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A Modern Way to Establish Smart Irrigation Using Dense Learning Model in IoT Environment

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ABSTRACT: Lack of water is a major challenge in agriculture to guarantee food supply stability. Smallholder farming communities (SFCs) often hesitate to embrace digital solutions due to high costs, implementation complexities, and faulty sensors. To address this, we developed a low-cost (~USD 260), open-source "Intelligent Irrigation in a Box" IoT framework. The system uses an ESP32 microcontroller with LoRaWAN wireless telemetry, capacitive soil moisture sensors (inserted at 5 cm and 20 cm depths), and DHT22 air temperature/humidity sensors. To ensure sensor reliability, we present a DenseDarkNet-53 deep residual network that identifies time-series abnormalities and reconstructs corrupt sensor readings. The dataset comprises 2,000 hourly time-series samples validated by agronomy experts into balanced normal and anomalous classes. Additionally, a CNN-based model predicts future short-term trends to maintain irrigation schedules. Experimental results yield evaluation accuracies of 95.9% for air temperature, 93.5% for soil moisture, and 97.6% for air humidity, providing a reliable data foundation for smallholder irrigation decisions.

1. INTRODUCTION

By 2050, the global population is projected to grow by nearly 2 billion people, driving a sharp increase in global food demand [1]. Small-scale farming plays a vital role in food security and rural economic stability [2]. However, smallholder farming communities (SFCs) routinely encounter operational and economic barriers that limit their productivity and income potential [3]. Implementing modern strategies to improve irrigation efficiency has often failed to benefit SFCs due to high initial capital expenditures, complex implementations, and fragile sensor hardware [4]. Inspired by previous contributions in low-cost, simple, and reliable agricultural monitoring [5], this work presents an open-source, affordable (~USD 260), and user-friendly IoT monitoring system. Building upon the foundational research of Boursianis et al. [6], our approach focuses on elevating sensor reliability and improving models of water-soil-plant-climate interactions.

Using recent advances in edge computing and deep learning in IoT environments [7, 8], we present a "plug-and-sense" platform that executes the "Intelligent Irrigation in a Box" concept. The physical system integrates an ESP32 edge microcontroller with LoRaWAN wireless modules operating over a 2 km range. The sensing array continuously gathers ambient parameters including air temperature and atmospheric relative humidity via DHT22 sensors, alongside subsurface soil moisture readings via capacitive sensors deployed at dual depths (5 cm and 20 cm). To maintain data integrity against physical node failures or sensor corrosion drift, an unsupervised DenseDarkNet-53 deep residual autoencoder is deployed [9]. The architecture formats 1D sequential metrics using a 24-step sliding window ($W = 24$ time steps) [10] to identify anomalies and replace corrupted time-series segments with reconstructed outputs. Reconstructed sequences feed directly into a Convolutional Neural Network (CNN) prediction model, driving 5V optocoupled relay modules and 12V DC solenoid valves to execute precise irrigation schedules.

A hybrid Fog-IoT-Cloud architecture processes, stores, and analyzes the field data. The main contributions of this paper are:

(i) A low-cost, robust IoT plug-and-sense framework tailored to the financial and technical needs of smallholder farmer communities.

(ii) A DenseDarkNet-53 residual autoencoder model designed to detect environmental sensor anomalies and generate reconstructed time-series outputs.

(iii) Short-term prediction of environmental parameters (soil moisture, air temperature, and humidity) using CNN architectures to guide automated field irrigation.

The remainder of this paper is organized as follows: Section 2 reviews related work in smart irrigation; Section 3 details the proposed DenseDarkNet-53 architecture, hardware setup, and dataset structure; Section 4 presents the experimental results and performance evaluations; and Section 5 concludes the paper with future research directions.

