

Greenhouse irrigation system based on AIoT

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ABSTRACT

Agriculture is one of the biggest consumers of fresh water. Different types of irrigation systems are available and used in agricultural greenhouses. These irrigation systems are traditional, which do not allow for water savings and have very high maintenance costs. Smart irrigation in agricultural greenhouses is an innovative approach that contributes to a more efficient use of water in agriculture by optimizing available resources and promoting a more sustainable and profitable production. Through the use of smart technologies such as the artificial intelligence internet of things (AIoT), smart irrigation allows adjusting the amounts of water provided to the actual needs of plants, based on factors from sensors such as temperature, air and soil humidity, crop growth stages, plant conditions, and soil types. This helps to avoid water waste and reduce the risks of water stress for plants, while improving the quality and yield of crops. This article presents a smart irrigation solution in greenhouses whose results have been validated by an experimental prototype.

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1. INTRODUCTION

In Algeria, agriculture accounts for approximately 70% of the total water usage in the country. Despite being the primary user of water resources, the agricultural sector makes a minimal contribution to the country's GDP. The agricultural sector suffers from a deficit of 30% in the field of agricultural production [1], [2]. The researchers concluded through statistics that the production of agricultural greenhouses is much better than the production of open agricultural fields, because there is a significant increase in the production of good-quality vegetables in the greenhouses. Greenhouses save water through drip irrigation, which is commonly used in arid highlands, semi-arid regions, and the desert. Our work aims to provide a solution to irrigation that can be used in semi-arid regions such as the Saoura (south-west of Algeria) [3], [4]. Our proposal is based on the use of smart technologies (wireless sensor networks, controllers, internet of things (IoT), ...) for the management of water distribution in an agricultural greenhouse. The concept of this work is known around the world under the term Smart Farming. In this work, we aim to develop an artificial intelligent irrigation system based IoT in a greenhouse to facilitate the task for farmers, guarantee a high production of agricultural products, and optimize water usage [3], [4].

This work contributes to the field by proposing a predictive AIoT irrigation framework that moves beyond reactive threshold-based irrigation toward data-driven adaptive decision-making using supervised machine learning models trained on real greenhouse data.

The remainder of this paper is organized as follows: first, we present a detailed table summarizing a study of related works enhanced with a synthesis showcasing the reasons behind our chosen approach. Next, we present our proposed system detailing the used components, their circuiting as well as our own greenhouse prototype. At the end of this paper, we conclude our work and discuss future work.

2. RELATED WORK

In this section, we conduct a table-summarized survey of existing works by comparing the different research in terms of the materials used and microclimatic parameters. Laksiri *et al.* [5] designed and optimized an IoT-based irrigation system tailored to Sri Lanka's agricultural needs, enabling water efficiency and better crop growth through automated environmental sensing and control. Leh *et al.* [6] implemented a smart irrigation prototype using NodeMCU and DHT sensors, allowing real-time monitoring of temperature and humidity via a user-friendly IoT interface. Lavanya *et al.* [7] developed a greenhouse monitoring framework that integrates Arduino Uno, NodeMCU, and IoT connectivity for basic climate sensing and early-stage crop health prediction.

Muosa *et al.* [8] proposed a GSM and WSN-based greenhouse monitoring system that supports automated irrigation without the need for constant internet access, making it suitable for remote areas. The developed system in [9] introduced a traceability mechanism using IoT for managing the early growth phase of crops in greenhouses, enhancing plant management and data logging. Ben *et al.* [10] built a standalone smart greenhouse system using Arduino microcontrollers, automating environmental management with minimal hardware cost and no internet. Achouak *et al.* [11] presented an intelligent greenhouse control mechanism focusing on automating irrigation and microclimate regulation using local sensor data and an embedded logic system. The developed system in [12] presented an IoT-based irrigation system using ESP8266 and soil moisture sensors, enhancing irrigation scheduling through real-time data feedback.

Ardiansah *et al.* [13] conducted a comprehensive review of recent advances in IoT-powered irrigation systems for greenhouses, identifying current limitations and the potential of AI integration. Pereira *et al.* [14] developed a cloud-connected drip irrigation system using ESP32, allowing farmers to monitor and adjust water delivery through mobile dashboards. Obaideen *et al.* [15] provided an extensive overview of IoT-driven smart irrigation technologies, highlighting AI and energy-efficient design as critical factors for scalability. Haj-Amor *et al.* [16] emphasized the use of AI-based soil-water modeling as a strategic tool for optimizing irrigation and managing agricultural sustainability in arid environments.

