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Design and deployment of an IoT-based monitoring system for hydroponic crops

Diseño y despliegue de un sistema de monitoreo basado en IoT para cultivos hidropónicos

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Abstract

The IoT is a technological trend that enables the application of intelligent systems between connected things. IoT is being applied in different fields, including agriculture, where new techniques such as hydroponics are booming. As the increase in ambient temperature and climate changes caused by global warming have negatively affected agricultural production and the rapid growth of the world's population, which will reach approximately 9.6 billion by 2050, the industrial pace of agriculture needs to be even faster and more precise. This research presents a scalable IoT monitoring system based on Sigfox technology with 89.37% prediction capabilities through neural networks for agricultural applications. An effective four-layer architecture consisting of perception, network, middleware, and application is provided. The system was experimentally tested and validated for five months by monitoring temperature, humidity, and nutrient recirculation control in a hydroponic system in Loja, Ecuador. The developed system is smart enough to adequately control the hydroponicenvironment based on the multiple input parameters collected, facilitating effective management for farmers and improving production.

Keywords: Hydroponics, Sigfox, Neural Networks, Ufox, Internet of Things, Smart Agriculture

Resumen

El IoT es tendencia tecnológica que hace posible sistemas inteligentes entre cosas conectadas. Su aplicación se encuentra en diferentes campos, uno de ellos es la agricultura, donde el uso de nuevas técnicas, como la hidroponía, está en auge. Es importante abordar esta área, porque la población mundial alcanzará un aproximado de 9600 millones de habitantes para el 2050, por ende, para satisfacer esta demanda se necesita que el ritmo industrial agrícola sea aún más rápido y preciso. Además, el aumento de la temperatura ambiente y los cambios climáticos por el calentamiento global también están afectando negativamente a la producción agraria. En esta investigación se presenta un sistema de monitoreo IoT escalable basado en la tecnología Sigfox con capacidades de predicción del 89,37 % a través de redes neuronales para aplicaciones agrícolas. Se proporciona una arquitectura efectiva de cuatro capas que consta de percepción, red, middleware y aplicación. Para la validación, el sistema fue construido, probado experimentalmente y validado mediante el monitoreo de la temperatura, humedad y control de la recirculación de nutrientes, en un sistema hidropónico de la ciudad de Loja en Ecuador, durante cinco meses. El sistema desarrollado es lo suficientemente inteligente para proporcionar la acción de control adecuada para el entorno hidropónico, en función de los múltiples parámetros de entrada recopilados, facilitando una gestión efectiva para los agricultores, por ende, mejorando su producción.

Palabras clave: hidroponía, Sigfox, redes neuronales, Ufox, Internet de las cosas, agricultura inteligente

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1. Introduction

The Internet of Things (IoT) is a cutting-edge technology that has brought multiple benefits to the population and organizations in recent years. One of the main benefits of using this innovative technology is the ability to produce and consume services in real-time. IoT offers solutions in different scenarios such as traffic, healthcare, security, smart homes and cities, etc. [1–3]. IoT technology is also used in different areas and levels of industrial and agricultural production in agriculture [4]. The main contribution of IoT in agriculture is monitoring, which helps automation and information gathering to have precision-controlled crops and greenhouses [5]. Precision agriculture aims to provide a decision-support system that helps farmers implement efficient farming practices to increase profitability, reduce environmental risks, and preserve natural resources [6, 7].

Agricultural monitoring applications use sensors or devices to help farmers collect relevant data that benefit crop growth and production. Some IoT-based approaches analyze and process data remotely by applying cloud services [8–10], which helps researchers and farmers make better decisions. A case study of IoT management that monitors variables such as wind, soil, atmosphere, and water over a large area is proposed in [11]. This study identifies agricultural monitoring solutions considering sites or subdomains to monitor soil, air, temperature, water, diseases, location, environmental conditions, pests, and fertilization. It also explains how IoT enhances human interaction through electronic devices, low-cost communication protocols, and communication technologies.

Sigfox wireless communication technology is an emerging low power wide area (LPWAN) technology that offers secure data transmission and low power consumption [12]. It uses unlicensed radio spectrum in the industrial, scientific, and medical (ISM) bands and enables two-way communication between users and sensors on an individual or group level. Therefore, Sigfox is suitable for IoT applications that only require the transmission of small data packets and low power consumption. Hernández et al. [9] present a relevant case where they design a scalable IoT-based monitoring system with prediction capabilities for agricultural applications, provide an effective four-layer architecture, and implement the connectivity of greenhouse monitoring system devices over the Sigfox network.

