Available online at www.ijournalse.org

Emerging Science Journal

(ISSN: 2610-9182)

Vol. 9, No. 2, April, 2025

Crop Monitoring System Using IoT, Solar Energy and Decision Tree Algorithm

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Abstract

Peru's diverse topographical regions offer optimal conditions for agriculture, but a lack of technology hinders efficiency, leading to food imports despite the country's potential. This paper aims to design an Internet of Things-based monitoring system where the specific objectives are focused on building a solar-powered power stage and integrating machine learning algorithms to help determine crop health. The development methodology includes the evaluation of the use of sensors to measure environmental and soil temperature and humidity, precipitation and hydrogen potential to help identify the health status of crops using machine learning algorithms (decision trees) and transmit the information to a Blynk real-time visualization server. The system components include a device based on an ESP32 module operating in low-power mode, a solar power stage, a data management stage with Blynk with Wi-Fi communication. The results show that the IoT device was adapted for outdoor environments protected by an IP65 housing and can operate for approximately 12 days with a 3000 mAh battery. The main result is that the Random Forest model stands out for having a 98% accuracy when inferring the state of crop conditions. Future improvements can include more efficient solar cells to improve the system's charging conditions.

Keywords:

Crop;
Monitoring System;
Internet of Things;
Solar Energy;
Decision Tree Algorithm.

Article History:

Received:	07	November	2024
Revised:	02	March	2025
Accepted:	09	March	2025
Published:	01	April	2025

1- Introduction

Peru is divided into three topographic regions: the coastal plains, the Andes Mountain range and the Amazon rainforest. This division offers an advantage so that agricultural activity is conducted optimally. To do this, it is necessary to monitor and record the data surrounding agricultural activities to know their future trends [1]. Additionally, monitoring data collected through strategically placed sensors in the fields helps farmers achieve better results [2, 3]. On the other hand, agricultural mechanization can increase land productivity, even on small-scale farms, considering the integration of information technologies. This modernization of the field allows to determine that the agro-industrial sector is growing [4, 5] and is one of the strongest candidates for the application of IoT in the next decade [6, 7]. Furthermore, Peru, being a country with great agricultural potential, is one reason for the importation of food products due to the little technology applied in agriculture. Without technology to make plant cultivation efficient, crops may be lost [8]. This is evidenced by the fact that since 1990, there has been an 8.3% share of agri-food exports worldwide, while in 2015 this figure was 13.8% according to the FAO [9].

Previously published studies have analyzed the information through a review of the state of the art. These studies present IoT-based solutions to improve agriculture and crop production. For example, in some cases an intelligent system

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DOI: http://dx.doi.org/10.28991/ESJ-2025-09-02-06

is proposed that controls the temperature in greenhouses using a dynamic graph data model to manage large volumes of information [10] and predict crop growth [11]. In this paper there is a gap in research because they do not use a computer vision system to help recognize diseases [12]. On the other hand, other research describes the use of an automated system using a PID controller [13] and data management with IoT to adjust irrigation [14]. But unlike other works, it does not integrate a solar energy stage, focusing only on the controller stage [15, 16]. Another paper proposes the development of a wireless sensor network to monitor temperature [17], ambient humidity, and soil moisture in fruit orchards [18]. In these cases, the use of artificial intelligence technologies and their integration to contribute to crop analysis is not mentioned [19].

In this context, some papers describe the integration of energy harvesting technologies with solar cells and the use of integrated machine learning algorithms, such as decision trees, for crop health detection in smart agriculture [20, 21], but the existing gap in research is related to the optimization of these algorithms on reduced hardware devices. These technologies are reported to enable more efficient and sustainable management of agricultural resources [22, 23], improving farmers' ability to monitor and control the conditions of their fields by adding information and communication technologies [24, 25]. Due to the gaps in research described above, the need to integrate IoT technologies, solar energy, and embedded artificial intelligence algorithms as a contribution to crop care is justified.

For this reason, the following question arises: How to design a control and monitoring system for the optimization of resources in an orchard to determine the state of the crop? To answer this question, the objective of designing a monitoring system for resource management applying IoT and solar energy using a machine learning algorithm to determine the health status of crops is defined. Furthermore, this objective is broken down into designing the system hardware, designing the embedded machine learning algorithm, designing the solar power stage, and designing the monitoring system configuration.

The system proposes as a novelty the integration of an IoT module with solar cells and embedded machine learning algorithms to automatically monitor the health of the crops. Furthermore, the motivation is aimed at having an automated and low-cost process that contributes to the productivity and quality of crops, which can be used by farmers and people interested in more effective management [26-28]. Furthermore, the integration of a machine learning algorithm, specifically decision trees, embedded in the system to determine the state of the crop, allows for more precise and real-time monitoring, optimizing the use of resources and improving agricultural productivity. The document is organized into five sections as follows: section 1 presents the introduction, section 2 the methodological process, section 3 shows the results, section 4 discusses the results, and section 5 concludes the study.

2- Material and Methods

The proposed system uses sensors for ambient and soil temperature and humidity, precipitation and hydrogen potential (pH). As a contribution to crop management, their health status is identified and determined using machine learning algorithms (decision trees), transmitting the information to an IoT Blynk data visualization server, providing a real-time view (Figure 1).