Although progress has been made in greenhouse irrigation systems based on IoT, the existing solutions primarily rely on threshold or rule control mechanisms where irrigation decisions are taken by predefined static values of soil moisture or environmental parameters. These approaches remain reactive and lack predictive intelligence capable of adapting to dynamic microclimatic variations. In contrast, the proposed AIoT-based greenhouse irrigation system integrates supervised machine learning models such as decision trees, logistic regression, and support vector machines trained on locally collected greenhouse data to enable predictive and adaptive irrigation control. The novelty of this work lies in the integration of AI-driven decision-making with a real-time IoT sensor network, supported by a locally generated dataset collected under semi-arid climatic conditions in the Bechar region in Algeria. Furthermore, the study provides a comparative evaluation of three machine learning models to determine the most suitable algorithm for actuator activation decisions. The system is designed as a deployment-ready architecture combining cloud processing, Firebase real-time database, and a mobile application interface for remote monitoring and control.

This study proposes an artificial intelligence of things-based greenhouse irrigation system. Its purpose is to improve the irrigation efficiency and support sustainable agricultural practices in semi-arid environments. While many existing smart irrigation systems rely primarily on IoT monitoring or rule-based control strategies, the proposed system integrates machine learning intelligence with IoT sensing infrastructure to enable predictive and adaptive irrigation decision-making.

The system evaluates multiple machine learning models, including decision trees, support vector machines, and logistic regression, to identify the most effective approach for irrigation control. It uses a real dataset collected from greenhouse sensors in Bechar, Algeria, including soil moisture, temperature, and humidity measurements. Unlike traditional threshold-based systems, the proposed solution provides adaptive irrigation decisions based on learned environmental patterns. Additionally, the system incorporates a cloud-based platform (Firebase) for real-time monitoring, data storage, and remote management of irrigation operations.

3. PROPOSED APPROACH

In this section, we showcase all the details regarding our proposed smart irrigation system for a smart greenhouse.

3.1. Block diagram of smart irrigation system

Figure 1 shows the block diagram of our smart irrigation system. This system consists of several hardware components connected to the Node MCU ESP-12 (microcontroller), namely the soil moisture sensor, the DHT 11 sensor (for air temperature and humidity), and the water pump, mist maker, and fan as actuators. These components work by querying a stream that includes the Firebase cloud to save and resend in real-time data, an AI framework called TensorFlow that contains ML algorithms used to analyse data in order to make optimal decisions to optimize water and the actuators' control, and finally the mobile app to inform the farmer of the state of the greenhouse.

Figure 2 presents the architecture of our system that illustrates all the steps and the used components and tools in order to develop an AIoT system for greenhouse irrigation and monitoring. Data transmission between the NodeMCU ESP-12 microcontroller and the cloud database is achieved using the MQTT protocol over Wi-Fi, which ensures low-latency communication and reliable synchronization of sensor data with the cloud platform. Once the data is collected from the sensors, it is stored in Firebase, which is a cloud-hosted NoSQL database server, for processing and analysis. In the cloud-based environment, the data undergoes rigorous pre-processing to ensure optimal quality and relevance of data. The initial phase allows treating missing values, which often occur due to intermittent connectivity or sensor malfunctions. To achieve uniformity in the disparate measurements, data such as temperature, humidity, and soil moisture are standardized using Min-Max scaling based on formula 1 illustrated below, used in the data preprocessing to justify the scaling of sensor inputs before feeding them into machine learning models. A pivotal step in the preprocessing journey is to divide data into training and test subsets. This division is important to avoid overfitting, a situation where a model can excel on its training data, which can fail to classify the unfamiliar data. By training the model on one subset and testing it on an unseen one, a more realistic gauge of the model's performance in real-world greenhouse irrigation scenarios is achieved.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where:

x' is the normalized value

x is the raw sensor reading

x_{max} x_{min} are the minimum and the maximum values for that parameter

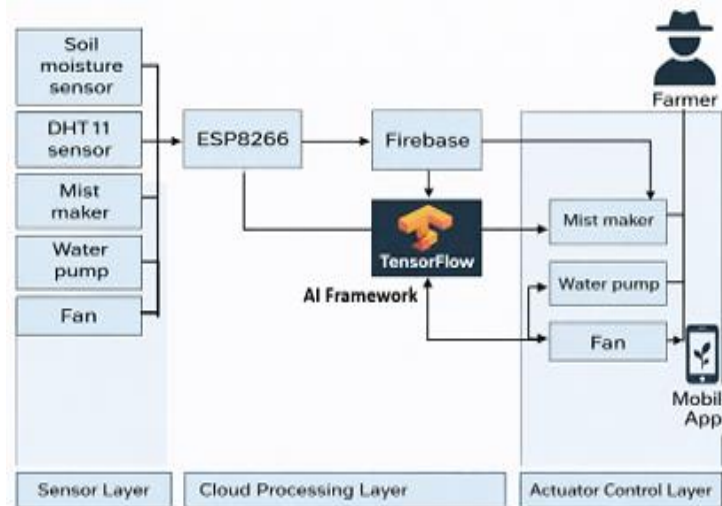


Figure 1. Block diagram of the proposed AIoT greenhouse irrigation system illustrating sensor layer, cloud processing layer, AI decision engine, and actuator control layer

