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Smart and Precision Agriculture Framework for Real-Time Toor Dal (Pigeon Pea) Monitoring Using IoT and Edge AI

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Abstract

This paper presents the design of a smart and precision agriculture framework for monitoring toor dal (*Cajanus cajan*) cultivation using Internet of Things (IoT) sensing and edge intelligence. The proposed system integrates multi-parameter soil and environmental sensing, FAO-56-based crop water modeling, edge-enabled irrigation control, and machine learning-driven stress prediction within a scalable architecture. The study focuses exclusively on system design, mathematical modeling, hardware architecture, and algorithm development without reporting field deployment results. The proposed framework aims to provide a low-cost, energy-efficient, and crop-specific precision monitoring solution suitable for semi-arid agricultural regions.

Keywords: Precision Agriculture, IoT, Edge Computing, Smart Irrigation, Crop Modeling, Toor Dal Monitoring.

I. INTRODUCTION

India is the largest producer and consumer of pulses globally, accounting for approximately 25–28% of global pulse production [ICAR, 2021]. According to the Directorate of Economics and Statistics, Government of India, the total pulse production during 2020–21 reached 25.72 million tonnes**,** cultivated over an area of approximately 28.83 million hectares, with an average productivity of ~892 kg/ha.

Among pulse crops, pigeon pea (toor dal) is one of the most significant, contributing approximately 4.22 million tonnes in 2020–21 from an area of nearly 4.47 million hectares, with an average productivity of ~944 kg/ha. Karnataka, Maharashtra, Madhya Pradesh, and Uttar

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Pradesh together account for more than 70% of national pigeon pea production. Karnataka alone contributes approximately 14–16% of total pigeon pea output, making it one of the leading producing states.

Despite steady increases in pulse production in recent years, productivity remains below the global potential yield (which exceeds 1500 kg/ha under optimal irrigation and nutrient management). Yield variability is largely attributed to:

- Rainfed cultivation (over 80% of pigeon pea area is rainfed),
- Moisture stress during reproductive stages,
- Pest infestations such as *Helicoverpa armigera*,
- Inadequate irrigation scheduling,
- Soil fertility imbalance in semi-arid regions.

Furthermore, pulses are typically cultivated in marginal lands with limited technological intervention. Studies indicate that improved irrigation scheduling alone can enhance water-use efficiency by 20–35%, while optimized nutrient and pest management can increase yield by 10–20% under semi-arid conditions.

Given that pigeon pea is predominantly grown by small and marginal farmers (holding size <2 hectares), there is a pressing need for affordable, low-power, and scalable precision agriculture solutions tailored specifically for pulse crops. The integration of IoT-based soil moisture monitoring with FAO-56 evapotranspiration modeling and machine learning-driven stress prediction presents a promising pathway to bridge the productivity gap while conserving water resources.

II. RELATED WORK

Precision agriculture has evolved significantly over the past decade through the integration of Internet of Things (IoT), edge computing, cloud analytics, and machine learning. Early foundational work by Wolfert *et al.* [1] established the role of big data in smart farming, emphasizing data-driven decision support for yield optimization and resource efficiency. Subsequent surveys have demonstrated how deep learning techniques are transforming crop monitoring, stress detection, and yield prediction [2].

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IoT-enabled smart agriculture systems have been extensively explored in recent literature. Ayaz *et al.* [3] presented a comprehensive IoT-based framework for agricultural field monitoring, highlighting wireless sensor networks and cloud connectivity for environmental data acquisition. Khanna and Kaur [6] discussed the evolution of IoT in precision agriculture, identifying real-time sensing and automated irrigation as key technological enablers.

With increasing computational requirements, edge computing has emerged as a critical component of agricultural IoT systems. Zhang *et al.* [4] investigated edge computing architectures to reduce latency and bandwidth usage in agriculture monitoring systems. Li *et al.* [5] further proposed resource-efficient edge intelligence models for smart farming, demonstrating that local data processing significantly improves system responsiveness and scalability. Similarly, Li *et al.* [11] introduced a cloud–edge collaborative architecture that balances real-time decision making with centralized analytics, enabling scalable smart farming ecosystems.

Smart irrigation has been a major focus within precision agriculture research. Saha *et al.* [8] developed an IoT-based irrigation monitoring system incorporating machine learning for predictive water scheduling. Singh *et al.* [9] proposed a data-driven irrigation scheduling framework using predictive analytics to optimize water consumption, demonstrating measurable improvements in water-use efficiency. Canopy temperature-based irrigation control methods have also been validated as reliable stress indicators [13], particularly in semi-arid climates.