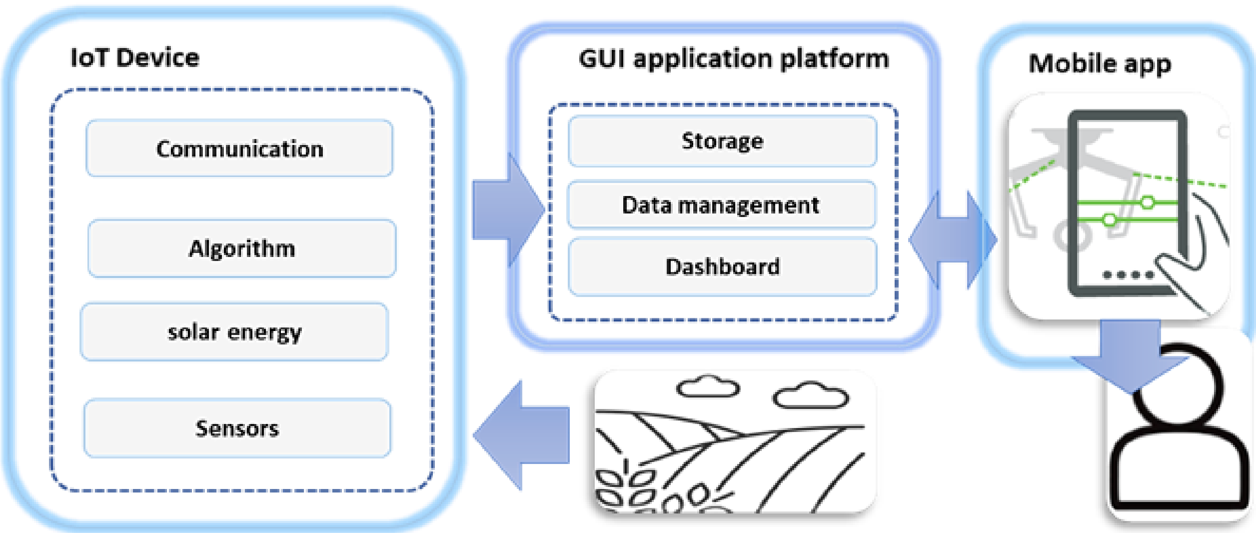


Figure 1. Scheme for the system proposal

2-1- Architecture

The components of the system are determined to specify its architecture. The system is composed of: a) an IoT device; b) Solar energy stage; c) Data management stage implemented with the Blynk MQTT platform and a communications broker called Mosquitto; d) Visualization interface using the Blynk platform. These integrated components are seen in Figure 2.

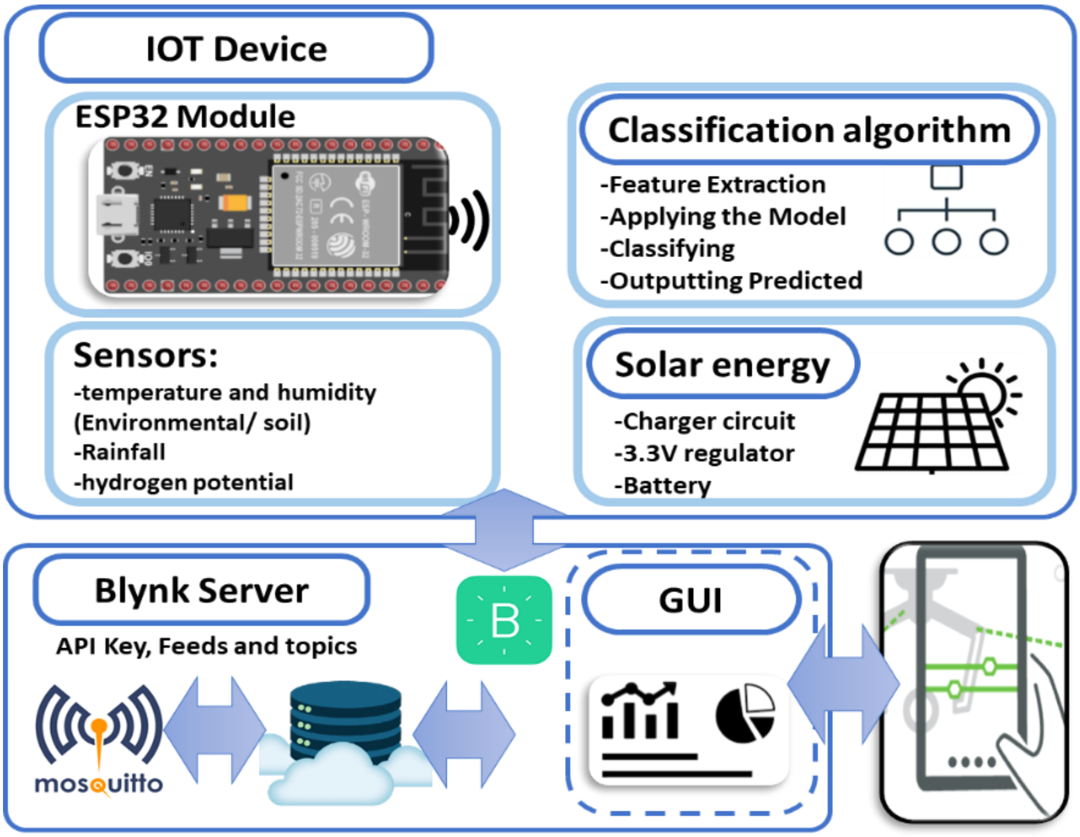


Figure 2. Architecture of the proposed system

2-2- IoT Device

The main hardware component of the system is composed of various sensors to monitor different environmental conditions of the crop field. These sensors include the DHT22 (air temperature and relative humidity), the DS18B20 (soil temperature), the FC-37 sensor for the presence and amount of rain, the GYML8511 for measuring ultraviolet radiation, the Gravity pH sensor, and the SINGLIAN soil moisture sensor (Figure 3). All these sensors are connected to an ESP32 module, which integrates firmware for data acquisition, processing, and transmission to the Blynk server using Wi-Fi.