The tested data used also for model evaluation. The cloud platform also hosts an API for users to access into the functionalities of the system. It saves and manages the system's data in Firebase by ensuring scalability, reliability, and security. Additionally, it can enable integration with other services and applications such as the weather API which provides future weather parameters such as temperature, humidity, wind speed, and precipitation forecasts. These weather insights which are displayed with all the

monitored parameters in the mobile app allow the farmer to be informed in real time and taking proactive measures.

The machine learning model, built using TensorFlow, is trained to capture the intricate relationships between sensor readings (temperature, humidity, and soil moisture), and actuator requirements. Sophisticated machine learning algorithms such as decision trees (DT), support vector machines (SVM), or logistic regression (LR) are employed for this purpose. Once the model is trained is then deployed in the cloud platform to enable real-time communication for predicting optimal actuator actions based on the learned patterns and relationships. This intelligent decision-making system improves resource efficiency, ensures the optimal environmental conditions, and empowers the farmer with precise and real-time monitoring and control strategies. The model of the connected circuits in Figure 3 shows the connection of the electronic components of our irrigation system. Table 1 illustrates the information on the used sensors.

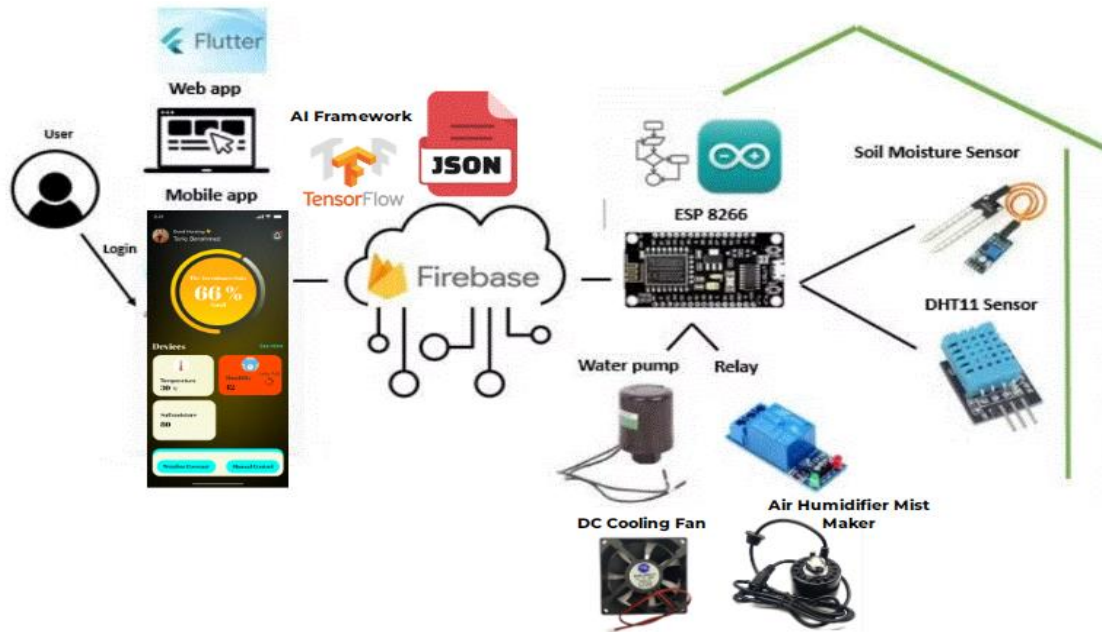


Figure 2. The architecture of our system

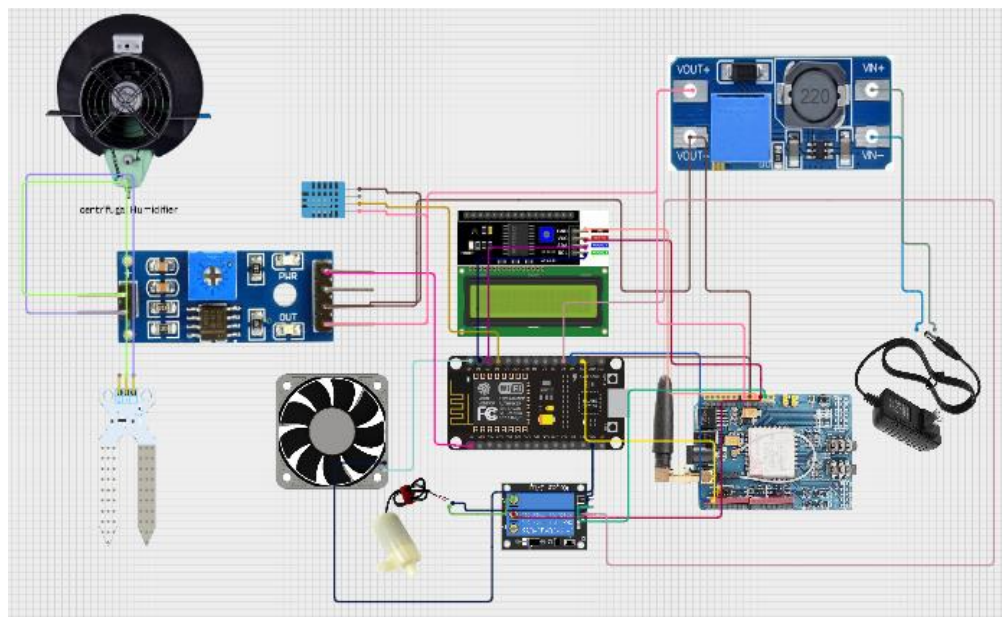


Figure 3. System circuit

Table 1. Sensor specifications

Sensor	Model	Range	Accuracy	Purpose
Soil moisture	Capacitive V1.2	0–100%	±3%	Irrigation control
Dht11	Temp/Humidity	0–50°C	±2°C	Climate monitoring

3.2. Experimentation: prototyping

In this section, we will present some screenshots to show the real-life operation of our smart irrigation system in a prototype greenhouse. Figure 4 illustrates the greenhouse on day 1, and Figure 5 illustrates the greenhouse after 7 days, showing the plant growth.