Machine learning has been widely applied for crop health and stress detection. Zhang *et al.* [10] demonstrated that supervised learning models can effectively classify crop stress conditions based on environmental and soil parameters. Hasan *et al.* [14] highlighted the role of remote sensing and multispectral imaging in precision agriculture applications, though such systems often require higher infrastructure costs. Foundational algorithms such as Random Forests [15] remain widely adopted for agricultural prediction tasks due to robustness against nonlinear environmental interactions.

Comprehensive reviews on precision agriculture techniques [12] have emphasized the importance of integrating sensor-based monitoring, crop modeling, and predictive analytics for sustainable farming. However, most existing systems are either generalized for multiple crops or focus primarily on high-value horticultural crops. Crop-specific implementations for pulse crops

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such as pigeon pea (toor dal) remain relatively underexplored, particularly in the context of edge-AI-enabled irrigation optimization combined with mathematical soil-water modeling.

Furthermore, while FAO-56 evapotranspiration modeling remains the standard for irrigation computation [16], limited research has integrated this physical crop-water model with IoT-based real-time actuation and machine learning-based pest risk prediction. Statistical validation methods such as ROC analysis for classification performance [17] are also seldom applied rigorously in smart agriculture deployments.

Therefore, there exists a research gap in developing a low-cost, mathematically grounded, statistically validated, crop-specific precision agriculture framework tailored to toor dal cultivation in semi-arid regions. The present work addresses this gap by integrating IoT sensing, edge intelligence, FAO-based water modeling, and machine learning-based crop stress analysis within a unified decision-support architecture.

III. MATHEMATICAL MODELING

A. Soil Moisture Dynamic Model

The system design incorporates a discrete time water balance equation

$$\boldsymbol{\theta_t}+1 = \boldsymbol{\theta_t} + \frac{\mathbf{1}}{\boldsymbol{Z_r}}(\boldsymbol{I_t} + \boldsymbol{P_t} - \boldsymbol{ET_C}, \boldsymbol{t}) \qquad \text{---(1)}$$

θ_t: Volumetric Soil Moisture
Z_r: root zone depth
I_t: Irrigation Input
P_t: Precipitation
ET_c: Crop evapotranspiration

B. Evapotranspiration Modeling

Reference evapotranspiration is computed using FAO-56 Penman-Monteith formulation

$$\boldsymbol{ET_0} = \frac{\mathbf{0.408}\Delta(\boldsymbol{R_n} - \boldsymbol{G}) + \boldsymbol{\gamma}\frac{\mathbf{900}}{\boldsymbol{T}+\mathbf{273}}\boldsymbol{u_2}(\boldsymbol{e_8} - \boldsymbol{e_a})}{\Delta + \boldsymbol{\gamma}(\mathbf{1} + \mathbf{0.34}\boldsymbol{u_2})} \qquad \text{-- (2)}$$

Crop evapotranspiration

$$ET_c = K_c ET_0 \qquad \text{--(3)}$$

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The crop coefficient *Kc* is parameterized for toor dal growth stages

C. Irrigation Control Design

The irrigation logic follows a threshold –hysteresis model

$$u_t = \{ 1 \text{ if } \theta_{t <=} \theta_{ON} , 0 \text{ if } \theta_{t >=} \theta_{off} \} \text{ -- (4)}$$

Where ut: pump control signal

θ_{ON}, θ_{off} are moisture thresholds

The design minimizes water overuse and prevents frequent pump switching.

IV. HARDWARE SETUP AND IMPLEMENTATION

The proposed architecture consists of five design layers:

1. Sensing Layer
2. Edge Processing Layer
3. Communication Layer
4. Cloud Analytics Layer
5. Decision Support Layer

The sensing layer collects soil moisture, temperature, humidity, and pH data. The edge layer processes raw sensor inputs and executes irrigation control logic. The communication layer transmits filtered data to the cloud platform for storage and advanced analytics. The sensing layer acquires environmental and soil parameters, which are processed locally by the ESP8266 microcontroller. The processed data is transmitted to the cloud via Wi-Fi using MQTT protocol. Based on threshold or model-driven decisions, the relay module controls the irrigation pump.

