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An Intelligent IoT and Machine Learning-Based Smart Irrigation System Using LoRaWAN

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Abstract

In this paper, we introduce the development of a smart agriculture system which unifies LoRaWAN-based Internet of Things (IoT) devices and machine learning in order to improve monitoring, cultivation, and watering processes in modernized agricultural activities. Based on Milesight IoT sensors and gateways, it monitors environmental data such as soil condition, air temperature, humidity, and wind speed 24/7 and transmits this information over a LoRaWAN network to a central cloud platform. The data is harvested by a Python backend and stored in an interactive Streamlit dashboard for real-time visualization and farm control. For efficient water usage, an irrigation prediction Random Forest Classifier was built based on a curated data set of 1,248 records and tested using unseen data. The model's accuracy approaches the perfect, with conductivity as the most important feature, correlated with the soil moisture. Cross-validation supported strong generalization with an average accuracy of 81.6%. The presented system highlights how integration of IoT and machine learning minimizes resource wastage, reduces manual interaction, and promotes sustainable robust agricultural practices. The implications of this study are to promote the development of -its-kind and scalable IoT-based smart farming systems in farms, so that farm resources can be more effectively utilized based on real-time dynamic data analytics.

Keywords: Internet of Things, LoRaWAN, Machine Learning.

1. Introduction

The Internet of Things (IoT) is considered an evolving technology across various domains (e.g., smart city, healthcare, and transportation), which facilitates the interconnection of billions of devices to handle, share, and process data in real time. Through sensors, connectivity protocols, and smart processing, IoT enables automation, efficiency, and conscious decision-making across every industry, including healthcare, manufacturing,

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transportation, and agriculture. IoT's capacity to collect and share information from anywhere and everywhere has become one of the building blocks of present and future technological development. [1]

In the agricultural field, the Internet of Things (IoT) plays a pivotal role in meeting current global demands. Rural and traditional agriculture, which typically relies on manual labor and decisions made through experimental or observational processes, generally fails to meet these needs, especially in light of climate change, shrinking arable land, and water scarcity. IoT-enabled smart agriculture systems offer solutions for agriculture and the food chain, including real-time monitoring, predictive analytics, and automated crop control. [2]

From the various IoT communication technologies, LoRaWAN (Long Range Wide Area Network) is an affordable, low-power, and long-range protocol that fits perfectly in agricultural scenarios. Its capability to enable large-area deployments with only limited infrastructure qualifies it also in the context of large farms and remote surroundings, where connection is not necessarily reliable. Deep integration of IoT sensors and LoRaWAN enables monitoring soil moisture, temperature, humidity, and many other essential metrics 24/7 without the cost or power drain of common monitoring systems. [3]

This work extends these achievements and develops a LoRaWAN and AI integrated smart agriculture monitoring and management system. The solution utilizes real-time data collection by Milesight IoT devices, with local data storage, and an interactive dashboard for visualization and control. An improved framework is proposed by combining with a Random Forest machine learning model, which can predict the irrigation demand on a given environmental condition, to minimize the excessive water use and avoid human control.

In addressing these challenges, this work provides a reusable model for precision agriculture by dealing with problems of scalability, interoperability, and efficiency. It describes how a combination of IoT, LoRaWAN, and machine learning can help sustainable agriculture and enhance crop yield alongside responsible resource consumption.

2. Related Works

In this section we review some of the related studies in the field of IoT and AI-based irrigation. We primarily focus on solutions that improve crop irrigation process, by monitoring the environmental parameters and controlling water reservoir usage.

Abuzanouneh et al. [4] developed an IoT and machine learning-based SI system (IoTML-SIS) to improve water management in smart agriculture. The platform used IoT sensors to sense soil moisture, humidity, temperature, and light intensity and then sent the sensing data to a cloud server, where the data were processed. The model based on the least squares-support vector machine (LS-SVM) using the artificial algae algorithm (AAA) was then adopted to discriminate the irrigation requirement. Experimental validation has proven the efficiency and accuracy of the proposed system, with the overall accuracy of the classification results reaching 97.5%. The model surpassed other methods, including KNN, SVM, and logistic regression, in precision, recall, and F-score and successfully shortened time to irrigation while reducing water consumption. It was concluded from the study that IoTML-SIS is a dependable and scalable technology for smart farming, which can be commercially applicable and implemented on a real-time basis in agricultural fields.