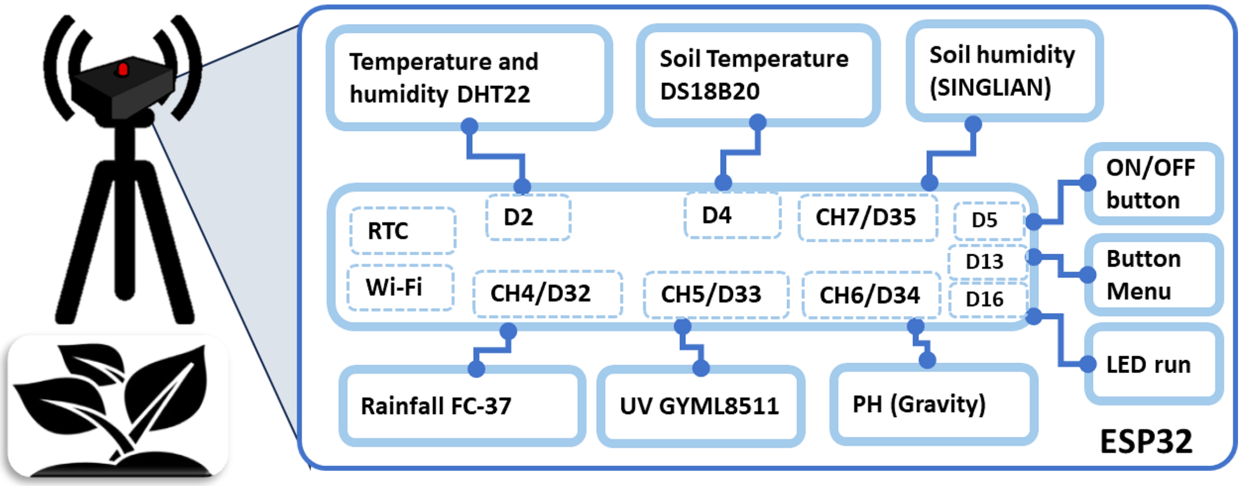


Figure 3. IoT device for reading sensors

In addition, it is configured to operate in a low power consumption mode, because it is necessary for it to operate without human intervention. Configuration and communication with the sensors are done using protocols such as One-Wire and digital signal readings, depending on the sensor. The data collected by the sensors is sent to the ESP32, where pre-processing and filtering of noisy signals is performed before transmitting the information to the data management platform.

2-3- Solar Energy Management Stage

The IoT device works autonomously for extended periods of time without the need for conventional electrical energy, using batteries with a solar energy charging circuit (Figure 4). In this case, a 5V and 4W solar cell is used to charge two 3.7V and 3000mAh lithium-ion batteries connected in parallel. The battery is charged through a TP4056 charging module to a maximum value of 4.2V, which is the input voltage to the TC1262 low voltage drop (LDO) regulator (minimum input of 3.5V), maintaining the output voltage at 3.3V.

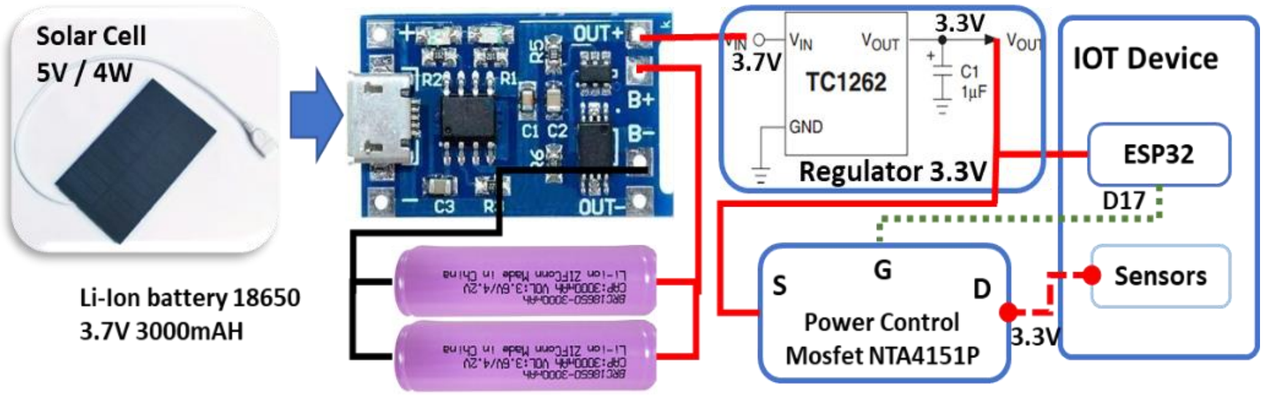


Figure 4. Energy stage with solar cell

On the other hand, the use of the NAT4251P MOSFET regulator allows the ESP32 of the IoT device to control the on and off the sensors to optimize power consumption. Connecting the gate of the MOSFET to pin D17 of the ESP32 activates current to the sensors to read data and then sends a low signal to turn them off. This method contributes to the reduction of energy consumption and the heat generated, prolonging the useful life of the battery-powered system.

2-4- Embedded Classification Algorithm

To determine the health status of the crops, a decision tree algorithm is integrated into the ESP32 using, initially, as inputs the ambient temperature (in degrees Celsius), the ambient humidity (in percentage), the soil temperature (in degrees Celsius) and Soil humidity (in percentage). In addition, the output variables are the categories of crop status: healthy (optimal temperature and humidity conditions), stressed (high temperature, low humidity), lack of water (low soil humidity), wet (high soil humidity and possible overwatering conditions) and cold (low temperature, risk of frost). The data were generated synthetically, as seen in Table 1, using a normal distribution for each crop state (Figure 5).