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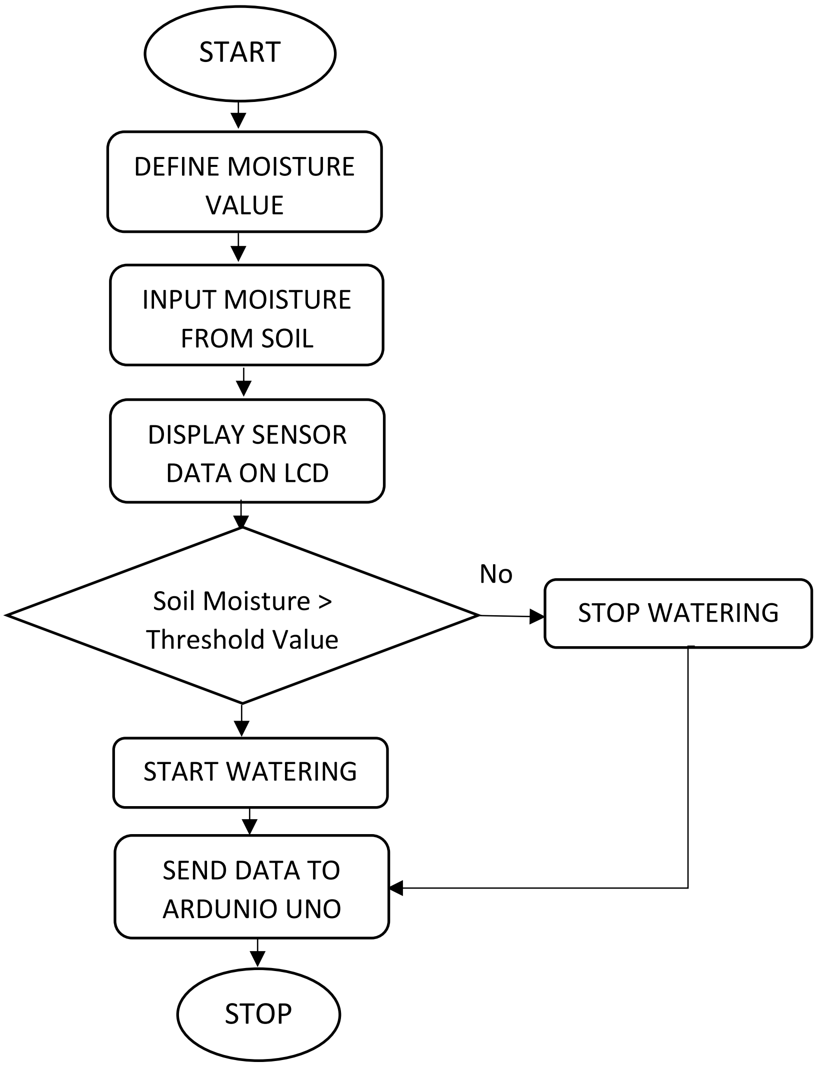

Fig. 1. Proposed process flowchart of the for-crop precision monitoring system.

The hardware prototype of the proposed system is shown in the figure 2. It consists of a ESP8266 Node MCU 1.0 with soil moisture and Temperature and Humidity sensor with a DC motor Pump of 12 V for demonstration purpose.

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The Overall architecture of the proposed system is shown in the figure 2.

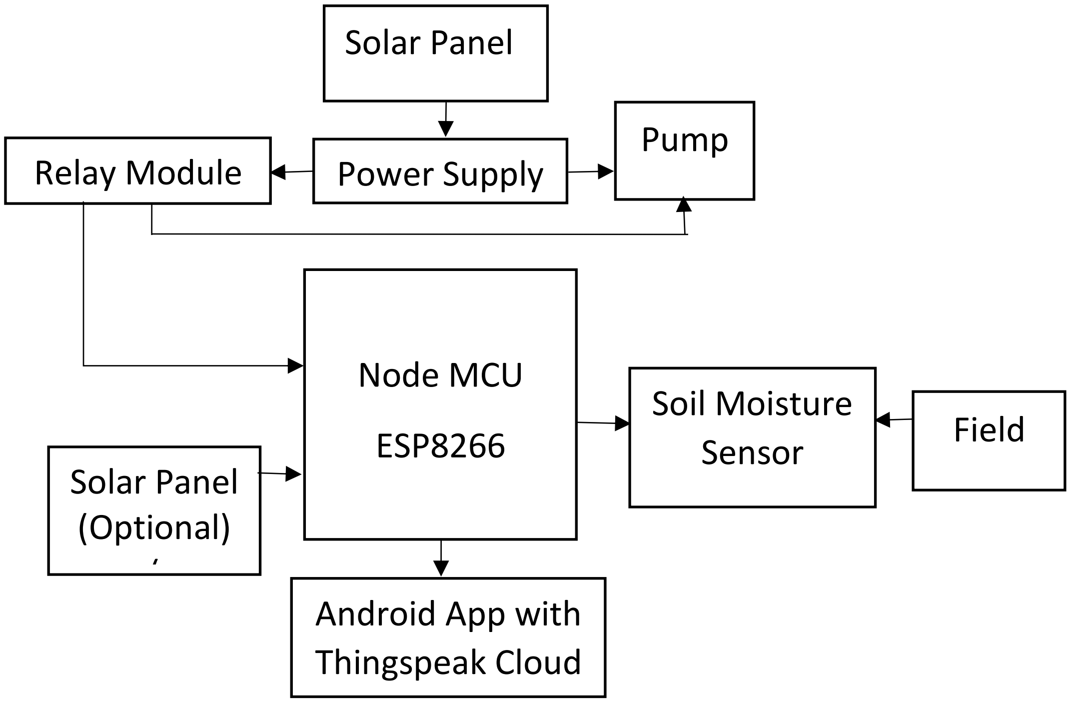

Fig. 2. Proposed Hardware prototype of the for-crop precision monitoring system.