Despite recent advances in IoT technologies, their implementation in agriculture remains challenging. One of the main problems is monitoring the variation of weather conditions in greenhouses or crop fields. It is necessary to efficiently place several measurement points within the crop fields to obtain more detailed information about the behavior of environmental conditions. This work aims to design and implement an IoT-based monitoring system for hydroponic crops using a scalable, modular, and low-cost system architecture.

The system monitors weather conditions and risk factors affecting crop growth, considering temperature and humidity as relevant variables. For this, a customized IoT device was built using the Sigfox network to send the data to the Internet, and the ThingSpeak platform was used to visualize and analyze the data. A machine learning algorithm was created to predict temperature considering humidity and the data collected by the system to simulate future changes in climate variables. The system was validated in a hydroponic lettuce system in Loja. The main contribution of this research is to propose the application of a practical and scalable system to monitor and control climatic conditions in crops. The IoT structure consists of a four-layer architecture: a sensing layer to collect crop information, a network layer to facilitate Internet connections, a middleware layer to enable cloud services, and an application layer to deliver specific information to users.

The research is divided into sections: Section 1, introduction; Section 2, materials and methods; Section 3, architecture of the proposed IoT monitoring system; Section 4, design and implementation of the system components; Section 5, experimental validation of the implemented monitoring system; and Section 6, conclusions and future directions of the research.

2. Materials and methods

This research was conducted at the Marieta de Veintimilla School in Loja, with a quantitative experimental approach to develop and implement an IoT system for monitoring and predicting environmental variables such as temperature, humidity, and UV radiation. For this, a phased model was proposed according to the proposed architecture.

The first phase was to develop the IoT prototype using Sigfox technology and electronic components of free software and hardware. The second phase was to collect temperature and humidity data using DTH22 and ML8511 UV sensors to determine UV radiation. A Ufox controller synchronized to a real-time clock (RTC) unit was used as a central module, which activates and deactivates a water pump that provides liquid and nutrients to a hydroponic growing system. Sigfox technology transferred the real-time information to the ThingSpeak IoT platform.

The third phase focused on a data analysis method based on neural networks. The information collected by the sensors was the basis for the learning model to predict the variables related to the system and thus predict the environmental conditions that affect plant growth. The final phase was to present the data to the user to monitor the status of the sensors and establish correlation. The inverse proportionality between the temperature and humidity variables, essential for determining cultivation parameters in the hydroponic system, was verified.

2.1. System architecture

The study of the Internet of Things (IoT) has resulted in extensive scientific literature. There are multiple architectures, frameworks, or conceptual models for IoT systems [13–17]. However, there is no single standard reference architecture that encompasses a variety of technologies. In [18, 19], the incorporation of IoT technologies for sustainable agriculture is discussed.

Figure 1 shows the proposed multi-layer architecture for the IoT-based hydroponic monitoring system. This design has four layers: sensing layer, network layer, middleware layer, and application layer, and streamlines production processes using a practical and scalable system. This means that the architecture allows monitoring several variables or an entire process at minimal cost, benefiting the cultivation process through hydroponic systems or smart farming.

