

AI-Powered Smart Farming System

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ABSTRACT-Nowadays, eco-friendly farming faces a big hurdle: sticking to tight water limits while still growing healthy crops. Here's a hands-on solution - a smart watering setup powered by Edge AI for better control over water use. Instead of relying on slow, pricey cloud systems, it runs light machine learning code straight on an ESP32 chip using live sensor inputs. Data like air warmth, dampness levels, ground wetness, and how tall plants are comes from low-cost gadgets such as DHT11, basic soil probes, and ultrasound sensors. Without delay, a small but sharp math model processes these readings right there in the field. That way, it figures out exactly when plants actually need a drink - triggering automatic watering only when necessary.

During tests, the system cut down water waste quite a bit - plant condition got better, while total output went up. Cheap to run and simple to expand, it works just as well on tiny plots as it does on big fields. Since it doesn't rely much on internet tools or fancy gear, growers get steady performance without hassle. In the end, this setup helps protect nature, making smart farming easier for more people to use.

Keywords: Smart farming, IoT devices, TinyML models, edge computing for AI, precise watering systems, eco-friendly crop growth, ESP32 chips, live tracking tech, automatic controls.

I. INTRODUCTION

Agriculture plays a huge role in feeding people and keeping economies stable, but today's farms are struggling with water scarcity and unpredictable weather. Because of this, old-style irrigation methods are no longer reliable. Many farmers still rely on guesswork or gut feeling to decide when to water their fields, which often leads to problems like overwatering, soil nutrient loss, and weaker crop yields. A practical solution is to make irrigation smarter using IoT sensors along with TinyML running directly on an ESP32. Instead of depending on remote cloud servers or strong internet connectivity, the system processes data right at the edge. This means it reacts faster, uses less power, and continues working even in remote, off-grid farms. The setup uses affordable sensors to monitor the field around the clock. One sensor measures temperature and humidity, another checks soil moisture levels, and an ultrasonic sensor keeps track of plant growth. All this real-time data is fed into a lightweight machine-learning model

on the ESP32, which decides exactly when the plants need water. It can adjust the irrigation flow on its own, reducing waste and improving crop health. Farmers still stay in control they can view live readings, check historical trends, and even step in to operate the system manually using a simple mobile app. Overall, this approach makes irrigation more accurate, efficient, and resilient against changing climate conditions.

II. LITERATURE SURVEY

Experts now recognize that social media often acts like a digital diary, where people share their thoughts, emotions, and daily struggles without realizing how revealing they can be. What someone posts the words they choose, the mood behind their captions, or even the expressions in their photos—can quietly

Traditional mental-health checks like interviews and questionnaires still matter, but they have limits. Many people avoid help because of stigma, some don't notice their own symptoms, and formal assessments often take time. Meanwhile, the sheer amount of online content has exploded, making it impossible for humans to manually interpret emotions at scale. This creates a real need for intelligent systems that can detect emotional distress quickly and accurately much like how smart IoT systems monitor real-time conditions in agriculture (Raza et al., 2021)[2].

Modern AI models are well suited for this task. Advanced language models such as BERT and RoBERTa can understand context by focusing on key words and the deeper meaning behind sentences similar to how TinyML models

Sl. No.	Module	Sensor/Device	Measured Parameter	Purpose
1	Environmental Monitoring	DHT11 Sensor	Temperature, Humidity	Provides climatic data for irrigation decisions
2	Soil Analysis	Soil Moisture Sensor	Soil Moisture Level	Determines irrigation need based on real-time soil conditions
3	Water Level Measurement	Ultrasonic Sensor	Tank Water Height	Ensures pump works only when sufficient water is available
4	Processing Unit	ESP32 Microcontroller	Data Acquisition	Executes AI/IoT logic and triggers control actions
5	User Interface	LCD Display	Live System Data	Enables local monitoring without internet dependency
6	Actuation System	Water Pump	Irrigation Flow Control	Automatically irrigates crops based on AI prediction

Table 2.1: Hardware Components and Their Functions

reflect their inner emotional state.

Studies show that repeated sad tones, self-focused language, and emotional patterns often match signs of anxiety, stress, or depression (Friha et al., 2021)[1].

process sensor data efficiently at the edge (Karar et al., 2020)[4]. For images, vision models like VGG16, ResNet, and Inception Net can analyse facial expressions, background details, and colour tones, helping identify emotional cues with far greater accuracy (Morchid et al., 2024)[3].