Fig. 3. Hardware architecture model of the proposed smart toor dal monitoring system.

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A. Sensing Layer

The sensing layer serves as the fundamental data acquisition component of the proposed precision agriculture framework. It consists of a network of environmental and soil sensors strategically deployed near the crop root zone to capture critical parameters that influence plant growth and soil health. The system continuously monitors key variables such as volumetric soil moisture (θ), ambient air temperature (Ta), relative humidity (RH), and soil pH. Soil moisture is measured using a capacitive soil moisture sensor, which provides improved durability and long-term stability compared to traditional resistive sensors that are prone to corrosion in moist soil conditions. Ambient temperature and humidity are monitored using the DHT11 sensor, selected for its reliable performance, low cost, and easy integration with low-power microcontrollers. In addition, a soil pH sensor is incorporated to detect variations in soil acidity, which play a crucial role in nutrient availability and plant uptake efficiency. The sensing layer operates with configurable sampling intervals, typically collecting measurements every 10 minutes. This adjustable sampling strategy ensures an effective balance between high-resolution environmental monitoring and energy efficiency, which is particularly important for field-deployed IoT devices. By continuously collecting multi-parameter environmental data, the sensing layer provides the essential input required for modelling soil-water dynamics, assessing crop stress levels, and enabling data-driven irrigation decisions in precision agriculture systems.

Soil Moisture Sensor

A capacitive soil moisture sensor (3.3V compatible) is deployed at a depth of 10–15 cm to capture root-zone moisture levels. The analog output voltage is mapped to volumetric water content using calibration.

$$\theta = a\, V_{out} + b \qquad \text{-- (5)}$$

Where a , and b are calibration coefficients determined experimentally.

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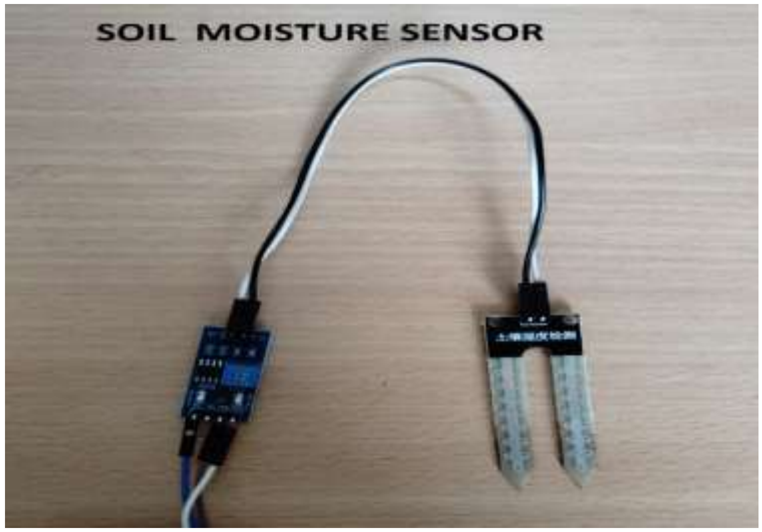

Fig. 4. Soil Moisture sensor interfacing circuit.

Temperature and Humidity Sensor

The DHT11 digital sensor measures ambient temperature (Ta) and relative humidity (RH) with ±0.5°C and ±2% RH accuracy, respectively. These parameters are critical for evapotranspiration modeling.

