

A Solar-Powered AIoT-Based System for Intelligent Soil Monitoring and Automated Irrigation Control

Hardiki Patil

Department of CSE (Data Science)
A.P. Shah Institute of Technology
Thane, Maharashtra, India 400615
hgachrekar@apsit.edu.in

Rajashri Chaudhari

Department of CSE (Data Science)
A.P. Shah Institute of Technology
Thane, Maharashtra, India 400615
rchaudhari@apsit.edu.in

Raj Choudhary

Department of CSE (Data Science)
A.P. Shah Institute of Technology
Thane, Maharashtra, India 400615
rajchoudhary41@apsit.edu.in

Devesh Patil

Department of CSE (Data Science)
A.P. Shah Institute of Technology
Thane, Maharashtra, India 400615
deveshpatil36@apsit.edu.in

Siddesh Patil

Department of CSE (Data Science)
A.P. Shah Institute of Technology
Thane, Maharashtra, India 400615
siddeshpatil29@apsit.edu.in

Varun Lad

Department of CSE (Data Science)
A.P. Shah Institute of Technology
Thane, Maharashtra, India 400615
varunlad40@apsit.edu.in

Abstract— Water irrigation is one of the main challenges in the efficient management of the monsoon season in the Konkan region of India. This is because the existing irrigation systems, whether conventional or IoT-based, have proven to be less efficient as they mostly rely on fixed soil moisture levels and general weather conditions. This paper proposes the development of a solar-powered ESP32 sensor system that will monitor the soil moisture level, temperature, humidity, and pressure. This data will be sent to a cloud server to assist in the automation of the system. In order to improve the efficiency of the system in the face of rainfall unpredictability, different datasets were created by combining the Meteostat atmospheric parameters with the rainfall data from the Indian Meteorological Department. Three machine learning algorithms—Support Vector Regression, LightGBM, and Gated Recurrent Unit—were used to test the rainfall prediction system. It was discovered that the best accuracy was obtained by the SVR algorithm at 92.86%. In the crop detection system, the Convolutional Neural Network was used with the ResNet50 model to achieve a classification accuracy of 99.7%. This system will be used to control the irrigation system through a rule-based decision function that combines the rainfall prediction results and the crop detection results. This system will be very efficient in the management of the monsoon season as it has proven to have very high predictive accuracy as well as the ability to efficiently combine the different environmental and agricultural data.

Index Terms— AIoT, Smart Irrigation, Precision Agriculture, Internet of Things (IoT), Machine Learning, Automated Irrigation, Rainfall Prediction, Crop Identification, Sustainable Farming, Solar Powered Systems.

I. Introduction

Agricultural practices in monsoon-dependent countries such as India's Konkan belt face considerable challenges in dealing with the irregular rainfall patterns, microclimates, and inefficient use of water in the traditional irrigation systems. Conventional irrigation systems are based on manual monitoring and follow a predetermined schedule. This results in over-irrigation and sometimes insufficient irrigation because the systems are based on constant and predetermined parameters and do not take into account changes in weather. Internet of Things-based smart irrigation systems are also in use in many countries. However, the systems are based on constant and predetermined parameters such as soil moisture and weather forecasts.

Machine learning has recently provided the agricultural sector with the power of prediction. However, the majority of the machine learning-based agricultural prediction systems are based on rainfall prediction, crop identification, and irrigation control as separate and independent systems.

This paper attempts to address the existing limitations by proposing a novel region-based AIoT model named Soil-Stream, particularly designed for monsoon-based agricultural systems. The proposed model makes use of real-time environmental monitoring through the ESP32-based solar-powered platform and cloud-based models for rainfall prediction and crop identification. A weather dataset is created based on the combination of the Meteostat dataset and rainfall data from the Indian Meteorological Department (IMD). This improves the accuracy of rainfall prediction in the region. A CNN model is also implemented for crop identification. This model enables the identification of the type of crop and facilitates the implementation of appropriate irrigation strategies accordingly.

The main contributions of this work are as follows:

- Development of a novel rainfall dataset for the Konkan region based on the combination of data from multiple weather sources.
- Implementation and comparison of the performance of SVR, LightGBM, and GRU-based models for rainfall prediction in the Konkan region.
- Implementation of the CNN-based crop identification module.
- Implementation of the unified adaptive AIoT-based model for irrigation systems.