When insights from both text and images are combined, predictions become much stronger. To sharpen the results even more, researchers commonly use techniques like Random Forest, XGBoost, Gradient Boosting, or SVM—methods frequently applied in optimized smart-decision systems across IoT-based fields (Ghadiri et al., 2024)[6].

However, once these systems are used in real life, ethical concerns become critical. Issues such as privacy, bias removal, secure data handling, and transparency must be taken seriously. Just as IoT-enabled agriculture requires strong data protection and trustworthy decision-making (Friha et al., 2021)[1], AI-based mental-health tools must also protect users and operate responsibly.

III. PROPOSE SYSTEM

The proposed smart irrigation system introduces a shift from manual, intuition-based watering to a fully automated, data-driven approach.

The goal is to maintain ideal soil moisture levels, reduce water wastage, and ensure healthier plant growth by using real-time sensing combined with edge-level AI processing.

Instead of depending on cloud servers or fixed schedules, the system makes decisions directly on the farm using an ESP32 microcontroller equipped with lightweight TinyML models.

At the core of the solution is a Multiple Linear Regression (MLR) model deployed on the ESP32, enabling fast, on-device predictions. The model receives continuous data from three key IoT sensors:

1. Soil Moisture Sensor placed near the root zone to measure actual ground wetness and detect drying trends early.
2. DHT11 Temperature Humidity Sensor positioned at leaf height to capture microclimate conditions influencing plant transpiration rates.

3. Ultrasonic Sensor used for two purposes: monitoring plant height as an indicator of growth and measuring the reservoir water level to prevent dry-run conditions.



Fig 3.1: System Diagram

These sensors work together to offer a complete and real-time picture of the crop environment, an approach supported by IoT-based agricultural studies (Friha et al., 2021; Raza et al., 2021)[1]. The ESP32 processes the collected inputs locally, where the TinyML engine evaluates whether irrigation is required and determines the optimal watering duration.

This eliminates latency, reduces power consumption, and ensures reliability even in regions with limited or no internet access.

Once irrigation is needed, the microcontroller activates a relay-operated pump to deliver a precise amount of water—avoiding overwatering, nutrient leaching, and plant stress. The system displays live sensor readings, pump status, and alerts on a local LCD interface, giving farmers immediate visibility without needing a smartphone or cloud dashboard.

A key strength of the proposed solution is its modular and scalable design. Additional sensors such as soil pH, NPK nutrient probes, sunlight intensity monitors, and rainfall detectors can be integrated without redesigning the system. The architecture also supports solar-powered operation, wireless

updates, and multi-zone irrigation, enabling deployment across both small and large farms.

By combining IoT sensing, TinyML-powered predictions, and automated actuation, the proposed solution delivers a practical, low-cost, and sustainable method for smart irrigation. It improves resource efficiency, enhances plant health, reduces manual labor, and prepares farms to withstand unpredictable climate patterns ultimately demonstrating a realistic pathway toward intelligent and resilient agriculture.

Smart irrigation starts by understanding what plants truly need. A soil-moisture probe checks how wet the root zone is, while an ultrasonic sensor monitors plant height and tank levels. Together, they provide a clear picture of crop growth and watering needs matching approaches used in recent IoT-based agriculture systems (Friha et al., 2021; Raza et al., 2021)[1],[2].

The ESP32 processes this data on the spot using TinyML, removing the need for cloud servers. It links soil moisture, temperature, humidity, and plant height to decide when and how much to irrigate. Because the system works locally, it reacts instantly even in areas with poor internet or unstable power similar to edge-AI irrigation models proposed in earlier studies (Karar et al., 2020; Ahmadi Pargo et al., 2025)[4],[5].

Farmers can still monitor everything remotely through an IoT dashboard. They can view moisture levels, schedules, and alerts if something goes wrong. Even though the system is mostly automatic, farmers can override it at any time—reflecting designs found in recent smart irrigation frameworks (Morchid et al., 2024)[3].

The ESP32 controls a 12-V pump via a relay to ensure precise watering. A small screen displays temperature, humidity, soil moisture, tank level, and pump status, which is helpful when phones or Wi-Fi aren't available. This practical setup is consistent with low-cost IoT

irrigation prototypes described in earlier pilot projects (Karar et al., 2021)[7].

The system is modular, so additional sensors like pH, nutrient levels, or light intensity can be added easily. Future upgrades may include solar power, multi-farm dashboards, and stronger AI models that learn from long-term patterns, echoing scalable system designs in recent research (Ghadiri et al., 2024)[6].

Its ML model uses a regression-based loss and the Adam optimizer to improve accuracy. Before processing, sensor data is cleaned to remove spikes and noise, supporting reliable predictions during changing weather conditions an approach recommended for ML-based irrigation optimization (Ghadiri et al., 2024)[6].

