latency, and posing challenges in regions with low or intermittent internet connectivity.

To address these shortcomings, this project proposes a self-contained, edge-computing–enabled Smart Agriculture system that unifies both irrigation automation and pest control into a single platform. The system is designed around the ARM7-based LPC2148 microcontroller, chosen specifically for its low power consumption, integrated 10-bit ADC channels, real-time response capability, and flexible peripheral interfacing. Unlike high-level microcontrollers like Raspberry Pi or ESP32, the LPC2148 provides a more deterministic and cost-efficient platform, ideal for rugged and remote field deployments where simplicity and reliability are paramount.

The system leverages LM35 temperature sensors distributed across the field to monitor localized heat zones, a soil moisture sensor to track water content, and a humidity sensor (POT-HG) to measure ambient conditions conducive to pest activity. These inputs are processed locally using two computational models: a rule-based thermal fusion algorithm for pest risk prediction and a logistic regression model to determine the need for irrigation based on soil moisture and real-time rain forecasts received via UART communication. Outputs such as a relay-driven water pump and an LED-based pest alert system are triggered accordingly. All actions and environmental readings are displayed on a 16x2 LCD, offering immediate, interpretable feedback without requiring cloud services or smartphone apps.

Simulation of the entire system has been successfully conducted using Proteus 8.13 and Keil µVision, ensuring logical correctness and real-world feasibility. This approach not only demonstrates how edge-level intelligence can optimize agricultural practices but also significantly reduces dependency on external infrastructure, making it suitable for deployment in rural or connectivity-challenged environments.

II. Motivation

The conceptual foundation of this project draws heavily from recent research in the domain of IoT-based smart agriculture, particularly works that focused on precision irrigation, environmental sensing, and pest control. While many existing systems have made advances in individual domains, few offer a unified, edge-based, offline-capable platform that combines intelligent irrigation with pest prediction. Our work bridges that gap by building on previous research while introducing notable improvements in autonomy, local computation, and modularity.

The decision to implement multi-zone temperature sensing was inspired by Sharma et al. [1], who emphasized the importance of microclimate monitoring to improve crop yield. Their findings guided our use of three spatially distributed LM35 sensors to capture local heat anomalies—critical for pest risk analysis. We enhanced this further by combining temperature data with humidity inputs in a rule-based thermal fusion model, enabling our system to estimate pest activity zones in real time without requiring external processing.

Modular sensor interfacing and environmental modelling techniques from Hasan et al. [3] also shaped our pest detection strategy. They emphasized the significance of humidity as a primary trigger for pest breeding—an insight that motivated our humidity-temperature fusion logic. By using a POT-HG sensor for humidity and integrating it with thermal readings, our system makes contextual pest predictions with low computational overhead.

Raja et al. [2] demonstrated that multiple sensors could be efficiently mapped and monitored using lightweight microcontrollers like NodeMCU. This validated our approach of using the LPC2148 ARM7 microcontroller, which offers an edge over NodeMCU in terms of real-time interrupt handling, built-in 10-bit ADC support, and deterministic processing. We replicated their sensor mapping techniques using simulated inputs (POTs and LM35s) in Proteus, confirming that low-cost platforms can handle multi-sensor fusion effectively when the software is optimized for embedded execution.

The irrigation subsystem builds on ideas introduced by Huque et al. [4], whose cloud-based system used soil moisture, temperature, and raindrop sensors to automate irrigation. While effective in data-rich environments, their approach was heavily reliant on internet access. Our system replaces this dependency by using a logistic regression model trained for edge inference, allowing the LPC2148 to make irrigation decisions autonomously based on soil moisture sensor input and real-time rain forecast via UART.

Relay-based automation for both irrigation and pest control were motivated by the work of Patil and Malviya [5], who explored ARM7-based greenhouse automation using environmental triggers. Inspired by their control logic, our system activates a relay-driven water pump when irrigation is needed and toggles pest-alert LEDs based on local thermal risk—entirely without external supervision.

Additionally, the use of LPC2148 itself is an important architectural decision. While many modern systems prefer high-level platforms like Raspberry Pi or cloud-tethered ESP32s, we opted for the LPC2148 due to its blend of affordability, low power consumption, real-time capability, and direct ADC interfacing. This microcontroller allows all computations—logistic, rule-based, and UART handling—to be executed at the edge with sub-2-second latency, making it ideal for rural or offline deployments.