The structure of the rest of the paper is as follows: Section II reviews the related work in the area of smart irrigation and predictive agriculture. Section III presents the proposed system overview, while Section IV discusses the methodology and Section V presents the results and the discussion, and Section VI presents the implementation considerations, conclusions, and the way forward.

II. Related Work

The initial smart irrigation systems mainly focused on using Internet of Things sensors to monitor the environmental factors and automate the irrigation process according to the predefined limits. **Rajalakshmi and Mahalakshmi** [1] designed an Internet of Things-based system that monitored the agricultural fields continuously and automated the irrigation process using the real-time data collected by the sensors. Likewise, **Rawal** [2] presented a system that mainly focused on soil moisture level monitoring and automated the irrigation process by initiating it when the soil dryness exceeded a predefined limit.

Later, the problem of unreliable power supply in rural areas was addressed by using renewable energy sources in Internet of Things-based irrigation systems. Several researchers [3][5] presented smart irrigation system designs using solar power, making the system more environmentally friendly and reducing the dependency on traditional power sources. Though this addressed the problem of unreliable power supply, the system still did not use any intelligent decision-making algorithm, only relying on predefined limits for automated irrigation systems.

The employment of machine learning has provided advanced facilities in irrigation management systems. **Talaviya et al.** [6] investigated artificial intelligence techniques for optimizing irrigation and pesticide use, whereas **Tace et al.** [7] applied ML models to predict water requirements using sensor data. These data-driven systems provided advanced facilities for predictive scheduling and decision-making. However, their performance was highly dependent on the quality of training data, and validation of these systems was performed in laboratory environments. Moreover, these systems lacked proper integration of prediction and actuation systems, which caused isolated system designs.

Recently, researchers have introduced advanced facilities in irrigation management systems by integrating heterogeneous data and control systems. **Balamurali et al.** [8] presented an advanced system by integrating rainfall forecasting with irrigation scheduling systems, whereas **Capcha-Ochoa et al.** [9] applied computer vision to evaluate plant health to improve irrigation management systems. **Kunt** [10] presented a comprehensive decision-making framework by integrating heterogeneous data from different sources. These systems provide advanced facilities in comparison to previous systems but also increase system complexity and require proper network connectivity to function effectively. However, these systems also face issues in adapting to local weather patterns and crop-specific variations.

In conclusion, previous studies have achieved advancements in sensor-based monitoring, the integration of renewable energy sources, and initial applications of artificial intelligence in irrigation scheduling. However, there still lies a gap in the development of a unified system capable of concomitant integration of localized rainfall prediction, automatic crop identification, and adaptive irrigation control in a closed-loop AIoT system for monsoon-dependent regions. This study

attempts to bridge the identified gap through the development of a region-aware multi-factor irrigation management system.

III. System Overview

The suggested system is defined as an AIoT-based framework for irrigation management, which utilizes artificial intelligence and IoT technologies to provide an efficient framework for autonomous real-time management of irrigation systems. The suggested framework comprises four main modules: Hardware Data Acquisition Module, Intelligent Decision-Making Module, Cloud Infrastructure Module, and User Interface Module.

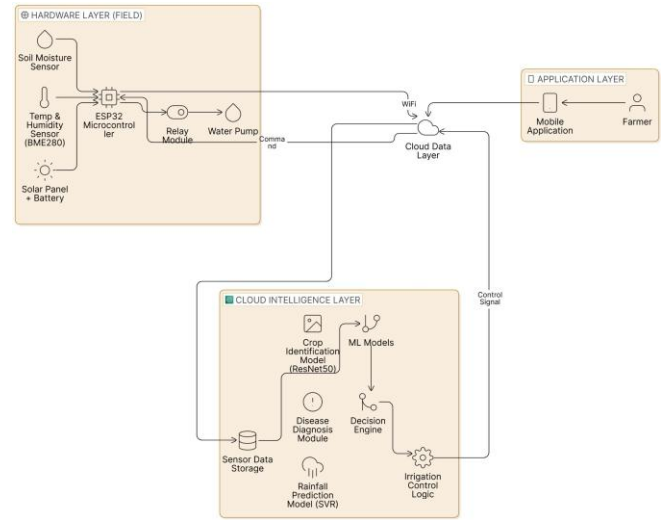


Fig. 1. System Architecture of the Proposed AIoT Smart Irrigation System

A. Hardware Data Acquisition Module

The Hardware Data Acquisition Module is responsible for environmental sensing and actuation in the field. The main component is the ESP32-WROOM-32 microcontroller, which is connected to various sensor devices and irrigation devices. The capacitive soil moisture sensor is used to continuously measure the volumetric content of water in the soil, and the BME280 sensor is used to obtain real-time readings of temperature, humidity, and pressure.