Our system combines the benefits of an automated autonomous system and a remotely manually controlled one, as chosen using the system’s accompanying mobile App. Figure 6 presents the control interface of our app, which presents the real-time climate parameters and auto adjustment of the humidity is activated, and the control of actuators is (manually or automatically) depending on the farmer's choice.

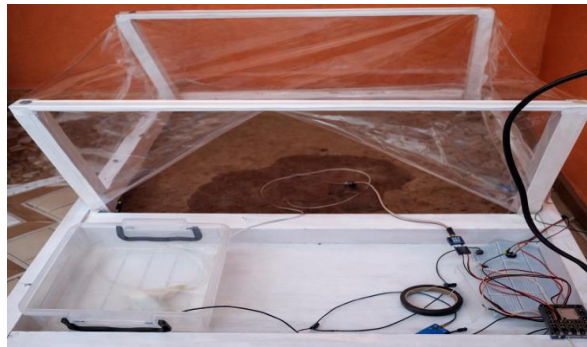


Figure 4. Our system on day 1



Figure 5. Our system on the 7th day

3.3. Dataset

Table 2 presents all the parameters captured by the various sensors placed inside the agricultural greenhouse over a range of dates that vary from Mars to April in the Bechar region, which is located in Algeria. The most important parameter is the soil moisture, which represents “the total amount of water, including the water vapor, in an unsaturated soil.” Soil moisture, sometimes also called soil water, represents the water in land surfaces. The volumetric soil water content (%) = [volume of water (cm3)/volume of soil (cm3)] × 100 [17]-[20].

The table also shows the relationship between the obtained parameters and when the actuators are going to be activated, which is an important point for training the machine learning models, the used data set is obtained locally using real sensors in order to get the real parameters of our region and increase the ability of our system to adapt to real air conditions in the deployment step [21]-[25].

The environmental data were continuously collected from the deployed sensors inside the greenhouse from March to April in the Bechar region. The sensing system recorded soil moisture, air temperature, and air humidity at regular hourly intervals, resulting in a dataset of approximately 1176 instances. This dataset was used for training and evaluating the machine learning models. For the experimental evaluation, the dataset was divided into training and testing subsets using a 70%-30% split, where approximately 823 samples were used for training and 353 samples for testing in order to ensure an unbiased evaluation of the predictive performance of the proposed models.