Table 1. Sample Data Set Used

	Temp (°C)	Hum (%)	Soil temp (°C)	Soil Moisture (%)	Crop Status
0	24.43	61.85	22.69	50.70	Healthy
1	26.20	66.31	21.66	43.88	Healthy
2	31.63	32.00	22.60	37.22	Stressed
3	30.15	30.17	25.03	31.82	Stressed
4	32.56	53.53	22.65	29.34	Lack of water
5	34.07	58.22	20.12	23.86	Lack of water
6	23.04	72.06	19.08	87.42	Wet
7	21.34	72.43	18.57	75.88	Wet
8	14.12	68.24	13.86	43.95	Cold
9	10.37	65.87	10.76	48.18	Cold

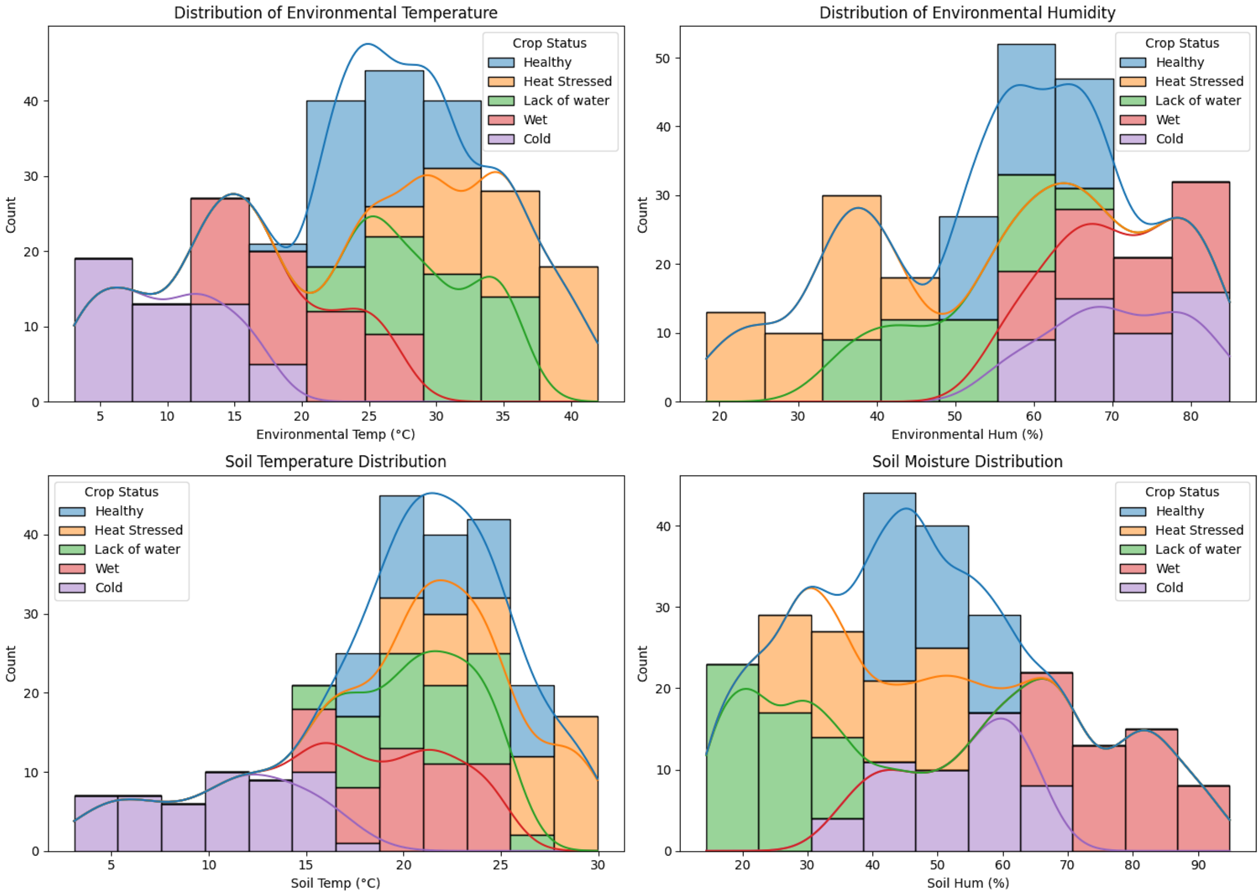


Figure 5. **Distribution of values according to crop categories**

Figure 5 shows the behavior of the data generated in the curves and overlays, providing a statistically robust and realistic representation of environmental behavior in an agricultural environment. The categories partially overlap, reflecting natural transitions between states. These distributions allow the predominant characteristics of each state to be visually identified, with healthy crops having values concentrated in optimal temperature and humidity ranges, while heat stress and water stress are associated with higher temperatures and lower humidity levels. With the generated data set, the algorithm was trained using the development environment in Python language with scikit-learn and the "micromlgen" library was used to convert the model to C++ language compatible with the ESP32.

Figure 6 shows the integration scheme of the IoT system with the Blynk platform for monitoring environmental variables. It can be seen that sensor data (such as temperature, humidity, rainfall, UV radiation, soil pH and crop status) are published as messages using Blynk.virtualWrite() commands over the Internet. The data is stored in a database and displayed on a dashboard. Communication is carried out using an HTTP API, allowing access to the information from any device.

