



Article

Real-Time Environmental Monitoring System for Open-Field Avocado Crops

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Abstract

The effects of climate change have altered precipitation patterns, causing extreme weather events that impact crop yields and increase the demand for agricultural production, which drives the need to implement emerging technologies. This research presents the design, construction, and validation of a real-time monitoring system for environmental parameters in open-field avocado orchards. A four-phase methodology was employed: (1) Establishment of required parameters and construction of the IoT architecture; (2) Design of the geometry and final elaboration of the system: modeling in SolidWorks, circuit diagrams in Fritzing, and system assembly; (3) Development of a mobile application: Android Studio and development of the autoencoder model with machine learning; and (4) Validation: Evaluation of the wireless link; system implementation and deployment of the mobile application. The results obtained include a system with a transmitter node equipped with sensors and a receiver, both incorporating ESP32 and nRF24L01+PA+LNA modules, with a wireless transmission range of 2300 m. A total of 2016 data records were stored on microSD and in the cloud, which can be queried, visualized, and analyzed through the mobile application via Bluetooth or Wi-Fi; the system also detects outlier data that can be used for decision-making in the agricultural sector.

Keywords: precision agriculture; IoT in agriculture; AI in agriculture; crop health monitoring; agricultural engineering



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1. Introduction

The agricultural sector plays a crucial role in the economic growth of a country [1], accounting for approximately 4% of GDP at the global level, while in low-income economies it can constitute more than 25% [2]. Rapid population growth has increased food demand, requiring agricultural production to increase by 70% by the year 2050 [3]. Increasing agricultural productivity through an efficient approach, using fewer resources and less human effort, is fundamental to ensuring long-term sustainable production [4,5]. At present, the

adoption of emerging technologies has proven to be key to mitigating the negative effects of intensive agricultural practices and optimizing the use of natural resources [6,7]. In particular, monitoring systems constitute an infrastructure that enables the observation of variables to detect anomalies and optimize processes in precision agriculture [8]. Likewise, the Internet of Things (IoT) has demonstrated the potential to transform open-field crops, making them more efficient in terms of time, cost, and sustainability [9]. Big Data analysis enables the massive processing of information for more informed decision-making [10,11]; and Artificial Intelligence (AI), through machine learning (ML) and deep learning techniques, improves yield prediction and the detection of problems in crops based on the analysis of large data volumes [12,13]. In this context, recent advances in control platforms, communication protocols, and embedded systems have led to the development of customized solutions for the monitoring and control of crops, soils, and microclimates [14]. Another important aspect concerns wireless communication technologies, classified according to transmission distance into short-range (≤ 10 m), medium-range (10 m to 100 m), and long-range (≥ 100 m), which play a fundamental role in the efficient operation of this type of system [15]. In addition, the continuous collection of critical variables is essential in agriculture, including temperature, which causes thermal stress by altering germination, vegetative growth, and photosynthesis [16]; relative humidity on the leaf surface, which promotes the proliferation of pathogens [17]; soil moisture deficiency, which induces internal water stress [18]; and excess ultraviolet (UV) radiation, which causes visible damage to leaves and fruits [19,20].

This research presents the design, development, and validation of a real-time monitoring system for environmental variables in open-field avocado orchards, considering air temperature, relative humidity, soil moisture, and UV radiation, structured through a four-layer IoT architecture that integrates circuit design in Fritzing, node assembly, a mobile application (app) developed in Android Studio, and a machine learning autoencoder model for the analysis of environmental data. Its main contribution is the field integration and validation of an IoT architecture oriented toward avocado cultivation that combines environmental data acquisition, long-range wireless communication with the nRF24L01+PA+LNA module, local and cloud storage, mobile visualization, and detection of atypical records through unsupervised learning. The result is an environmental monitoring system comprising a transmitter (TX) node that captures environmental variable information through sensors, and a receiver (RX) node that stores and transmits data to the cloud, both equipped with a microcontroller, wireless communication module, and directional antennas, enabling data transmission at 10 min intervals with coverage of up to 2300 m. The records can be retrieved, visualized, and analyzed in an app via Bluetooth Low Energy (BLE) or Wi-Fi, alongside an autoencoder model for the detection of atypical environmental patterns.

Literature Review

In recent years, various studies have reported innovative solutions for monitoring atmospheric, environmental, and nutritional parameters, seeking to optimize resource management, increase productivity, and streamline agricultural processes. Regarding agricultural monitoring systems, Routis and Roussaki [21] presented a prototype based on Raspberry Pi 4B and Arduino Mega that integrates temperature, UV radiation, and soil moisture sensors, employed ZigBee (IEEE 802.15.4) communication via XBee Series S2 modules, and incorporated a weather condition forecasting model; Islam et al. [22] developed an ESP8266-based system integrated with environmental sensors and ML algorithms, capable of providing fertilizer recommendations; Chapungo and Postolache [23] implemented a system with Arduino Uno and LoRaWAN connectivity, deployed in a rural area for 24 h,

reaching a distance of 1000 m, while Suhag et al. [24] employed GSM communication technologies for soil moisture and water level control. Likewise, Sabu et al. [25] built an IoT-based smart sensor node incorporating temperature, soil moisture, and pH sensors for water condition management through a cloud platform; Ahmed et al. [26] developed a temperature, soil moisture, and light intensity measurement system for large agricultural areas using ESP32 and LoRa communication, achieving both simulation and real-time experimental validation; Kalaivani et al. [27] proposed a smart agricultural infrastructure that measures real-time indicators, sends data to the cloud, and visualizes them through graphs. Finally, Azhari et al. [28], Woo-García et al. [29], and Abidin et al. [30] reported the use of nRF24L01+ modules integrated with a Power Amplifier (PA) and a Low Noise Amplifier (LNA) in a wireless sensor network (WSN) for monitoring temperature, relative humidity, and light intensity via Arduino Uno at distances of up to 1000 m under line-of-sight conditions.

In greenhouses, Zeping et al. [31] designed a smart environmental variable control system based on ESP32 and the Home Assistant platform with ZigBee sensors, reaching distances of 140 m under line-of-sight conditions; Sacaleanu et al. [32] proposed a web platform for the acquisition, storage, and visualization of environmental data with LoRaWAN within a WSN; Sagheer et al. [33] presented an IoT infrastructure integrated with sensors, actuators, and devices, improving water and energy use efficiency; additionally, Arregoces-Guerra et al. [34] developed an IoT system implementing nodes with temperature, humidity, and light intensity sensors with LoRaWAN communication, operating for three months of continuous monitoring and visualizing records through a web platform; Guijarro-Rubio et al. [35] used ESP32 and ESP8266 for measuring environmental conditions over 21 continuous hours, while Hernández-Morales et al. [36] presented an artificial neural network model for weather prediction 24 h in advance, using data collected from an IoT monitoring system validated over three months.

Regarding specific crops, Abu Snehneh and Shabaneh [37] designed and built a control system for hydroponic lettuce using ESP32, Wi-Fi connectivity, and pH, water level, and temperature sensors; data were managed in the Blynk application for water pump activation. In open-field plantations, particularly vineyards, Pero et al. [38] incorporated IoT sensors and ML models for agricultural optimization, developing regression and classification models for frost prediction, soil moisture, and diseases such as downy mildew, obtaining short-term forecasts with R^2 values of up to 0.98 and accuracy of up to 97%; Shahab et al. [39] built an IoT-based smart agricultural platform for monitoring environmental and nutritional patterns, implemented in a rice field using cloud-connected sensors and an app with AI for irrigation, fertilization, and disease diagnosis support; López-Velasco et al. [40] used LoRa TTGO T-Beam 32 modules and an Arduino Mega board for environmental monitoring in banana plantations, reaching distances of up to 1140 m and monitoring system parameters through web and mobile interfaces; Cruz et al. [41] presented an IoT platform using LoRa communication and a YOLOv5-based detection model, capable of identifying seven common diseases with 92% precision. On the other hand, Torres-Quezada et al. [42] integrated soil moisture sensors with remote sensing to optimize irrigation management and assess water stress in avocado orchards; Rahman et al. [43] incorporated climatic variables and indices derived from Sentinel-2 imagery to predict alternate bearing via ML models, using TabPFN and obtaining Accuracy = 0.88 and AUC = 0.95; and Moreno-Bernal et al. [44] presented a system integrating Arduino Mega and GSM/GPRS communication, collecting 8832 records of environmental parameters relevant to plantation management.