Figure 7 illustrates the variation of soil moisture as well as the timing of irrigation. The value of soil moisture also depends on air temperature and air humidity existing in the greenhouse. These last two parameters also influence the irrigation.

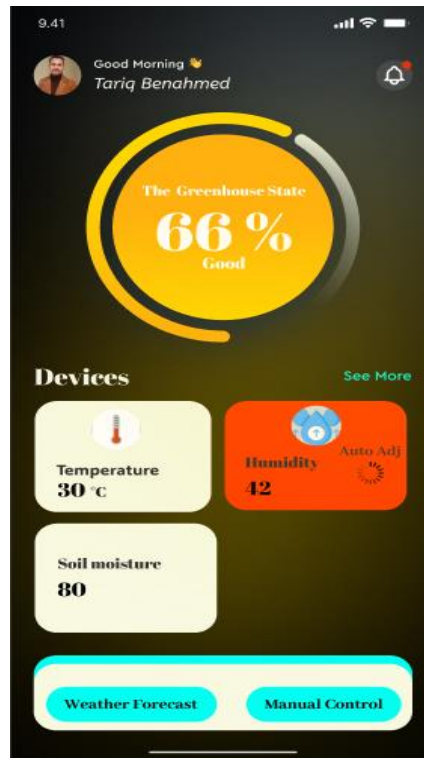


Figure 6. App home page control

Table 2. Dataset captured by the deployed sensors and the state of the used actuators

Date	Soil moisture (%)	Air temp (°c)	Air humidity (%)	Pump	Fan	Humidifier
12 Mar	74	31	42	1	1	1
15 Mar	76	30	48	0	0	0
18 Mar	72	32	40	1	1	1
21 Mar	80	29	55	0	0	0
25 Mar	70	33	38	1	1	1
28 Mar	85	28	60	0	0	0
01 Apr	74	31	43	1	1	1
05 Apr	77	30	50	0	0	0
09 Apr	79	32	47	0	1	0
13 Apr	81	30	52	0	0	0
17 Apr	73	33	41	1	1	1
21 Apr	75	31	45	0	1	0
25 Apr	82	29	58	0	0	0
29 Apr	77	32	39	0	1	1

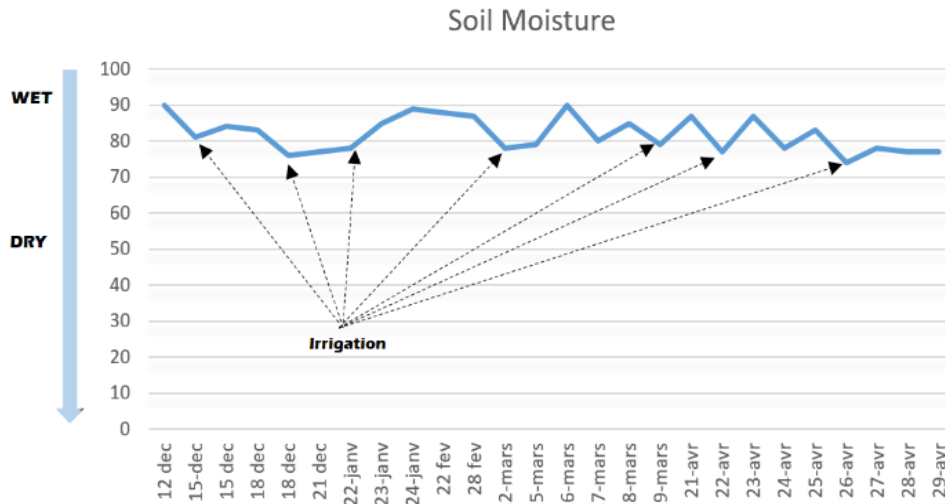


Figure 7. Variation of soil moisture and time of irrigation

When comparing the performance of DT, logistic regression (LR), and SVM for the irrigation and monitoring system, their performance was evaluated based on accuracy, precision, recall, and F1 score. The experimental evaluation method used was the confusion matrix, as shown in Table 3 for the decision tree classifier. The evaluation metrics were computed from the confusion matrix.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{4}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

where:

True positive (TP): correctly classified positive cases, true negative (TN): Correctly classified negative cases, false positive (FP): Incorrectly classified negative cases, false negative (FN): incorrectly classified positive cases.

Based on the comparison illustrated in Figure 8 and Table 4, the decision tree model shows a better performance by achieving high precision, recall, and F1 score. In the development of our smart aquaculture system using IoT and machine learning techniques, the decision tree classifier played an important role in decision-making processes by achieving the highest performance. The main hyperparameters used in the experiments include criterion (gini) for the DT, kernel (rbf) for the SVM, and solver (lbfgs) for LR.