Collectively, these inspirations helped shape a unified and efficient smart agriculture system that overcomes limitations found in prior work. The integration of intelligent pest detection and irrigation control on a standalone embedded platform makes our design both scalable and deployable in diverse agricultural settings

III. Methods and Materials

System Architecture

The Smart Agriculture system is designed around a modular, embedded architecture that enables real-time environmental sensing, intelligent decision-making, and autonomous actuation using a low-cost yet capable platform. At the heart of the system is the ARM7-based LPC2148 microcontroller, chosen for its low power consumption, real-time performance, built-in 10-bit ADC channels, UART support, and flexible GPIO mapping. These features collectively support the full integration of sensing, processing, and control logic entirely at the edge, eliminating dependency on cloud computing or continuous internet connectivity.

The architecture comprises three primary layers: the input (sensor) layer, the processing layer, and the output (actuator and interface) layer. These layers interact through clearly defined analog and digital pathways, with the LPC2148 acting as the central coordinator for data collection, processing, and decision execution. The input layer consists of five analog sensors:

- A soil moisture sensor connected to ADC0 (P0.27), which measures the volumetric water content in soil,
- A humidity sensor (POT-HG) interfaced via ADC1 (P0.28), providing a relative humidity estimate,
- Three LM35 temperature sensors connected to ADC2 (P0.29), ADC3 (P0.30), and ADC4 (P0.25), respectively. These sensors are distributed across different zones in the field to capture microclimatic variations, critical for pest detection.

In addition to these sensors, a UART-based virtual terminal provides rain forecast data to the system in binary form (1 = rain predicted, 0 = no rain). This data is received via the LPC2148's UART0 interface (RXD0 – P0.1), simulating external weather services and enhancing irrigation decision-making through predictive input.

The processing layer is entirely handled by the LPC2148, which reads the sensor data via its ADC channels and interprets it using two embedded logic models. A rule-based pest risk detection model analyzes the temperature and humidity patterns to determine pest threat levels (LOW, MEDIUM, or HIGH), while a logistic regression model uses soil moisture and forecast input to compute the probability of irrigation necessity. These models are executed sequentially in real-time and do not rely on cloud services, ensuring offline functionality and rapid response.

The output layer includes a relay module connected to P0.22, which controls the water pump for irrigation, and an LED indicator on P0.23 to signal pest risk when the severity exceeds a defined threshold. Additionally, a 16x2 LCD is used to display system states such as soil moisture, humidity, pest status, and irrigation alerts. The LCD is interfaced in 4-bit mode using data lines D4–D7 mapped to P0.8–P0.11, while RS and EN signals are mapped to P0.22 and P0.23 respectively, using time-multiplexing for shared output control. This static hardware-software architecture ensures low-latency feedback, minimal component count, and easy simulation in Proteus 8.13. A schematic block diagram illustrating all component relationships and data flow is provided in Figure.

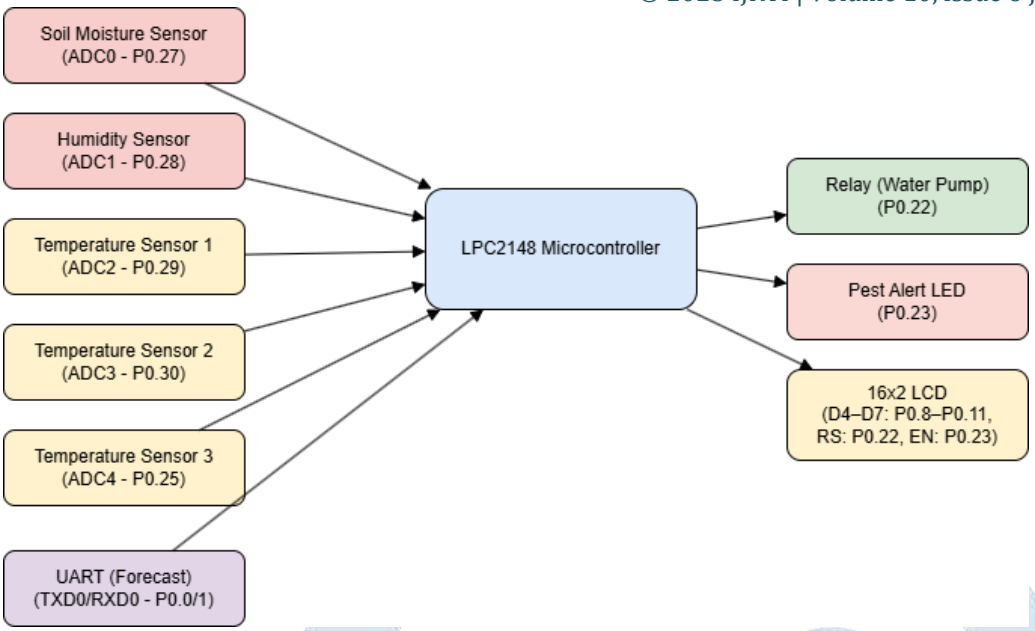

Figure 1. This figure shows the components used in the project

Methodology

The proposed system adopts an edge-based, closed-loop decision-making methodology that bridges real-time environmental sensing with intelligent actuation for both irrigation and pest control. The methodology has been designed to ensure minimal latency, zero cloud dependency, and full offline operability — making it highly suitable for resource-constrained agricultural environments.