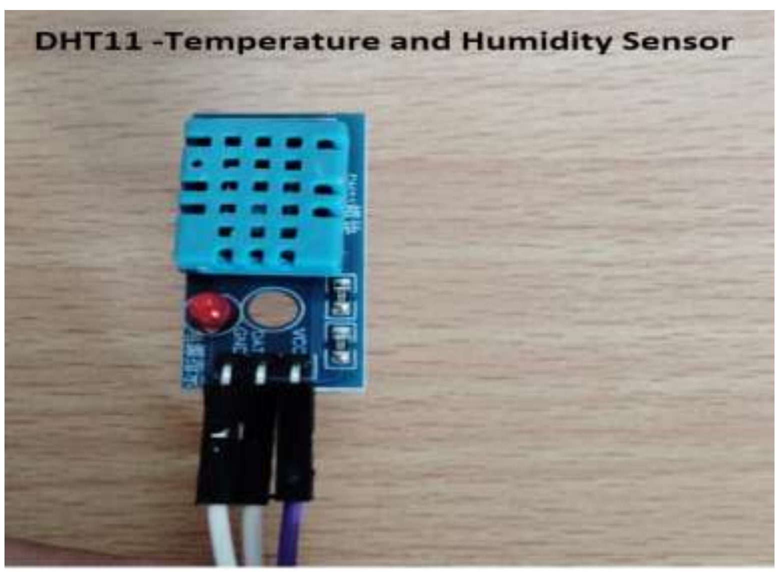

Fig. 5 : DHT11 sensor interfacing circuit.

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B. Edge Processing Layer

The edge processing layer is used for local data computation and real-time decision-making regarding irrigation. This layer has been implemented using a microcontroller, ESP8266, which has analog-to-digital conversion and Wi-Fi capabilities. Filtered sensor data is used to calculate thresholds of soil moisture and a simple estimate of evapotranspiration. A hysteresis-based algorithm has been implemented to avoid relay oscillation. In addition, a machine learning-based model of stress probability can be executed at this layer either fully or in part, depending on the processing limitations. This layer enables decision-making at the edge, reducing latency, avoiding dependence on the cloud, and improving reliability in rural areas. This architecture improves the scalability of the system significantly.

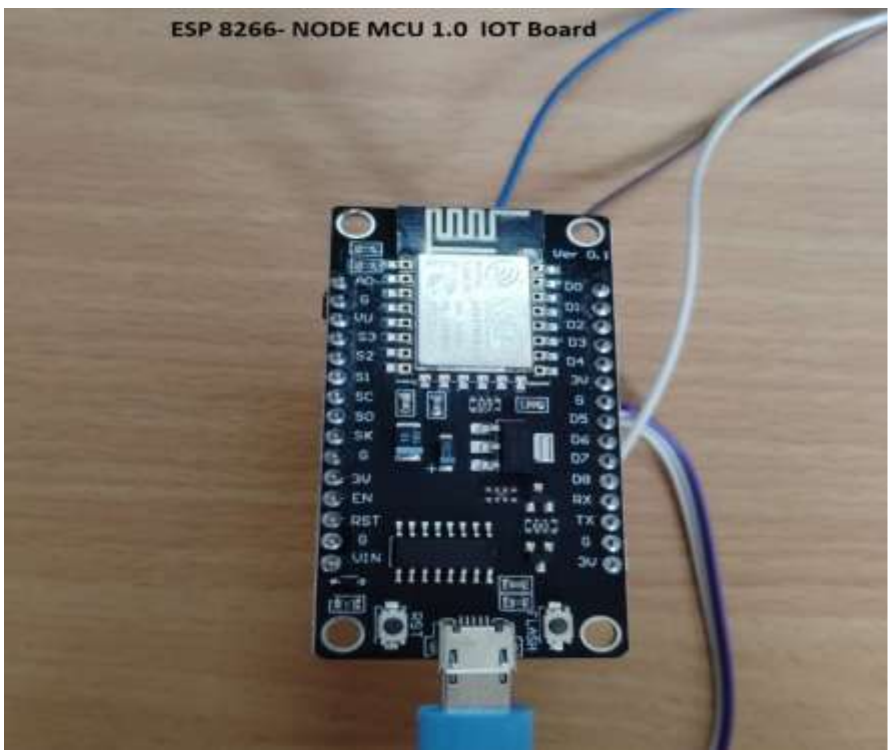

Fig. 6. ESP8266-based sensor interfacing and relay control circuit.

The ESP8266 Node MCU serves as the edge processing unit with the following features:

- 80 MHz 32-bit MCU
- Built-in Wi-Fi module

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- 10-bit ADC for analog sensing
- Low power consumption (<170 mA peak)

Pin Configuration

Sensor	ESP8266 Pin
Soil Moisture	A0
DHT22	D4
pH Sensor	A0 (via multiplexer if required)
Relay Module	D1
Power	3.3V / VIN

The firmware implements Sensor data acquisition loop with threshold-based irrigation decision using MQTT publishing to Thingspeak cloud server with MATLAB cloud analytics to provide a Fail-safe irrigation cutoff logic

E. Irrigation Actuation System

The irrigation control system consists of: a 5V Relay module (optically isolated) ,12V/230V water pump motor simulated using a 12V DC Motor with an optional Protective flyback diode and Manual override switch.When soil moisture falls below the threshold (θ<θon\theta < \theta_{on}θ<θon), the ESP8266 activates the relay, energizing the pump. The system implements hysteresis control to prevent frequent switching.