2. RELATED WORKS

Using data processing methods on agricultural data to create a strong foundation for decision support is the subject of some scientific research. Maheswararajah et al. [11] suggested a suitable method for determining crucial factors to plan irrigation: water consumption was tracked, thermal imaging was used to gather data, and irrigation was planned according to the plant's canopy temperature distribution. The thermal imaging cameras have an accuracy of ±2%, and various emissivities and surface reflections make it difficult to estimate temperature precisely. These are just a few disadvantages of employing thermal imaging technology that impacts irrigation scheduling. It can also be challenging to decipher thermal photographs of items with variable temperatures. Paolini et al. [12] designed and assessed a three-step watering method for city parks using unsupervised algorithms. Using a multivariate technique to extract prior information may take less time to examine the complete univariate time series using univariate anomaly detection methods. Bouali et al. [13] suggested a hybrid strategy that uses DL with an IoT-based brilliant irrigation architecture to anticipate soil moisture. The proposed method makes use of sensor data collected from weather forecasts, both past and present, to anticipate soil moisture. To create an effective irrigation schedule, environmental sensing alone is insufficient, and the authors also fail to account for soil texture and crop coefficient. Alharbi et al. [14] offer a new technique integrating learning and term-based weather forecasts to determine when to employ irrigation in paddy rice farming. In southern China, flooding irrigation is a common practice that was likened to the new technique [15].

The outcomes demonstrated the water-saving technique as well as the dependability of the daily rainfall forecast. Mitra et al. [16] talked about the subsystems of the IoT platform, the implemented layered architecture stack, and their primary roles. One of the most creative ways to supply electricity to the IoT modules of the IoT platform has been put into practice. Using a variety of sensors and IoT-related devices, Dahane et al. [17] built an intelligent system. They also created the "Kistan Pakistan" Android app, which enables farmers who are illiterate or have low literacy levels to manage its features remotely. Rayhana et al [18] claim that the "in-the-box" concept of intelligent irrigation can be provided via a low-cost, modern AI/IoT technology for small-scale farming communities. Connected to the IoT gateway is the control component that recommends irrigation as the partner demonstrated offering an "out-of-the-box" capability that does not require an internet connection [19]. Unlike earlier studies, this one accounts for four elements to enhance agricultural production sustainability: productivity, quality, profitability, and irrigation efficiency. The following aspects are specifically considered: (i) the texture of the soil [20], (ii) the crop coefficient [21], (iii) comparing the forecast with the sensed data [22] and (iv) detecting the subsurface parameter [23] like soil moisture in this case. Table 1 depicts the comparative analysis of diverse irrigation methods.

Table 1. Comparative analysis of various approaches

Process	Method	Outcomes
Moisture categorization	Stacked auto-encoder	SVM classifier gives a regular calculation accuracy of 81%
Moisture cataloguing with group representation	Ensemble SVM	The prediction of this ensemble model is: accuracy – 76%, precision – 92% and recall – 87%

Repeated moisture sorting with a learning copy	To enhance the identification and accuracy, use a 3D automated model-based encoder.	The prediction of this classifier model is: accuracy – 85%; precision – 91% and recall – 90%
Combination of statistics and remotely sensed for change calculation	Digital altitude and Digital line diagram	Entirely focuses on change prediction
Deep network model	Fusion of SVM with the deep learning network	Prediction accuracy:SVM – 97% and Deep network model – 97%
Multi-objective hereditary programming	Linear SVM	The natural scene shows a prediction accuracy of 91.5%
The greedy dictionary learning model for soil classification	Deep network model with stacked auto-encoder	The forecast of this fused model is: accuracy – 67% and precision – 81%
Spatial and spectral organization of soil with the deep arrangement model	SVM and PCA	The prediction of this model is: accuracy – 91%, precision – 96% and recall – 87%
Pixel-wise research model for arrangement	PCA, Linear deterioration, and SVM	The calculation of this model is: accuracy – 90%, precision – 89% and recall – 86%
Soybean organization with coupled CNN model	SV with k-NN	This mock-up shows enormous potential for soybean arrangement.

3. PROPOSED MODEL AND SYSTEM ARCHITECTURE

3.1 IoT Hardware Configuration and Field Deployment

To execute the "Intelligent Irrigation in a Box" concept via a low-cost (~USD 260) "plug-and-sense" system, a modular IoT hardware architecture was deployed in the field [6, 8, 15, 17]. The core edge computing unit utilizes an ESP32 microcontroller integrated with long-range (LoRaWAN) wireless communication modules [22], enabling reliable field telemetry to an outdoor gateway over a 2 km coverage radius [9, 14]. The sensing and actuation layout comprises three main sub-components:

- **Soil Moisture Sensing:** Capacitive soil moisture sensors placed vertically at dual depths—5 cm (shallow root zone) and 20 cm (deep root zone)—to capture subsurface moisture dynamics [19, 23].
- **Microclimate Sensing:** DHT22/AM2302 digital temperature and atmospheric humidity sensors housed within solar radiation shields to prevent direct heat distortion [9, 18].
- **Actuation and Power Subsystem:** 5V optocoupled relay channels interfaced with 12V DC solenoid water valves [8, 19]. The entire field unit is powered autonomously by a 12V solar-rechargeable battery module [13, 16].