The overall methodology can be divided into three stages: data acquisition, on-device analysis and decision-making, and autonomous output control. This section outlines the functional flow of the system and the logic executed at each stage.

At the start of the system cycle, the LPC2148 microcontroller initiates analog-to-digital conversions through its built-in 10-bit ADC module to acquire real-time values from five analog sensors: a soil moisture sensor (ADC0), a humidity sensor (ADC1), and three LM35 temperature sensors (ADC2, ADC3, and ADC4). These temperature sensors are spatially distributed across the field (left, center, and right zones) to monitor local heat variations, which are essential for identifying microclimatic conditions favorable to pest activity.

Simultaneously, a UART-based virtual terminal input is read by the LPC2148 through RXD0 (P0.1), providing binary weather forecast data from an external source or simulation. This data is used to model the probability of rainfall, which directly influences irrigation decisions.

Once sensor data has been collected, two internal decision-making routines are executed. The first is the pest risk detection logic, which operates using a rule-based thermal-humidity fusion model. It evaluates the number of zones where temperature exceeds a defined pest risk threshold (e.g., 35°C) and checks whether the humidity level crosses a biologically significant value (e.g., 60%). Based on these conditions, pest activity is classified into LOW, MEDIUM, or HIGH risk. For example, if two or more temperature zones exceed the threshold and humidity is high, a HIGH pest risk is indicated. The result is used to trigger a pest alert LED if the classification reaches MEDIUM or HIGH levels. The second routine is a logistic regression–based irrigation decision engine. It takes the current soil moisture percentage and the binary rain forecast input to compute a probability score indicating whether irrigation is required. If the computed probability exceeds 0.5, the relay connected to the water pump is triggered via GPIO (P0.22), activating irrigation. This predictive model improves over traditional threshold-only systems by incorporating external predictive data (forecast) into the decision, thereby optimizing water usage.

After both decisions are executed, the system enters its output update phase. A 16x2 LCD module is used to display live information such as Current soil moisture percentage, Humidity percentage, Pest risk level (LOW / MED / HIGH) and Irrigation status (ON/OFF).

This display ensures transparency to the user without requiring mobile apps or cloud dashboards. The LCD operates in 4-bit mode and is driven by LPC2148 GPIO pins (P0.8–P0.11 for data, P0.22 for RS, and P0.23 for EN), multiplexed to share control lines with the relay and LED.

The entire cycle is executed continuously in a real-time loop with a delay buffer (~2 seconds), providing near-instantaneous responsiveness to changing environmental conditions.