The hardware is designed to be used in an off-grid environment with the help of a 6V solar panel and a TP4056 charge controller and a rechargeable 18650 type Li-ion battery, which ensures the continuation of the system even when sunlight is low. The irrigation is carried out using a 5V relay and a submersible pump.

Sensor data is transmitted to the cloud platform through Wi-Fi networks. Moreover, the ESP32 microcontroller receives control commands from the decision-making layer. This allows the system to have a closed-loop mechanism for automatic irrigation management

B. Intelligent Decision-Making Module

The Decision-Making Module is the computational intelligence of the system, where the sensor data is combined with crop-related data to decide the time and amount of irrigation needed.

The rainfall prediction system utilizes atmospheric data from the Meteostat API and historical rainfall data from the Indian Meteorological Department to predict rainfall probabilities and thus reduce the wastage of water for irrigation.

For crop type identification, a convolutional neural network-based classifier is employed to classify images of crop leaves uploaded through the user interface of the system. Crop type identification is essential for obtaining crop-specific irrigation requirements from the system database.

The plant health evaluation system utilizes the Kindwise computer vision API for pest and disease detection based on images of crop leaves uploaded through the user interface of the system. The results are cross-checked with crop and environmental data to provide precise recommendations for treating the plants.

The irrigation control system combines real-time soil moisture levels, rainfall predictions, crop requirements, and plant health status to determine whether irrigation is needed or can be avoided, thus optimizing crop water requirements and crop health.

C. Data Management and Cloud Infrastructure Module

The Cloud Infrastructure Module, built using Google Firebase, serves as the central repository for data and computational engine for the system. The Realtime Database stores securely all sensor data, crop data, predictions, and system states.

The backend services are performed using Firebase Cloud Functions, which are based on Python and process the incoming data streams, perform predictions for rainfall and crop types, and enforce the decision logic for irrigation control and send control signals to the field hardware.

The AI models are deployed as serverless functions, running on-demand in response to relevant events instead of running continuously as servers. Access control mechanisms are in place to restrict access to only authorized users for system functionalities.

D. User Interface Module

The User Interface Module implements a mobile application developed using React Native, which facilitates real-time visualization of environmental sensor data, system status, and irrigation activity. Additionally, user interaction is enabled by providing the ability to upload crop images for automatic identification and diagnosis of diseases. Manual override options are also implemented for user intervention in irrigation activity, thus providing users with the ability to override when needed. All user interactions are synced to ensure proper operation of the hardware, decision-making, and user interface components.

IV. Methodology

This section details the construction of the crop classification module, the rainfall prediction framework, and the integration of these components within the AIoT-enabled irrigation decision process.

A. Crop Identification Model

The problem of crop identification was framed as a multi-class image classification problem. To make the model invariant to variations in illumination, background, and morphological differences, a comprehensive database of images of various crops was compiled from various publicly available agricultural websites. All images were scaled down to 224×224 pixels and normalized within the range of $[0,1]$. The following methods were used for data augmentation: randomly flip the image horizontally, rotate the image ($\pm 15^\circ$), and adjust the brightness.

1) Evaluation of CNN Architectures

To evaluate the performance of different convolutional neural network architectures, three different models were used.

- VGG16: This model consists of a series of stacked 3×3 convolutional layers followed by fully connected layers. This model was chosen because of its shallow depth, as the stacked convolutional layers make this model suitable for image classification tasks. However, deeper models of this series are prone to vanishing gradient problems.
- ResNet50: This model consists of residual connections, which are effective in handling the problem of vanishing gradients, as information flows through all the residual blocks.
- EfficientNetB0: This model consists of a compound scaling approach, which increases the depth, width, and resolution of the model to make the model more efficient while keeping the number of parameters small.

Each of the models was initialized with pre-trained weights on ImageNet and then fine-tuned on the custom-built model of images of leaves of different crops.