Table 3. Confusion matrix of DT in water pump activation

	Predicted: no water pump activation	Predicted: water pump activation
True: no water pump activation	TN = 72	FP = 4
True: water pump activation	FN = 9	TP = 41

Table 4. Summarizes the performance measures of the different classification models

ML model	Accuracy	Precision	Recall	F1 Score
LR	0.85	0.92	0.74	0.82
DT	0.90	0.91	0.83	0.87
SVM	0.84	0.85	0.73	0.78

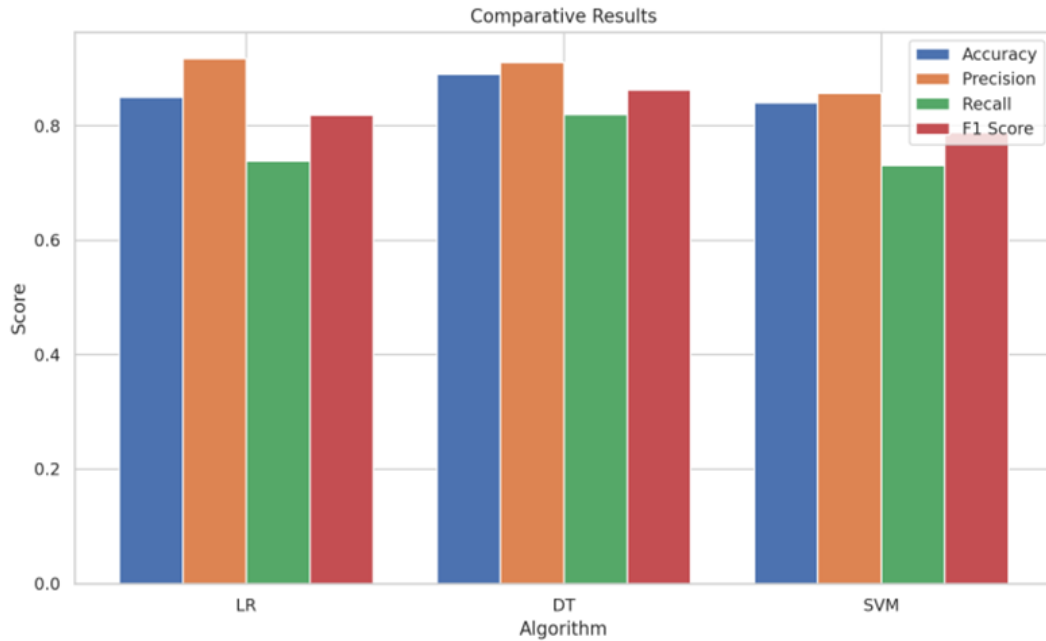


Figure 8. Comparative results of the used algorithms

In this work various training parameters can be adjusted to refine the performance of decision trees for that we relied on the default parameters to guarantee consistency and replicability specifically the criterion for the quality of a split is set to "gini" which is a measure used to measure the impurity of the data illustrated in (6), the maximum depth of the tree was left undefined (allowing the tree to expand until all leaves are pure), the minimum samples split is set to 2 and the minimum samples leaf is set to 1. By employing these default values, the foundational benchmark for the system's performance is established, which can serve as a reference point for future iterations and optimizations.

$$\text{Gini} = 1 - \sum_{i=1}^n p_i^2 \quad (6)$$

Where:

- p_i is the probability of class ii at a given node.
- n is the number of classes.

Among the three used models, decision trees have shown a better performance than SVM and logistic regression due to their ability to manipulate nonlinear relationships between obtained data and actuators activation by providing clear decision rules and interpretable feature importance scores, unlike SVM, which functions as a black box. Decision trees provide an obvious transparency in decision-making steps such as activating the water pump when soil moisture levels are under 80. Additionally, DT is more efficient than SVM in terms of computation, which requires complex kernel optimization. Logistic Regression struggled with the multi-class nature of actuator activation, while DT managed it in an effective way. Furthermore, DT achieved a higher recall (82%), making it more reliable in detecting critical water conditions and reducing fish mortality, whereas SVM had difficulties generalizing due to imbalanced data.

As illustrated in Table 5, the integration of artificial intelligence with IoT infrastructure enables predictive irrigation decisions, which improve water efficiency compared to traditional manual or threshold-based IoT systems.

Table 5. Summarizes the performance measures of the different classification models.