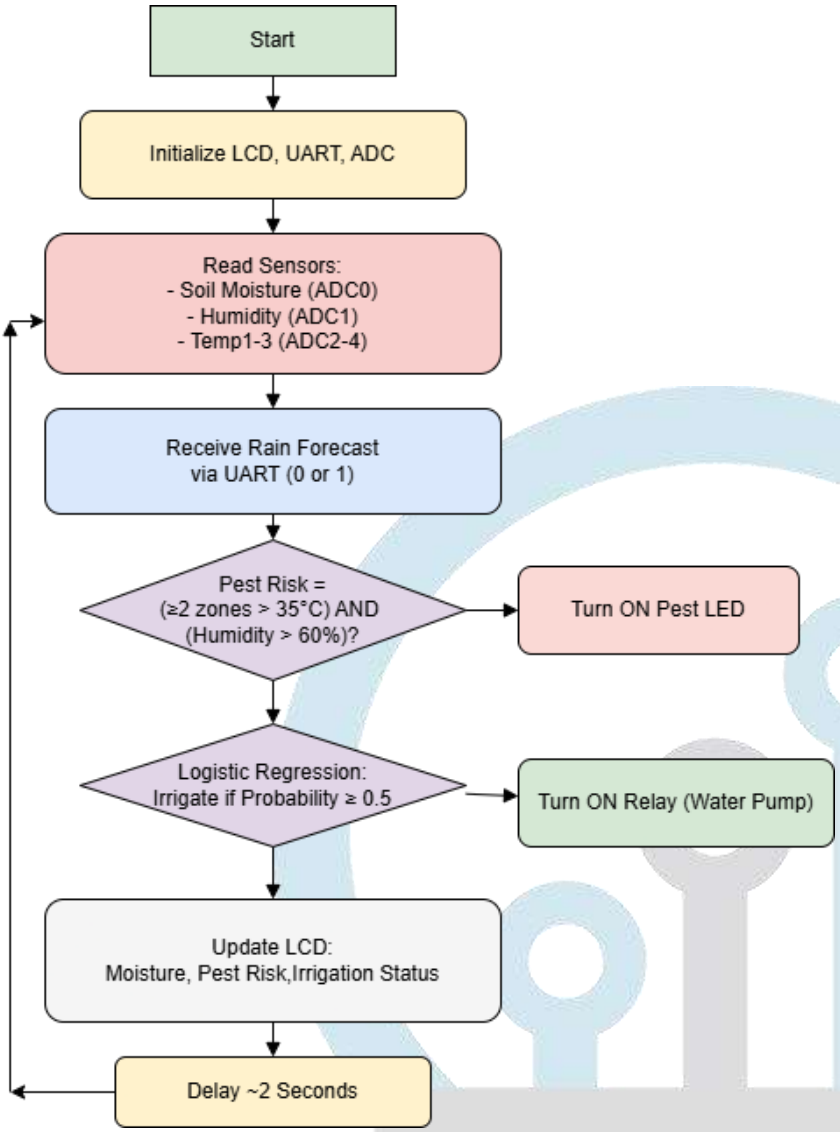

Figure 2. shows the flow chart of proposed methodology

IV. MATHEMATICAL MODELLING

The decision-making components of the proposed Smart Agriculture system rely on two lightweight yet effective computational models: (1) a logistic regression model for determining irrigation necessity based on soil moisture and forecast input, and (2) a rule-based thermal-humidity fusion model for pest risk prediction. Both models are executed entirely on the LPC2148 microcontroller using real-time sensor inputs, enabling edge-level autonomy and responsiveness.

Logistic Regression Model for Irrigation Decision

Logistic regression is a commonly used binary classification model suitable for low-resource embedded systems. In this system, the logistic model estimates the probability PPP that irrigation is needed, based on two key features → x_1: Soil moisture percentage (from ADC0), x_2: Rain forecast input via UART (1 = rain predicted, 0 = no rain). The logistic regression model is defined as:

$$P(\text{Irrigate}) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2)}}$$ where β_0: Bias term, β_1: Weight for soil moisture, β_2: Weight for forecast input

In this implementation, the coefficients were experimentally tuned for simulation as follows: $\beta_0 = 5.0, \beta_1 = -0.08, \beta_2 = -2.0$

These values reflect the intuitive behavior that as soil moisture increases, the need for irrigation decreases. If rain is predicted, the need for irrigation is also reduced. The decision rule is as follows:

$$If\ P(Irrigate) \geq 0.5 \Rightarrow TurnONRelay(WaterPump)$$

If P(Irrigate) $\geq 0.5 \Rightarrow$ *Turn ON Relay (Water Pump)*

$$If\ P(Irrigate) \geq 0.5 \Rightarrow TurnONRelay(WaterPump)$$

Rule Based Model for Pest Risk Prediction

Pest activity is influenced by environmental conditions, particularly temperature and humidity. Rather than using a machine learning classifier, a rule-based model was employed to minimize complexity and ensure deterministic execution on LPC2148. The system uses the following inputs: T_1, T_2, T_3: Temperature values from three LM35 sensors and **H**: Humidity value from the POT-HG sensor. The decision rule applied is if two or more of T_1, T_2, T_3 exceed 35°C, and Humidity $H \geq 60\%$. Then pest risk is classified as **HIGH**. The logic can be expressed as:

$$\textbf{Pest Risk} = \begin{cases} \textbf{HIGH}, \textbf{if} \sum_{i=1}^{3} \mathbf{1}(Ti > \mathbf{35}) \geq \mathbf{2} \textbf{ and } \boldsymbol{H} \geq \mathbf{60\%} \\ \textbf{MEDIUM}, \textbf{if} \sum_{i=1}^{3} \mathbf{1}(Ti > \mathbf{35}) = \mathbf{1} \textbf{ and } \boldsymbol{H} \geq \mathbf{60\%} \\ \textbf{LOW}, \textbf{otherwise} \end{cases}$$

Here, the summation $\sum (T_i > 35°C)$ represents the count of temperature zones exceeding the 35°C threshold. It acts as an indicator function that returns 1 if the condition is true, and 0 otherwise. Based on the classification, pest LED is turned ON for MEDIUM or HIGH risk and it remains OFF when the risk is LOW.