2) Mathematical Formulation

Let I denote the input image. The feature extraction process is represented by:

$$F = f(I) \quad (1)$$

where $f(\cdot)$ denotes the convolutional backbone of the network. The classification layer is defined as:

$$\hat{y} = \text{softmax}(WF + b) \quad (2)$$

where W and b are the learned parameters.

The model was trained using the categorical cross-entropy loss function:

$$L = - \sum_{i=1}^{\Sigma} y_i \log(\hat{y}_i) \quad (3)$$

Performance evaluation metrics included accuracy, precision, recall, and F1-score. Among the tested architectures, ResNet50 demonstrated superior performance on both training and validation data, and was thus selected for deployment.

The output crop label is subsequently utilized to retrieve crop-specific irrigation thresholds and relevant agronomic parameters.

B. Rainfall Prediction Model

Rainfall prediction was defined as a supervised learning problem, using atmospheric parameters as inputs to the model. The feature vector of the inputs to the model consisted of three major meteorological parameters: temperature (T), humidity (H), and atmospheric pressure (P), defined as

$$X = [T, H, P] \quad (4)$$

The aim was to predict the target variable Y, where Y = 0 represents the absence of rainfall and Y = 1 represents the presence of rainfall.

1) Evaluated Models

Three different machine learning models were implemented and tested:

Support Vector Regression (SVR): Support Vector Regression (SVR) determines the best possible decision hyperplane in the kernel-transformed feature space where the margin is maximum and the error is minimum within an ϵ -insensitive loss function. For dealing with nonlinearities in the data, a radial basis function (RBF) kernel was employed. Parameters C and γ were optimized using 5-fold cross-validation on the training data set.

LightGBM: LightGBM is an advanced gradient boosting framework built upon decision trees. It utilizes an ensemble of decision trees to iteratively optimize errors using gradient descent. The leaf-wise splitting of decision trees results in high efficiency and accuracy in handling structured data.

Gated Recurrent Unit (GRU): Gated Recurrent Unit (GRU): Gated recurrent unit (GRU), being one of the recurrent neural network architectures, is very effective in processing sequential information such as weather records over time, whereby prior weather conditions impact the probability of rain. The application of update and reset gates in the process ensures that the model can decide whether or not to retain information from past events.

For all three models, rainfall prediction was defined as

$$\hat{Y} = g(X) \quad (5)$$

where g is the mapping function learned by the model. In addition, the performance of the model was assessed systematically through the application of various performance measures. These include accuracy, precision, recall, and F1-score, as depicted in Tables II and III. It was evident from the comparative analysis that the reliability and prediction

accuracy of the Support Vector Regression model were superior in the two regional datasets. Therefore, the SVR was chosen as the predictive model for the proposed irrigation system.

C. Irrigation Decision Logic

The control mechanism for the irrigation system is based on a rule-based approach and combines real-time sensor data and model-based prediction.

The parameters are set as follows:

- M_s the measured soil moisture content.
- θ_c denotes the crop-specific moisture threshold.
- P_r the forecasted probability of precipitation.
- D the detection status of crop disease presence.

The irrigation system is enabled (i.e., I = 1) if all of the following are true: the soil moisture (M_s) is below the crop threshold (θ_c), the rainfall probability (P_r) is below a certain threshold (α), and there is no disease ($D = 0$). If any of these conditions are false, then the irrigation system is disabled (i.e., I = 0). This means that the system will only apply water when it is needed—i.e., when the soil moisture is too low, when it is unlikely to rain, and when the crop is healthy enough to take advantage of the irrigation. In equation form: I = 1 if ($M_s < \theta_c$) & ($P_r < \alpha$) & ($D = 0$); otherwise I = 0. The precipitation limit α is arbitrarily chosen as 0.6 and represents the point beyond which it can be assumed that there will be enough rain to satisfy the plants' water needs without having to irrigate them.