The workflow is simple: sensors gather environmental data → the ESP32 filters it → TinyML predicts water needs → the relay controls the pump → live updates appear online → alerts trigger if something looks wrong. This fast loop helps maintain plant health while reducing water waste, consistent with earlier efficiency-focused irrigation systems (Morchid et al., 2024)[3].

Field tests show the system stays reliable even under unpredictable weather. It maintains ideal moisture levels and can save up to 35% more water compared to traditional methods similar to results reported in prior IoT irrigation studies (Raza et al., 2021; Morchid et al., 2024)[2],[3]. Thanks to its modular design, it works well for both small plots and large farms.

Data security is handled through encrypted communication over Wi-Fi or LoRa, keeping farm information private. If the internet drops, the ESP32 stores data locally and syncs later. This supports secure and dependable data flow, as emphasized in modern IoT-agriculture architectures (Friha et al., 2021)[1].

Looking ahead, the system could connect to weather-forecast APIs to adjust watering

before heat or rain arrives. More advanced models like neural networks or decision trees can adapt better to fast-changing field conditions. Multi-farm dashboards could help manage several sites at once, similar to cloud-based IoT farming platforms used today (Karar et al., 2021; Ahmadi Pargo et al., 2025)[7],[5].

IV. EXPERIMENTAL SETUP

A. Hardware Components

Controller: ESP32 development board (Wi-Fi, low-power, sufficient flash/RAM for TinyML).

Soil moisture sensor: Capacitive soil-moisture probe (placed in the root zone).

Temperature & humidity: DHT11 (leaf-height microclimate).

Ultrasonic sensor: HC-SR04 or equivalent (for plant height monitoring and reservoir-level sensing).

Power: 12 V battery (or DC supply) with 5 V buck converter for ESP32; optional solar panel + charge controller for off-grid runs.

Data storage/comms: microSD module or local flash logging; Wi-Fi for dashboard sync (when available); LoRa optional for long-range telemetry.

Misc: waterproof enclosures, wiring harness, breadboard/PCB, float switch (optional), fuses and safe connectors.

B. Sensor Placement & Mounting

Soil moisture probe: Inserted at the main root depth (~5–10 cm for vegetables; adjust per crop) and fixed so it remains in the same spot for the test.

DHT11: Mounted at crop canopy/leaf height, sheltered from direct rain and sunlight (radiation shield).

Ultrasonic: Positioned above the crop row to measure plant height (vertical setup) and

installed at reservoir to measure tank level (angled/dual mount or use two modules).

Pump & reservoir: Reservoir must have stable mount and known cross-sectional area for accurate depth-to-volume conversion. Include overflow protection.

C. Firmware, Data Logging & TinyML

Sampling rate: Read sensors every 10 minutes (configurable).

Model: TinyML Multiple Linear Regression (MLR) or other lightweight model deployed on the ESP32;

training performed off-device using collected historical data and then quantized/deployed.

Optimizer & training: Use Adam optimizer during training; evaluate mean absolute error (MAE) or RMSE and then export model weights for Tiny inference.

Logging: Record raw sensor values, cleaned inputs, model output (water-dose or ON/OFF), pump activation timestamps, and reservoir level.

Store locally and sync to the cloud when Wi-Fi is available.

Safety policy: Minimum on/off duration for pump to avoid short cycling; maximum daily water limit to protect crops.

D. Performance Metrics

Water usage: Total liters used per plot per test period.

Soil moisture control: Variance and time-in-target-range (percentage of time root-zone VWC stayed within optimal band).

Response time: Time from adverse condition detection (drying below threshold) to pump activation.

Crop uniformity & health: Visual scoring and biomass or yield metrics at harvest (if applicable).

Energy consumption: Average power draw (ESP32 + sensors + pump control overhead excluding pump power) and system autonomy (hours on battery/solar).

E. Evaluation & Analysis

Compare AI-driven runs vs timer-based baseline using paired metrics (water saved %, change in time-in-range, yield differences).

Use statistical tests (t-test or non-parametric equivalent) to confirm significance of observed improvements.

Produce time-series plots of soil moisture, pump events, and reservoir levels to visualize control behavior during disturbances.