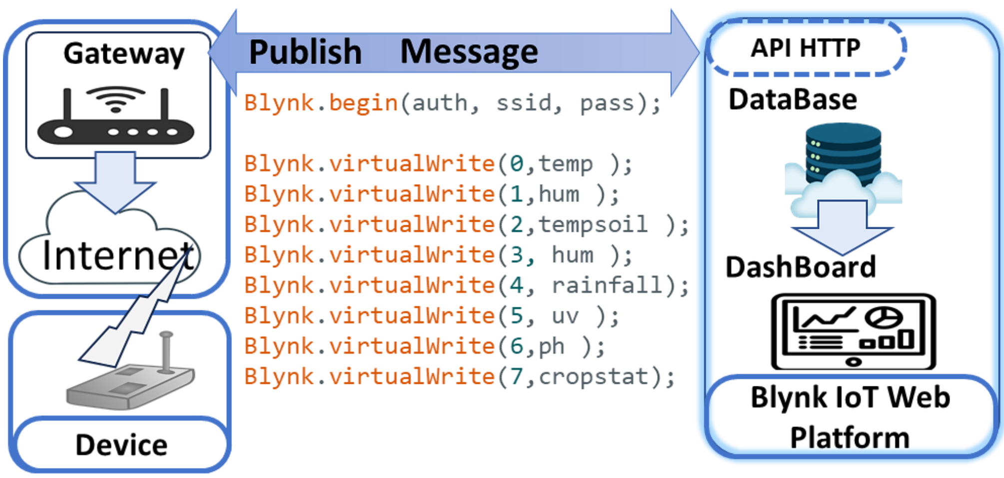


Figure 6. **Network architecture**

To start training the machine learning models, it is necessary to evaluate their behavior and perform the conversion using the Python language (Table 2) with the following steps:

- Split the data into training and test sets using train_test_split from sklearn.model_selection.
- Data preprocessing because some models are sensitive to feature scaling (StandardScaler from sklearn.preprocessing to standardize features (line 2))
- Training the models using the scikit-learn (sklearn) library. For this, SVC is used (for SVMs), DecisionTreeClassifier (decision trees), and for random forests RandomForestClassifier (Line 5, 7 and 9)
- Evaluation of the models using metrics such as precision, recall, F1-score, and confusion matrix.
- Conversion of the models to C++ language using micromlgen (line 12).
- Integration of the model into the IoT device program by importing the file generated in the program and importing and applying the class and function DecisionTree::predict(features).

Table 2. Model creation and conversion code

Line	Instruction
1	pip install micromlgen
2	scaler = StandardScaler()
3	X_train_scaled = scaler.fit_transform(X_train)
4	X_test_scaled = scaler.transform(X_test)
5	svm_model = SVC()
6	svm_model.fit(X_train_scaled, y_train)
7	dt_model = DecisionTreeClassifier()
8	dt_model.fit(X_train, y_train)
9	rf_model = RandomForestClassifier()
10	rf_model.fit(X_train, y_train)
11	c_code = port(svm_model)
12	cprint(c_code)

2-5- Blynk Monitoring Interface

For the operation of the system, a network architecture based on Wi-Fi wireless communications is used. The data acquired by the IoT device is sent to Blynk's MQTT server for which it is necessary to configure the widgets and data types (Figure 6). A project template and the value display Gauges are configured, which allows their accessibility from a smartphone with the Blynk application installed. The transmitted parameters are:

- Temp (virtual pin V0): Environmental temperature
- Hum (virtual pin V1): Environmental humidity
- Tempsoil (virtual pin V2): Soil temperature
- Humsoil (virtual pin V3): Soil moisture
- Rainfall (virtual pin V4): Measured amount of rain
- UV (virtual pin V5): UV index
- Ph (virtual pin V6): pH level
- cropstat (virtual pin V7): Crop status, prediction made by the decision tree model.

In the case of configuration in the Blynk application, widgets are configured and added for each parameter to be monitored using virtual pins that correspond to the data sent from the device. Once the widgets are configured, the Blynk app will display the data in real time as it is received.

3- Results

In Figure 7 you can see the IoT device designed for crop monitoring in operation. It is tripod-mounted for stability in various types of terrain, and the electronics are protected by an IP65-rated housing. The system has a temperature diffuser, and the rain sensor is mounted on the top of the device, along with the UV sensor.

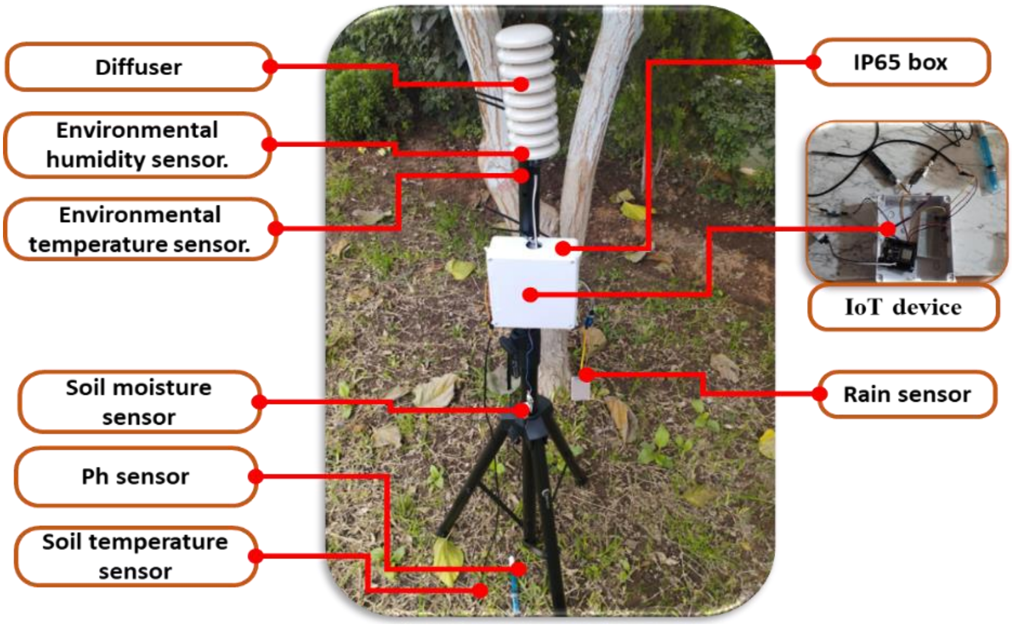


Figure 7. IoT device integrated into a structure for pilot testing

For the analysis of the energy stage with a 3000mAh battery, the modes of normal operation (75mA), data transmission (150mA), and deep sleep (0.05mA) are considered with a data publication interval every 10 minutes. The device can operate for approximately 16.56 days, considering the energy consumption in the described operating modes (Table 3), and a correction factor of 0.75 must be considered, obtaining a duration of 12 days.