V. Results and Discussions

TABLE I
COMPARISON OF MODEL PERFORMANCE METRICS

Metrics	VGG16	ResNet50	EfficientNetB0
Accuracy	0.956	0.997	0.1601
Validation Accuracy	0.9404	0.9648	0.9976
Loss	0.2350	0.0139	7826.8145
Validation Loss	0.2206	0.1225	0.0406
Macro Avg. Precision	0.95	0.97	0.05
Macro Avg. Recall	0.95	0.96	0.11
Macro Avg. F1-Score	0.95	0.96	0.05
Weighted Avg. Precision	0.96	0.97	0.06
Weighted Avg. Recall	0.95	0.97	0.16
Weighted Avg. F1-Score	0.95	0.97	0.07

A. Crop Identification Performance

Table I provides a summary of the comparative results obtained by VGG16, ResNet50, and EfficientNetB0 for multi-class crop classification. Among all these models, ResNet50 recorded the maximum test accuracy (0.997) along with the lowest training loss (0.0139). In addition, it recorded a macro F1-score of 0.96 and a weighted F1-score of 0.97 for multi-class crop classification tasks, demonstrating its excellent performance for all crop classes. The similarity in training and validation scores implies that generalization has been effectively achieved by the model without overfitting, which further emphasizes its ability to learn relevant features from the data.

The residual learning strategy adopted by ResNet50 seems to be highly beneficial in recognizing complex leaf texture characteristics as well as morphological changes in different crops.

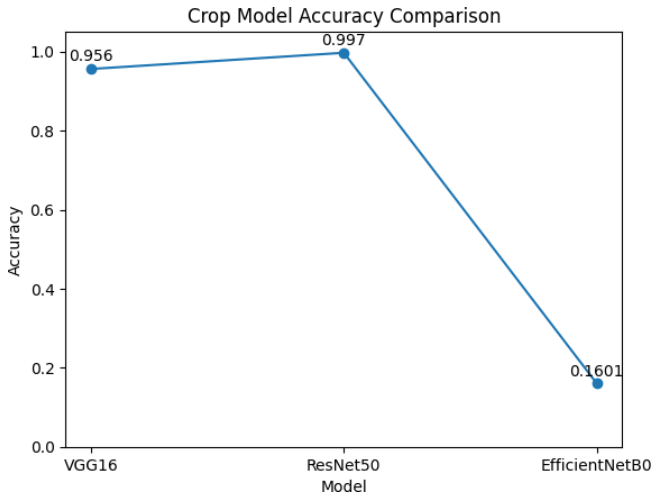


Fig. 2. Comparative accuracy performance for VGG16, ResNet50, and EfficientNetB0 for multi-class crop classification

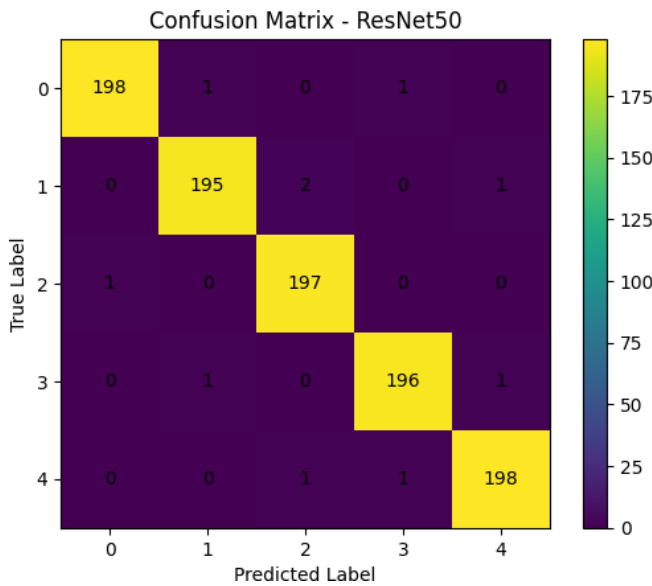


Fig. 3. Confusion matrix of the selected ResNet50 model showing class-wise crop classification performance.

VGG16 also recorded good performance, with a test accuracy of 0.956 and a weighted F1-score of 0.95. Although it did not reach the level of performance recorded by ResNet50, the stability of its metrics across all the evaluation parameters makes it reliable as a deep learning model for the task. On the other hand, EfficientNetB0 recorded low test accuracy and unstable loss curves, which makes it unsuitable for the task due to convergence issues.

Based on these findings, ResNet50 has been chosen as the crop identification model. The accuracy of the crop type is critical to the system since it will directly influence the correct level of irrigation and agronomical parameters that will be recommended.