Sensor Data Conversion Modes

All sensor readings are first converted from ADC digital values to physical units using linear conversion models. For **LM35 Temperature Sensors:** $T(°C) = (Vout1023 \times 3.3V) \times 100T(°C) = \left(\frac{V_{\text{out}}}{1023} \times 3.3V\right) \times 100T(°C)$

This converts the analog voltage from the LM35 sensor (scaled to a 10-bit ADC) into temperature in degrees Celsius. For **Soil Moisture and Humidity (via POTs).** $Percent = (ADC1023 \times 3.3V) \times 100\text{Percent} = \left(\frac{ADC}{1023} \times 3.3V\right) \times 100Percent$

This linear formula assumes POT output is proportional to the environmental parameter and scales the 10-bit ADC output to a percentage (0–100%). These conversion formulas ensure all features used in the logistic and rule-based models are scaled appropriately and accurately reflect real-world conditions.

V. Software and Hardware Implementation

The Smart Agriculture system was developed using a layered integration of embedded hardware and structured C-based firmware. The hardware components were interfaced through the LPC2148 microcontroller and simulated using Proteus 8.13, while the software logic was compiled and uploaded using Keil µVision with the ARM7 compiler suite.

Hardware Design

The hardware implementation focuses on integrating five analog sensors, output modules (relay, LED, LCD), and a UART interface to the LPC2148 microcontroller. The sensor-to-port and GPIO assignments were chosen to optimize ADC utilization and maintain clear modularity.

The LPC2148, based on ARM7TDMI architecture, provides two 10-bit ADCs (14 total analog input channels), UART0 and UART1, 45 GPIO pins and Low power consumption. Its internal ADCs allow direct interfacing with LM35 and POT sensors without external ADCs or signal conditioning.

The following table shows the LPC2148 connections:

Type	Component	LPC2148 Connection	Description
Input Sensor	Soil Moisture Sensor	ADC0 (P0.27)	Reads soil water content
Input Sensor	Humidity Sensor (POT-HG)	ADC1 (P0.28)	Measures ambient humidity
Input Sensor	Temperature Sensor 1 (LM35)	ADC2 (P0.29)	Left zone temperature
Input Sensor	Temperature Sensor 2 (LM35)	ADC3 (P0.30)	Center zone temperature
Input Sensor	Temperature Sensor 3 (LM35)	ADC4 (P0.25)	Right zone temperature
Input Signal	Rain Forecast (UART)	RXD0 (P0.1)	Simulated weather forecast input
Output Device	Relay (Water Pump Control)	GPIO P0.22	Activates irrigation when needed
Output Device	Pest Alert LED	GPIO P0.23	Turns ON for MED/HIGH pest risk
Output Device	16x2 LCD Display	RS: P0.22, EN: P0.23	Shared control pins (multiplexed)
		D4–D7: P0.8–P0.11	Data pins in 4-bit mode

Table 1. shows the connections of each component and the port

Sensor Interfacing: All the sensors are connected to their respective ports as shown in the table. Each sensor provides an analog voltage proportional to its physical quantity, read via LPC2148 ADC channels.

UART Virtual Terminal: UART0 was configured to receive simulated binary input (1 = rain predicted, 0 = no rain) via RXD0 (P0.1). This simulates real-time weather API input in Proteus.

Output Modules: The output components of the system include a relay module to control the water pump for irrigation, a pest alert LED, and a 16x2 LCD display for real-time feedback. The relay is activated whenever the irrigation logic determines a need for watering, providing automated control of the pump. The LED serves as a visual indicator of pest risk, turning on when the system classifies the risk as medium or high based on temperature and humidity inputs. The LCD display operates in 4-bit mode and provides

live updates on key parameters such as soil moisture, pest status, and irrigation activity. To optimize GPIO usage, the relay, LED, and LCD control signals are managed using timed multiplexing without conflict.

