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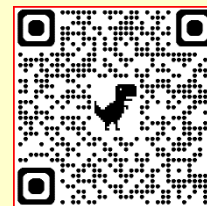
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Development of an IoT System for Intelligent Monitoring of Tomato Harvesting and Postharvest Processes Using Data-Driven Decision Making (DDDM)

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ABSTRACT

This study presents the development and functional validation of an Internet of Things (IoT) architecture for data-driven decision-making (DDDM) in the intelligent monitoring of tomato harvest and postharvest processes. The architecture integrates data acquisition, processing, storage, and visualization to transform contextualized measurements into operational states, priority levels, and actionable insights. The methodology comprised a systematic literature review, the design and implementation of the IoT platform, and a controlled functional pilot. A controlled scenario generator produced synthetic measurements representing normal operation, warning, critical, and communication-loss conditions. Eight predefined scenarios were executed twenty times each, resulting in 160 executions. In each execution, the operational state, priority level, and actionable insight generated by the architecture were compared with the expected outputs established by the configured decision rules. The architecture achieved 100% total agreement for the three evaluated outputs across all 160 executions, demonstrating functional consistency within the controlled scenarios. These results are limited to the implemented interpretation process and do not establish agronomic validity, sensor accuracy, or performance under real operating conditions. Future work will evaluate the architecture in real cultivation and postharvest environments using calibrated sensors and direct process measurements, allowing the operational ranges to be verified and adjusted according to context-specific agronomic criteria.

KEY WORDS: Internet of Things (IoT), Data-Driven Decision-Making (DDDM), Smart Agriculture, Tomato Postharvest Monitoring, Decision Support System.

INTRODUCTION

The digitalization of the agricultural sector has become an alternative for addressing current challenges in agricultural production. In this context, Agriculture 4.0 incorporates technologies such as the Internet of Things (IoT), artificial

intelligence, and data analytics to obtain continuous information about production processes and promote evidence-based management (Navarro et al., 2020; Sharma & Shivandu, 2024). This evolution has expanded the capacity to observe crops through systems that collect, transmit, and store measurements from different zones. However, data availability creates operational value when the

data are interpreted within their context and used to guide decisions. From this perspective, data-driven decision-making (DDDM) proposes that actions should not be based solely on isolated observations, but on organized information linked to previously established criteria (Araújo et al., 2023).

For crops such as tomato (*Solanum lycopersicum* L.), monitoring conditions during cultivation and postharvest is particularly relevant because changes occur in both stages and need to be identified in a timely manner. Several studies document the use of sensors, web platforms, and communication mechanisms to observe variables related to soil, irrigation, the environment, and product preservation after harvest (Hemming et al., 2020; Thilakarathne et al., 2023; Shankaraswamy & Radhika, 2024). These resources allow IoT systems to bring together measurements that may previously have been dispersed and present them continuously. Therefore, monitoring provides a basis for recognizing the behavior of the variables; however, displaying the readings alone does not necessarily make it possible to determine what condition they represent or which one requires more immediate attention.

According to contemporary scientific literature, IoT solutions applied to agriculture are generally structured through components intended for the acquisition, communication, processing, and presentation of information. A transition can also be observed from systems focused primarily on collecting and storing data toward proposals that integrate additional resources to analyze them and contribute to agricultural management (Navarro et al., 2020). Despite these advances, limitations related to connectivity, interoperability, costs, scalability, training, and information management still exist and hinder the adoption of these technologies in different production contexts (Elijah et al., 2018; Tzounis et al., 2017; Villa-Henriksen et al., 2020). In addition to these conditions, a functional limitation can be identified, as some systems focus on presenting values, charts, or alerts without clearly showing the relationship between the received measurement, the criterion used, and the information that can guide a decision.

This reveals a gap between monitoring and data-driven decision-making. When a measurement is presented in isolation, it may report the value of a variable, but it does not necessarily establish its operational meaning unless the source zone, corresponding stage, timestamp, and configured range are considered. Similarly, an alert loses its usefulness when it does not maintain an understandable relationship with the condition that triggered it and the associated recommendation. Consequently, monitoring is not sufficient if the architecture does not transform measurements into operational states and actionable information in a traceable manner. Although proposals have been developed to support agricultural decisions through data, the literature still indicates the need to integrate different sources of information and strengthen the interpretation mechanisms that make it possible to respond to the identified conditions in a timely manner (Araújo et al., 2023; Sharma & Shivandu, 2024).