Gujar and Jagtap. [5] presented an Intelligent Irrigation System based on IoT and machine learning for improving crop productivity and reducing water wastage. The system was composed of soil moisture, temperature, and humidity sensors, a microcontroller (ESP8266), and a web interface for visualizing real-time monitoring and controlling. Twenty days' worth of 15 min interval data (1920 observations) were used to train and test three machine learning classifiers, K Nearest Neighbor (KNN), Decision Tree (DT), and Support Vector Machine (SVM). The evaluation results demonstrated that Decision Tree performs the best (due to a 100% success rate), followed by KNN (99%) and SVM (64%). The motor ON/OFF was correctly controlled, and the system showed a high potential to be applied in fields, greenhouses, and domestic gardening. The authors stated that the system presents itself as a cost-effective and up-scalable technology for precision irrigation and proposed that it could be further developed by the integration of evapotranspiration prediction and fertilizer management.

Codeluppi et al. [2] present LoRaFarM, a modular IoT architecture for smart farming implemented with LoRaWAN. The platform was tested in the Podere Campáz farm in Italy, where it was validated in vineyard and greenhouse applications. It used LoRaWAN-supported End Nodes for soil temperature and humidity sensors and a multi-protocol gateway (mpGW) for the integration of heterogeneous communication technologies. Data was sent to a middleware layer to perform authentication, as well as handling the storage and retrieval using MQTT and HTTP APIs, where the information was viewed by the farmers through a web dashboard and a mobile app. The study spanned up to three months, sampling environmental variables every 10–30 minutes, with data yields over 80% in the majority of cases. By employing solar-powered LoRaWAN nodes, we achieved long-term autonomy, their theoretical lifetime up to 84 days without being recharged. The authors believe that LoRaFarM is a scalable, low-cost, and energy-efficient platform for precision agriculture, and suitable for heterogeneous farm working environments, to solve much dependence on wired technology.

Citoni et al. [6] investigated the impetus of LoRaWAN prospective IoT ecosystems in driving smart agriculture developments. Their review emphasized urgent demands on precision agriculture to meet the predicted 70% increase in food production demand across the globe by 2050. They have researched advantages of LoRaWAN—ultra-low power, long-distance, and scalability, which are very suitable for agricultural IoT applications, including automatic irrigation, greenhouse monitoring, soil testing, and cattle feeding management. Use cases showed that LoRaWAN solutions were able to reach high numbers of cattle or large areas of fields without the need for heavy maintenance. Nevertheless, the analysis also found several open problems such as packet collisions, duty cycle restrictions, and scale limitations that result in poor packet delivery ratios (PDR) in dense networks. The authors recommend the use of Adaptive Data Rate (ADR), replicating the message and spreading factor tuning in order to counter these problems. They argued that LoRaWAN, coupled with adaptive algorithms and community-based infrastructures such as The Things Network, offers an inexpensive and sustainable communication infrastructure for smart agriculture.

Almufareh et al. [7] proposed a smart LoRaWAN IoT device for real-time monitoring and control in smart agriculture that combines the use of anomaly detection and predictive modeling. The architecture integrated IoT sensors with LoRaWAN technology and ML algorithms for enhancing decision-making practices in farming. In particular, an Isolation Forest approach was applied to temperature and humidity, and Linear Regression and Random Forest were used to perform a predictive analysis of the environmental parameters. The system was tested on a large dataset of environmental telemetry ($n > 405{,}000$), achieving a high prediction accuracy where Random Forest resulted to be superior to Linear Regression (R2 = 0.978 vs. 0.800; MSE = 0.162 vs. 1.449). Results indicated that anomalies were associated with large changes in humidity and temperature, thus proving the capability of the framework to detect important environmental transitions. The study concluded that combining LoRaWAN with ML increases efficiency, sustainability, and resource optimization that allow farmers to keep track of large expanses of land, source anomalies, and even automate irrigation and pest management in real time.