Software Design

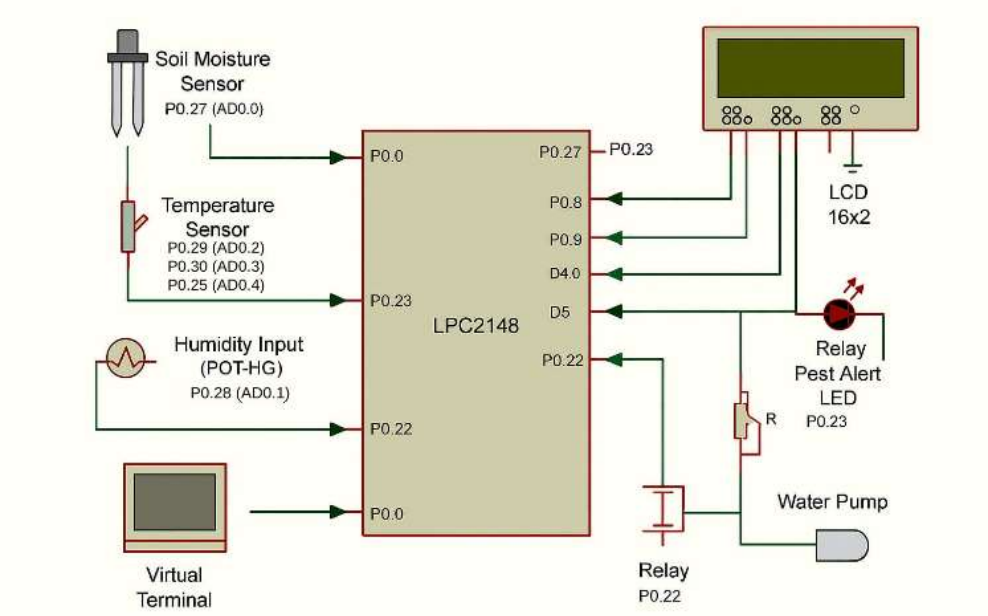

Figure 3. shows the port connections of each component to the microcontroller.

Firmware for the LPC2148 was written in embedded C using Keil µVision. Key modules include initialization routines, ADC reading, UART input handling, model logic execution, and output display.

The software implementation begins with the initialization of all essential peripherals, including ADC channels for sensor input, UART0 for forecast communication, GPIOs for output control, and the LCD in 4-bit mode. Once initialized, the system continuously reads analog values from all sensors and converts them into voltage, which is then scaled to physical units such as temperature, humidity, or soil moisture percentage. The rain forecast is received as a binary input over UART and parsed into the decision-making logic.

Pest detection is carried out using a simple rule-based approach where the system counts how many temperature zones exceed a defined threshold and evaluates this against the humidity level to classify pest risk. For irrigation control, a logistic regression model calculates the probability of needing irrigation based on real-time soil moisture and forecast data. If the probability exceeds a defined threshold, the relay controlling the water pump is activated.

The LCD continuously displays updated sensor values, pest risk levels, and irrigation status, refreshing approximately every two seconds to provide ongoing feedback to the user.

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VI. Simulation And Testing

To verify the correctness and real-time responsiveness of the proposed system, comprehensive simulations were conducted using Proteus Design Suite 8.13 and Keil µVision IDE. The testing process focused on evaluating sensor behavior, system decision-making accuracy, peripheral outputs, and the overall functional loop under various simulated environmental conditions.

Simulation Environment

The simulation was conducted entirely in a virtual environment using the following toolchain: **Proteus 8.13**: For circuit-level simulation of sensors, LPC2148 microcontroller, relay, LED, LCD, and UART terminal. **Keil µVision 5**: For writing, compiling, and debugging embedded C code tailored to the ARM7 (LPC2148) microcontroller.

The Proteus schematic included all the system modules — five analog sensors (simulated using potentiometers), a UART terminal, relay and LED outputs, and a 16x2 LCD display. The compiled hex file from Keil was loaded into the LPC2148 model in Proteus.

Sensor Simulation

Each analog sensor was emulated using a rotary potentiometer in Proteus. **Soil Moisture (ADC0)** and **Humidity (ADC1)** were simulated by adjusting POT-HG inputs. **Temperature Sensors (ADC2–ADC4)** were simulated independently to mimic varied heat conditions across the field.

By varying the potentiometers, Pest conditions such as "2 zones > 35°C + high humidity" could be manually triggered. Irrigation decision scenarios (e.g., dry soil with no rain) could be tested.

UART Input Testing

A virtual UART terminal was connected to LPC2148's RXD0 pin to simulate rain forecast input. Sending '1' indicated forecasted rainfall. Sending '0' indicated no rain. This input directly influenced the logistic regression output and was visible in both LCD messages and relay behavior.