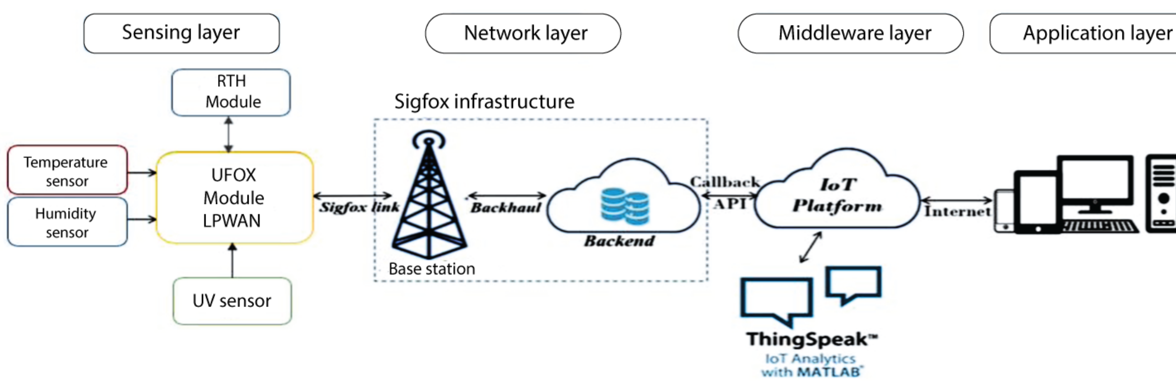

Figure 1. Proposed architecture for the monitoring system

Optimal plant growth conditions depend on the needs and requirements of each plant. Therefore, an environmental monitoring system is essential to maximize effective and sustainable crop production. Generally, the microclimatic parameters that determine crop productivity must be continuously monitored and controlled to create an optimal environment. However, climatic heterogeneity can cause significant differences in quantitative and qualitative plant characteristics, productivity, and the development of various diseases. The sensing layer shows the connected sensors and devices that enable remote climate monitoring.

Some environmental factors that affect plant growth are temperature, relative humidity, CO_2, light, and water [20]. For this case study, the IoT device includes only temperature, relative humidity, UV radiation, and water and nutrient monitoring sensors. These sensors are connected to a digital, analog, and PWM input of a Ufox microcontroller with a Sigfox module integrator for communication. The RTC module connects using an I2C interface to the controller that controls the time for the recirculation of nutrients to the system. It has a real-time calendar that turns on a pump every four hours for ten minutes, sufficient time for adequate growth of the lettuce plants.

Communication technologies play an essential role in the implementation of IoT systems. There are several standards for data transmission between sensors and IoT platforms. They can be classified as short-range wireless networks (e.g., Zigbee, Bluetooth, Z-Wave, Wifi, etc.) or long-range wireless networks (GPRS, 3G, 4G, and 5G). Short-range networks restrict the ability to provide global coverage, while conventional long-range networks are expensive and require much power. Consequently, IoT applications have driven a new type of wireless technology called low-power wide area network (LPWAN) [21]. These further wireless communications are better suited to machine-to-machine (M2M), and IoT devices; LoRaWAN, Sigfox, and NB-IoT are among the leading LPWAN technologies for IoT implementation. Each business activity has different requirements and specifications for IoT connectivity, such as coverage, performance, packet size, power consumption, cost, etc.

For hydroponic system monitoring applications, it is crucial to establish connections to use low-cost hardware with long-distance coverage and low power consumption, and scalability. This is why the connectivity of the proposed system to the IoT device over a Sigfox network was established. Once the data were collected at the IoT device, the LPWAN module sent the data to the Internet using the Sigfox network. The data communication followed the Sigfox protocol, where each device has a unique ID to route and sign the messages.

Agricultural data analysis requires involving farmers in creating data processing services to optimize the crop production cycle. Because of this, a scalable middleware layer was integrated to develop, implement, and operate the software. The middleware or service layer is where users' software services or applications are created and managed. This layer was generated using the ThingSpeak platform, which supports service management and data processing.

An IoT system user interface that allows the monitoring, visualization, and interpretation of data coming from the system's sensors was proposed. A web application interface was integrated into the Sigfox back-end platform through its application programming interfaces (APIs). The web API integration is based on HTTPS REST requests with the POST method and provides the interface from the protocol stack to the application. Therefore, the web application displays the measurements collected from the sensors, triggering calls through the Sigfox REST API. The ThingSpeak platform interface was used to streamline this process, as shown in Figure 2.

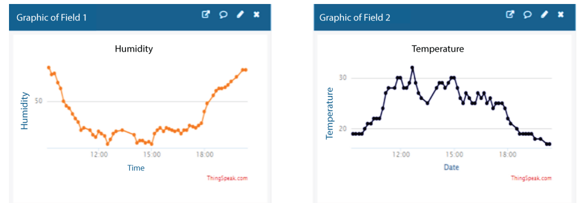

Figure 2. Data visualization and monitoring

2.2. Implementation of IoT-based monitoring system

Figure 3 shows the diagram of the IoT device created to monitor temperature, humidity, and UV radiation. This prototype comprises four main components: a communication module, temperature and humidity sensor, UV radiation sensor, and RTC control. This device can be powered by batteries or mains electricity. Figure 4 shows the implemented IoT device; the Ufox communication module that enables wireless connection to the cloud through the Sigfox network service is shown inside a yellow rectangle.