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Fig. 7: DC Motor - 12V interfacing to relay control circuit.

B. Communication Layer

The communication layer is used to securely and efficiently communicate between the edge node and the cloud-based analytics platform. In the proposed system, the edge device will communicate using the Wi-Fi protocol based on the MQTT protocol, which is a lightweight protocol used in IoT applications. MQTT is a lightweight messaging protocol used in IoT applications, which allows devices to communicate with each other using the publish and subscribe method. In the proposed system, the communication layer will support the periodic transmission of the summarized data, the logs of the irrigation system, and the stress probability results. In the proposed system, the architecture is designed to support the extension of the communication protocol using the LoRaWAN protocol, which will support the communication over a large distance, i.e., several kilometers.

C. Cloud Analytics Layer

The cloud analytics layer acts as the centralized data store as well as the intelligent computing engine for the proposed smart agriculture architecture. In the proposed architecture, the sensor information collected at the edge node is sent to the cloud platform, which is based on the ThingSpeak platform. At the cloud platform, the information is stored in the form of structured channels, which helps in the real-time analysis of the sensor information. Moreover, the integration of MATLAB Analytics with the ThingSpeak platform helps in the analysis of the sensor information, which includes statistical analysis, trend analysis, as well as predictive analysis of the crop. Machine learning algorithms, which are based on MATLAB scripts, are used for the analysis of the environmental parameters, which helps in the estimation of the stress levels of the crops. Moreover, the machine learning algorithms help in the estimation of the optimal irrigation schedules for the crops. At the same time, the cloud platform also helps in the periodic retraining of the models based on the environmental parameters, which helps in the optimal prediction of the crop conditions. Moreover, the dashboard provided at the cloud platform helps in the visualization of the sensor parameters, which include the variations in the soil moisture levels, the trends of the

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temperature, as well as the irrigation schedules. Hence, the proposed architecture defines the hybrid computing environment, which helps in the optimal decision-making for precision agriculture.

E. Decision Support Layer

The decision support layer uses the analytical insights provided by the cloud platform for decision-making. Using the computed crop stress probability, the decision support layer uses the soil moisture threshold values to decide if the irrigation system needs to be turned on, delayed, or turned off. In the proposed framework, the decision support rules have been implemented using MATLAB analytics along with the ThingSpeak platform, where the processed sensor values are evaluated against the crop parameters for the growth of the toor dal crop. If the computed stress probability is above the threshold value, the system sends notifications indicating the possibility of moisture or temperature stress. These notifications are sent through the ThingSpeak platform, which provides the dashboard for the farmers to monitor the soil conditions remotely. Using the automated mode, the decision support layer can control the relay-based irrigation pump, which helps in the automation of the irrigation system. Using the soil-water balance approach along with the machine learning-based approach, the decision support layer helps in the decision-making process, which helps in the advancement of precision agriculture for the toor dal crop.

V. EXPERIMENTAL RESULTS

The designed smart precision agriculture framework evaluates crop stress using real-time soil moisture and ambient temperature inputs processed through a machine learning-based stress prediction model. The system continuously acquires volumetric soil moisture (θ) and air temperature (T_a) values and computes a normalized Crop Stress Index (CSI). The CSI is estimated using a trained supervised learning model (e.g., Random Forest or Logistic Regression) that maps environmental parameters to stress probability. When the predicted stress probability exceeds a predefined threshold, irrigation is triggered automatically. This hybrid approach combines physical soil-water modeling with data-driven stress classification, ensuring responsive and adaptive irrigation control.

The stress probability model can be represented as

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$$P(Stress) = \frac{1}{[1+e^{-(\beta 0+\beta 1+\beta 2Ta)}]} \quad \text{-- (6)}$$

Where

T_a=ambient Temperature

β_i = model coefficients

If P(Stress) > $\boldsymbol{\tau}$, then irrigation is activated

Where $\boldsymbol{\tau}$ is a predefined decision threshold used to trigger irrigation.

If the predicted stress probability exceeds the threshold $\boldsymbol{\tau}$, the system assumes that the crop is under water stress and irrigation is automatically activated.