Yahia et al. [8] compared the performance of DT and SVM algorithms in the context of a smart irrigation system. A real-world dataset collected by IoT-controlled sensors for soil moisture, temperature, humidity, and rainfall was used to evaluate the performance of the two classifiers for irrigation status prediction. The Decision Tree model obtained 97.14% accuracy with high interpretability and was suitable for small or moderate complexity data. In comparison, SVM performed better in terms of generalization, where F1-score and accuracy can reach up to 98% with regards to both standard test cases as well as larger or more complex patterns. The authors stated that despite being simple and transparent, DT has inferior prediction results for large and high-dimensional irrigation data compared with SVM. The work underscored the significance of choosing an appropriate algorithm according to dataset size and computational complexity, and also showed how ML enables precision water management and sustainable agriculture.

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3. Problem Statement

In traditional farming practices, manual monitoring is practiced and decision-making can cause inefficiencies, waste of resources, and lower yields of crops. The absence of smart and intelligent sensing and predictive analytics capabilities prevents farmers from making informed decisions on irrigation, fertilization, and pest control. Furthermore, smart agriculture systems that already exist suffer from interoperability, scalability, and adaptability for different types of environments.

This paper seeks to overcome these issues by proposing an intelligent agricultural paradigm using IoT technology. Through the combination of LoRaWAN technology, network management protocols, and machine learning algorithms, innovative and organic solutions will be developed that will be scalable and in real-time, and will enhance resource management, crop forecasting, and the overall sustainability of the farm, thereby becoming an example of a replicable model for modern agriculture as seen in figure 1.

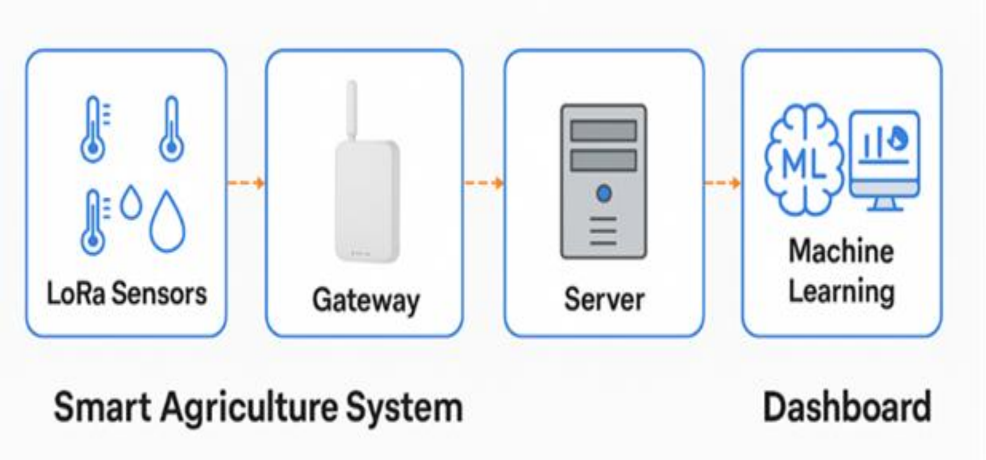

Figure 1: High-Level Design of Smart Agricultural System.

4. System Design

Our system design includes LoRaWAN gateways that collect environmental measurements (air/soil temperature, humidity, conductivity) from IoT sensors and transmit data to the Milesight cloud platform. Python backend services extract this data via an API for CSV storage, while Streamlit enables real-time dashboard visualization. The stored datasets support machine learning analysis for predictive insights as shown in the figure 2.