The data from the proposed device were validated by comparing humidity, temperature, and UV radiation data from the TuData project (http://tudata.info/), a form of meteorological data collection in Loja.

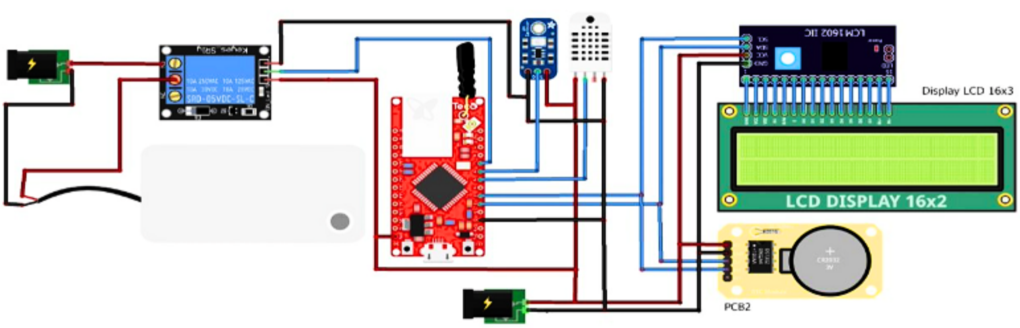

Figure 3. IoT device diagram

Figure 4. IIoT device implementation

Figure 5 and Figure 6 show the close relationship between the data obtained in January, demonstrating that the IoT sensor sent consistent and valid information related to the TuData weather measurement system.

The DHT22 sensor was used as a digital interface to measure humidity and temperature. A capacitive sensor was incorporated to calculate the percentage of relative humidity in the air, and a microcontroller was used to convert analog to digital values. The humidity measurement range was 0 to 100%, with an accuracy of 2%. The temperature measurement range ranged from -40 to 80 degrees Celsius with a measurement accuracy of fewer than ±0.5 degrees Celsius at a resolution of 0.1 degrees. The sensing time was 2 seconds. The power supply range was 3 to 6 volts DC. Only one wire or conductor cable not exceeding 20 meters is required for connection to the microcontroller.

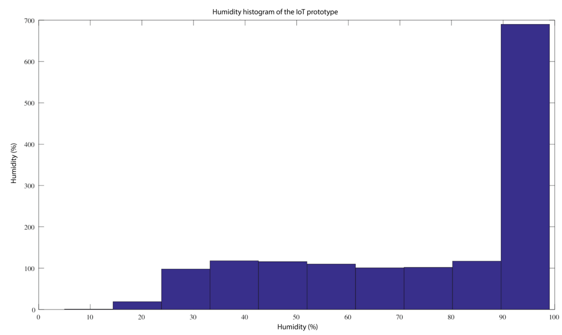

Figure 5. Humidity histogram of the created IoT device.

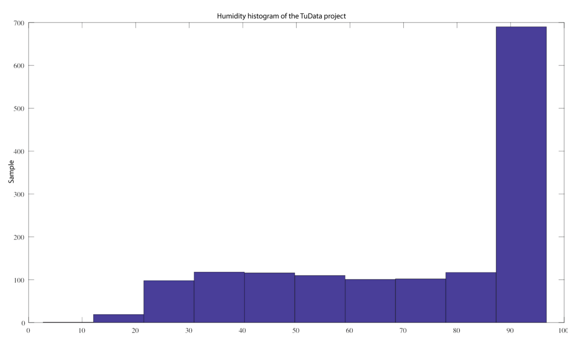

Figure 6. Relative humidity histogram of the TuData project.

