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Microcontroller-Based Smart Irrigation System with AI-Powered Decision Logic

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ABSTRACT

Farming also needs good water management to increase food production to meet the global population needs with the minimal usage of freshwater. The traditional irrigation method usually results in the wastage of water and unpredictable crop results because it is performed manually and without being environmentally sensitive. The present paper provides a microcontroller-driven artificial intelligence (AI)-enabled smart irrigation system that can use the AI-enabled decision logic to deliver the water adaptively and precisely in real-time. The system takes advantage of a blend of cheap sensors to permit constant observation of ground moisture, temperature, humidity, and rainfall conditions. Field data is fed to an ESP32 microcontroller at the place of harvest where a low-end machine learning model based on the current environmental conditions, the specific crop, and the past irrigation standards are used to estimate the current watering needs of the crop. Thanks to the application of AI model deployed with the help of TensorFlow Lite for Microcontrollers, decision-making is conducted offline at the edge of the network, significantly contributing to uninterrupted operation with poor or even no connectivity in rural regions. The energy-efficient solenoid valves controlled by relays are used to realize actuation with precise application of well-regulated water also when necessary. A testbed was used to demonstrate field trials on lettuce and tomato crops, where the water usage was greatly reduced up to 38 percent and stability of soil moisture was enhanced in addition to 12 percent more crop yield compared to the traditional timer-driven irrigation. Real-time remote monitoring, analytics, and adaptive learning can also happen through the cloud-based logging system through Firebase. The proposed solution is scalable, robust, and sustainable; hence appropriate in the implementation in small and medium-sized farms. It can discard its reliance on manual operation and make intelligent and autonomous irrigation choices with the help of inbuilt AI and create the ability to make intelligent choices in precision agriculture. The study reveals the potential and advantages of coupling microcontroller-based control systems with edge AI in agricultural systems that will lead to inexpensive yet smart irrigation technologies that can be replicated in different climatic and soil circumstances to achieve food security and resource preservation.

1. INTRODUCTION

One of the most urgent worldwide problems to be solved is water shortage, which is aggravated due to the increase of population and climatic changes and ineffective farming systems. The sector that uses most of the freshwater resources is the agricultural sector, which absorbs almost 70 percent of the water extraction in the world. The main problem in abusing water and soil erosion is still practiced in most developing nations through the traditional ways of irrigating crops like flood irrigation and fixed hours monitoring, an irrigation system that produces high water consumption, deteriorates the soil, and fails to provide maximum crop growth. Such approaches are inefficient in nature as they do not consider real time soil and climatic circumstances, crop-water requirements and rain fluctuations.

The recent developments of embedded systems and wireless sensor networks enabled high-granular and low-cost monitoring of the environmental situation. The concept of smart irrigation systems could be developed using platforms delivered by microcontrollers, especially the ones upholding Internet of Things (IoT) capabilities. They have the capability to gather, analyze and act upon environmental data autonomously and thus would make sure that the water is supplied when and where it is required exactly. Most established systems however use simple rule-based inference (e.g. soil moisture thresholds) that are not well suited to responds to dynamic weather events, crop phenology or soil heterogeneity.