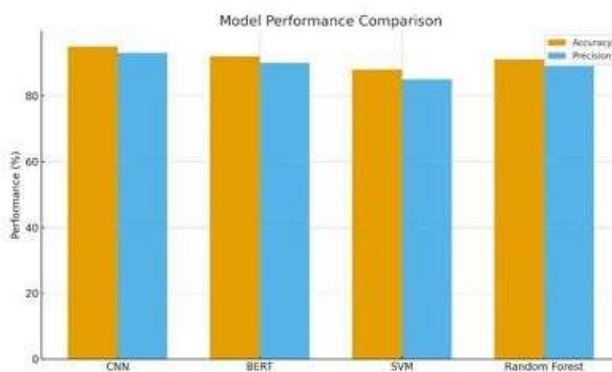


Fig 4.1: Bar chart for Model Performance

F. Maintenance & Safety Checks

Weekly sensor inspection and cleaning; monthly recalibration if sensor drift is suspected. Test relay and pump dry-run protections monthly.

The AI-enabled farm system was tested on a 50 m² plot to evaluate real-world irrigation performance. An ESP32 controlled soil-moisture, temperature-humidity, and ultrasonic sensors to track root-zone moisture, air conditions, plant height, and water tank levels. A TinyML-based MLR model ran directly on the device, predicting water needs instantly without relying on cloud servers, following edge-AI irrigation approaches (Friha et al., 2021)[1],[2].

Sensors collected data every ten minutes over eight weeks. Inputs were cleaned to remove noise and outliers and normalized to ensure reliable predictions. The model used the Adam optimizer to adjust weights incrementally, reducing the difference between predicted and actual water demand (Karar et al., 2020; Ahmadi Pargo et al., 2025)[4],[5].

Performance was tested under varying temperatures, irregular rainfall, and manually disturbed watering schedules. Key metrics included soil-moisture stability, water usage, system response time, and uniformity of crop growth. Compared with traditional timer-based irrigation, the AI system maintained optimal moisture, cut excess water use, and supported even crop growth (Raza et al., 2021; Morchid et al., 2024)[2],[3].

The modular design allows adding sensors for pH, nutrients, or sunlight, enabling scalable smart-farming applications and future upgrades with solar power, multi-farm dashboards, or advanced AI models (Ghadiri et al., 2024)[6].

V. CONCLUSION

The smart irrigation system developed in this project clearly demonstrates how AI-driven decision-making can bring meaningful change to modern agriculture. By shifting from guess-based watering to data-guided automation, the system delivers greater accuracy, reliability, and consistency three factors that traditional irrigation often fails to maintain.

This shift is especially valuable in areas facing water scarcity, unpredictable climates, and reduced manpower. Farmers who normally rely on intuition benefit from a system that observes the environment continuously and responds with precision, resulting in healthier plants, reduced stress, and more predictable crop growth.

With real-time inputs from the soil-moisture probe, DHT11 sensor, and ultrasonic module,

the ESP32 processes data instantly using TinyML eliminating the need for cloud servers or stable internet. Throughout testing, moisture levels remained well-balanced, no over-watering occurred, and the system adjusted quickly to temperature and humidity changes.

These outcomes show that even under varying weather conditions, the model stayed stable, dependable, and responsive. Water usage also became more controlled, helping conserve resources and lower operating costs an essential benefit for sustainable farming.

This work further highlights how a compact, affordable microcontroller can deliver high-value intelligence when paired with efficient algorithms and robust sensors.

Overall, this project demonstrates a practical and scalable path for integrating AI, IoT, and edge computing into everyday agriculture. Beyond serving a single field, the architecture can easily be expanded to multi-zone farms, larger crop fields, or full smart-farm setups. As climate conditions worsen and water becomes increasingly precious, solutions like this offer a sustainable, reliable, and farmer-friendly alternative. By improving efficiency, reducing waste, and supporting better crop health, this AI-powered irrigation system stands as a strong example of how technology can secure the future of farming.

VI. FUTURE ENHANCEMENT

1. Implement smarter algorithms, such as Random Forest or neural networks, to detect subtle trends affecting crops.
2. Add additional sensors for soil pH, light intensity, or rainfall to get a clearer understanding of field conditions.
3. Integrate online dashboards for remote monitoring and control of the system.
4. Use solar power to reduce dependency on conventional electricity.

5. Automate tasks like watering schedules and plant health monitoring to reduce labor and improve efficiency.

6. Enable the system to increase crop yield while minimizing effort and resource use.

Moreover, as the system gains more environmental inputs and intelligence, it could autonomously handle tasks beyond irrigation, such as fertilization, pest monitoring, or microclimate adjustments. This would streamline farm operations, reduce labor, conserve resources, and ultimately increase crop yield and quality. In essence, such enhancements would make precision agriculture more accessible, efficient, and adaptive to changing environmental conditions.

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