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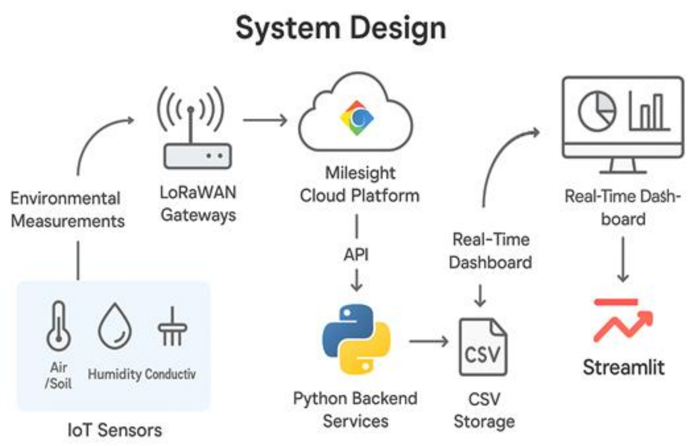

Figure 2: Low-Level Design of Smart Agricultural System.

5. LoRa-WAN Technology

LoRaWAN (Long Range Wide Area Network) is one of the most popular low-power wide area network (LPWAN) protocols that is instrumental for providing scalable and energy-efficient communication for Internet of Things (IoT) applications, especially in remote scenarios where there is minimal infrastructure available, e.g., agricultural fields.

With a physical layer that utilizes chirp spread spectrum (CSS) modulation, LoRa technology achieves strong, long-range, yet low-power connections. LoRaWAN is the media access control (MAC) layer in which the communication of devices is managed in a star topology, where end devices (EDs) are capable of sending their collected data to a single centralized gateway (GW). [8]

In addition, for smart agriculture, LoRaWAN has emerged as an effective connectivity infrastructure for distributed sensors that control environmental and soil-associated factors such as temperature, humidity, pH, etc. Being based on the sub-GHz ISM band (e.g., 868 MHz in Europe, 915 MHz in the US), this technology penetrates through foliage and across the landscape, which makes it suitable for large-scale agricultural monitoring deployment. Its adaptive data rate (ADR) changes the transmission parameters including SF, BW, and TP, in order to maximize range, reliability, and energy efficiency, based on the environmental condition. [8]

Different from other LPWAN technologies, like NB-IoT, LTE-M, and SigFox, LoRaWAN has the advantage in the capability of deploying a stand-alone network as well as being free from cellular infrastructure. It supports a private and customizable network without incurred subscription fees, which means a tremendous price advantage, especially for agricultural scenarios. In addition, LoRaWAN devices can run for over 10 years on a single battery, which

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minimizes the large-scale sensor network maintenance cost because of its low-power characteristic. [9]

But LoRaWAN has its limitations also. The technology is restricted by duty cycle regulations (usually 1%) in the unlicensed ISM band, which constrains the transmission rate and may cause reporting delay. In addition, concurrent transmissions in dense networks can cause signal collision and interference. [8]

However, LoRaWAN is still a promising technology for enabling smart agricultural practices. Due to the potential of long-range communication, potential energy savings, and relatively easy rollout, LoRa is a critical enabler for creating data-driven, scalable, and durable agricultural solutions.

6. Implementation

6.1. Sensors Configuration

First, the sensors were installed in their designated place and connected to the LoRaWAN gateway as shown in the figure 3

Figure 3: LoRaWAN Gateway and Sensors Installation.

6.2. Cloud Integration

After the sensors and LoRaWAN gateway were connected together and an internet gateway was provided for the LoRaWAN gateway, the devices were added to the Milesight cloud platform, as shown in the figure 4.