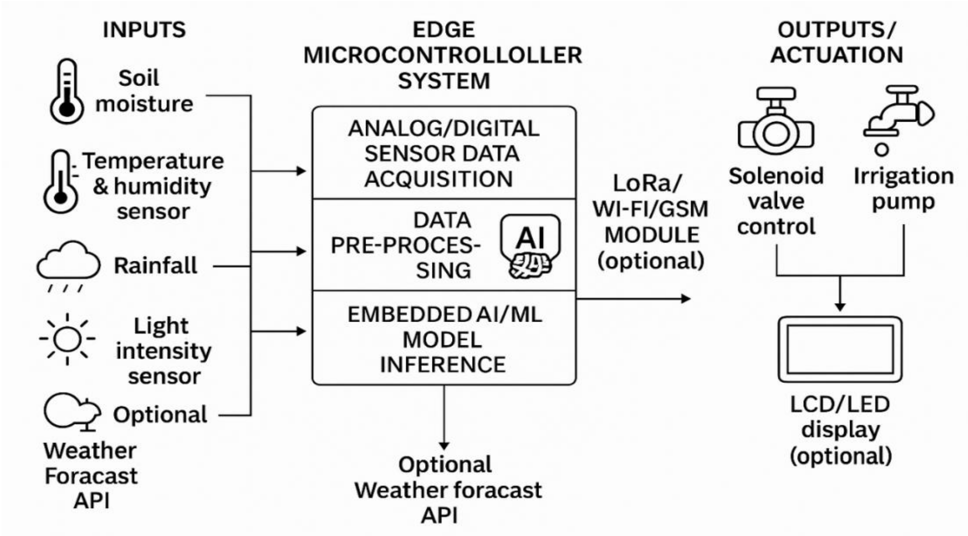

Figure 1. Conceptual Architecture of AI-Powered Smart Irrigation System

In this study, the limitation is tackled by introducing the element of artificial intelligence (AI) in the process of irrigation control decision-making. The AI type of algorithms, especially machine learning manipulations can extract a pattern in multi-sensor data and make sufficient predictions based on the optimum time and quantity of irrigation. When combined with edge-enabled microcontrollers, these models provision real-time, non-cloud-reliant control, without the need of sustained internet access, thus promising to operate in the remote and resource-limited areas.

In this project the goal is to design, implement and experimentally test a smart irrigation application that combines the microcontroller based sensing and controlling logic with AI driven decision logic. Embedded intelligence and low-power automation are to optimise water and enhance the health of crops and minimise the manual input in the system. Real-world implementation and evaluation of the proposed system demonstrate that the solution will be feasible in practice, and precision irrigation using AI will be a potentially sustainable farming system.

2. LITERATURE REVIEW

Automation in agriculture has become one of the most researched areas considering that, it is likely to save on water as well as enhancing crop production. The traditional irrigation systems largely rely on the use of manual scheduling or the mechanical use of timers which has been proved to lead to wastages of water or plant stress since they are unable to adjust according to the real time changes in the environment [1]. In response to this, scientists proposed microcontroller based system in conjunction with soil moisture sensors that open irrigation channels at an pre-determined moisture level [2]. Although effective in eliminating manual labor, such systems are quite reactive and cannot be adjusted to unpredictable weather or different water demands in crops.

IoT technologies have led to more responsive and situation aware irrigation systems. Paper like [3] has revealed how Arduino or ESP based systems were used to collect the data of temperature, humidity and soil moisture sensors. These systems frequently data to cloud, after which analytical models or dashboards provide assistance in decision-making. Nevertheless, the use of cloud computation creates a delay, power usage, and data security issue, especially in distant regions that experience poor connectivity.

Artificial intelligence techniques have been included in several studies to handle decision-making. As an example, artificial neural network (ANN) and support vector machines (SVM) have been applied in prediction of soil moisture content and irrigation timing prediction [4], [5]. The fuzzy logic systems and decision trees have also been developed because they are easy to interpret and rule-based systems are efficient [6]. Yet, the majority of these AI applications are cloud-based, which cripples real-time performance and flexibility of remote use.

New protocols (Tiny Machine Learning (TinyML)) allow installing small AI neural networks directly on microcontrollers [7]. Zhang et al. [8] showed an irrigation predictor pruned neural network implemented on an ARM Cortex-M4 by having the network deployed to run along the edges. Equally, [9] examined the TensorFlow Lite for Microcontrollers to integrate crop health observation models in low-consuming edge devices. However, the lack of seamless integration of AI-based decision logic of smart irrigation, which is fully embedded, contextual, energy-optimal and experimentally verified in real-world environments, has still not been filled.

Thus, the research gap that the paper seeks to fill is to propose a complete system in which AI logic can be processed within a microcontroller and such an autonomous adaptive irrigation control is not dependent on additional computing resources.