System type	Control type	Water use	Intelligence level
Manual irrigation	Human decision	High	None
IoT-based irrigation	Threshold-based control	Medium	Reactive
Proposed AIoT system	Machine learning decision	Low	Predictive

In addition to evaluating the predictive performance of the machine learning models, the proposed AIoT system was analyzed in terms of irrigation efficiency. Unlike traditional fixed-schedule irrigation, the AIoT system activates irrigation only when environmental conditions require it. Experimental observations show that this adaptive strategy reduces irrigation events by approximately 25–30%, resulting in an estimated 20–25% water saving while maintaining suitable plant growth conditions.

This system does not require the presence of farmers in the fields, as it can be operated from anywhere through the mobile application (the farmer's smartphone). This reduces the need for labor and saves a lot of time. The proposed system also offers other advantages. It provides only a portable amount of water for the crops, thus saving water that would otherwise be wasted due to traditional irrigation.

Although the proposed AIoT-based greenhouse irrigation system demonstrates promising results, several limitations should be acknowledged. First, the dataset used for training the machine learning models is relatively small, which may limit the generalization capability of the models. Second, the system considers a limited number of environmental parameters, such as soil moisture and temperature, humidity data, while other important agronomic variables, including evapotranspiration and solar radiation, were not incorporated. In addition, the proposed system was validated on a prototype-scale greenhouse, which may differ from large commercial greenhouse environments. Finally, the study focused on irrigation decision optimization and did not evaluate the long-term impact on crop yield or productivity, which remains an important direction for future work.

4. CONCLUSION

In this article, we have implemented an AIoT smart irrigation control system in a greenhouse. This system allows automatic or manual control of actuators such as a water pump based on data issued from soil moisture sensors, air humidity sensor, and an air temperature sensor via a mobile application. The latter enables the system to provide remote Wi-Fi monitoring of greenhouse irrigation. This system improves food production, optimize water consumption, and simplify farmers' tasks. For our future work, we hope to apply this system in a real agricultural greenhouse, while adding other parameters such as plant evapotranspiration values, soil type, plant type, lighting, integrating this system with other systems such as aquaculture surveillance in order to create a fertilization system.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Seddiki Nouredine	✓	✓		✓	✓	✓				✓		✓		✓
Benahmed Khelifa				✓		✓	✓	✓		✓				

C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**ditng

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors state no conflict of interest.




DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available because they form part of an ongoing research project and may contain information requiring controlled access.