2. Materials and Methods

2.1. Materials

For the construction of the prototype, the following components were used: an ESP32-DevKitC-32 development board based on the ESP-WROOM-32 Wi-Fi and Bluetooth module (Espressif Systems, Shanghai, China), equipped with a USB Type-C interface and a CH340C USB-to-UART bridge, a soil moisture sensor (HD-38), an ultraviolet radiation sensor (GUVA-S12SD), an air temperature and relative humidity sensor (AM2302 DHT22), a 10 μ F capacitor, a 220 Ω resistor, a 2.4 GHz Yagi-type directional antenna, an SMA to RP-SMA adapter, 18650 lithium-ion cells, nRF24L01+PA+LNA modules, a microSD card reader, a charging module (SM5308), and SolidWorks Premium 2023 SP4.0, Fritzing 0.9.10 Beta, Arduino IDE 2.3.4, Android Studio Otter 2025.2.1, and Python 3.10 software.

2.2. Methodology

For the development of the environmental monitoring system, the methodology described in Figure 1 was considered.

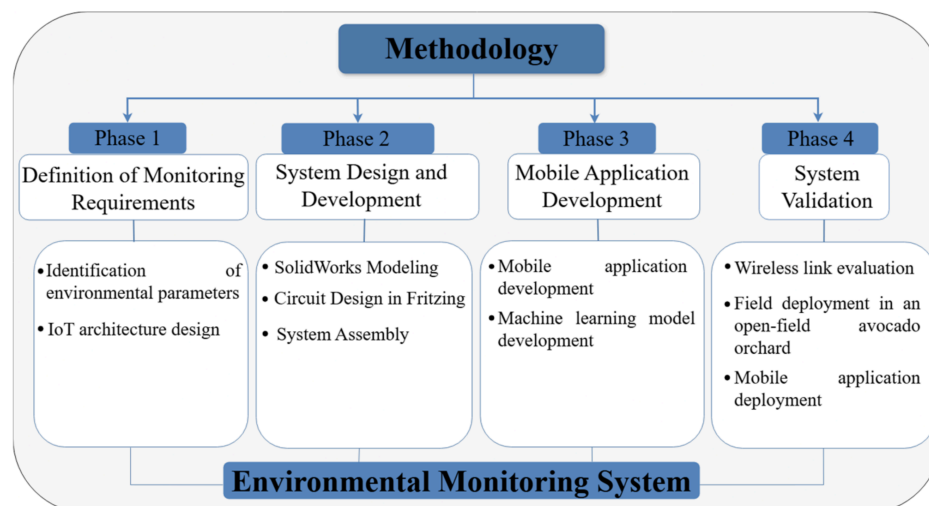


Figure 1. Methodology process.

2.2.1. Determination of Environmental Parameters

Considering the direct influence on the development and health of the crop, the environmental parameters that affect avocado growth were identified (Table 1).

Table 1. Environmental parameters considered for avocado crop monitoring.

Parameter	Influence on the Crop
Temperature [16,45]	Germination, vegetative growth, photosynthesis, and thermal stress.
Relative humidity [17,46]	Leaf area, pathogen proliferation, and plant health.
Soil moisture [47]	Water availability, water and nutrient absorption, and water stress.
UV radiation [20,48]	Foliar and fruit damage, crop quality, and productivity.

Furthermore, the reference ranges for air temperature, relative humidity, and soil moisture were established based on technical manuals and agroclimatic studies from the literature (Table 2).

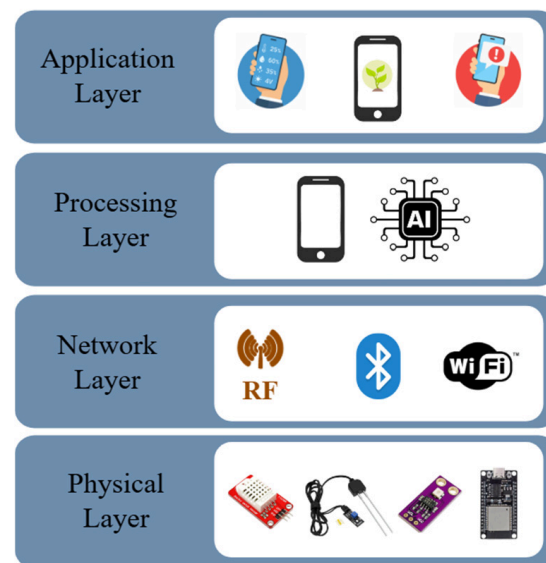
Table 2. Reference ranges of environmental parameters for avocado crop cultivation.

Parameter	Normal Range
Temperature (°C) [16,45]	28–33
Relative humidity (%) [17,46]	60–65
Soil moisture (%) [47]	30–50

UV radiation is expressed through the ultraviolet index (UVI) on a dimensionless scale from 0 to 11, standardized by the World Health Organization [49].

2.2.2. IoT Architecture Construction

The IoT architecture is composed of four layers, three of basic design (Physical, Network, and Application) and one for processing (Figure 2) [36].

**Figure 2.** IoT system architecture.

Physical Layer

At the physical layer, the system integrates a TX node and an RX node, both comprising an ESP32 microcontroller, an nRF24L01+PA+LNA module, and a 2.4 GHz Yagi directional antenna. The TX node incorporates air temperature, relative humidity, and soil moisture sensors for the acquisition of environmental variable data. UV radiation is measured with the GUVAS12SD sensor, from which the UVI is obtained [50,51]. The RX node includes a microSD card for local storage of received records; accordingly, the power supply packages of both nodes are assembled independently, using five 18650 lithium-ion cells with a nominal capacity of 1200 mAh per cell connected in parallel, reaching a total of approximately 6000 mAh per node. Battery capacity in watt-hours is obtained using Equation (1):

$$E = \left(\frac{6000 \text{ mAh}}{1000} \right) \times 3.7 \text{ V} \approx 22.2 \text{ Wh} \quad (1)$$

where E is the available energy, expressed in watt-hours, and V is the battery voltage [52].

The average power consumed by each node is estimated from the measured supply voltage and average current, Equation (2):

$$P = V \times I$$

$$P = 5.14 \text{ V} \times 0.0569 \text{ A} \approx 0.293 \text{ W} \quad (2)$$

where P is the average power consumed, expressed in watts (W), V is the supply voltage expressed in volts, and I is the average current consumed in amperes [52].

The theoretical autonomy of each node is estimated from the ratio between the available battery energy and the average power consumed, Equation (3):

$$t = \frac{E}{P}$$

$$t = \frac{22.2 \text{ Wh}}{0.293 \text{ W}} \approx 75.8 \text{ h} \quad (3)$$

where t is the theoretical autonomy time expressed in hours, E is the available energy in watt-hours, and P is the average power consumed in watts [52].

The selection of components considered the system requirements, device compatibility, low power consumption, and ease of integration. In this regard, the ESP32 was chosen for its Wi-Fi and Bluetooth communication capabilities; the environmental sensors for enabling the recording of the variables defined for crop monitoring; and the nRF24L01+PA+LNA module and the 2.4 GHz Yagi directional antenna for facilitating a longer-range wireless link through increased gain and communication directionality [53].