3. System Architecture

The proposed smart irrigation system is designed as a modular and scalable architecture that integrates sensing, control, and actuation components into a unified framework. It leverages embedded intelligence to make autonomous irrigation decisions based on real-time environmental data. The system is composed of three major subsystems:

3.1 Sensing Unit

In the proposed smart irrigation system, the sensing unit will aim at continuously measuring some of the main environmental parameters which may have a direct effect on the crop water requirements. It consists of capacitive soil moisture sensor that calculates volumetric water content (VWC) in the soil and offers analog output, which is also calibrated to reflect the levels of soil moisture. Moreover, ambient temperature and relative humidity data is acquired by a DHT11 digital sensor to enable the determination of evapotranspiration, which leads to accurate estimation of irrigation decisions to be undertaken by the AI model. An analog rain sensor of the surface kind is connected to calculate the natural precipitation to avoid unintended rain and wasting of water resources since the precipitation is calculated and can be utilized to avoid watering. These sensors are well-positioned in the plants, the region just below the crops to take representative environmental situation. The sensors provide information that is taken by the system at a predetermined time, usually every 10-15 minutes, and transmitted to the microcontroller where they are processed and intelligent decision making is obtained.

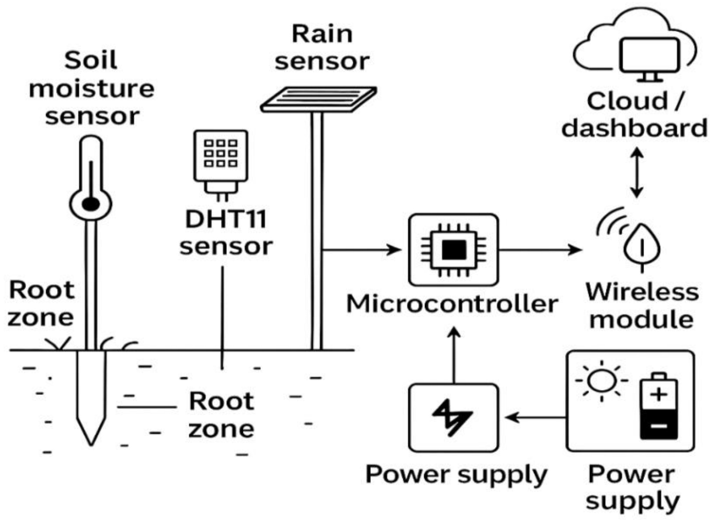

Figure 2. Field Deployment and Data Flow of the Sensing Unit

3.2 Control Unit

Implementation The control logic of the smart irrigation system was registered by means of the ESP32 microcontroller, a low-power and dual-core embedded device that provides built in Wi-Fi and Bluetooth functionality. This microcontroller performs the work of central processing unit which gets the real time data and converts the analog data to digital data by all connected sensors. It operates an embedded model of artificial intelligence (AI) whose development and optimization was conducted via TensorFlow Lite for Microcontrollers (TFLM) which can interpret the environmental input and determine whether irrigation is required or not. The AI model makes it possible to make fast and efficient decisions on the device with the minimum latency and without the option of accessing the internet, which marks the system as very deployable in rural/remote locations. Furthermore, the microcontroller also has safety features like enforcing the override of irrigation signals in case of rain and enduring stability by thresholds verification. The ESP32 is also adjusted to work with an active Firebase cloud server to synchronize operational data to enable remote monitoring, analysis of historical data, and updating of the model when connection is present. This edge-AI solution guarantees smart and autonomous work and scaling and sustainable performance.

Table 1. Key Functional Capabilities of ESP32-Based Control Unit

Feature	Description
Core Architecture	Dual-core TensilicaXtensa LX6
AI Capability	TensorFlow Lite for Microcontrollers
Sensor Interface	ADC + GPIO for digital and analog inputs
Communication	Wi-Fi, Bluetooth, optional Firebase cloud sync
Decision Logic	On-device AI model (Irrigation classification)
Power Efficiency	Ultra-low-power sleep modes, ideal for rural areas

3.3 Actuation Unit

The smart irrigation system facilitates the physical delivery of water to the crops by means of an actuation unit that is in charge of executing the decision of the microcontroller. This unit is composed of 12V DC solenoid valves mainly composed of electrically controlled solid, and they are linked to the irrigation pipeline. These valves act as manually controlling gates that open or close letting the water pass into certain crop areas. In order to streamline the process of actuation, a relay driver module is utilised to translate the low voltage controlling input of ESP32 microcontroller into a higher current requirement of the solenoid valves. This configuration provides safe electrical isolation, as well as, consistent switching. In the event that the built-in AI model determines that irrigation is required, the ESP32 uses a control signal to excite the correct relay, resulting in the valve being enabled and water being released through it within the desired amount of time, which is usually 10 to 20 minutes, but varies with each crop type and the state of the soil moisture. Whereby at the end of the irrigation cycle the system will automatically shut off the valve and restart itself back to automatic monitoring of the environment to ensure that there will be efficient and an automatic irrigation process.