Output Verification

1. **Relay and Pump Control:** The relay (connected to P0.22) was observed activating whenever the irrigation probability exceeded the defined threshold. A virtual LED represented the water pump, toggling ON/OFF as expected.
2. **Pest LED:** The pest warning LED (P0.23) activated precisely under HIGH or MEDIUM pest risk scenarios, confirming the correct evaluation of temperature zones and humidity levels.
3. **LCD Display:** A 16x2 LCD connected in 4-bit mode displayed Soil moisture (%), Pest risk classification (LOW / MED / HIGH) and Irrigation status (ON / OFF). The display updated continuously every ~2 seconds with new sensor readings and decisions.

Timing and Loop Performance

The system demonstrated excellent loop timing. Sensor acquisition and processing was <100 ms. LCD update and UART parsing was <50 ms. Total loop cycle including display was ~2 seconds (as designed). This confirmed that all decisions (relay and LED activation) were made with low latency and high consistency — critical for real-time agricultural control.

Observations

The system functioned correctly across a wide range of simulated conditions wirh no false triggers or misclassifications were observed under any test scenario. The modular simulation model in Proteus made it easy to visualize and debug each component's behavior.

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression, “One of us (R. B. G.) thanks . . .” Instead, try “R. B. G. thanks”. Put applicable sponsor acknowledgments here; DO NOT place them on the first page of your paper or as a footnote.

VII. Results and Discussion

The simulation of the Smart Agriculture system using LPC2148 demonstrated reliable and intelligent decision-making under various simulated field conditions. The outputs validated both the pest detection logic and irrigation control model, while maintaining system responsiveness, real-time feedback, and offline operability.

System Performance Overview

The complete system cycle — from sensing to output actuation — consistently executed within a ~2-second loop. This was sufficient to detect and respond to changes in soil moisture, temperature, humidity, and rain forecast in near-real time.

- Average loop delay (including display refresh): ~2.1 seconds
- ADC conversion and scaling: <100 ms
- LCD refresh and output triggering: <80 ms

This proves that even with limited resources, the LPC2148 microcontroller can handle parallel environmental monitoring and control logic without external processing.

Pest Detection Behaviour

The pest detection model performed effectively under multiple scenarios. The LED indicator accurately reflected pest severity levels with no false positives were observed when only one parameter (e.g., high temp or high humidity alone) was triggered.

Best Condition	Expected Risk	Pest LED Status
2 Temp Zones >35°C And Humidity = 65%	HIGH	ON
1 Temp Zone > 35°C And Humidity = 62%	MEDIUM	ON
No Zone > 35°C or Humidity < 60%	LOW	OFF

Table 3. shows pest detection on basis of various factors

Irrigation Decision Accuracy

The logistic regression model was consistent in computing irrigation decisions based on sensor values. The system effectively prevented over-irrigation when rain was forecasted and response to dry conditions was prompt and reliable. Example test cases:

Soil Moisture	Forecast	Probability	Relay Status
25	0	0.56	ON
48	1	0.18	OFF
32	0	0.42	OFF
15	0	0.70	ON

Table 4. shows irrigation control on basis of forecast and moisture

LCD Output Feedback

The LCD served as a real-time dashboard for sensor status and control decisions. It displayed: Live moisture readings (converted from ADC), Pest status (LOW / MED / HIGH) and Irrigation status (ON / OFF). This made debugging easier during simulation and improves user transparency in field deployment scenarios where cloud/app access is unavailable.

Strengths of the System

The proposed system shows way for a fully autonomous operation without cloud dependency where accurate pest and irrigation decisions using edge-level logic. It provides Real-time output response with low latency. We also get visual feedback via LCD even in offline mode.

Limitations and Observations

- Pest risk detection is based on static threshold rules; it may miss subtler environmental patterns.
- Forecast input is binary and simulated; real-world use would require GSM or weather API integration.
- POT-based sensor emulation (for simulation) lacks physical variability present in real-world sensors

VIII. Comparative Analysis

The proposed Smart Agriculture system was benchmarked against recent research works focusing on IoT-based irrigation control, environmental monitoring, and pest detection. While numerous studies have addressed one or more of these aspects, the integration of edge-based dual decision-making (for both irrigation and pest risk) into a compact embedded system sets this project apart.