Network Layer

At the network layer, wireless communication between the TX node and the RX node is established through the nRF24L01+PA+LNA transceiver module and a 2.4 GHz Yagi directional antenna, considering the link configuration and the data packet structure. The TX node was configured to operate in deep sleep mode with a 10 min activation interval, selected to balance power consumption and the recording frequency of environmental variables; shorter intervals increase power consumption while decreasing data fluctuation, whereas longer intervals reduce energy usage and increase record variability. Each cycle activates the ESP32 of the TX node for sensor data acquisition and transmission to the RX node via the wireless link, returning to deep sleep mode until the next interval (Figure 3a).

For local communication, the TX node is configured as a Bluetooth Low Energy (BLE) device, while the mobile application implements the connection with the Android Bluetooth application programming interface (API), including the BluetoothAdapter, BluetoothDevice, BluetoothGatt, and BluetoothLeScanner classes (Figure 3b).

Likewise, the RX node employs the Wi-Fi connectivity of the ESP32 to synchronize the records with Firebase Realtime Database (free tier), which enables real-time remote synchronization of environmental records and facilitates integration with the ESP32 and the mobile application via API, offering a suitable alternative for data storage and retrieval through a storage structure in JavaScript Object Notation (JSON) format. This enables access to the information, and in turn the mobile application retrieves the stored data via Wi-Fi connection (Figure 3c) [53].

Processing Layer

At this layer, data from the monitoring system are processed through two complementary and independent mechanisms. The first corresponds to the autoencoder model executed in the mobile application, which jointly evaluates the combination of the four normalized environmental variables. The established threshold (0.0814) for the records was obtained using Equation (4) [54]:

$$\tau = \mu_e + 2\sigma_e$$

$$\tau = 0.02414 + 2(0.02863) = 0.08140 \approx 0.0814 \quad (4)$$

where τ = anomaly detection threshold, μ_e = mean reconstruction error, and σ_e = standard deviation.

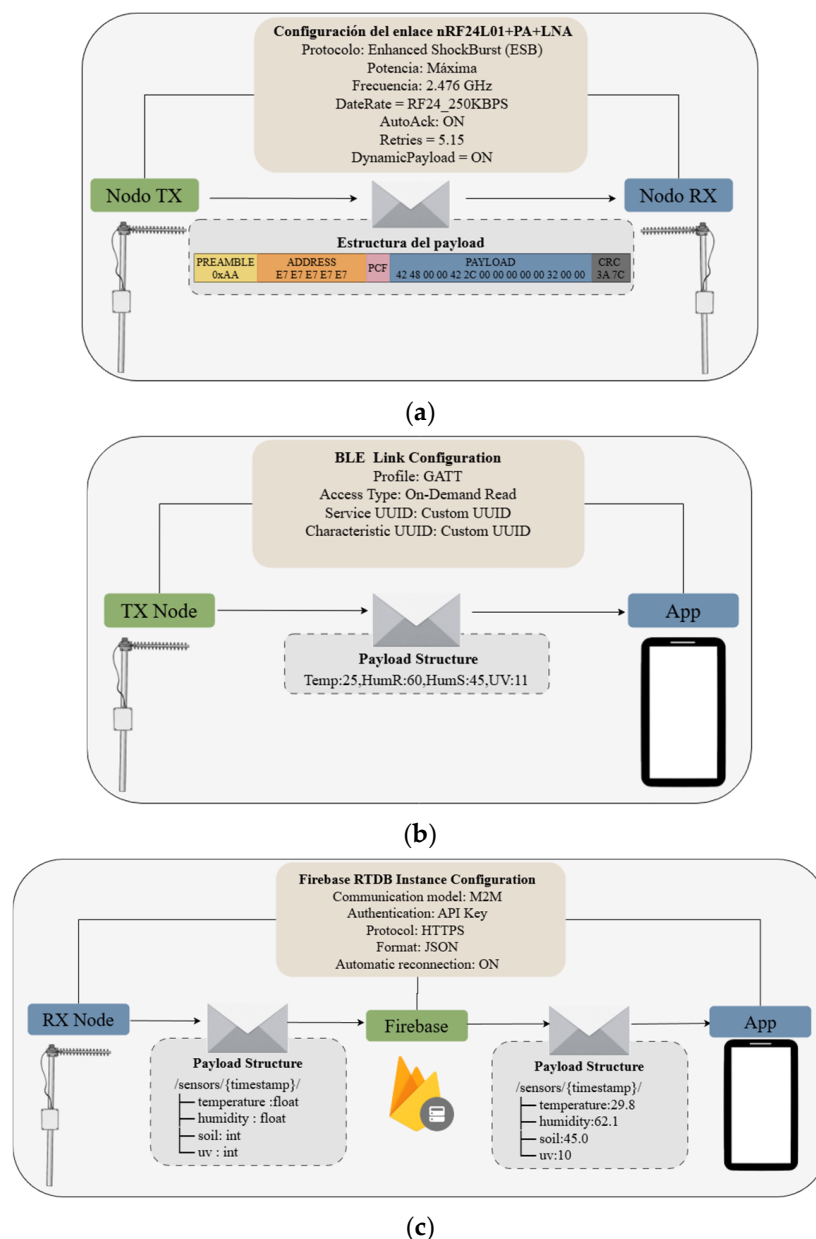


Figure 3. (a) Communication Scheme and Packet Structure of the nRF24L01+PA+LNA Modules. (b) BLE Communication Scheme and Packet Structure. (c) Firebase RTDB communication instance and packet structure.

Errors exceeding the threshold are identified as anomalous. The second mechanism generates alerts through percentiles: P_5 (values below the lower bound of the interval) indicates a “Low” alert, and P_{95} (values above the upper bound of the interval) indicates a “High” alert, while readings within the interval are classified as “Normal”. The percentiles are dynamically recalculated as new records are incorporated; therefore, these are not universal agronomic intervals, but rather dynamic statistical limits derived from the observed behavior of the crop. Both mechanisms can be activated simultaneously or independently, enabling the identification of both deviations in individual variables and atypical combined patterns (Figure 4).

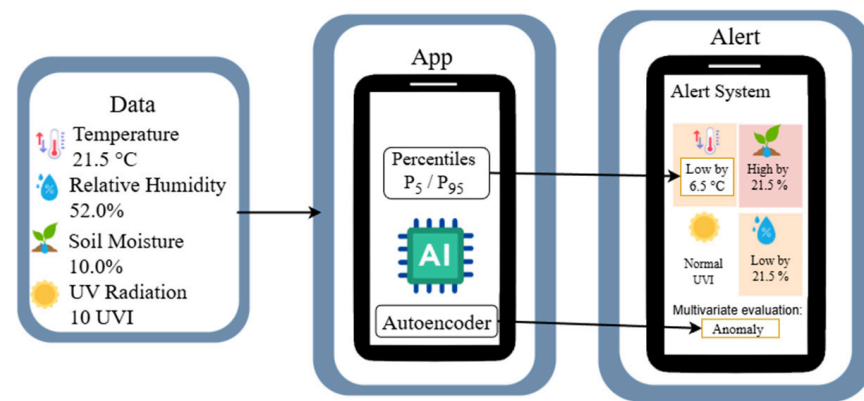


Figure 4. Processing flow on the mobile device.

Application Layer

Finally, at this layer, the mobile application is developed in Android Studio using Java, oriented toward the visualization, retrieval, and management of information generated by the environmental monitoring system. The application enables access to the data collected by the TX node and managed by the RX node through the connections established at the network layer, both for local retrieval and remote access to information. Here, the acquired records are available under a local and remote storage scheme, favoring information retrieval during temporary communication interruptions, as well as the analysis of environmental variables through individual alerts based on statistical limits and the AI model for the identification of multivariate anomalies (Figure 5).