Table 3. Energy consumption evaluation

Parameter	Value
ESP32 power consumption	
• In normal operation	75mA
• Transmitting data via Wi-Fi	150mA
• In deep sleep mode	50µA (0.05mA)
Battery duration	
• Battery capacity	3000mAh / 3.7V Li-Ion
Data publication interval	
• Data publication	Every 10 minutes
• Active time (transmitting)	30 seconds
• Time in deep sleep mode	9 minutes and 30 seconds (570 seconds)
Total number of readings per hour	
• Readings per hour	60 minutes / 10 minutes per reading = 6
Energy consumption per hour	
• Consumption during transmission	
○ Each transmission	150mA y dura 30 seconds
○ Consumption per transmission	150mA×(30s/3600s)=1.25mAh
○ Each transmission	6 × 1.25mAh = 7.5mAh
• Consumption during deep sleep	
○ Each sleep period	50µA and lasts 570 seconds
○ Consumption per sleep period	50µA × (570s/3600s) = 0.0079mAh
○ For six sleep periods per hour	6 × 0.0079mAh = 0.0474mAh
• Total consumption per hour	7.5mAh (transmission) + 0.0474mAh (deep sleep) = 7.5474mAh
Total time in hours on battery	
• Battery capacity	3000mAh
• Operating time in hours	3000mAh / 7.5474mAh = 397.48 hours
Total days of operation	
• Days of operation	397.48 hours / 24 hours/day = 16.56 days

In the case of the three models evaluated, it is observed that Random Forests stands out with a precision of 98%, a recall of 98%, and an F1-score of 97.61%, surpassing the other two models and offering the best overall performance (Table 4). The confusion matrix of the three models indicates that the SVM correctly classifies 96% of the positive and negative instances, reflecting high precision and recall. The decision tree also shows similar precision and recall, although slightly higher in recall (96.18%), which indicates a slight improvement in the identification of positive instances (Figure 8).

Table 4. Model evaluation metrics

Model	Accuracy	Recall	F1-score	Parameters
SVM	0.96	0.96	0.957	kernel='rbf', C=1.0, gamma='scale'
Decision tree	0.96	0.9618	0.956	criterion='gini', max_depth=None, min_samples_split=2
Random Forests	0.98	0.98	0.976	n_estimators=100, criterion='gini', max_depth=None, min_samples_split=2

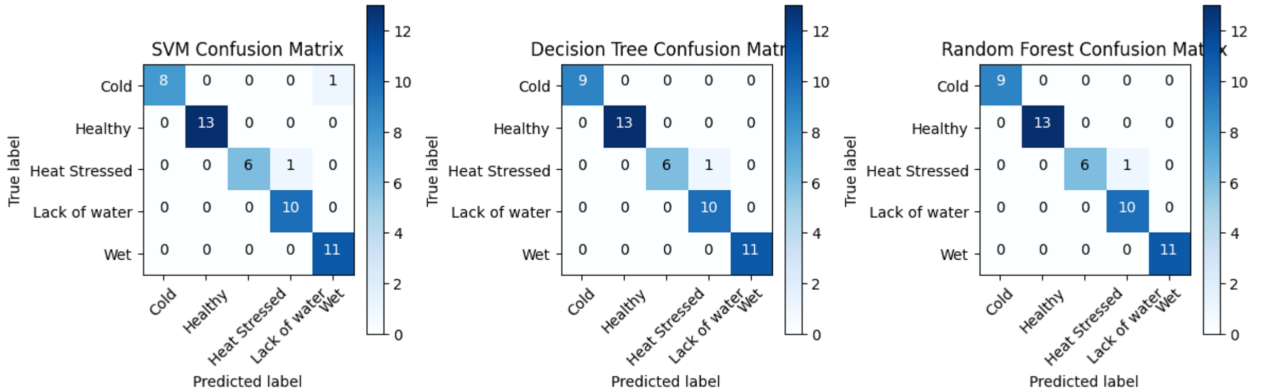


Figure 8. Model confusion matrix

The tree begins with a split by "Soil Moisture (%) <= 65.935", with a gini of 0.8, indicating high impurity in the distribution of 200 samples. Each subsequent node is more specific, divided by parameters such as "Ambient Temperature (°C)" or "Ambient Humidity (%)". In one of the cases there is a node with "Soil Moisture (%) <= 24.999" with a gini of 0.306 and 53 samples all classified as "Heat Stressed" (Figure 9).