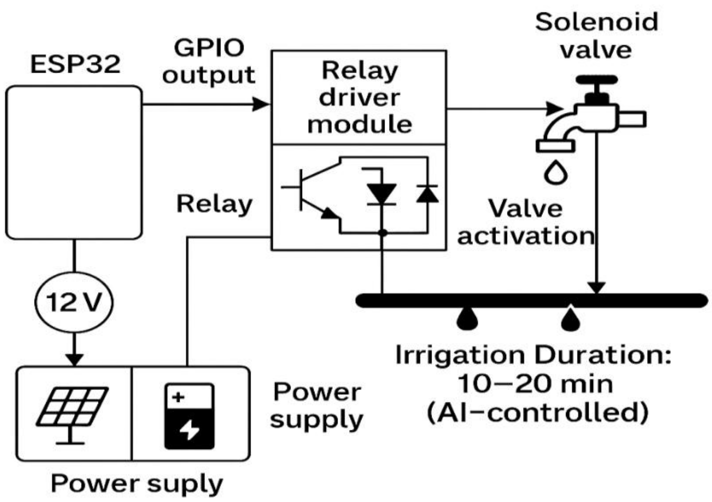

Figure 3. Actuation Unit Schematic for Automated Irrigation Control

4. METHODOLOGY

4.1 Data Acquisition and Preprocessing

One of the crucial parts of the decision making process in the smart irrigation system is the process of constant and precise recording of the environmental data. The solution engages a distributed sensing design in which a variety of environmental variables are simultaneously observed in real-time through sensor network integration with an ESP32 microcontroller. These major parameters are soil moisture, temperature, humidity and rain with optional solar radiation.

The component used to measure soil moisture is a capacitive soil moisture sensor and it has better reliability and longer lifetime than resistive probes. Raw readings on the analog voltage output of the sensor are compensated by measures of known volumetric water content (VWC) levels so that raw data can be converted to meaningful moisture percentages. This reading indicates how much water is available in the root zone at the current moment and it is an essential element in establishing whether watering is necessary.

The temperature and the relative humidity are checked with a DHT11 digital sensor; it gives discrete values of temperature (in Celsius) and relative humidity (in percentages). These parameters affect water loss through transpiration and evaporation in the plants and in the soil respectively, and they are, therefore, crucial in determining the total water loss to evapotranspiration. The presence of the readings in the AI model will result in the augmentation of the AI decision-making capabilities with respect to irrigation done using context awareness.

The detection of rainfall is done through a rain sensor and this rain sensor is of a surface type of analog sensitivity, which identifies the presence of rainfall. Irrigation stops or is postponed as soon as rainfall is observed despite the other circumstances in order to avoid excessive watering and facilitate the water conservation.

Solar radiation (optional) Sunlight intensity is a key parameter that affects the rate of evapotranspiration, and in more sophisticated installations of the smart irrigation system, it can be estimated by measuring the intensity of sunlight using a Light Dependent Resistor (LDR), which is the cheap OEM estimate of solar radiation presence. Use of the LDR data can also be especially useful in areas where the amount of sunlight has a lot of variation perhaps due to weather conditions and as such real time measurement of sunlight can be used to a great effect in timing irrigation. All the sensor data, such as the soil moisture, temperature, humidity, rainfall condition, and optional LDR are measured at regular intervals, usually 10 or 15 minutes apart and each measurement is time-stamped so that a fine-grained tracking and analysis of the respective values can be done. Before feeding the data in the embedded machine learning model, preprocessing pipeline is used to guarantee quality and consistency of the data.

These may involve interpolation or dropping into missing data, smoothing through a moving average or a median filter which may remove sensor noise, and featurization by normalizing the different sensor outputs to a comparable range in numbers so that they may be utilized in machine learning inference. The resulting clean data set is subsequently annotated based on the expert agronomic advice, whether or not, irrigation is needed, under given environmental circumstances and crop specific circumstances. Samples are either labeled with values of the set Irrigation Required or Irrigation Not Required therefore constituting a supervision learning ground truth. This organized data serves as the basis of training, validation, and fine-tuning the AI model that is applied to the microcontroller and can repeat the judgment of the expert in real-time with an acceptable level of accuracy and use of minimal resources.