For this reason, the central purpose of this research is to develop an IoT architecture for the intelligent monitoring of representative conditions during tomato cultivation and postharvest, grounded in data-driven decision-making (DDDM). The proposal establishes a flow in which each measurement is contextualized, compared with configured criteria, and transformed into an operational state and an actionable insight. The contribution of the study focuses on the DDDM-oriented architecture and its functional validation, not on the independent development of sensors, increased productivity, loss reduction, or system testing under field conditions. In accordance

with this scope, the evaluation is limited to a controlled functional pilot intended to verify whether the proposal maintains the relationship between the measurement, its interpretation, and the information presented to support decision-making.

RESEARCH ELABORATIONS

This research is an applied study in technological development and innovation focused on the design and functional validation of an IoT architecture for the intelligent monitoring of tomato (*Solanum lycopersicum* L.) harvest and postharvest processes through data-driven decision-making (DDDM). The proposal does not only present measurements as isolated values, it establishes a processing chain that receives operational data, interprets them according to previously configured criteria, and transforms them into operational states and actionable insights to support decision-making.

A mixed-methods approach was adopted for the study, with a predominant quantitative component directed toward technological development, prototype implementation, and comparison between the generated results and the expected outputs. This approach is complemented by a qualitative component based on the synthesis of evidence obtained through a systematic review of contemporary scientific literature. Integrating both components makes it possible to substantiate the system requirements and assess the functional behavior of the proposed artifact. This is consistent with design science research, in which developing and evaluating an artifact constitute the central axis of the research process (Peffer et al., 2007).

The study is limited to a functional pilot conducted in a controlled environment. Therefore, it does not seek to calculate the actual reduction in losses, evaluate the physicochemical quality of the product, analyze operator performance, measure technology adoption, or determine the metrological accuracy of the sensors under field conditions. The validation focuses on assessing whether the architecture consistently converts plausible synthetic measurements into operational states and actionable insights while maintaining the relationship among the input data, the criterion used to interpret them, and the resulting output.

The input variables were determined from the operational parameters selected for the pilot. Soil moisture, pH, and NPK measurements are included for the crop, while temperature is considered for the minimum postharvest component. The timestamp, source zone or node, stage, and configured ranges are also integrated because these elements provide the context required to interpret each measurement. The output variables comprise the operational state, classified as suitable, warning, or critical; the corresponding actionable insight; and decision traceability. The evaluation considers agreement between the expected and generated states, as well as the match between the expected and obtained insights.

A systematic literature review was conducted according to the PRISMA 2020 guidelines to provide scientific support for selecting the variables, conditions of interest, and interpretation rules (Page et al., 2021). The search was performed in Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar and was complemented by manually reviewing the reference lists of key studies. Combinations of controlled and free-text terms in English and Spanish were used: ("Internet of Things" OR IoT OR "Internet de las Cosas") AND (tomato OR jitomate OR "*Solanum lycopersicum*") AND (harvest OR postharvest OR cosecha OR postcosecha OR monitoring OR sensors OR "data-driven decision-making" OR DDDM). The publication interval covered 2016 to

2026 to maintain the currency of the technological evidence.

The inclusion criteria primarily considered peer-reviewed scientific articles written in English or Spanish that addressed tomato crop or postharvest monitoring, the use of sensors or IoT architectures, data integration and storage, or interpretation mechanisms intended to support operational decisions. Duplicate records, documents for which the full text could not be verified, publications outside the defined period, studies unrelated to the scope, and studies in which the method or variables used could not be identified were excluded.

Table 1 summarizes the selection process.

Phase	Description	Number of records
Identification	Records identified in Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar through the established search strategy	1,248
	Additional records obtained through a manual review of the reference lists of key articles	47
	Total number of records before duplicate removal	1,295
	Duplicate records removed	298
Screening	Records available for title and abstract	997

	screening after duplicate removal	
	Records excluded for not meeting the scope, language, publication period, or publication type criteria	812
Eligibility	Full-text articles assessed for eligibility	185
	Articles excluded because they did not address IoT monitoring of tomato or related crops, did not allow the method or variables to be identified, or did not provide elements applicable to data interpretation and decision support	165
Inclusion	Studies included in the qualitative synthesis and systematic review report	20

The PRISMA-based selection process resulted in the inclusion of twenty primary and review studies. These studies provide evidence concerning IoT architectures, data acquisition and storage, operational variables, and decision-support mechanisms in agricultural and postharvest environments. Table 2 summarizes the selected studies and indicates the specific contribution of each one to defining the requirements of the architecture and the functional pilot.