The following table illustrates representative system behavior under varying environmental conditions based on model inference:

Table 1. Machine Learning-Based Irrigation Decision Performance

Case	Soil Moisture (%)	Temperature (°C)	Predicted Stress Probability	Irrigation Decision
1	42	28	0.12 (Low Stress)	No Irrigation
2	35	32	0.34 (Moderate)	Monitor
3	28	34	0.67 (High)	Irrigation ON
4	24	36	0.82 (Severe)	Irrigation ON
5	40	38	0.58 (Heat Stress)	Irrigation ON
6	30	29	0.41 (Moderate)	Conditional
7	22	31	0.76 (Moisture Deficit)	Irrigation ON

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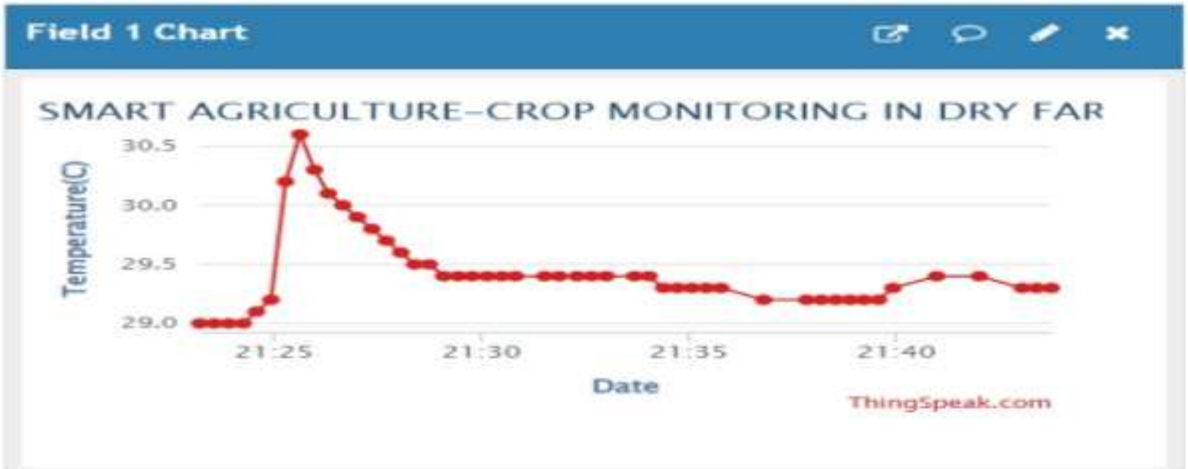