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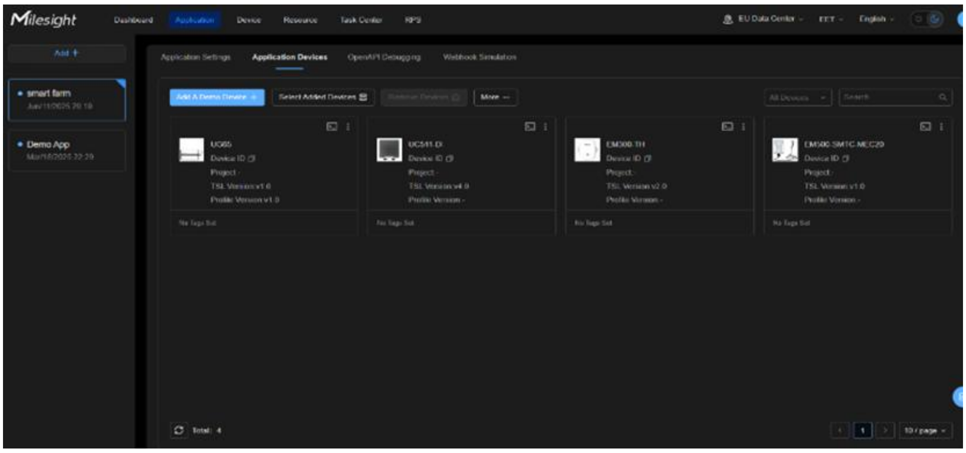

Figure 4: Milesight Cloud Platform.

6.3. Collect and Store Sensors Data

Using the Python script shown in Appendix A via API connection with the Milesight cloud platform, we can get and store the data in the CSV file every ten minutes, in addition to using the OpenWeatherMap API to know wind speed and cloud cover, as shown in the figure 5.

deviceId	timestamp	date	conductivity	humidity	soil_moisture	temperature	cloudcove	wind_spee	soil_type	plant_type	latitude	longitude
'1932859857184325633	6/24/2025 11:23	6/24/2025	549		13.42	28.4	0	7.18	calcareous	olive	31.86786	19.97778
'1932859378999115777	6/24/2025 11:22	6/24/2025		59		30.3	0	7.18	calcareous	olive	31.86786	19.97778
'1932859857184325633	6/24/2025 11:33	6/24/2025	549		13.42	28.4	0	7.18	calcareous	olive	31.86786	19.97778
'1932859378999115777	6/24/2025 11:32	6/24/2025		59		30.4	0	7.18	calcareous	olive	31.86786	19.97778
'1932859857184325633	6/24/2025 11:43	6/24/2025	550		13.47	28.5	0	7.18	calcareous	olive	31.86786	19.97778
'1932859378999115777	6/24/2025 11:42	6/24/2025		59		30.3	0	7.18	calcareous	olive	31.86786	19.97778
'1932859857184325633	6/24/2025 11:53	6/24/2025	549		13.47	28.5	0	7.95	calcareous	olive	31.86786	19.97778
'1932859378999115777	6/24/2025 11:52	6/24/2025		59		30.4	0	7.95	calcareous	olive	31.86786	19.97778
'1932859857184325633	6/24/2025 12:03	6/24/2025	550		13.42	28.6	0	7.95	calcareous	olive	31.86786	19.97778
'1932859378999115777	6/24/2025 12:02	6/24/2025		61		30.1	0	7.95	calcareous	olive	31.86786	19.97778
'1932859857184325633	6/24/2025 12:13	6/24/2025	550		13.47	28.6	0	7.95	calcareous	olive	31.86786	19.97778
'1932859378999115777	6/24/2025 12:12	6/24/2025		60.5		29.8	0	7.95	calcareous	olive	31.86786	19.97778
'1932859857184325633	6/24/2025 12:23	6/24/2025	550		13.47	28.6	0	7.95	calcareous	olive	31.86786	19.97778
'1932859378999115777	6/24/2025 12:22	6/24/2025		60.5		30.1	0	7.95	calcareous	olive	31.86786	19.97778
'1932859857184325633	6/24/2025 12:43	6/24/2025	550		13.47	28.6	0	7.9	calcareous	olive	31.86786	19.97778
'1932859378999115777	6/24/2025 12:52	6/24/2025		61		29.6	0	7.9	calcareous	olive	31.86786	19.97778
'1932859378999115777	6/24/2025 12:42	6/24/2025		60.5		29.6	0	7.9	calcareous	olive	31.86786	19.97778
'1932859857184325633	6/24/2025 12:53	6/24/2025	551		13.47	28.6	0	7.9	calcareous	olive	31.86786	19.97778
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'1932859857184325633	6/24/2025 13:13	6/24/2025	551		13.47	28.6	0	7.9	calcareous	olive	31.86786	19.97778
'1932859378999115777	6/24/2025 13:22	6/24/2025		61.5		29.4	0	7.9	calcareous	olive	31.86786	19.97778

Figure 5: Sensors Data from CSV File.