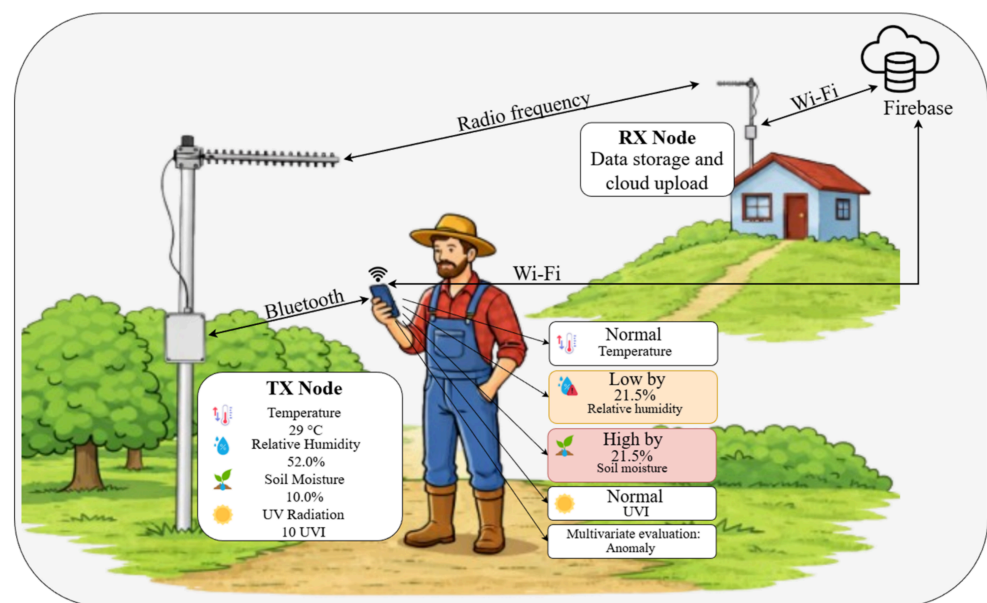


Figure 5. General system architecture diagram.

2.2.3. System Geometry Design and Construction

SolidWorks Modeling, Fritzing Diagrams, and System Assembly

To ensure precision and fit between the electronic and structural components of the system, the geometric design was developed in SolidWorks considering the dimensions and distribution of the components integrated into the TX and RX nodes. The selection of the ESP32 was based on its dual communication capabilities (Wi-Fi and Bluetooth), the environmental sensors (HD-38, GUVA-S12SD, DHT22) for the measurement of the monitored variables in avocado cultivation, and the nRF24L01+PA+LNA module and a

2.4 GHz Yagi directional antenna for their longer-range wireless link through increased communication gain. This modeling enabled the definition of the internal arrangement of elements prior to physical assembly, and the electronic diagrams in Fritzing were used to visualize the electrical connections (Figure 6a,b).

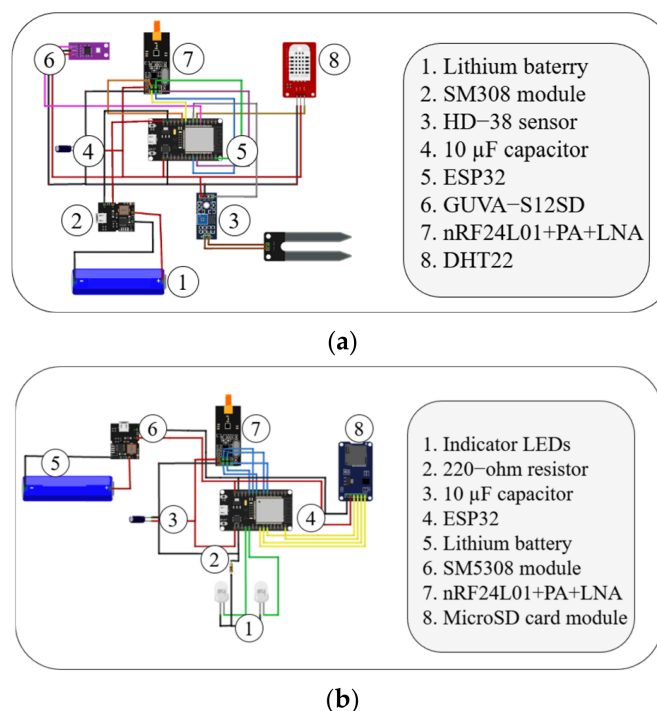


Figure 6. (a) Schematic diagram of the TX node electronic components. (b) Schematic diagram of the RX node electronic components.

For the final assembly of the system, the electronic components of the TX and RX nodes were integrated within the enclosures defined in the geometric design, following a three-stage sequence: assembly of the electronic boards, power supply, and mounting of the components, organizing the physical integration of the prototype.

2.2.4. Mobile Application Development

The mobile application was developed as a tool oriented toward the monitoring, analysis, and interpretation of environmental data recorded by the system, implemented in Java in an Android Studio Otter 2025.2.1 environment with compatibility for Android 7.0 Nougat or higher, allowing access to cloud-stored records and visualization of readings from a mobile device that can be queried remotely from the cloud and locally via BLE by the user. Additionally, access to an alert system where the farmer can visualize the reading thresholds is provided (Figure 7).

2.2.5. Machine Learning

Machine learning was carried out through an unsupervised ML model based on an autoencoder neural network that receives as input a vector comprising four normalized variables, generating as output the reconstruction of the vector [55]. Its architecture consists of an input layer of four variables, an encoder with eight neurons and ReLU activation, a bottleneck of two neurons with ReLU activation, a decoder with eight neurons and ReLU activation, and an output layer of four neurons with sigmoid activation, compiled with the Adam optimizer and the mean squared error loss function (Figure 8).

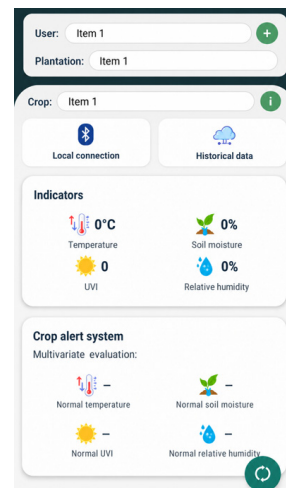


Figure 7. Graphical user interface of the application design.

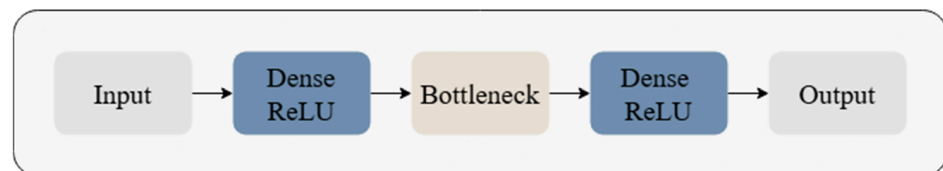


Figure 8. Autoencoder model architecture.

For training, 2016 unlabeled multivariate records collected every 10 min over 14 days under uncontrolled environmental conditions were used; each record included values of air temperature, relative humidity, soil moisture, and UV radiation. These variables were normalized to an interval of 0 to 1 using the Min-Max method, with 80% of the data used for training carried out over 30 epochs with a batch size of 32, record randomization, and 20% validation. Anomaly detection was performed based on the reconstruction error between the original and reconstructed values. Records with a reconstruction error less than or equal to the established threshold were classified as normal, whereas those exceeding the limit were identified as anomalous. The trained model was evaluated on a set of 2016 records, computing the mean reconstruction error and comparing it against the threshold of 0.0814. Finally, the model was implemented in Python 3.10 (Python Software Foundation, Beaverton, OR, USA) with TensorFlow/Keras and integrated into the mobile application using the TensorFlow Lite 2.16.1 and TensorFlow Lite Support 0.4.0 libraries.