2.3. Prediction

Artificial neural networks (ANNs) application for data analysis has increased considerably nowadays due to their multiple uses and advantages, such as adaptive learning, fault tolerance, and real-time operations [22]. ANNs predict climatic variables, greenhouse-type environments, and implicit variables, such as humidity, temperature, altitude, etc. ANN techniques are based on mathematical models that simulate the principles of biological neural networks, with the ability to learn from their environment [23]. They are generally distributed in layers and interconnected through a network architecture [24], where three layers can be distinguished: the input layer, the hidden layer, and the output layer. Other Machine Learning (ML) approaches, such as support vector machines, fuzzy logic, genetic models, etc., can be used in predicting weather variables. Still, the ANN model has an easy-to-implement structure and has shown better harmony between performance and complexity [25]. Based on a supervised analysis, an ML algorithm was defined using the R language to analyze the patterns of a hydroponic system to predict temperature as a function of humidity following a three-layer model (input layer, hidden layer, and output layer) [23], because this structure is related to Kolmogorov's theory, which states that any continuous function can be approximated by a network with a hidden layer [26]. Figure 7 shows the implemented three-layer ANN

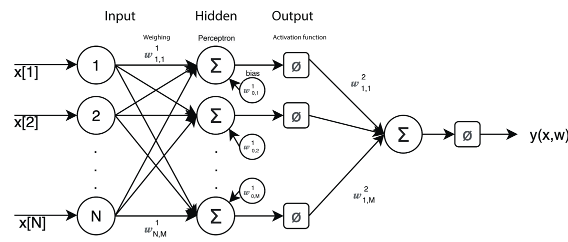

Figure 7. Structure of the proposed neural network.

The prediction of temperature (x) over time (m) is expressed as [26], using equation (1).

$$\hat{x}\,[m] = \sum_{j=0}^{M} w_{j,1}^{(2)} \phi(a_j) \tag{1}$$

With (2):

$$a_j = \begin{cases} 0 & if\ j = 0 \\ \sum_{i=0}^{N} \omega_{i,j}^{(1)} x\,[i] = X^T W_j^{(1)} & otherwise \end{cases} \tag{2}$$

Where $\phi(aj)$ is the output of the j-ésima neuron with activation function, $\phi(aj) = tahn(a_j)$, $x = (1, x\,[1], \ldots, x\,[N])^T$ the vector of input signals, and $w = \left\{w_1^{(\iota)}, \ldots, w_M^{(\iota)}\right\}$, whit $W_j^{(\iota)} = \left(W_{1,j,\ldots,W_{N,j}^{\iota}}^{\iota}\right)^T$ for $\iota = 1, 2$, the sets of all network weight and bias parameters. The transpose of a vector is denoted by $()^T$, and the identity activation function $f\,(z) = z$ determines the total output of the neural network. Finally, the network is trained with a Resilient Backpropagation algorithm to calculate the error gradient.

3. Results and discussion

The proposed IoT monitoring system was implemented in a hydroponic system for growing lettuce in Loja, Ecuador. Soilless cultivation is becoming an effective technique for planting certain vegetables. Optimal temperatures for lettuce cultivation are cold climates ranging between 15 and 18 degrees Celsius, maximum temperatures between 18 and 24 degrees Celsius, and relative humidity of 70% [27]. The quantitative analysis of this study aims to provide information on the current understanding of new IoT technologies and their impact on existing production methods.

The size of the hydroponic system studied is approximately 400 plants, as shown in Figure 8. Ambient temperature and humidity measurements were taken every 10 minutes, totaling 144 samples daily for five months between January and May 2022. However, samples were missing due to some communication, power, or other failures. We estimated the missing samples using the nearest-neighbor imputation technique to solve this problem.

The ThingView application was used as a mobile user interface for real-time monitoring, interpretation, and visualization. This application functions as the interaction interface between the user and the system for precision crop control and monitoring. Figure 9 shows the measurement dataset from the web user interface.