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6.4. Real-Time Dashboard

Using the Streamlit Python library script shown in Appendix B can read the sensors data from the CSV file and visualize that in the real-time dashboard, as shown below.

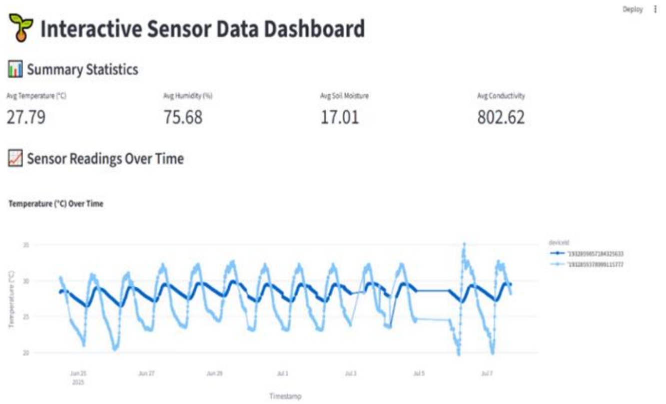

Figure 6: Summary Statistics and Temperature Dashboard.

7. Machine Learning-Based Irrigation Prediction System

Here we discuss the development and performance of a machine learning model for irrigation prediction in a smart farm system. The objective is to automatically determine if irrigation is required by using sensor data, which may lead to water conservation and less manual intervention.

7.1. Dataset Summary

We begin with a small labeled dataset consisting of 2502 instances. A total of 1248 records were left after the filtering and cleaning. This subset was applied for training and validation of the machine learning model. The generalization of the model was evaluated with never-seen data (145 records) in the real-world context.

7.2. Model Type and Architecture

A Random Forest Classifier was selected due to its resilience, interpretability, and ability to work well with small-medium data sets. The model was implemented in a Scikit-learn pipeline with preprocessing and classification blocks. Random Forest was set with 100 estimators with maximum depth 5 and balanced class weights.3. Feature Selection and Rationale

7.3. Feature Selection

The features we ended up utilizing for training were air_temperature, cloudcover,

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wind_speed, hour, and conductivity. These attributes have been chosen due to their relevance to the domain and their high degree of correlation to irrigation demand:

- Conductivity: The most important of all predictors (with nearly 61% importance), describing the degree of soil moisture.
- Temperature and Wind: Affects evaporation rate and plant water requirement.
- Cloudcover: Indirectly affects sunlight exposure.
- Hour: To account for diurnal variation in moisture and temperature.

Characteristics such as latitude, longitude, is calcareous, and day of year were dropped because of their low correlation and model contribution.

7.4. Label generation and the role of soil moisture

For the target label (irrigation need), the soil moisture column was used. More concretely, if soil_moisture < 15.0, it was set to 1 (irrigation required), otherwise 0. Though soil moisture plays a part in deciding if irrigation is needed, it was removed from the feature set to prevent leakage. Adding it as a feature would let the model "cheat" by having exactly the value that was used to produce the label.