Comparison with Existing Works

The following table summarizes how this system compares with related studies in terms of core functionalities:

Feature/ Study	Pest Detection	Smart Irrigation	Local Decision Making	Microcontrollers Used	Interdependency
Sharma et al. (2021) [1]	No	Yes	No (Cloud)	ESP 8266	Required
Nayagam et al. (2023) [6]	Yes (GPU sim)	No	No (Distributed sim)	None (Server-based)	Required
Huque et al. (2023) [4]	No	Yes	No (Mobile-App Driven)	Node MCU	Required
Patil & Malviya (2012) [5]	No	Yes	No (Rule-based)	ARM7 (LPC2148)	No
Our Proposed System	Yes (Rule Based)	Yes (Logistic Model)	Yes (Full edge logic)	ARM7 (LPC2148)	No

Table 5. compares various research papers with our project

Highlights of Innovation

Your project introduces several unique contributions compared to the reviewed studies:

Dual Functionality (Irrigation + Pest Detection): Most related systems focus on irrigation control only. Pest detection is often omitted or offloaded to cloud models.

Local Intelligence Both decision-making models (logistic and rule-based) execute entirely on-device using the LPC2148. This avoids delays and failures due to network unavailability.

Use of Lightweight ML at the Edge: Unlike cloud-hosted AI, the logistic regression model enables predictive irrigation decisions with minimal computation, ideal for microcontroller-based systems.

Minimal Hardware, Maximum Utility: The entire solution is built around a single microcontroller without any external computing module, cloud server, or app.

Simulation-Validated Design All functionalities were tested virtually using Proteus 8.13 and Keil µVision, allowing thorough debugging and replicability.

Practical Benefits

- Suitable for rural and low-connectivity zones
- No need for mobile apps or external interfaces
- Low power consumption and low cost
- Easily extensible (e.g., SD card logging, GSM alerts)

IX. Conclusion

This project presents a low-cost, autonomous Smart Agriculture system capable of executing real-time irrigation control and pest risk detection entirely on the edge, without the need for internet connectivity or cloud processing. Built on the ARM7-based LPC2148 microcontroller, the system integrates multiple analog sensors — including soil moisture, humidity, and three temperature sensors — to monitor environmental conditions across multiple zones.

By implementing a logistic regression model for irrigation prediction and a rule-based fusion model for pest risk classification, the system demonstrates intelligent, responsive behaviour that adapts to varying field conditions. Outputs such as relay-driven water pump control and LED-based pest alerts are triggered based on real-time sensor fusion, while a 16x2 LCD provides live user feedback. The entire system was developed and successfully validated through virtual simulation using Proteus 8.13 and Keil µVision.

In contrast to most existing IoT agriculture systems that depend on cloud infrastructure or mobile applications, this design offers complete offline functionality and rapid decision-making. These features make it especially suitable for deployment in rural or low-

connectivity areas where conventional IoT systems often fall short.

With its accurate logic, modular architecture, and validated performance, this system provides a solid foundation for future smart farming applications that prioritize resilience, simplicity, and autonomy.

X. Future Work

While the current implementation successfully achieves autonomous irrigation and pest risk detection using embedded logic, several enhancements can be pursued to improve scalability, adaptability, and real-world applicability. Future work may include the following directions:

Field Deployment with Real Sensors

The current simulation relied on potentiometers to emulate sensor values. In the next phase, actual LM35 temperature sensors, capacitive soil moisture probes, and DHT11 or HIH4000 humidity sensors can be integrated and tested in a real agricultural setup. This would allow validation under natural environmental fluctuations and soil diversity.

GSM or LoRa-based Remote Notification

Integrating a GSM or LoRa module would allow the system to send SMS alerts or push data wirelessly to a central dashboard. For example, notifications could be sent to farmers indicating pest alerts or irrigation events, enhancing remote awareness without needing constant supervision.

Data Logging via SD Card or EEPROM

To enable performance tracking and research analytics, the system could be extended with an SD card module or EEPROM memory. Logged data such as temperature trends, pest activity hours, and irrigation frequency would support data-driven farming insights.

Solar-Powered Implementation

To enhance energy independence in off-grid environments, the system can be redesigned with solar charging support and energy-efficient components. This would allow 24/7 autonomous operation even in rural areas without reliable power supply.

Enhanced Pest Detection via Thermal Imaging

While the current rule-based pest detection is effective, integrating a low-resolution thermal imaging sensor (e.g., AMG8833 Grid-EYE) could allow precise heat mapping of the crop area. Combined with basic image processing, this could detect early pest breeding zones more accurately.

Machine Learning Integration (Offline Inference)

More advanced ML models such as decision trees or fuzzy logic systems can be explored and optimized for embedded execution. These could refine decision thresholds and improve adaptability to diverse crop and soil types — all while maintaining edge-only inference.

Web-based Dashboard or Mobile App (Optional Enhancement)

Though the current design avoids internet dependency by choice, an optional Wi-Fi module (ESP8266 or ESP32) could allow for data visualization via a mobile app or web portal when connectivity is available.

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