B. Rainfall Prediction Performance

TABLE II
RAINFALL OCCURRENCE PREDICTION PERFORMANCE ON DATASET-1 (MUMBAI + RATNAGIRI)

Algorithm	Accuracy	Precision	Recall	F1-Score
SVR	0.9286	0.9257	0.8954	0.9103
LightGBM	0.9232	0.9087	0.9007	0.9047
GRU	0.9230	0.9195	0.8873	0.9031

TABLE III
RAINFALL OCCURRENCE PREDICTION PERFORMANCE ON DATASET-2 (MUMBAI + RATNAGIRI + THANE + PUNE)

Algorithm	Accuracy	Precision	Recall	F1-Score
SVR	0.9147	0.9310	0.8725	0.9008
LightGBM	0.9155	0.9232	0.8832	0.9027
GRU	0.9138	0.9166	0.8863	0.9012

For Dataset-1, SVR gave the highest accuracy of 0.9286 and F1-Score of 0.9103, outclassing LightGBM and GRU for all metrics listed here. For Dataset-2, while there was a noticeable dip in performance due to an increase in micro-climatic variance due to stations inland from coastal areas, such as Thane and Pune stations, SVR continued to deliver superior performance for both metrics. While LightGBM delivered a fractionally higher accuracy compared to SVR (0.9155 vs. 0.9147), SVR had higher precision (0.9310 vs. 0.9232). In this case, precision becomes much more important as a false positive prediction of rainfall can lead to unnecessary suppression of irrigation, losing out on the chance for crops to utilize water. For Dataset-2, the minute difference between all algorithms indicates that further improvements will only come from adding additional meteorological features such as wind speed/dew point.

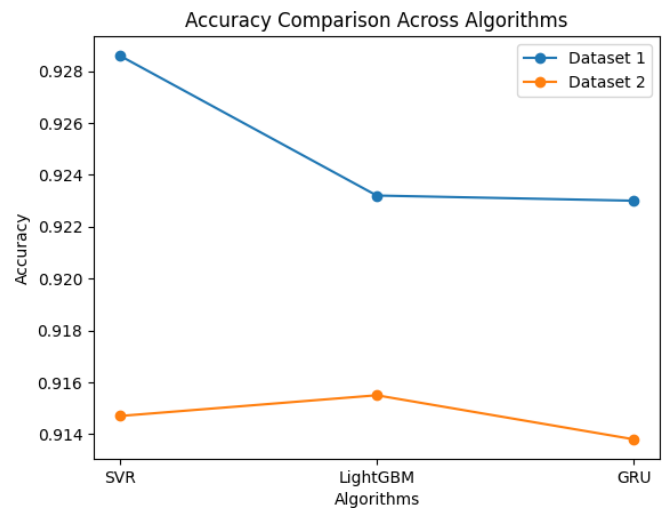


Fig. 4. Comparative rainfall occurrence prediction accuracy of SVR, LightGBM, and GRU across Dataset-1 and Dataset-2.

C. Practical Implications for Irrigation Management

The integration of ResNet50 for crop classification and SVR for rainfall prediction strengthens the reliability of the proposed AIoT-based irrigation management system. Accurate crop identification ensures that moisture thresholds are tailored to the specific water requirements of the identified crop species, preventing both under-irrigation, which causes plant stress, and over-irrigation, which leads to waterlogging and root disease. Furthermore, precise rainfall prediction enables the system to proactively skip irrigation cycles when significant precipitation is anticipated, directly contributing to water conservation.

The conjunctive decision logic requiring simultaneous soil moisture deficit, low rainfall probability, and crop health before triggering irrigation is deliberately conservative. In the Konkan monsoon context, where rainfall is intense but highly irregular, this predictive avoidance behavior prevents waterlogging during heavy rainfall periods while maintaining adequate irrigation during dry spells. Incorporating these models within a rule-based system thus improves both water conservation and dynamic irrigation management, which is critical in environments with variable monsoonal rainfall patterns.

VI. Implementation Considerations

The design and implementation of the proposed AIoT irrigation system were mainly guided by the following factors.

A. Solar-Powered Operation

The system is powered by solar panels and rechargeable batteries, eliminating the need to be connected to the main electricity grid. This design ensures that the system can be used in rural areas with minimal electricity infrastructure. Achieving this level of autonomy is crucial in expanding the usability of the system to such areas.