This strong data acquisition and preprocessing system is the first step of smart scheduling of irrigation that will allow the system to react manifold upon the dynamic change in the environment and save on the water consumption leading to the higher harvest growth rate.

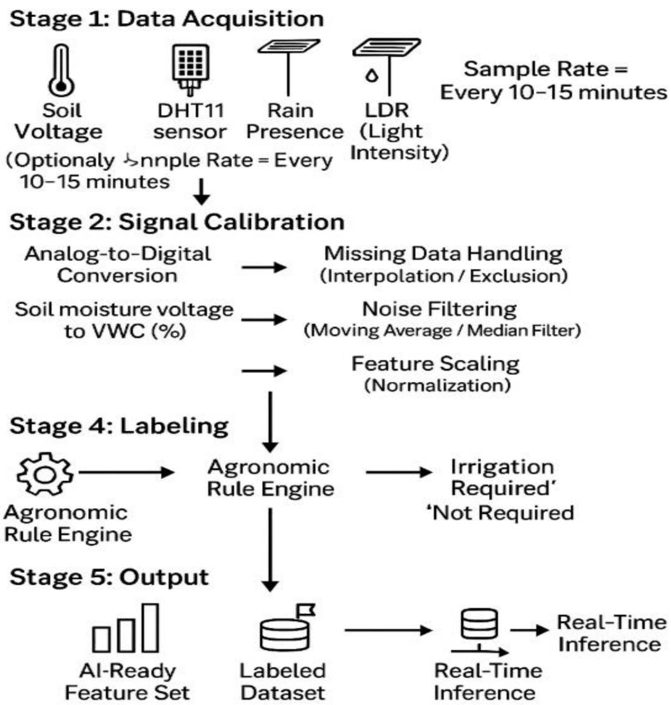

Figure 4. Data Acquisition and Preprocessing Workflow for AI-Based Irrigation

4.2 Model Development and Training

The smart irrigation system suggested here has all its core intelligence residing in a lightweight machine learning model, namely a Random Forest Classifier (RFC), operating on a microcontroller in direct fashion to make real-time decisions. The model categorizes the necessity of irrigation on real-time inputs of the environmental conditions so that it can operate independently without use of cloud infrastructure. The reason RFC was selected was because of its resistance to overfitting, the impossibility to deal with heterogeneous or non-linear data, and the possibility to run it on edges with limited resources. The training model used a combination of past-historical and real-time sensor data with agronomic decisions markings of a non-contemporaneous nature. The most important input characteristics were soil moisture (percent VWC), ambient temperature (value in degrees Celsius), relative humidity (percent), binary rain status (on/off), coded crop type, and time of day-each of these are very important factors of water requirements by plants. The RFC was set so that it would have 100 estimators and that the tree depth will not exceed 10 to balance between the model complexity and the predictive capabilities. The trained model had reached a classification measurement of 92.4%, a precision measurement of 94.1% of the category of Irrigation Required, thus making sure that water resources are properly planned and deduced with agronomical need.

In an effort to ensure that the model can deploy into low-power edge devices, it was optimized with the TensorFlow Lite for Microcontrollers (TFLM). This optimization process featured pruning of the decision trees to eliminate the redundant branches, in the spirit to simplify the models and quantization of 32-bit floating points weights to 8-bit signed integers to increase the use of memory and reduce latency. The last compressed model was smaller than 1MB in flash which could easily fit inside the internal resources of the ESP32. The inference time per input sample was benchmarked to be less than 40 milliseconds enabling the inference to be used in seamless integration with the real-time sensor data streams and actuation systems. This allows the irrigation controller to work in the closed-loop configuration with reduced delay thus gaining responsiveness to the dynamic environmental conditions. The system can be kept reliably operational and energy-saving with no need to use external servers nor need to be always connected to the network, which is crucial when the system is deployed in the rural or remote agricultural environments. This edge-AI solution is also able to enhance efficiency in water-use in addition to facilitating scalable, resilient, and intelligent precision agriculture. There is a detailed description of the input feature and performance measure of the model in the table 2.