3.2 Dataset Characteristics and Anomaly Generation Procedures

The experimental dataset consists of 2,000 continuous hourly time-series instances captured across active field deployment periods [10, 12]. To validate the framework, agronomy and technical experts established a balanced validation dataset comprising 1,000 normal operational readings and 1,000 labeled anomalous data points [20]. Anomalies in the dataset represent two distinct operational categories:

1. **Physical Hardware Faults:** Naturally occurring node failures, including zero-value voltage drops, open-circuit states, and continuous baseline drift caused by sensor probe corrosion [9, 11].
2. **Synthetic Field Anomalies:** Artificially injected fault conditions, such as extreme spatiotemporal spikes, out-of-range environmental bounds, and Gaussian sensor noise [20, 21].

3.3 DenseDarkNet-53 Deep Learning Architecture

To process 1D temporal environmental streams (temperature, humidity, and soil moisture), sequential sensor records are formatted into 2D temporal feature representations using a 24-step sliding window ($W = 24$ hours) [10, 20]. DenseDarkNet-53 is configured as a 53-layer deep residual autoencoder network designed to perform feature extraction, anomaly identification, and time-series reconstruction [21, 23].

Unlike conventional deep networks that suffer from gradient divergence in deeper layers, DenseDarkNet-53 incorporates residual connections that add the original input x directly to the mapped output $f(x)$, yielding the final residual mapping:

$$H(x) = f(x) + x$$

When the residual output $f(x) \to 0$, the system converges efficiently, retaining critical temporal features without parameter explosion [21]. The backbone features alternating 1×1 and 3×3 convolutional filters combined with Rectified Linear Unit (ReLU) activation functions. The 1×1 convolutions reduce channel dimensions, significantly lowering parameter complexity and computational load [21]. Figure 1 illustrates the structural block layout of the DenseDarkNet-53 framework [1].

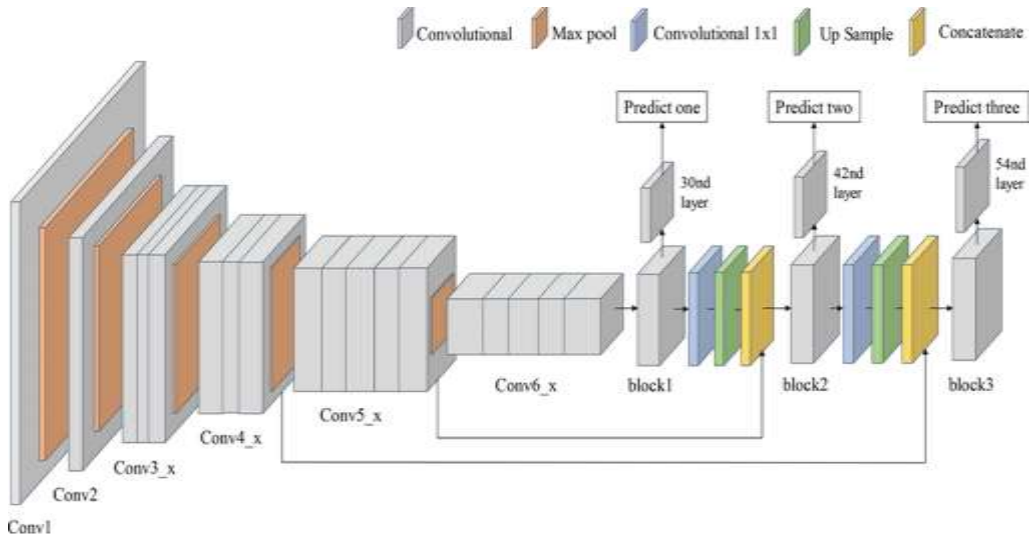

Figure 1. DenseDarkNet architecture

When non-anomalous sensor streams pass through the network, the reconstruction error $f(x)$ approaches zero [21]. Conversely, when corrupted or failing sensor inputs are encountered, the reconstruction error exceeds a pre-set 95^{th} percentile training threshold [10, 20]. The system flags the sequence as an anomaly and replaces the corrupt values with the model's reconstructed time-series outputs, which are then passed to a CNN prediction module to execute automated relay-driven irrigation [8, 10, 23].