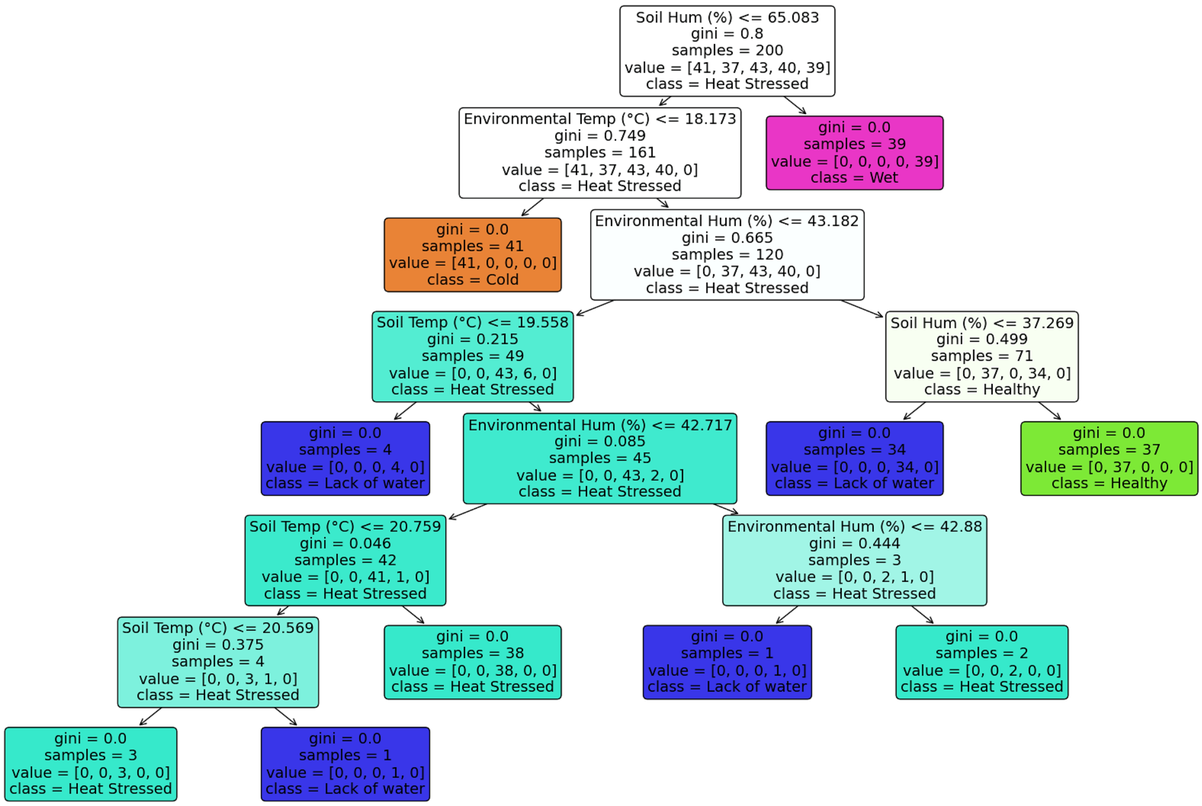
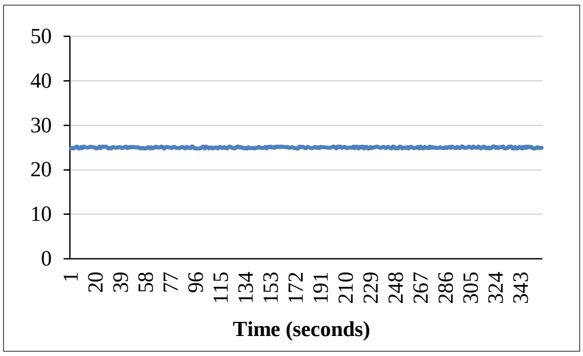


Figure 9. Decision tree model diagram

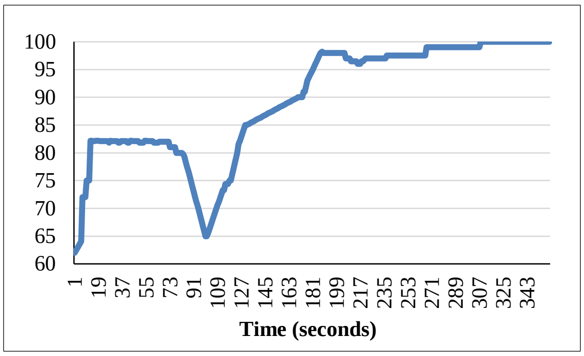
In the case of the mobile application, it has been organized so that soil and environmental conditions can be observed separately. In the weather conditions section, temperature, luminescence and humidity data are displayed. In another section, the soil conditions can be seen, showing the data from the temperature probe, four used humidity probes of the same type and the pH value (Figure 10).

Figure 10. Real-time indicator

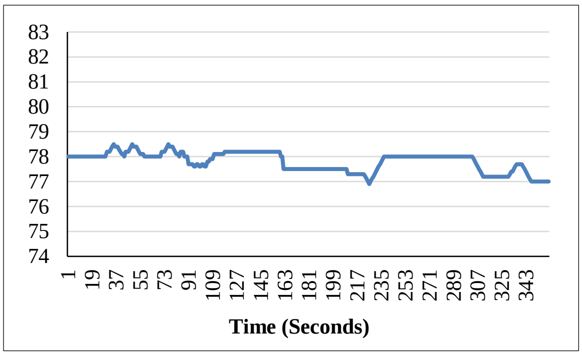
The results obtained were shown in Blynk's visual components as a function of time (Figure 11), using Chinese onion crops in an orchard as a pilot test. The investigation identified that soil moisture is maintained at 60%, ambient temperature between 14°C and 22°C (Figure 11-a), and soil pH between 5.5 and 7.8. The collected data, displayed in real time, are used for future statistical analysis, allowing the ideal conditions for cultivation to be determined. Figure 11-b shows the luminescence observed during the early hours of the morning, evidencing an increase in luminosity as the day progresses. Furthermore, Figure 11-c presents the ambient humidity, measured with a DHT22 sensor. Figure 11(d) illustrates soil moisture, obtained with four probes inserted at different depths for a more precise measurement, with data taken in the morning after irrigation, showing that probes 1, 2, and 3 record 100% of humidity, while probe 4, the deepest, shows 88% humidity. Soil moisture stability at 60% and variations in luminosity throughout the day could be used to dynamically adjust irrigation schedules and determine the optimal amount of water needed based on soil depth, considering the data shown in Figure 11. In addition, soil pH analysis could help predict and prevent problems related to crop nutrition, adjusting fertilization more accurately.