Table 2. Studies included in the systematic review (n = 20), organized by thematic relevance and chronology

Authors (Year)	Title / Main source	Journal / Type	Main contribution
Navarro et al. (2020)	A Systematic Review of IoT Solutions for Smart Farming	Sensors	PRISMA review of IoT solutions that identifies implementation challenges and areas of opportunity
Thilakarathne et al. (2023)	Towards making the fields talks: A real-time cloud enabled IoT crop management platform for smart agriculture	Frontiers in Plant Science	Low-cost IoT platform that incorporates several sensors to monitor and automate tomato cultivation
Sharma & Shivandu (2024)	Integrating artificial intelligence and Internet of Things (IoT) for enhanced crop monitoring and management in precision agriculture	Sensors International	Integration of AI and IoT to identify production patterns and predict yield
Soni et al. (2025)	Artificial intelligence and machine learning in precision agriculture: Trends, challenges, and future directions	IJCRT	Review of trends, costs, the digital divide, and perspectives on AI and machine learning in precision agriculture
Sánchez-Fleitas (2026)	Agricultura 4.0: sistemas de información geográfica e inteligencia artificial para la optimización productiva	Agroecología Global	Use of GIS and AI to promote production optimization and evidence-based management in regional contexts
Hernández Fernández et al. (2023)	Evaluación de las pérdidas durante la obtención de puré de tomate en mini-industria	Agroecología Global	Measurement of 10.82% losses caused by mechanical and physiological damage during reception, rinsing, and sorting
Araújo et al. (2023)	Intelligent Data-Driven Decision Support for Agricultural Systems—ID3SAS	IEEE Access	Integration of data acquisition, storage, analysis, and runtime reasoning to support data-driven agricultural decisions

Talavera et al. (2017)	Review of IoT applications in agro-industrial and environmental fields	Computers and Electronics in Agriculture	Review of IoT applications in agro-industrial and environmental fields, focused mainly on sensors and networks
Ray (2017)	Internet of things for smart agriculture: Technologies, practices and future direction	J. Ambient Intelligence and Smart Environments	Overview of technologies, practices, and perspectives concerning IoT applied to smart agriculture
Villa-Henriksen et al. (2020)	Internet of Things in arable farming: Implementation, applications, challenges and potential	Biosystems Engineering	Study of IoT implementation, applications, challenges, and transfer potential in arable farming
Pathare & Al-Dairi (2021)	Effect of Simulated Vibration and Storage on Quality of Tomato	Horticulturae	Evidence on the effects of vibration, mechanical damage, and storage conditions on tomato quality
Elijah et al. (2018)	An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenges	IEEE Internet of Things Journal	Overview of the benefits and challenges associated with IoT and data analytics in agriculture
Saxena et al. (2025)	Deep learning-driven IoT solution for smart tomato farming	Scientific Reports / PMC	Integration of sensors, cameras, and deep learning for environmental monitoring and automatic maturity identification
Isah et al. (2026)	Intelligent Evaporative Cooling Systems for Post-Harvest Fruit and Vegetable Preservation: A Systematic Review	AgriEngineering	PRISMA review of systems combining IoT and machine learning to preserve fruits and vegetables after harvest, including tomatoes
Hemming et al. (2020)	Cherry Tomato Production in Intelligent Greenhouses—Sensors and AI for Control of Climate, Irrigation, Crop Yield, and Quality	Sensors	Application of sensors and artificial intelligence to climate, irrigation, yield, and quality control in tomato greenhouses
Lee et al. (2022)	An Automated, Clip-Type, Small Internet of Things Camera-Based Tomato Flower and Fruit Monitoring and Harvest Prediction System	Sensors / Biosensors	Low-cost IoT camera for monitoring flowers and fruits and predicting harvest
Tzounis et al. (2017)	Internet of Things in agriculture, recent advances and future challenges	Biosystems Engineering	Review of advances and future challenges in agricultural IoT, with particular attention to sensors and connectivity
Shankaraswamy & Radhika (2024)	Sensor, IoT-based post-harvest shelf life determination of tomato through machine learning predictive analysis	Journal of Environmental Biology	Estimation of postharvest tomato shelf life using IoT sensors and predictive machine learning models
Ibarra-Cabrera et al. (2024)	Tomato Urban Gardening Supported by an IoT-Based Monitoring System and a Mobile Application	Sensors	Tomato monitoring experience using an IoT system and mobile application in small-scale urban environments
Guo et al. (2026)	A digital framework for smart greenhouse tomato cultivation	Computers and Electronics in Agriculture (recent)	Comprehensive digital framework incorporating IoT monitoring for smart tomato cultivation in greenhouses

The synthesis of the selected studies showed a common trend toward modular architectures that integrate data acquisition, communication, storage, processing, and visualization. The literature also identifies the need to move beyond systems dedicated only to displaying readings by incorporating mechanisms that interpret measurements and connect them with traceable alerts, priorities, or recommendations (Araújo et al., 2023; Sharma & Shivandu, 2024).