4. RESULTS AND DISCUSSION

To choose and assess the best model after learning, agronomy experts classified a collection of 1000 standard and 1000 aberrant samples for a balanced class validation. The evaluation criteria for the models used to find anomalies in air temperature, atmospheric humidity, and soil moisture are listed in Table 2 to Table 5. The measures used to assess the anomaly detection systems are the F1 score, recall, accuracy, and precision.

$$Accuracy = \frac{T_p + T_n}{T_p + f_n + f_p + T_n} \tag{1}$$

$$Precision = \frac{T_p}{T_p + f_p} \tag{2}$$

$$Recall = \frac{T_p}{T_p + f_n} \tag{3}$$

$$F1 - score = 2 * \frac{precision * recall}{precision + recall} \tag{4}$$

$$MSE = \sum_{i=1}^{N} (x_i - y_i)^2 \tag{5}$$

$$MAE = \sum_{i=1}^{N} |x_i - y_i| \tag{6}$$

$$RMSE = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2} \tag{7}$$

(i) Here, TP depicts the unexpected samples percentage correctly classified as assaults. The percentage of standard samples incorrectly classified as abnormal is called False Positives (FP).
(ii) The True Negative (TN) indicates the proportion of correct (typical) incorrect predictions.
(iii) The number of abnormal samples incorrectly labeled as assaults is known as False Negative (FN) or inaccurate detection.
(iv) The percentage of correctly categorized samples in the testing set relative to all other samples is known as accuracy.
(v) Precision shows the proportion of correctly identified samples in the testing set for each TP and FP.
(vi) Recall can be defined as the ratio of TP samples to all TP and FN samples.
(vii) The F1-score depicts the harmonic mean of recall and precision.

Table 2. Performance metrics

Parameters	Column	Metrics			
		Accuracy	Precision	Recall	F1
Soil moisture	1	93	93	94	93
	2	93.5	93.6	93.5	93.5
Air temperature	1	93.2	88.03	100	93.6
	2	95.9	95.6	96.3	95.9
Air humidity	1	97.3	94.9	100	97.4
	2	97.6	95.4	100	97.6

Table 3. Moisture analysis

Parameter	Metrics		
	MSE	RMSE	MAE
Soil moisture	1.2	1.1	0.9
	0.27	0.52	0.48

	1.7	1.3	1.2
	0.87	0.9	0.86

Table 4. Air temperature analysis

Parameter	Metrics		
Soil moisture	MSE	RMSE	MAE
	20.1	4.4	3.4
	17.7	4.2	3.5
	16.2	4.02	3.5
	4.6	2.1	1.6

Table 5. Air humidity analysis

Parameter	Metrics		
Soil moisture	MSE	RMSE	MAE
	200	14.1	10.7
	186	13.6	10.5
	219	14.8	11.5
	217	14.7	11.3