7.5. Training and Testing Results

The model was built using Random Forest and was trained on 1248 clean records. It is perfect out of 250 samples on the test set, with almost perfect recall and precision. Only one record was misclassified. The contribution was in favor of conductivity (over 61%). We validated by 5-fold cross-validation with an average accuracy of 81.6%, with good generalizability considering the fold varieties, as shown in figure 7.

```
Dataset size: 1248
Train samples: 998, Test samples: 250

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      1.00       141
           1       0.99      1.00      1.00       109

    accuracy                           1.00       250
   macro avg       1.00      1.00      1.00       250
weighted avg       1.00      1.00      1.00       250

Confusion Matrix:
[[140   1]
 [  0 109]]

Model saved as irrigation_model.pkl

Feature Importances:
conductivity: 0.6134
air_temperature: 0.1909
wind_speed: 0.1305
cloudcover: 0.0349
hour: 0.0303

5-Fold Cross-Validation Accuracy Scores:
Scores: [0.432      1.         1.         0.95582329 0.69076305]
Mean Accuracy: 0.816
Std Deviation: 0.224
```

Figure 7: Summary of Model Performance

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7.6. Correlation Matrix

The correlation matrix captures the linear relationships between variables employed in the irrigation prediction model. In particular, soil moisture and conductivity exhibit an extremely strong positive relationship (+0.95), which confirms that conductivity may be considered a good representative of soil moisture and justifies its use in the model instead of soil moisture to avoid data leakage. Wind speed correlations with soil moisture (–0.49) and conductivity (–0.57) were moderately negatively related (increasing wind speed tends to dry the soil). Similarly, hour is positively related to temperature (+0.53), corresponding to the daily heating pattern. These relationships confirm the choice of features and show that all of them bring non-redundant information and strengthen the predictive power of the model, as represented in the following figure.

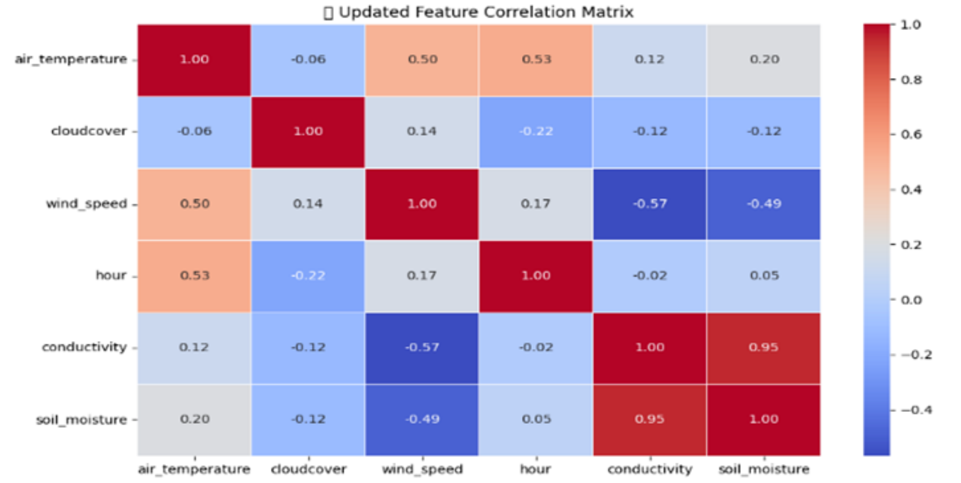

Figure 8: Correlation Matrix

7.7. K-Fold Cross-Validation

The generalization of the model was validated using 5-Fold Cross-Validation. It enabled us to test the model on new data partitions, thus preventing overfitting and providing a more realistic view of how the model would work in practice. Although our hold-out test set provided 100% accuracy, the cross-validation average was 81.6%, assuring fairly high confidence in general while a small variance due to dataset size was noted as represented in Figure 9.

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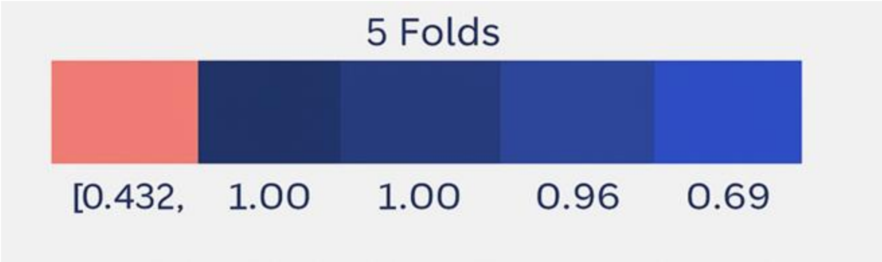

Figure 9: The Output Values after Applying Cross-Validation

7.8 Evaluation

We also tested the model for its generalization on a totally new dataset, which is unseen (145 records), as depicted in figure 10 below.