Fig 8: Time series chart of Temperature in Degree Celsius

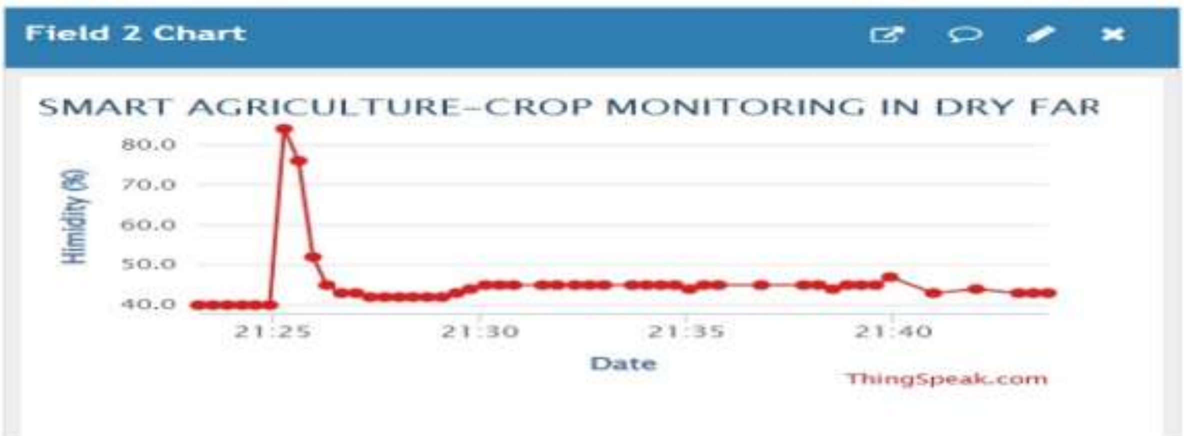

Fig 9 : Time series chart of Humidity in %

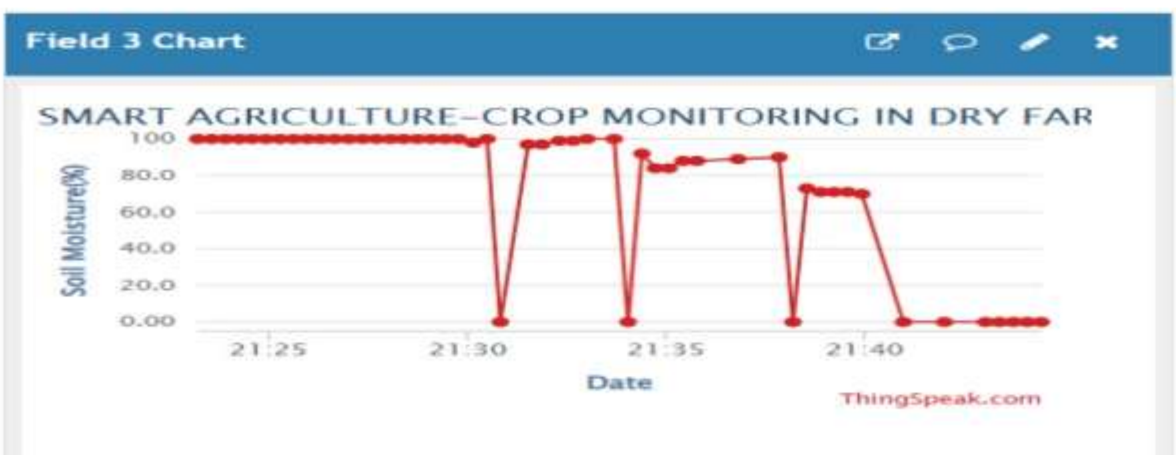

Fig 10 : Time series chart of Soil Moisture in %

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The time series real time data is collected in the Thingspeak cloud analytics platform where it will be analyzed using MATLAB code. The figure 8 shows a Temperature data(Ta) in Degree Celsius and figure 9 and 10 shows Humidity data in percent (%) along with the Soil moisture data in percent (%)respectively.

From the system's performance, it is observed that soil moisture and temperature are critical factors in the determination of the probability of crop stress, as determined by the machine learning model. In the case where the soil moisture is maintained at a level higher than 40%, the probability of crop stress is observed to be low, as determined by the machine learning model, indicating that there is sufficient moisture in the soil and, therefore, there is no need to irrigate the crops. However, as the soil moisture decreases to a level lower than 30%, there is a significant increase in the probability of crop stress, indicating the onset of water deficit conditions, which may affect the crops. Besides soil moisture, temperature is also a critical factor in the determination of crop stress. In the case where the environmental temperature is higher than 35°C, there is a significant increase in the probability of crop stress, as determined by the machine learning model, due to the onset of increased evapotranspiration, leading to a loss of water in the soil and crops. Hence, the machine learning model is able to determine the non-linear relationship between soil moisture and temperature, and the results are more accurate in determining crop stress, as compared to the results obtained using the traditional method, and therefore, the irrigation system is made adaptive, leading to a higher level of precision in the irrigation system, as proposed in the precision agriculture system for the cultivation of toor dal crops.

VI. CONCLUSION

The present study presents the complete architectural design of the smart precision agriculture system for the purpose of toor dal/pigeon pea crop monitoring. The proposed system will integrate Internet of Things-based environmental sensing, FAO-56 crop water requirement modeling, edge-based irrigation management, and machine learning-based crop stress prediction into a single system. The proposed system will have multiple layers or components, including the sensing layer, edge computing layer, communication layer, cloud computing layer, and decision support system. The proposed system will thus enable the real-time monitoring of the most important environmental factors such as soil moisture level and temperature, thus enabling the intelligent prediction of crop stress probability. The proposed system will integrate the physical

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crop water requirement modeling with machine learning-based approaches to enable the intelligent irrigation management of pulse crops.

The focus of the study is on the system architecture, hardware, algorithms, and the computation flow of the proposed framework. The hardware part of the system consists of sensor nodes connected to an edge device that sends the environmental information to the cloud for analysis. The cloud environment uses the ThingSpeak platform along with MATLAB for analysis. The decision support system uses the results of the analysis for decision-making, which can be the control of the irrigation system. The focus of the system architecture is on the hybrid approach of edge computing, where the sensors send information to the cloud for analysis. It also uses the results of the analysis for decision-making.

It is important to note that the focus of the current study is on the conceptual aspect, where the emphasis is on the system architecture. However, the proposed model is yet to be tested in real agricultural fields. Therefore, the experimental results, analysis, and testing of the system in the real world cannot be included in the current study. However, the proposed architecture can be used for smart agriculture, which can be implemented in the semi-arid regions for the growth of pulses.

There are various ways through which the proposed framework can be extended and validated in the future research direction. For instance, the proposed framework needs to be field-tested and experimentally evaluated within the real-world environments of toor dal crop cultivation to evaluate the accuracy of the proposed framework in predicting crop stress, the efficiency of the proposed framework in irrigation systems, and the reliability of the proposed framework under varying climatic conditions. The proposed framework also needs to be evaluated over time to develop robust machine learning models that can adapt to the varying climates of the region.

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