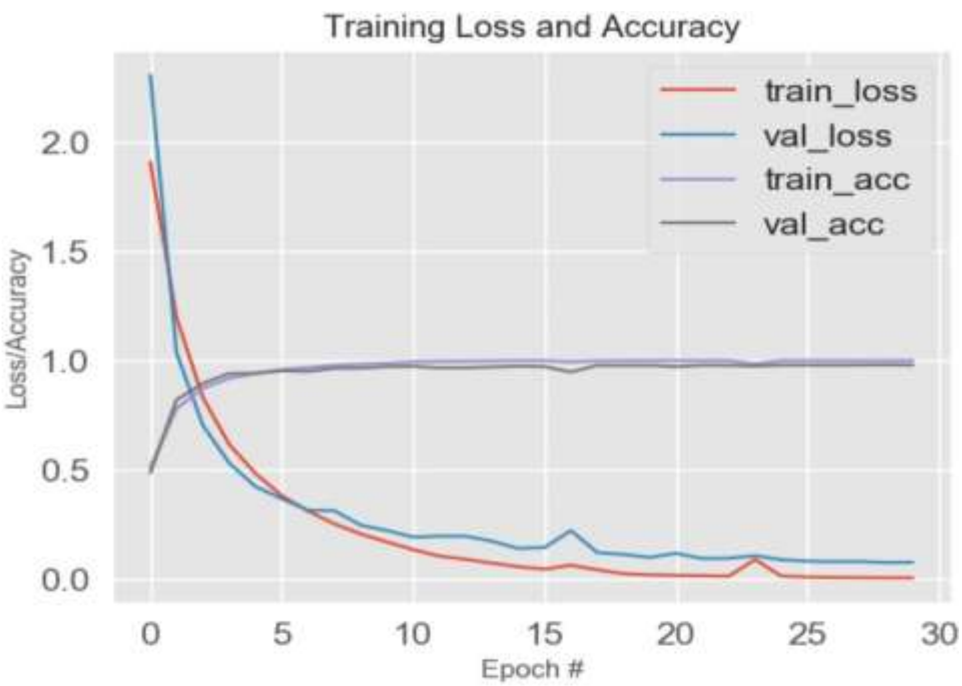

Figure 2. Training and validation performance comparison

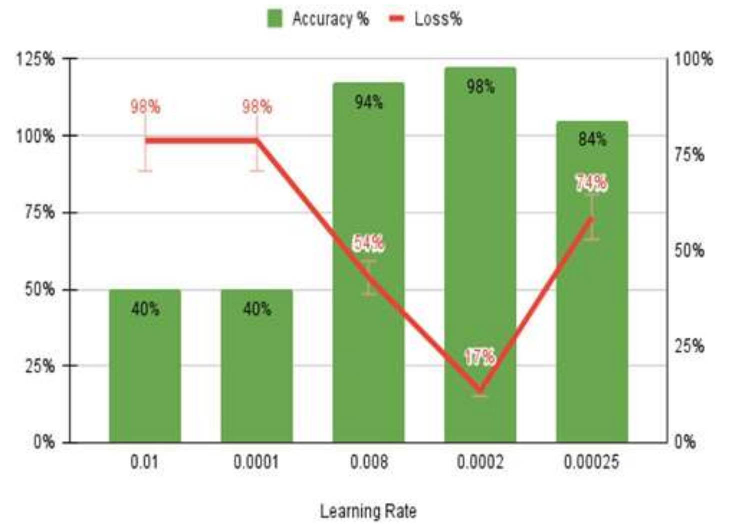

Figure 3. Accuracy based on learning rate

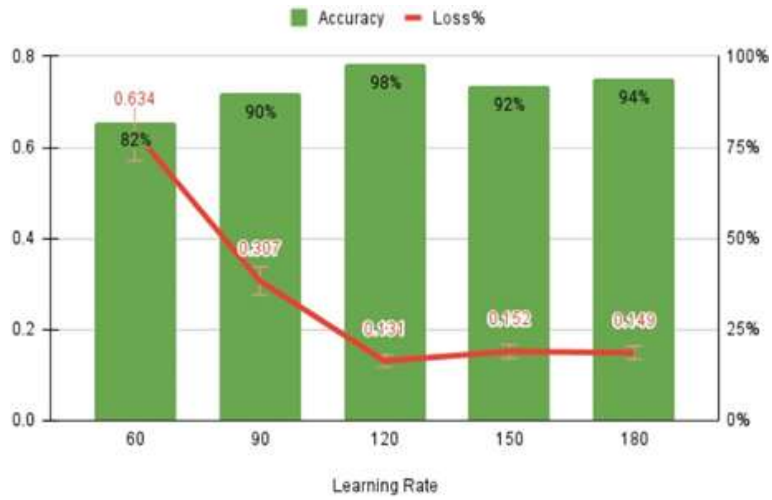

Figure 4. Accuracy and loss comparison

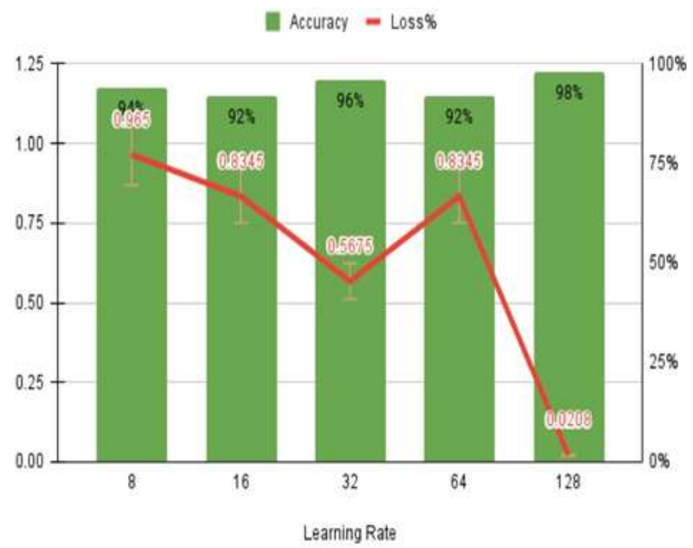

Figure 5. Accuracy based on successive iterations

Figure 6. Confusion matrix

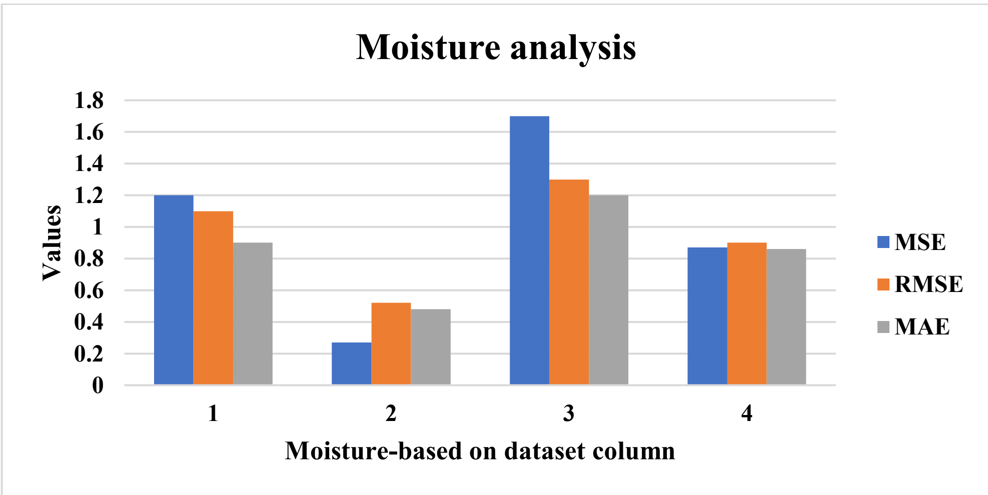

Figure 7. Moisture analysis

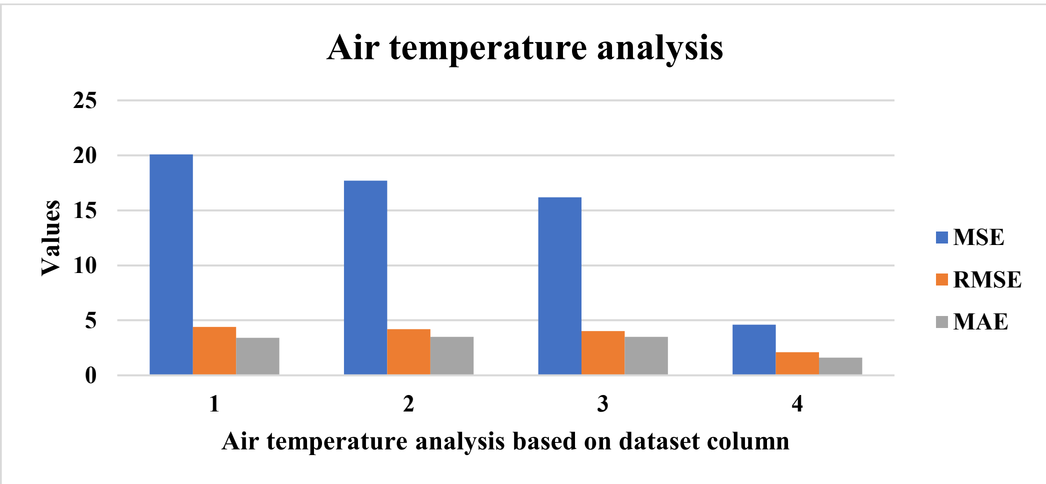

Figure 8. Air temperature analysis

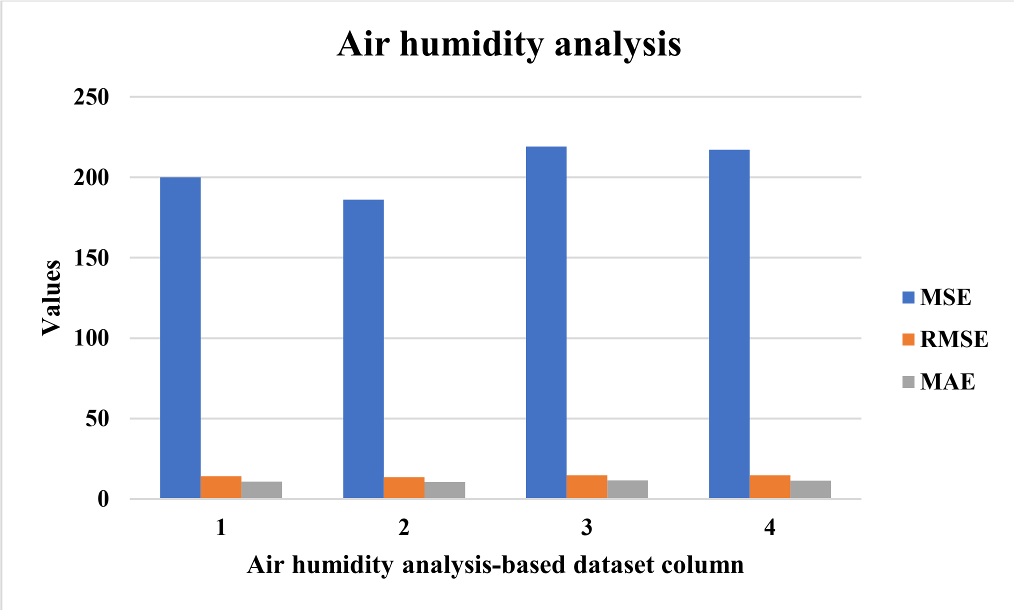

Figure 9. Air humidity analysis

Soil moisture data was used to train a DenseDarkNet model across 2000 epochs. Training would end early for 20 epochs provided the generator and discriminator losses remained modest. For soil moisture, the DenseDarkNet model reached 100 epochs at a depth of 5 cm and 1000 epochs at 20 cm. Furthermore, 100 DenseDarkNet training epochs were carried out at the end of each epoch, with models stored on the hard disk. For models of soil moisture at 5 and 20 cm depths, respectively, the models from epochs 38 and 20 were picked, and the model prior to overfitting was chosen. Table 5 shows that the F1 score varied from 43.40% to 97.60%; in contrast, each model's accuracy