REFERENCES

- [1] APS, "Agriculture in Sahara," Algérie Presse Service, 2021. [Online]. Available: <https://www.aps.dz/ar/economie/58690-70>. Accessed: May 11, 2021.
- [2] L. Zhang *et al.*, "CCropLand30: High-resolution hybrid cropland maps of China created through the synergy of state-of-the-art remote sensing products and the latest national land survey." *Computers and Electronics in Agriculture*, vol. 219, no. 108672, 2024, doi: 10.1016/j.compag.2024.108672.
- [3] R. R. Shamshiri *et al.*, "Advances in greenhouse automation and controlled environment agriculture: A review," *Biosystems Engineering*, vol. 203, pp. 23–45, 2021, doi: 10.1016/j.biosystemseng.2020.11.017.
- [4] H. Navarro-Hellín, R. Torres-Sánchez, F. Soto-Valles, and C. Albaladejo-Pérez, "A wireless sensors architecture for efficient irrigation water management," *Agricultural Water Management*, vol. 151, pp. 64–74, 2015, doi: 10.1016/j.agwat.2014.10.022.
- [5] Laksiri *et al.*, "Design and optimization of IoT based smart irrigation system in Sri Lanka," in *Proc. IEEE 14th International Conference on Industrial and Information Systems (ICIIS)*, 2019, doi: 10.1109/ICIIS47346.2019.9063272.
- [6] M. Leh *et al.*, "Smart irrigation system using Internet of Things," in *Proc. IEEE 9th International Conference on System Engineering and Technology (ICSET)*, 2019, doi: 10.1109/ICSEngT.2019.8906497.
- [7] Lavanya *et al.*, "A greenhouse monitoring and crop prediction system implemented using IoT, Arduino Uno and NodeMCU," *International Journal of Recent Technology and Engineering (IJRTE)*, 2019, doi: 10.35940/IJRTE.D1001.1284S519.
- [8] H. A. Muosa and A. M. Hamed, "Remote monitoring and smart control system for greenhouse environmental and automation irrigation based on WSNs and GSM module," *IOP Conference Series: Materials Science and Engineering*, vol. 928, 2020, Art. no. 032037, doi: 10.1088/1757-899X/928/3/032037.
- [9] G. Amarillo *et al.*, "A traceability system to crop of seedlings in greenhouse based IoT," *IEEE Access*, vol. 6, pp. 67528–67535, 2018, doi: 10.1109/ACCESS.2018.2877293.
- [10] Z. B. Saidj, "Gestion d'une serre agricole à base d'Arduino," Master's thesis, Université Mouloud Mammeri de Tizi-Ouzou, Tizi Ouzou, Algeria, 2018.
- [11] T. Achouak *et al.*, "Mécanisme intelligent pour la gestion d'une serre agricole," Ph.D. dissertation, Université Tahri Mohammed Béchar, Béchar, Algeria, 2020.
- [12] M. L. Dwarakanath, S. Ranganath, S. Giridhar, and K. C. Vineeth, "IoT based greenhouse irrigation system," *International Journal for Research in Applied Science and Engineering Technology (IJRASET)*, vol. 9, no. 3, pp. 2189–2194, Mar. 2021, doi: 10.22214/ijraset.2021.33181.
- [13] I. Ardiansah, N. Bafdal, A. Bono, E. Suryadi, and S. Nurhasanah, "An overview of IoT based intelligent irrigation systems for greenhouse: Recent trends and challenges," *Journal of Applied Engineering Science*, vol. 20, no. 3, pp. 702–713, 2022, doi: 10.5937/jaes0-35224.
- [14] G. P. Pereira, M. Z. Chaari, and F. Daroge, "IoT-enabled smart drip irrigation system using ESP32," *IoT*, vol. 4, no. 3, pp. 221–243, 2023, doi: 10.3390/iot4030012.
- [15] K. Obaideen *et al.*, "An overview of smart irrigation systems using IoT," *Energy Nexus*, vol. 7, Art. no. 100124, 2022, doi: 10.1016/j.nexus.2022.100124.
- [16] Z. Haj-Amor, T. Araya, T. K. Acharjee, S. Bouri, and R. Anlauf, "Soil-water modeling as a tool for sustainable soil resources management: Progress and future directions," in *Water, Land, and Forest Susceptibility and Sustainability*, vol. 2, pp. 71–96, 2023, doi: 10.1016/B978-0-443-17634-3.00008-7.
- [17] T. Talaviya, D. Shah, N. Patel, H. Yagnik, and M. Shah, "Implementation of artificial intelligence in agriculture for optimisation of irrigation and crop production," *Artificial Intelligence in Agriculture*, vol. 4, pp. 58–73, 2020, doi: 10.1016/j.aiaa.2020.04.002.
- [18] E. A. Abioye *et al.*, "A review on monitoring and advanced control strategies for precision irrigation," *Computers and Electronics in Agriculture*, vol. 173, no. 105441, 2020, doi: 10.1016/j.compag.2020.105441.
- [19] H. M. Jawad, R. Nordin, S. K. Gharghan, A. M. Jawad, and M. Ismail, "Energy-efficient wireless sensor networks for precision agriculture applications: A review," *Sensors*, vol. 17, no. 8, Art. no. 1781, 2017, doi: 10.3390/s17081781.
- [20] Y. Kim, R. G. Evans, and W. M. Iversen, "Remote sensing and control of an irrigation system using a distributed wireless sensor network," *IEEE Transactions on Instrumentation and Measurement*, vol. 57, no. 7, pp. 1379–1387, 2008, doi: 10.1109/TIM.2008.917198.
- [21] K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: A review," *Sensors*, vol. 18, no. 8, Art. no. 2674, 2018, doi: 10.3390/s18082674.
- [22] V. P. Kour and S. Arora, "Recent developments of the Internet of Things in agriculture: A survey," *IEEE Access*, vol. 8, pp. 129924–129957, 2020, doi: 10.1109/ACCESS.2020.3009298.
- [23] R. Desislavov, F. M. Plumed, and J. H. Orallo, "Trends in AI inference energy consumption: Beyond the performance-vs-parameter laws of deep learning," *Sustainable Computing: Informatics and Systems*, vol. 38, Art. no. 100857, 2023, doi: 10.1016/j.suscom.2023.100857.
- [24] T. G. Hoffmann *et al.*, "Small Peltier element to detect real-time heat flux between apple and environment during postharvest storage," *Computers and Electronics in Agriculture*, vol. 213, 2023, doi: 10.1016/j.compag.2023.108247.
- [25] S. S. Gill *et al.*, "Transformative effects of IoT, Blockchain and Artificial Intelligence on cloud computing: Evolution, vision, trends and open challenges," *Internet of Things*, vol. 8, Art. no. 100118, 2019, doi: 10.1016/j.iot.2019.100118.




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