2.2.6. Wireless Link Evaluation

The determination of the range and stability of the system's wireless communication link was performed at distances of 100 m, 300 m, 500 m, 1000 m, 2000 m, and 2300 m under line-of-sight conditions in the locality of Chichihualco, municipality of Leonardo Bravo, Guerrero, Mexico, at latitude 17°38'30.46" N, longitude 99°40'29.51" W, and altitude 1420 m a.s.l. The TX node transmission was programmed in the Arduino IDE environment using the C++ language to continuously send 12-byte data packets through the nRF24L01+PA+LNA module. In this test, the packets correspond to an evaluation payload generated solely to measure the range and stability of the wireless link; therefore, they did not include environmental readings from the monitoring system. During the tests, the TX node was fixed on the rooftop of a dwelling, while the RX node was moved to each of the established distances, recording the number of packets received during a period of two minutes (120 s).

2.2.7. System Implementation in an Avocado Orchard

The system implementation was carried out under uncontrolled environmental conditions in an avocado orchard (2 ha), located at the same site where the wireless link was evaluated (Figure 9).

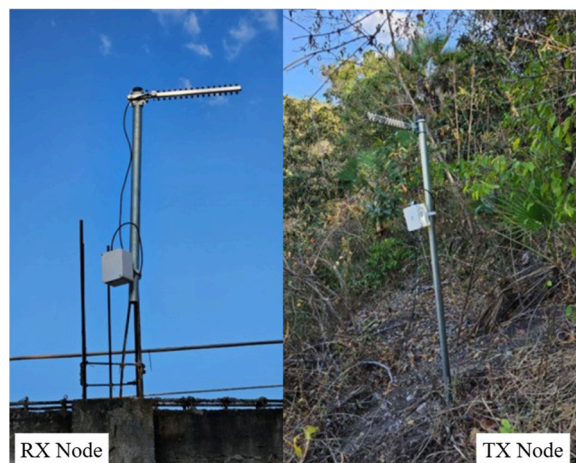


Figure 9. Node implementation.

The node was installed in the avocado orchard; the soil moisture sensor probe was placed at a depth of 20 cm, the UV radiation detector was installed on the upper part of the enclosure oriented toward the sun, and the air temperature and relative humidity sensor was fixed on the protective cover. Subsequently, the TX node was directed toward the RX node, located on the rooftop of a dwelling and aimed toward the TX node. Data collection was performed every 10 min over 14 consecutive days, obtaining 2016 multivariate records stored locally on a microSD card and in the cloud (Figure 10).

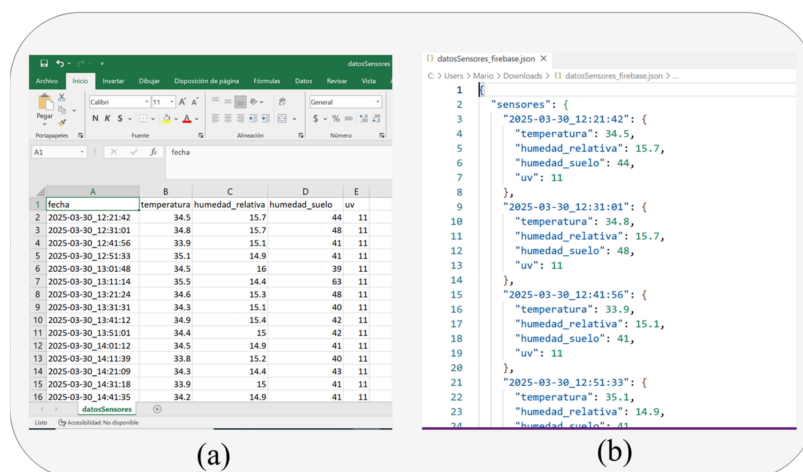


Figure 10. System validation: (a) local file stored on the microSD card and (b) Firebase RTDB database file.

2.2.8. Mobile Application Deployment on a Mobile Device

For the operation of the app and visualization of monitored parameters, the .apk file is installed on the SM-S928B device with Android 16 operating system (Figure 11).

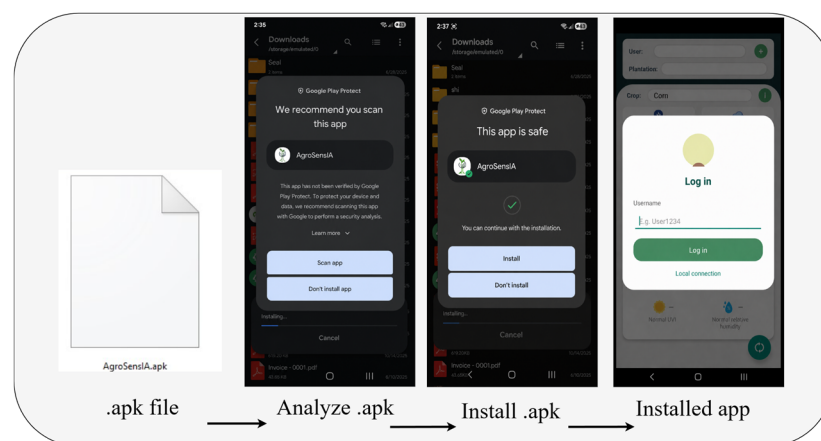


Figure 11. Installation flow of the mobile application.

3. Results

The reference ranges considered for air temperature, relative humidity, and soil moisture were 28–33 °C, 60–65%, and 30–50%, respectively. UV radiation was monitored through the UVI on a scale of 0 to 11. These values are established as agronomic references to contextualize the monitored variables without constituting the final classification criterion of the system.

The IoT architecture and the system are structured into four layers: physical, network, processing, and application. The physical layer integrates the TX and RX nodes, environmental sensors, communication modules, directional antennas, power supply packages with lithium-ion cells, and local storage via a microSD card. The network layer enables wireless transmission between nodes, local retrieval via BLE, and remote synchronization with Firebase RTDB. The processing layer incorporates the AI model based on an autoencoder for the analysis of environmental records, while the application layer enables the visualization, retrieval, and interpretation of information from the app.

3.1. Model Training

During autoencoder training, the predominant patterns are successfully reconstructed, and the parameters shown in Table 3 are obtained.

Table 3. Autoencoder model training.

Parameter	Value
Final loss	0.0209
Validation loss (val_loss)	0.0375
Mean squared error (MSE)	0.02414
Standard deviation of MSE	0.02863
Reconstruction threshold	0.0814

The trained model was applied to 2016 records as a post-training analysis stage. In this evaluation, a mean reconstruction error of 0.00734 was obtained; the error distribution shows that the majority of records present values close to zero, indicating that the model adequately reconstructs the patterns learned during training. In contrast, a reduced number of records reflect errors exceeding the threshold of 0.0814, evidencing deviations with respect to the predominant patterns of the dataset. A total of 0.99% of the evaluated data exceeded the reconstruction threshold, triggering alerts as an anomalous environmental pattern representing environmental combinations less frequent relative to the patterns learned by the autoencoder. This occurs because the model is developed with unsupervised

learning and the records do not have labels that allow the distinction of environmental fluctuations, sensor irregularities, or events requiring agronomic action. Furthermore, the warnings are not interpreted as automatic intervention instructions for the farmer; rather, they are considered indicators for the joint review of the recorded variables and their temporal behavior (Table 4).

Table 4. Evaluation of the trained autoencoder model.

Parameter	Value
Number of evaluated records	2016
Mean reconstruction error	0.00734
Records detected as anomalies	20 (0.99%)
Maximum reconstruction error	0.22695

3.2. Validation

Regarding wireless link performance, the experimental evaluation shows that the system maintained communication at all analyzed distances (100 m to 2300 m) under line-of-sight conditions. The results demonstrate a slight decrease in the mean packets received per second (PPS) as distance increases, with greater variability in the measurements related to the sensitivity of the link to the alignment of the directional antennas due to the increasing distance between the TX and RX nodes. Nevertheless, the link remains operational up to 2300 m, demonstrating its viability for open-field agricultural monitoring applications under the evaluated conditions (Table 5).