Figure 8. Case study hydroponic system

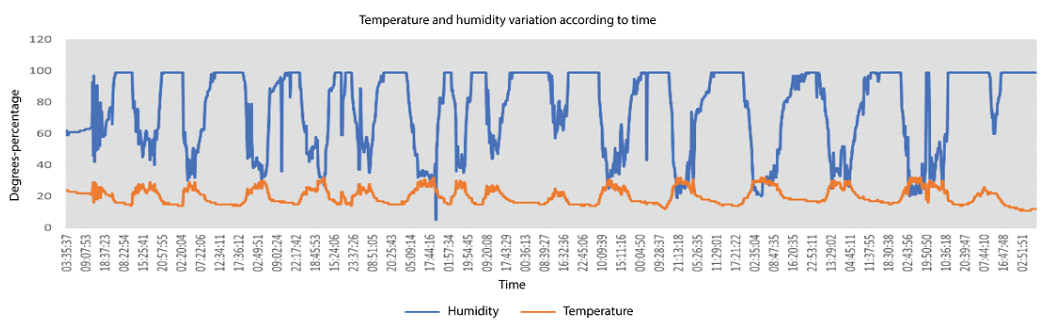

Figure 9. Temperature and humidity measurements

3.1. Training and testing of ANNs

Before the training and testing process for the adjustment of the prediction model, it was necessary to define the origin of the data taken from sensors with IoT technology. These data were transmitted and captured in real-time during January and May 2022, considering this time is the winter season according to the climatic zone. It was possible to collect 6000 records purified through a cleaning and validation process to obtain a total of 5063 base records for the experimentation that served as the primary input of the neural network.

The training data considered 70 % of the total validated records, while the remaining 30 % was used in testing. In the experimentation practice, a data normalization process was performed to achieve a better coupling between the model and the data, where d_{max} is the highest value in the data set and d_{min} is the lowest; $r_{max} = 1$, and $r_{min} = -1$ represent the maximum and minimum values for the corresponding range mapping.

$$\bar{d}_s\,[kT] = \left[\frac{d_s\,[kt] - d_{min}}{d_{max} - d_{min}}(r_{max} - r_{min})\right] + r_{min} \quad (3)$$

After the training process, the optimized weights and ANN biases were accurately calculated. The test data set was evaluated using the root mean square error (RMSE) and a confusion matrix to assess the accuracy of the predictions by performing a supervised analysis. The RMSE established the absolute level of fit that the model generated on the data by comparing the value predicted by the ML model with the actual value in the dataset [28] (equation (4)).

Where $\hat{y}$ is a vector containing a data set of n predictions, and y is the vector of actual values to evaluate the denormalized prediction results compared to the simulated unscaled data.

$$RMSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \quad (4)$$

3.2. Prediction results

Implementing a design of homogeneous experiments was necessary to obtain the results. The primary variable analyzed was the number of neurons to be established in the network's hidden layer to determine the best scenario. The variables were also validated using correlation indexes, showing the association level between two quantitative random variables. A degree of correlation is considered to exist when the data of one variable varies systematically with the values of the other [29].

Figure 10 shows a significant negative correlation index between the temperature and humidity variables corresponding to -0.95, which can be considered a strong negative correlation.

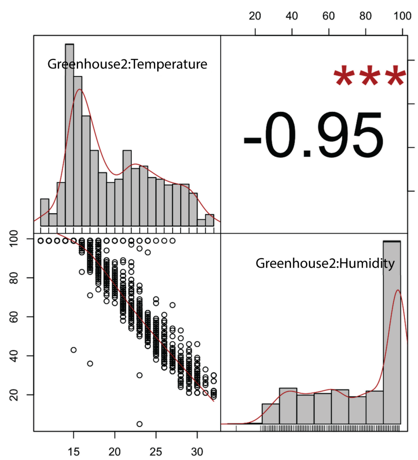

Figure 10. Correlation index.

The design of experiments emphasizes the number of neurons within the hidden layer of the network and the interconnections generated by the relationships between them. The experiments were validated by randomized cross-validation. Table 1 shows the model, the number of neurons in the hidden layer, the RMSE value generated, and the prediction accuracy obtained.

The model that best fits this type of data is ANN 4, which consists of four neurons in the hidden layer and has a better performance, with an RMSE value of 0.11 and an accuracy of 89.37 %, according to the supervised data analysis. Figure 11 shows the structure of the neural network.