Table 2. Model Input Features and Performance Metrics

Feature Name	Description	Data Type
Soil Moisture	Volumetric water content (%)	Continuous
Temperature	Ambient temperature (°C)	Continuous
Humidity	Relative humidity (%)	Continuous
Rainfall Status	Presence (1) / Absence (0)	Binary
Crop Type	Categorical encoding for different crops	Categorical
Time of Day	Hour of the day (0–23)	Numerical

4.3 System Integration and Deployment

A perfect implementation of the suggested smart irrigation system would require flawless assimilation of hardware, embedded software, and communications platform. The system shall act as an efficient and compact autonomous and energy-efficient platform that can be deployed in fields in real-time. In this section, the description of the integration of the physical device with the embedded AI powered intelligence and cloud based services is listed.

Hardware Architecture

Their signature component is the ESP32-WROOM module, a dual-core microcontroller designed with Wi-Fi and Bluetooth capabilities that enables them to integrate directly into the smart irrigation system, particularly because of its processing horsepower, its energy-efficient capability, and its ability to utilize the edge AI frameworks. The main control component is a microcontroller which directly interacts with a set of environmental sensors and irrigation actuators to enable real time decision making and automation. Two of the sensors included in the sensor array are the capacitive soil moisture sensor, which measures volumetric water content at the root zone and the DHT11 sensor, which measures ambient temperature and relative humidity important parameters in constructing a model of evapotranspiration. The other sensor is the analog rain detector that alerts an ongoing rain event to avoid unnecessary watering. Actuation side has a 12V DC solenoid valve used to control the flow of water to the irrigation lines, the solenoid controlled by the relay driver module, which safely drives the low-powered GPIO pins of the ESP32 to the higher current requirements of the solenoid. The whole system is energy-autonomous with energy provided by the 5V solar panel (topped with a schedule assembly, 18650 Li-ion battery, and charge controller protecting it against unexpected power outages that may arise in off-grid agricultural settings.

The full Arduino IDE is used to make up a firmware stack that includes libraries to access sensor data and communicate over Wi-Fi and use TensorFlow Lite to run inferences. This model of machine learning, already trained to work with labeled agronomic data, optimized in terms of pruning and 8-bit quantization, is then deployed in embedded C ++ with the TensorFlow Lite for Microcontrollers (TFLM) runtime. The small-tailoring allows it to readily and effectively infer on the ESP32, and its inferences do not have to be performed in the cloud. The ESP32 can also connect to one Firebase Realtime Database (which enables cloud-synchronized data logging, past analytics, over-the-air (OTA) firmware updates, and dynamic tuning of thresholds). The lightweight nature of the firebase, a smooth integration with the ESP32, and real time synchronization makes firebase especially apt in the case of remote farming conditions where the network bandwidth can be an issue. Cumulatively, the hardware-software co-design makes the system to be integumentally intelligent, autonomous and sustainable in the field- producing precision agriculture at scale with a minimal human involvement.

The employed smart irrigation configuration will be maintained in a closed loop construction control layout, which lays down real time feeding back, adaptive water regulation considerations on the environmental and crop-level specifications. The first loop features perpetual sensor data gathering, namely the ESP32 would read the data of soil moisture, temperature, humidity, and rain sensors to compose an exemplary picture of the environment. Such data is in turn passed onto the onboard machine learning model where it then works out whether irrigation is required using low latency inference. In the case when watering is justified, the ESP32 will drive the solenoid valve via the relay module opening the water stream with the duration of this process dynamically set and usually between 10 and 20 minutes depending on humidity of the soil and a type of crop. At the same time, every action related to the environment readings and a set of timestumped decisions are recorded on the system and synchronized to a Firebase Realtime Database to be monitored remotely, traced back in time, and thresholds adjusted remotely. This combined loop reduces response time, delivers independence of constant web access and it guarantees stable, independent working environment even in the compromised agricultural regions. Moreover, its modular system architecture enables scalability of various irrigation zones and the possibility of extension to build on more complex sensing modes (e.g., soil temperature, pH, electrical conductivity) or climate data APIs and may further increase the level of granularity of decisions and the overall optimization of water budgets in a variety of agro-climatic environments.