- Predictions: All predictions were label = 0 (no irrigation needed).
- Predicted probabilities were between 0.06 and 0.12.

This shows the model was not only robust but also responsive to subtle changes in soil moisture or environmental variables.
And model behaves soundly for real-world performs reliably on real-world inputs and adapts sensibly based on conductivity levels. The histogram of predicted probabilities for this new data further confirmed it: the model kept on predicting no need to irrigate with very low confidence, well below the decision boundary (0.5).

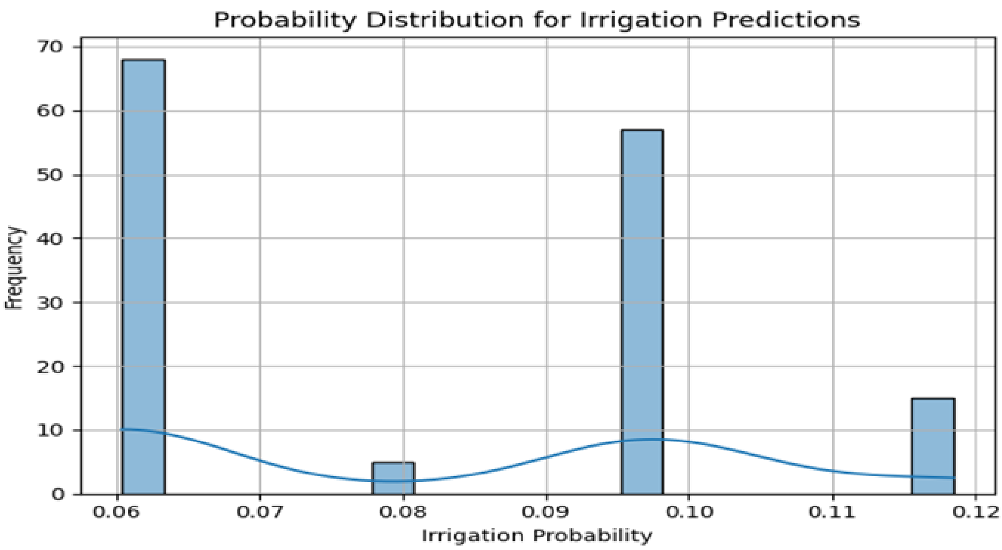

Figure 10: Probability Distribution for Irrigation Predictions .

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8. Conclusion

In this research paper we have presented a successful design and implementation of a IoT and machine learning-based smart irrigation solution with focus on optimizing the irrigation process.

We have exploited real-time environmental parameters, obtained from LoRaWAN sensors, to develop a cloud-based framework that predicted and analyzed the optimum irrigation conditions. This included avoiding inefficient water usage and delayed irrigation timing.

Specifically, we have deployed Random Forest algorithm in our prediction framework, which has resulted in highly accurate results. In addition, we have concluded that soil conductivity was the major feature that determined the exact irrigation requirement.

Moreover, using LoRaWAN as the main network connectivity solution ensured reliable communication over long distance, and maintaining low sensor-power consumption. This entitled the developed framework cost-effective and suitable for remote and large-scale applications.

Finally, the results obtained in this research assure that merging IoT and AI in the irrigation process can yield in promising and successful management of the water resources and crop production.

Future studies can focus on expanding the research implemented in this paper by carrying out further investigation on additional agriculture and irrigation parameters such as pest detection, soil fertilization and crop yield forecasting. This can lead to in developing advanced farming technologies that contribute the global food security and environmental sustainability.

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