Table 5. Wireless link performance.

Distance (m)	Average (PPS)	Standard Deviation	Range (PPS)
100	1666.50	0.50	1666–1667
300	1665.51	0.50	1665–1666
500	1664.92	0.80	1664–1666
1000	1664.44	1.11	1663–1665
2000	1662.33	1.66	1660–1665
2300	1662.47	1.66	1660–1665

Furthermore, the system was established with a wireless link of up to 2300 m; this is noteworthy given that the nRF24L01+PA+LNA is commonly employed in short-range wireless communications. Nevertheless, the configuration used between directional antennas and node alignment enables the extension of its application to a greater range. In addition, the system implementation was carried out in the most distant avocado crop of the community, enabling communication between nodes.

During the implementation period, the TX and RX nodes exhibited an experimental autonomous operating time of approximately 48 h. This value was lower than the estimated theoretical performance of 75.8 h; the discrepancy between both values is not experimentally characterized in this study and is therefore not attributed to a specific cause. Nevertheless, the literature identifies as potential factors the difference between the nominal capacity and the effective available capacity of lithium-ion batteries under real operating conditions, as well as the influence of ambient temperature on their performance [56,57]. For extended periods of operation, ultra-low power consumption techniques and solar panels are reported in the literature as alternatives to extend the autonomy of wireless nodes [58,59]. These strategies are not evaluated in this study; consequently, it was necessary to recharge both nodes every two days to ensure monitoring continuity, requiring optimization for extended periods of operation without periodic recharging interventions.

The app records, visualizes, and analyzes in real time the data from the system; the final output enables the presentation of the status of each environmental variable with interpretive labels generated by the application. During implementation, air temperature is identified as “high by 21.5 °C”, soil moisture as “low by 10.0%”, UV radiation as “normal”, relative humidity as “high by 22.0%”, and the autoencoder model as (multivariate evaluation: anomaly) (Figure 12).

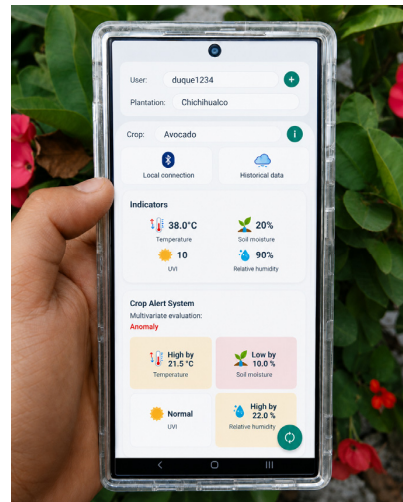


Figure 12. Mobile application.

4. Discussion

The IoT architecture implemented in the environmental monitoring system enabled the structured integration of sensors, communication protocols, and storage and visualization services. This design is consistent with Guijarro-Rubio et al. [35], who identified that the functional separation of layers facilitates integration in smart agricultural systems. Likewise, the developed system distributes its specific functions through the physical, network, processing, and application layers, which is in agreement with Ahmed et al. [26], Hernández-Morales et al. [36], Shahab et al. [39], Kalaivani et al. [27], and Guijarro-Rubio et al. [35], who report that multilayer architectures improve information management in precision agriculture applications by providing scalability, modularity, and interoperability between devices.

Regarding the architectural design implemented in the system, it is similar to that of Hernández-Morales et al. [36], who also adopted a four-layer division to optimize data flow. The functional balance between the components implemented in the system (sensors, communication protocols, and storage and visualization services) differs from that of Routis and Roussaki [21] and Islam et al. [22], who prioritize components such as centralized processing in the system. With respect to the monitoring of environmental parameters (temperature, relative humidity, soil moisture, and UV radiation), it partially agrees with Moreno-Bernal et al. [44], who add a different parameter (soil temperature) for the monitoring of avocado crops. Data acquisition from monitoring is recorded at 10 min intervals, which contrasts with Abidin et al. [30], Zeping et al. [31], Woo-García et al. [29], Lopez-Velasco et al. [40], and Chapungo and Postolache [23], who use an interval of one to five minutes, which increases the operational wear of the system.

The proposed system incorporates an energy strategy based on deep sleep mode during inactive periods, consistent with Arregoces-Guerra et al. [34], who also implement this type of strategy for energy optimization. Regarding data storage, the system incorporates a continuous dual storage mechanism on a local microSD card and in the Firebase Realtime Database, which contributes to improving data storage reliability in

the event of communication failures. Similarly, Abidin et al. [30] and Zeping et al. [31] implement strategies incorporating local data storage cards to prevent connectivity interruptions and maintain data recording continuity. The hardware developed in this proposal achieved a range of 2300 m under line-of-sight conditions, unlike Abidin et al. [30], Woo-García et al. [29], Zeping et al. [31], and Routis and Roussaki [21], who obtained a coverage of 120 m to 800 m by implementing nRF24L01+ or ZigBee technologies. Finally, an unsupervised autoencoder model was implemented in the mobile application for the statistical analysis of data for environmental diagnostics. In contrast to Routis and Roussaki [21], Islam et al. [22], Hernández-Morales et al. [36], Pero et al. [38], and Shahab et al. [39], which rely on supervised models, the proposed system uses an unsupervised autoencoder and does not require manually labeled environmental records.

5. Conclusions

The environmental monitoring system for avocado orchards developed in this project considers four environmental parameters that influence crop growth and health, establishing reference ranges for each variable. The four-layer architecture enables the acquisition, transmission, storage, and visualization of information, facilitating efficient integration of components (sensors, communication protocols, and cloud services).

The results obtained following 14-day field validation demonstrated that the system achieved wireless communication of up to 2300 m under line-of-sight conditions. The incorporation of an unsupervised learning model in the app establishes an appropriate approach for anomaly detection in agricultural contexts where manual data labeling is limited or nonexistent. The use of emerging technologies, long-range wireless communication, and AI within an architecture oriented toward autonomous agricultural monitoring in this research contributes to precision agriculture for efficiency and sustainability in this type of practice.

As future work, it is proposed to optimize the power supply system to increase node autonomy through the evaluation of ultra-low power consumption techniques and the use of solar panels, to incorporate battery level monitoring mechanisms and preventive recharging alerts, and to strengthen the physical protection of the system against adverse weather conditions, primarily rain and humidity. Furthermore, the integration of additional sensors such as wind speed and direction, and the implementation of automatic data resynchronization mechanisms following communication interruptions, are proposed with the aim of improving the operational continuity of the system in the field.