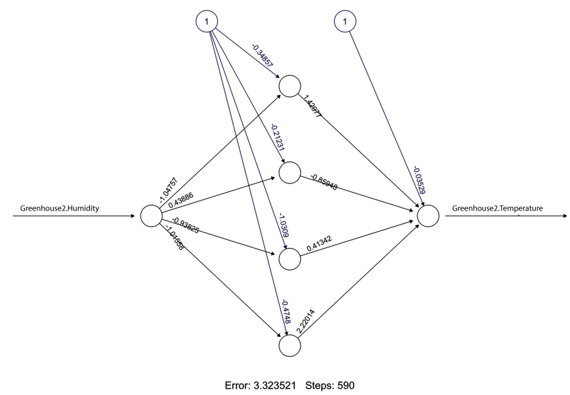

Figure 11. Neural network structure

Table 1. Model indications

Model	Neurons	Algorithm	Activation function	Learning rate	Threshold	RMSE	Accuracy
RNA 1	1	Resilient Backpropagation	Sigmoid	0.01	0.01	0.14	87.33%
RNA 2	2	Resilient Backpropagation	Sigmoid	0.01	0.01	0.13	88.01%
RNA 3	3	Resilient Backpropagation	Sigmoid	0.01	0.01	0.14	87.1%
RNA 4	4	Resilient Backpropagation	Sigmoid	0.01	0.01	0.11	89.37%
RNA 5	5	Resilient Backpropagation	Sigmoid	0.01	0.01	0.14	87.33%

Considering the variables analyzed, the experimental environment, and the data obtained, it can be stated that the temperature can be predicted with 89.37 % accuracy as a function of humidity, according to the experiments performed and the ANN 4 model defined. Figure 12 shows the prediction results. The predicted values were compared with the actual temperature measured by the IoT system for one week

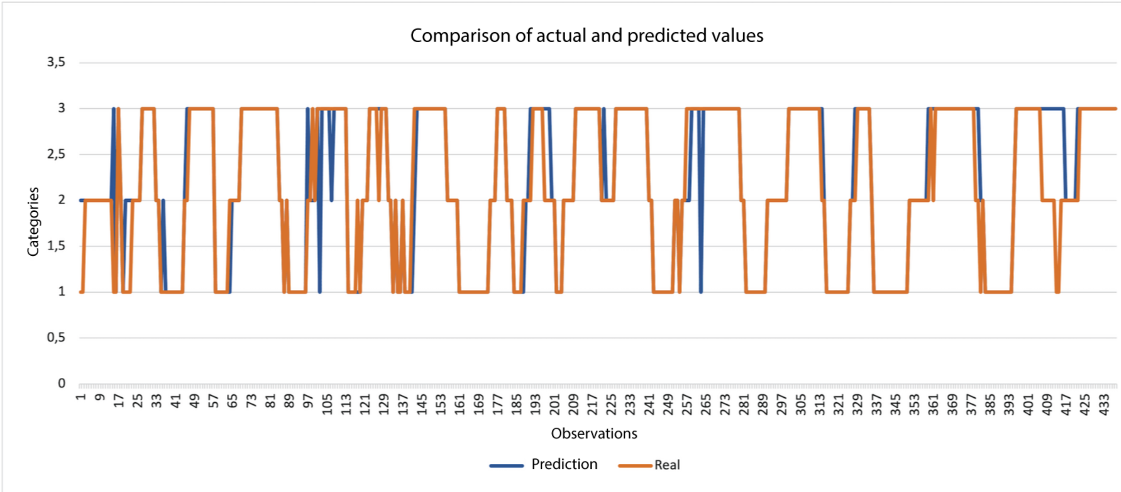

Figure 12. System temperature and expected temperature.

4. Conclusions

This research presented an IoT-based monitoring system for smart agriculture, designed and implemented to provide optimal conditions and cost-effective solutions for plant cultivation methods and life cycles of hydroponic systems. The system design, implementation, and machine learning application for environmental prediction were analyzed in detail. The IoT system was experimentally validated by monitoring temperature and humidity for five months. The system availability rate during this period was approximately 85 % due to human failures and packet loss. The case study demonstrated that 100% spatial coverage of the system could be achieved with only one IoT device for a hydroponic system with a capacity of 400 plants. Accurate automatic control for nutrient recirculation was conducted with 100 % functionality through the control of the RTC module.

A data-driven prediction model was implemented using an artificial neural network. The results showed that the ANN model could be used to predict temperature as a function of humidity; with a simple three-layer ANN and four neurons in the hidden layer, the prediction accuracy was 89.37 %. Compared to similar solutions, the proposed IoT framework is more flexible and meets the requirements for optimizing productivity and sustainability through emergent communication. Further studies will focus on experimental greenhouse validation using automatic control and long-term temperature and humidity predictions. Another relevant topic for future research could be implementing and evaluating specific operations and/or strategic decision-making using the proposed IoT system architecture.

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