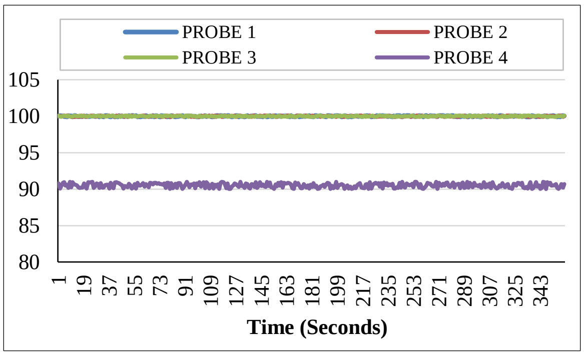
(a) Environmental temperature



(b) Environmental light



(c) Environmental humidity



(d) Soil moisture

Figure 11. Sensor parameters visual interface

The implementation of IoT and machine learning for monitoring variables such as soil moisture, temperature, and pH shows an advance over previous research that does not incorporate optimized algorithms or real-time analysis for these conditions [10]. In particular, the performance of the Random Forest model with an accuracy of 98% highlights the feasibility of integrating efficient algorithms on reduced hardware, addressing one of the main gaps mentioned in previous articles reviewed in the state of the art [11, 12]. Furthermore, the ability of the system to operate for 12 days with an optimized energy design contrasts with studies that do not consider the integration of solar energy technologies or energy efficiency [20].

4- Discussion

In the case of the IoT device, its structure with IP65 protection guarantees protection against dust and water, prolonging the useful life of the device. Additionally, the temperature diffuser ensures accurate measurements of ambient temperature and humidity by avoiding direct sun exposure, while the strategic arrangement of the rain and UV sensor maximizes the collection of precipitation and ultraviolet radiation data. These features have enabled reliable data collection for remote monitoring and informed decision-making in agricultural management.

Regarding the power consumption of the device, its approximate duration was determined to be 12 days before the battery runs out in extreme conditions without solar energy, and a correction factor of 0.75 was applied to ensure a controlled shutdown, which provides a more accurate estimate. accurate and realistic of the autonomy of the device in adverse conditions. The system has a total consumption per hour of 7.5474mAh and at least 3000 mAh must be generated when using a 5V solar panel, considering that the minimum power needed would be 37.737 W (7.5474mAh×5V) which is achieved with a 5V solar panel. 5V and 250mA.

The three models evaluated, SVM, Decision Tree, and Random Forests, demonstrated adequate performance in terms of recall and F1-score. Although all of them showed effectiveness, the Decision Trees model was chosen due to its simplicity for microcontrollers, lower memory consumption, and fast execution speed. Furthermore, its hierarchical structure facilitates interpretation, making it an attractive choice in environments with limited resources. The confusion matrices revealed that SVM and Decision Tree achieved high precision and recall rates in the classification of positive and negative instances, and the random forest model diagram showed a progression towards pure leaves, evidencing a good capacity for generalization and interpretation based on quantitative metrics (Figures 8 and 9). Despite the better performance of the Random Forest, it was decided to implement a decision tree model because they offer a simpler and more visual interpretation of the results. Furthermore, the decision tree model has lower computational complexity, making it more suitable for implementation on resource-constrained hardware, such as the system's IoT devices. The choice of the decision tree was also based on the balance between performance and simplicity so that it can operate in real time and under energy and hardware constraints.

In the mobile application based on monitoring environmental and soil conditions, separate sections were defined to observe each type of condition individually, in real time, through Blynk's visual components, conducting a pilot test with crops of Chinese onion. Blynk has been crucial in the monitoring system due to its intuitive interface, remote accessibility, and use of widgets, accelerating the development of the application.

5- Conclusion

The system has proven to be an effective and efficient solution for remote monitoring of environmental and soil conditions in an agricultural environment, providing accurate, real-time data for informed decision-making. In the case of the IoT device hardware, its integration in a tripod structure and protection with an IP65 box guarantee durability and resistance to adverse conditions such as dust and water, while its temperature diffuser and the strategic arrangement of the rain and UV sensors allow obtaining optimal measurements.

In relation to the models evaluated, the Decision Tree model had the greatest simplicity of implementation in hardware, which is ideal for environments with limited resources, in addition to the fact that understanding its operation is simple due to its hierarchical structure. The system demonstrated an effective duration of continuous operation of 12 days in extreme conditions without solar energy, which, added to its integration with the 5V and 250mA solar panel, ensures the generation of sufficient energy to keep the system operational. On the other hand, the implementation of an application using Blynk is critical to integrating remote accessibility to information using widgets in real time, improving the response capacity and management of the field.

For future research, it is recommended to explore the integration of control technologies and the automation of agricultural tasks, such as irrigation and fertilization. In addition, more devices can be implemented to form sensor networks and obtain information in different microclimates within the area of interest. Finally, long-term studies could be conducted to evaluate the impact of the system on crop productivity and sustainability.

6- Declarations

6-1- Author Contributions

Conceptualization, R.Y., L.C., and S.N.; methodology, R.Y.; software, L.C. and S.N.; validation, R.Y., L.C., and S.N.; formal analysis, R.Y.; investigation, L.C. and S.F. ; resources, L.C. and S.F.; data curation, R.Y.; writing—original draft preparation, R.Y.; writing—review and editing, R.Y., L.C., and S.N.; visualization, R.Y.; supervision, R.Y.; project administration, R.Y., L.C., and S.N.; funding acquisition, R.Y. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available in the article.

6-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6-4- Institutional Review Board Statement

Not applicable.

6-5- Informed Consent Statement

Not applicable.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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