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References

1. FAO. *El Papel de la Agricultura en el Desarrollo de los PMA y su Integración en la Economía Mundial*; FAO: Roma, Italy, 2002. Available online: <https://www.fao.org/4/Y3997S/Y3997S00.pdf> (accessed on 24 July 2026).
2. Banco Mundial. *Agricultura y Alimentos—Panorama General*. 2024. Available online: <https://www.bancomundial.org/es/topic/agriculture/overview> (accessed on 24 July 2026).
3. FAO. *La Agricultura Mundial en la Perspectiva del año 2050*; FAO: Roma, Italy, 2009.
4. World Bank. *A Roadmap for Building the Digital Future of Food and Agriculture*; World Bank: Washington, DC, USA, 2021. Available online: <https://www.worldbank.org/en/news/feature/2021/03/16/a-roadmap-for-building-the-digital-future-of-food-and-agriculture> (accessed on 24 July 2026).
5. Zhang, H.; Zhu, H. The Impact of Agricultural Digitization on Land Productivity: An Empirical Test Based on Micro Panel Data. *Land* **2025**, *14*, 187. [\[CrossRef\]](#)
6. Karunathilake, E.M.B.M.; Le, A.T.; Heo, S.; Chung, Y.S.; Mansoor, S. The Path to Smart Farming: Innovations and Opportunities in Precision Agriculture. *Agriculture* **2023**, *13*, 1593. [\[CrossRef\]](#)
7. Santiteerakul, S.; Sopadang, A.; Yaibuathet Tippayawong, K.; Tamvimol, K. The Role of Smart Technology in Sustainable Agriculture: A Case Study of Wangree Plant Factory. *Sustainability* **2020**, *12*, 4640. [\[CrossRef\]](#)
8. Lloret, J.; Tomás, J.; García, M. A wireless sensor network deployment for soil moisture monitoring in precision agriculture. *Sensors* **2021**, *21*, 7243. [\[CrossRef\]](#) [\[PubMed\]](#)
9. Villa-Henriksen, A.; Edwards, G.T.C.; Pesonen, L.A.; Green, O.; Sørensen, C.A.G. Internet of Things in arable farming: Implementation, applications, challenges and potential. *Biosyst. Eng.* **2020**, *191*, 60–84. [\[CrossRef\]](#)
10. Bhat, S.A.; Huang, N.F. Big data and AI revolution in precision agriculture: Survey and challenges. *IEEE Access* **2021**, *9*, 110209–110222. [\[CrossRef\]](#)
11. Alahmad, T.; Neményi, M.; Nyéki, A. Applying IoT Sensors and Big Data to Improve Precision Crop Production: A Review. *Agronomy* **2023**, *13*, 2603. [\[CrossRef\]](#)
12. van Klompenburg, T.; Kassahun, A.; Catal, C. Crop yield prediction using machine learning: A systematic literature review. *Comput. Electron. Agric.* **2020**, *177*, 105709. [\[CrossRef\]](#)
13. Espinel, R.; Herrera-Franco, G.; Rivadeneira García, J.L.; Escandón-Panchana, P. Artificial Intelligence in Agricultural Mapping: A Review. *Agriculture* **2024**, *14*, 1071. [\[CrossRef\]](#)
14. Fuentes-Peñailillo, F.; Gutter, K.; Vega, R.; Silva, G.C. Transformative Technologies in Digital Agriculture: Leveraging Internet of Things, Remote Sensing, and Artificial Intelligence for Smart Crop Management. *J. Sens. Actuator Netw.* **2024**, *13*, 39. [\[CrossRef\]](#)
15. Soussi, A.; Zero, E.; Sacile, R.; Trincherio, D.; Fossa, M. Smart Sensors and Smart Data for Precision Agriculture: A Review. *Sensors* **2024**, *24*, 2647. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Tzatzani, T.T.; Morianou, G.; Tül, S.; Kourgialas, N.N. Air Temperature as a Key Indicator of Avocado (Cvs. Fuerte, Zutano, Hass) Maturation Time in Mediterranean Climate Areas. *Agriculture* **2023**, *13*, 1342. [\[CrossRef\]](#)
17. Kimaru, K.S.; Muchemi, K.P.; Mwangi, J.W. Effects of anthracnose disease on avocado production in Kenya. *Cogent. Food Agric.* **2020**, *6*, 1799531. [\[CrossRef\]](#)
18. Erazo-Mesa, E.; Ramírez-Gil, J.G.; Sánchez, A.E. Avocado cv. Hass needs water irrigation in tropical precipitation regime: Evidence from Colombia. *Water* **2021**, *13*, 1942. [\[CrossRef\]](#)
19. Farooq, M.S.; Riaz, S.; Abid, A.; Umer, T.; Zikria, Y.B. The role of IoT technology in agriculture: A systematic literature review. *Electronics* **2020**, *9*, 319. [\[CrossRef\]](#)
20. Domingues Neto, F.J.; Carneiro, D.C.D.S.; Silva, M.D.S.; Tecchio, M.A.; Leonel, S.; Pimentel Junior, A.; Ono, E.O.; Rodrigues, J.D. Sun Protection as a Strategy for Managing Heat Stress in Avocado Trees. *Plants* **2024**, *13*, 2854. [\[CrossRef\]](#) [\[PubMed\]](#)
21. Routis, G.; Roussaki, I. Low power IoT electronics in precision irrigation. *Smart Agric. Technol.* **2023**, *5*, 100310. [\[CrossRef\]](#)
22. Islam, M.R.; Oliullah, K.; Kabir, M.M.; Alom, M.; Mridha, M.F. Machine learning enabled IoT system for soil nutrients monitoring and crop recommendation. *J. Agric. Food Res.* **2023**, *14*, 100880. [\[CrossRef\]](#)
23. Chapungo, N.J.; Postolache, O. Evaluación experimental de la confiabilidad de la conectividad LoRaWAN en áreas rurales remotas de Mozambique. *Sensors* **2025**, *25*, 6027. [\[CrossRef\]](#) [\[PubMed\]](#)
24. Suhag, S.; Jadaun, S.; Shukla, A.; Singh, N.; Johri, P.; Parashar, N. IoT-based soil nutrition and plant disease detection system for smart agriculture. In *Proceedings of the 10th IEEE International Conference on Communication Systems and Network Technologies*; IEEE: New York, NY, USA, 2021; pp. 478–483. [\[CrossRef\]](#)
25. Sabu, D.; Alagumariappan, P.; Sankaran, V.; Pittu, P.S.K.R. Design and Development of Internet of Things-Based Smart Sensors for Monitoring Agricultural Lands. *Eng. Proc.* **2023**, *58*, 13. [\[CrossRef\]](#)
26. Ahmed, M.A.; Gallardo, J.L.; Zuniga, M.D.; Pedraza, M.A.; Carvajal, G.; Jara, N.; Carvajal, R. LoRa-based IoT platform for remote monitoring of large-scale agriculture farms in Chile. *Sensors* **2022**, *22*, 2824. [\[CrossRef\]](#) [\[PubMed\]](#)
27. Kalaivani, T.S.; Kamireddy, T.; Govindakumar, S. IoT-Enabled Soil and Crop Monitoring System Using Low-Cost Smart Sensors for Precision Agriculture. *Eng. Proc.* **2025**, *118*, 77. [\[CrossRef\]](#)