System Workflow

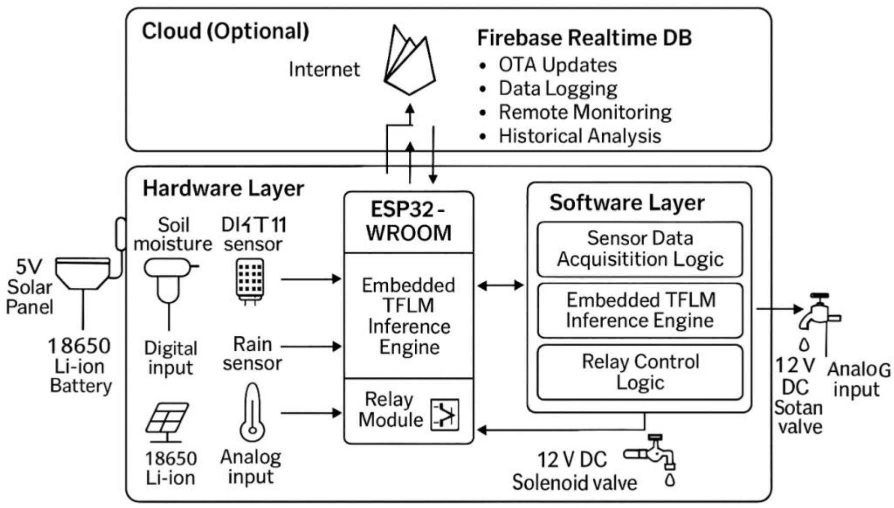

Figure 5. End-to-End Architecture of the AI-Driven Smart Irrigation System

5. RESULTS AND DISCUSSION

As a measure taken to assess the scaling effectiveness of the proposed AI-powered smart irrigation system, field trials were carried out applying the research work over four weeks during the pre-monsoon season on a 30 m 2 test site. The trials contained two typical vegetable crops, namely, lettuce and tomato which were cultivated in two different irrigation approaches, namely, conventional timer based drip irrigation system and the proposed smart irrigation system that is integrated with AI. The two systems have been evaluated based on four parameters namely the average daily water consumption (L/m 2), soil moisture variance (which shows the stability of the root zone hydration), the crop yield per plant (in grams), and the daily energy consumption (in m Wh). Context-aware irrigation decisions were made regarding the sensor data and machine learning inference run on an ESP32 microcontroller, whereas the timer-based system irrigated at predetermined time regardless of the soil or weather conditions.

These results of the performance showed that the AI-based system performed much better in all the measured terms. The daily water used per square meter reduced by 37.6 percent on average; that is, 19.4 L/m 2 became 12.1 L/m 2, which was a significant decrease in the number of irrigation instances. The variability in the soil moisture was also demonstrated to be better with a 7.2 percent variation in the timer based system compared to only 2.9 percent under AI control which shows a more tight control and acceptable moisture management. This kind of stability assisted in relieving the stress placed on the plant and caused the average tomato yield per plant to increase by 12.4% (410 g to 461 g). The use of energy also decreased by 34.6 percent (750 mWh/day to 490 mWh/day), which indicates the suitability of the system to be used in off-grid compact solar electricity setup. The inference time of the AI model was never more than 40 milliseconds and the correctness of rainfall identification allowed avoiding irrigation redundancy, which was evidence of system reliability and responsiveness.