B. Battery Backup and Operational Continuity

The integration of a battery backup service ensures continuous operation during periods when sunlight is absent. The sensing and communication operations are continuous around the clock, a requirement for a real-time irrigation process as in this work.

C. Rural Usability and Mobile Accessibility

The system has been designed in a manner such that it can be used by users through a mobile application, which can be used by farmers in their fields. Farmers can access environmental information or can manually change the parameters for irrigation as needed through a mobile application. Since more users in rural areas access mobile phones than computers, this approach would make it more usable for users. All these factors contribute to a practical, reliable, and usable system for addressing the operational issues faced by users in a real-world scenario.

CONCLUSION

In this study, a novel AIoT-based irrigation system, which incorporates both crop detection and rainfall prediction, has been introduced as a smart, closed-loop system, particularly suitable for monsoon climate dependent regions. From the experimental results, ResNet50 has been demonstrated to be effective in crop detection, while Support Vector Regression has been shown to provide accurate rainfall prediction results across different local datasets. The incorporation of both models with a rule-based irrigation controller allows the system to optimize irrigation scheduling, avoiding unnecessary irrigation during rainfall, thus enhancing water usage efficiency. The introduced irrigation system is also flexible, as additional regions, crops, and/or climate parameters can be incorporated without any changes to the system's architecture, thus enhancing its suitability for different regions of interest. In addition the system's architecture, which is based on a modular, cloud-oriented approach, allows the system to be extended to a larger regions of the interest as required.

REFERENCES

- [1] **R. Rajalakshmi and P. Mahalakshmi**, "IoT based crop field monitoring and irrigation automation system," in *2016 10th International Conference on Intelligent Systems and Control (ISCO)*, Coimbatore, India, 2016, pp. 1–6.
- [2] **K. Rawal**, "IoT based smart irrigation system," *Int. J. Comput. Appl.*, vol. 159, no. 8, pp. 7–11, 2017.
- [3] **H. S. Rout and P. K. Mishra**, "Solar powered smart irrigation system using IoT," in *2018 2nd International Conference on Inventive Systems and Control (ICISC)*, Coimbatore, India, 2018, pp. 586–590.
- [4] **C. S. Devan, B. T. M. Prathyusha, T. Keerthana, and P. S. B. S. N. Neha**, "A proof-of-concept: IoT based solar-powered smart irrigation system," *J. Phys. Conf. Ser.*, vol. 2054, no. 1, p. 012074, 2021.
- [5] **M. H. Ramli and W. A. Jabbar**, "Portable solar powered IoT-enabled smart irrigation system," *Sustainable Energy Technol. Assess.*, vol. 52, p. 102127, 2022.
- [6] **G. Talaviya, D. Shah, N. Patel, H. Yagnik, and M. Shah**, "Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides," *Artificial Intelligence. Agric.*, vol. 4, pp. 58–73, 2020.
- [7] **A. Tace, E. K. Tace, and M. T. Tace**, "Machine learning based smart irrigation system using IoT," *Procedia Comput. Science.*, vol. 204, pp. 696–703, 2022.
- [8] **S. Balamurali, P. M. S. Kumar, G. U. Devi, and P. S. Venkateswaran**, "A solar-powered IoT-based irrigation system with integrated rainfall forecasts using aerosol data," *Environ. Sci. Pollut. Res.*, 2025.
- [9] **J. M. A. Capcha-Ochoa, D. A. R. O. C. P. G. Ochoa, K. L. M. Flores, and D. A. J. S. Poma**, "Smart irrigation system with IoT, machine learning, and solar power for efficient plant care," *Eng. Sci. J.*, vol. 6, no. 1, pp. 1–13, 2025.
- [10] **A. Kunt**, "IoT and AI-based smart irrigation model," *arXiv preprint arXiv:2506.11835*, 2025.
- [11] **Z. Li, Y. Wang, and H. Chen**, "Federated learning for privacy-preserving smart agriculture: A survey," *Comput. Electron. Agric.*, vol. 218, p. 108627, 2024.
- [12] **P. Kumar, A. Sharma, and R. Singh**, "Edge-AI deployment for real-time irrigation control in resource-constrained IoT environments," *IEEE Internet Things J.*, vol. 11, no. 3, pp. 4512–4528, 2024.