28. Azhari Nasution, T.I.; Sinaga, S.H.; Sudiati. Design of monitoring system temperature and humidity using DHT22 sensor and NRF24L01 based on Arduino. *J. Phys. Conf. Ser.* **2023**, *2421*, 12018. [[CrossRef](#)]
29. Woo-García, R.M.; Pérez-Vista, J.M.; Sánchez-Vidal, A.; Herrera-May, A.L.; Osorio-de-la-Rosa, E.; Caballero-Briones, F.; López-Huerta, F. Implementación de una red de sensores inalámbricos para mediciones ambientales. *Technologies* **2024**, *12*, 41. [[CrossRef](#)]
30. Abidin, Z.; Falah, R.; Setyawan, R.A.; Wardana, F.C. Wireless sensor network using nRF24L01+ for precision agriculture. *Bull. Electr. Eng. Inform.* **2025**, *14*, 1003–1013. [[CrossRef](#)]
31. Zeping, L.; Abdullah, N.; Ishark, M.K. Smart greenhouse climate control with real-time fault detection and energy-aware automation. *Smart Agric. Technol.* **2026**, *13*, 101707. [[CrossRef](#)]
32. Sacaleanu, D.I.; Matache, M.G.; Rosu, S.G.; Florea, B.C.; Manciu, I.P.; Perisoara, L.A. IoT-Enhanced Decision Support System for Real-Time Greenhouse Microclimate Monitoring and Control. *Technologies* **2024**, *12*, 230. [[CrossRef](#)]
33. Sagheer, A.; Mohammed, M.; Riad, K.; Alhajhoj, M. A Cloud-Based IoT Platform for Precision Control of Soilless Greenhouse Cultivation. *Sensors* **2021**, *21*, 223. [[CrossRef](#)] [[PubMed](#)]
34. Guerra, P.A.; Arias, J.F.R.; Martinez, M.U.; Yepes, J.P.M.; Bedoya, J.W.B. Monitoreo de cultivos bajo invernadero utilizando tecnologías 4.0. *Cienc. Tecnol. Agropecu.* **2023**, *24*, 12. [[CrossRef](#)]
35. Guijarro-Rubio, O.E.; Vinocunga-Pillajo, D.R.; Del Real-Fleites, O.; Guardado-Yordi, E.; Pérez-Martínez, A. Monitoring of environmental variables in greenhouse crops through an IoT wireless sensor network. *DYNA* **2025**, *92*, 47–56. [[CrossRef](#)]
36. Hernández-Morales, C.A.; Luna-Rivera, J.M.; Villarreal-Guerrero, F.; Delgado-Sánchez, P.; Guadiana-Alvarado, Z.A. IoT-based spatial monitoring and environment prediction system for smart greenhouses. *IEEE Lat. Am. Trans.* **2023**, *21*, 602–611. [[CrossRef](#)]
37. Abu Sneineh, A.A.; Shabaneh, A.A. Design of a Smart Hydroponics Monitoring System Using an ESP32 Microcontroller and the Internet of Things. *MethodsX* **2023**, *11*, 102401. [[CrossRef](#)] [[PubMed](#)]
38. Pero, C.; Bakshi, S.; Nappi, M.; Tortora, G. IoT-driven machine learning for precision viticulture optimization. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2024**, *17*, 2437–2447. [[CrossRef](#)]
39. Shahab, H.; Naeem, M.; Iqbal, M.; Aqeel, M.; Ullah, S.S. IoT-driven smart agricultural technology for real-time soil and crop optimization. *Smart Agric. Technol.* **2025**, *10*, 100847. [[CrossRef](#)]
40. López-Velasco, B.; Ruiz-García, A.; Cebada-Reyes, J.G.; Villaseñor-Perea, C.A. IoT-based environmental monitoring and prediction of banana moisture content in a solar greenhouse dryer. *IEEE Lat. Am. Trans.* **2024**, *22*, 881–890. [[CrossRef](#)]
41. Cruz, M.; Mafra, S.; Teixeira, E.; Figueiredo, F. Smart Strawberry Farming Using Edge Computing and IoT. *Sensors* **2022**, *22*, 5866. [[CrossRef](#)] [[PubMed](#)]
42. Torres-Quezada, E.; Fuentes-Peñailillo, F.; Gutter, K.; Rondón, F.; Marmolejos, J.M.; Maurer, W.; Bisono, A. Remote Sensing and Soil Moisture Sensors for Irrigation Management in Avocado Orchards: A Practical Approach for Water Stress Assessment in Remote Agricultural Areas. *Remote Sens.* **2025**, *17*, 708. [[CrossRef](#)]
43. Rahman, M.M.; Robson, A.; Bekker, T. Machine Learning Approaches for Assessing Avocado Alternate Bearing Using Sentinel-2 and Climate Variables—A Case Study in Limpopo, South Africa. *Remote Sens.* **2025**, *17*, 3935. [[CrossRef](#)]
44. Moreno-Bernal, P.; Arizmendi-Peralta, P.; Hernández-Aguilar, J.A.; Peralta-Abarca, J.C.; Velásquez-Aguilar, J.G. IoT platform for monitoring nutritional and weather conditions of avocado production. In *ICSC-CITIES 2022*; Springer Nature Switzerland AG: Cham, Switzerland, 2023; pp. 95–109. [[CrossRef](#)]
45. Domínguez, A.; García-Martín, A.; Moreno, E.; González, E.; Paniagua, L.L.; Allendes, G. Identifying Optimal Zones for Avocado (*Persea americana* Mill.) Cultivation in Iberian Peninsula: A Climate Suitability Analysis. *Land* **2024**, *13*, 1290. [[CrossRef](#)]
46. CODESIN. *Manual Para el Establecimiento del Cultivo del Aguacate*; CODESIN: Sinaloa, México, 2021.
47. SAGARPA. *Potencial del Cultivo de Aguacate (Persea Americana Mill.) en México—Planeación Agrícola Nacional 2017–2030*; SAGARPA: Ciudad de México, México, 2017. Available online: <https://www.gob.mx/cms/uploads/attachment/file/257067/Potencial-Aguacate.pdf> (accessed on 24 July 2026).
48. Barnes, P.W.; Robson, T.M.; Zepp, R.G.; Bornman, J.F.; Jansen, M.A.K.; Ossola, R.; Wang, Q.W.; Robinson, S.A.; Foereid, B.; Klekociuk, A.R.; et al. Interactive effects of changes in UV radiation and climate on terrestrial ecosystems, biogeochemical cycles, and feedbacks to the climate system. *Photochem. Photobiol. Sci.* **2023**, *22*, 1049–1091. [[CrossRef](#)] [[PubMed](#)]
49. WHO, WMO, UNEP, ICNIRP. Global Solar UV Index: A Practical Guide. 2002. Available online: <https://www.who.int/publications/i/item/9241590076> (accessed on 24 July 2026).
50. Sales-Lérida, D.; Grosso, J.; Martínez-Jiménez, P.M.; Manzano, M. A Low Cost and Eco-Sustainable Device to Determine the End of the Disinfection Process in SODIS. *Sensors* **2023**, *23*, 575. [[CrossRef](#)] [[PubMed](#)]
51. Adafruit Industries. Analog UV Light Sensor Breakout—GUVA-S12SD. Available online: <https://www.adafruit.com/product/1918> (accessed on 24 July 2026).
52. Castro-Bello, M.; Roman-Padilla, D.B.; Morales-Morales, C.; Campos-Francisco, W.; Marmolejo-Vega, C.V.; Marmolejo-Duarte, C.; Evangelista-Alcocer, Y.; Gutiérrez-Valencia, D.E. Convolutional Neural Network Models in Municipal Solid Waste Classification: Towards Sustainable Management. *Sustainability* **2025**, *17*, 3523. [[CrossRef](#)]

53. Chamara, N.; Islam, M.D.; Bai, G.F.; Shi, Y.; Ge, Y. Ag-IoT for crop and environment monitoring: Past, present, and future. *Agric. Syst.* **2022**, *203*, 103497. [[CrossRef](#)]
54. Li, Y.; Ni, Z.; Xiao, B. Domain Knowledge-Enhanced Process Mining for Anomaly Detection in Commercial Bank Business Processes. *Systems* **2025**, *13*, 545. [[CrossRef](#)]
55. Chen, S.; Guo, W. Auto-Encoders in Deep Learning—A Review with New Perspectives. *Mathematics* **2023**, *11*, 1777. [[CrossRef](#)]
56. Peng, J.; Meng, J.; Chen, D.; Liu, H.; Hao, S.; Sui, X.; Du, X. A Review of Lithium-Ion Battery Capacity Estimation Methods for Onboard Battery Management Systems: Recent Progress and Perspectives. *Batteries* **2022**, *8*, 229. [[CrossRef](#)]
57. Lv, S.; Wang, X.; Lu, W.; Zhang, J.; Ni, H. The Influence of Temperature on the Capacity of Lithium Ion Batteries with Different Anodes. *Energies* **2021**, *15*, 60. [[CrossRef](#)]
58. Dobrilovic, D.; Pekez, J.; Desnica, E.; Radovanovic, L.; Palinkas, I.; Mazalica, M.; Djordjević, L.; Mihajlovic, S. Data Acquisition for Estimating Energy-Efficient Solar-Powered Sensor Node Performance for Usage in Industrial IoT. *Sustainability* **2023**, *15*, 7440. [[CrossRef](#)]
59. Citroni, R.; Mangini, F.; Frezza, F. Efficient Integration of Ultra-low Power Techniques and Energy Harvesting in Self-Sufficient Devices: A Comprehensive Overview of Current Progress and Future Directions. *Sensors* **2024**, *24*, 4471. [[CrossRef](#)] [[PubMed](#)]

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