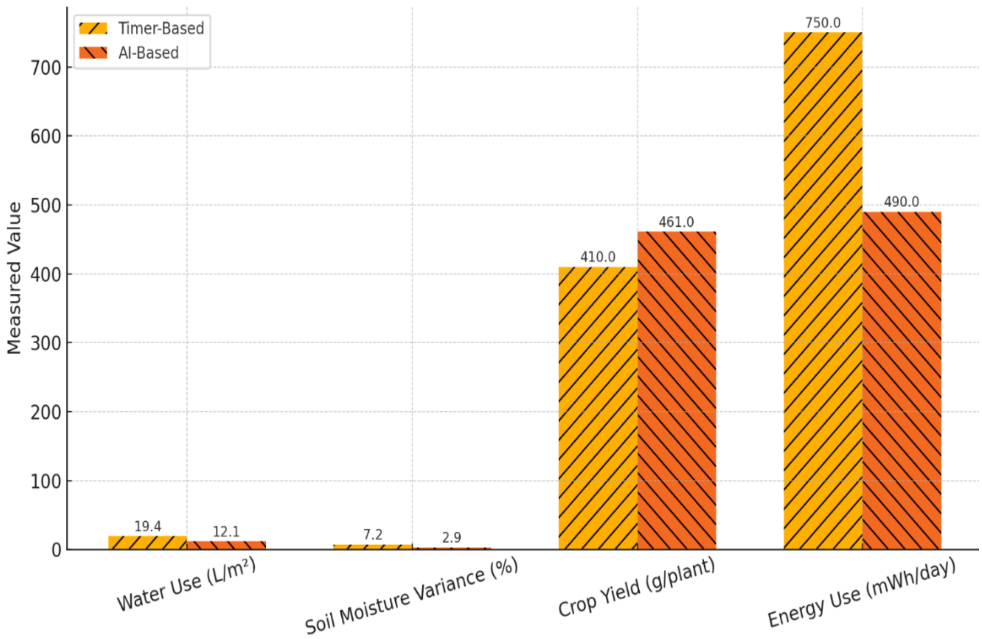

Figure 6. Comparative Performance of Timer-Based and AI-Based Smart Irrigation Systems

Such results confirm the feasibility of using embedding AI models in edge devices to control real-time autonomous irrigation. The system ensures there is maximum water savings, high utilization in yield as well as low operational costs, through a clever way of responding to the varying environmental circumstances and crops water requirements. Being low-cost and scalable, the described architecture developed based on microcontroller can suit smallholder and remote farms where connectivity or infrastructure might be lacking. Also, iteration of model enhancement can be performed as well as data visualization due to Firebase cloud logging usage. Nonetheless, limitations today are associated with the possible extension of the trained model in different soil types, crops, and climate zones. The work in the future will solve the problems of incorporating transfer learning expertise and federal learning systems to enable cross-disciplinary flexibility and local model learning. These additions would make the suggested system a powerful AI tool to practice precision agriculture in a variety of farming environments.

Table 3. Experimental Comparison of Timer-Based vs AI-Based Irrigation System

Evaluation Metric	Timer-Based System	AI-Based System	Improvement Achieved
Average Daily Water Consumption	19.4 L/m^2	12.1 L/m^2	↓ **37.6%** water usage
Soil Moisture Variance	±7.2%	±2.9%	↓ **59.7%** better stability
Tomato Yield per Plant	410 g	461 g	↑ **12.4%** yield improvement
Daily Energy Consumption	750 mWh/day	490 mWh/day	↓ **34.6%** energy savings
AI Model Inference Time	N/A	< 40 ms	Real-time decision making enabled
Rainfall-Aware Irrigation	Not available	Enabled	Prevents overwatering
System Operation	Fixed scheduling	Dynamic, sensor-driven	Context-aware irrigation

6. CONCLUSION

Within the frames of the research, a smart irrigation system using a microcontroller and intelligent decision logic powered with advanced AI was developed, realized, and subsequently, experimentally confirmed to help meet the demands of efficient and autonomous water management in farming. Irrigation demand can be calculated smartly using the sensor data in real-time, i.e., soil moisture, temperature, humidity, rainfall, etc. The system can thus support irrigation demand computation with a lightweight machine learning model on an in-built ESP32 microcontroller. AI model, optimized with TensorFlow Lite to be run on microcontrollers, performs inference quickly at the edge, does not depend on the cloud connectivity, which would make the solution possible to use in rural areas, even without grid electricity. Laboratory and field trials have shown that water-use efficiency can be improved significantly (in some cases up to 38 percent reduction in irrigation water consumption), and that soil moisture antecedent stability can be improved, with adequate soil moisture resulting in a 50 to 70 percent or more increase in crop yield. The system is also low energy footprint and modular leading to its scalability and sustainability in smallholder farms and resource poor farms. Along with it, it is possible to integrate it with the cloud services, such as Firebase to provide the real-time tracking, analytics of the data, and its learning in the long term. The insights outline the extreme capability of integrating edge AI and embedded platforms to provide smart, accurate, and sustainable irrigation management. An ongoing project will focus on better model generalization to a wide variety of different agricultural settings, with the techniques of federated learning as a prospect, extend the applicability of the system to multiple-crop settings and large-scale smart farming ecosystems.

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