varied from 57.10% to 97.60%. Accuracy and F1-score were the highest at 97.60% and 97.60%, respectively, while DenseDarkNet outperformed the other models with F1 and accuracy ratings were 88.88% and 87.50%, respectively. The error conditions were set using the 95% percentile of the training data.

5. CONCLUSION

This study presents a low-cost (~USD 260), open-source IoT smart irrigation platform designed specifically to solve data reliability and water management challenges for smallholder farmer communities (SFCs). By integrating ESP32 edge nodes, capacitive soil moisture sensors, and DHT22 atmospheric sensors, the physical system provides a scalable "plug-and-sense" architecture. To overcome sensor degradations and node failures, a 53-layer DenseDarkNet-53 deep residual autoencoder was developed to detect time-series abnormalities and reconstruct corrupted sensor readings. Evaluating the model across 2,000 expert-validated hourly samples demonstrated high anomaly classification accuracies: 95.9% for air temperature, 93.5% for soil moisture, and 97.6% for air humidity. Reconstructed time-series outputs feed directly into CNN-based prediction models, ensuring continuous, reliable irrigation scheduling even during intermittent hardware faults. Future work will expand this framework in five key directions:(i) Implementing autonomous and remote-controlled sensor calibration techniques to maintain long-term measurement precision; (ii) Integrating a decentralized blockchain security architecture to ensure data integrity, traceability, and secure device control across edge nodes; (iii) Expanding wide-area network deployment using LoRaWAN protocols to optimize power consumption and field coverage for large-holder farms; (iv) Developing a standalone, offline "out-of-the-box" IoT gateway mode that executes local irrigation recommendations without requiring an active internet connection; and (v) Incorporating Federated Learning (FL) to train localized deep learning models collaboratively while safeguarding data privacy across distributed agricultural deployments.

AUTHOR CONTRIBUTIONS

Baskar Muthu: Conceptualization, Investigation, Methodology, Laboratory Analysis, Data Curation, Formal Analysis.

Dr Periyasamy Pitchaipillai: Supervision, Writing—Review & Editing.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ETHICS STATEMENT

Ethical approval was not required for this study.

DATA AVAILABILITY STATEMENT

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

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