However, limitations related to costs, connectivity, interoperability, training, and data management remain. These factors must be considered even when validation is conducted under controlled conditions (Navarro et al., 2020; Elijah et al., 2018).

Based on this evidence, the main limitations and technological tools relevant to the DDDM-oriented architecture were synthesized, as presented in Table 3. Within the study, this synthesis guides the

organization of the prototype, the selection of inputs, and the logic used to interpret them without attributing results regarding losses,

product quality, or performance under field conditions to the pilot.

Table 3. Main limitations and technological tools considered for the DDDM architecture

Category	Element / Limitation or tool	Description and examples	Relevance and sources
Limitation	High technology costs	Investment required for sensors, gateways, connectivity, maintenance, and software updates	Soni et al. (2025); Navarro et al. (2020); Elijah et al. (2018)
Limitation	Digital divide and training	Limited technological literacy among small- and medium-scale producers, together with resistance to change	Soni et al. (2025); Sánchez-Fleitas (2026); study introduction
Limitation	Connectivity and infrastructure in rural areas	Insufficient network coverage, intermittent power supply, and latency within production areas	Villa-Henriksen et al. (2020); Tzounis et al. (2017)
Limitation	Security and ethical data management	Privacy, data ownership, cybersecurity threats, and technological dependence	Soni et al. (2025); Elijah et al. (2018)
Limitation	Gap between monitoring and decision support	Systems limited to displaying readings without transforming them into operational states, priorities, and traceable recommendations	Araújo et al. (2023); Sharma & Shivandu (2024)
Limitation	Interoperability and scalability	Difficulties integrating devices from different manufacturers and moving a prototype into a production environment	Navarro et al. (2020); Talavera et al. (2017)
Tool	Microcontrollers and nodes	Use of ESP32, Arduino Uno/Mega, and Raspberry Pi as gateways or edge computing nodes	Thilakarathne et al. (2023); Saxena et al. (2025); predominant use
Tool	Operational variables included in the pilot	Soil moisture, pH, and NPK for the crop, together with temperature for the minimum postharvest node	Hemming et al. (2020); Thilakarathne et al. (2023); Shankaraswamy & Radhika (2024)
Tool	Communication and storage	Lightweight mechanisms for transmitting information, storing data temporarily or remotely, and preserving the timestamp, zone, and operational context	Thilakarathne et al. (2023); Navarro et al. (2020)
Tool	Interpretation rules	Comparison with configurable ranges to convert readings into suitable, warning, or critical states and connect them with explicit recommendations	Araújo et al. (2023); Sharma & Shivandu (2024)
Tool	Visualization and traceability	Status and alert dashboard, event history, and relationship among the reading, threshold, state, and recommendation	Araújo et al. (2023); Ibarra-Cabrera et al. (2024)

Considering the type and focus of the research, the established variables, the evidence gathered through PRISMA, and the limits defined for the functional pilot, the following staged procedure is proposed to apply the DDDM-oriented IoT architecture.

Methodological application proposal

The first step involves integrating the pilot requirements based on the systematic review and the decisions related to the study scope. Soil moisture, pH, and NPK are selected as representative crop variables, together with temperature for the minimum postharvest thermal node. The zone or node, stage, timestamp, and configured ranges are also defined as contextual elements. The expected states and insights are added to these elements and serve as references for each test case.

The second step consists of designing the functional architecture according to the principles of modularity, traceability, context-based configuration, and separation of functions. Modularity facilitates system organization without restricting it to a single variable or node. Traceability maintains the relationship between each measurement and its resulting output, while contextual configuration makes it possible to use ranges consistent with the corresponding zone, stage, and variable. Finally, the separation of functions distinguishes the processes of receiving, storing, interpreting, and presenting information.

Within the architecture, the flow begins by receiving records from the crop zones and the minimum postharvest thermal node. Each record is then validated and stored together with its time and source metadata. The interpretation module retrieves the applicable range, compares the received value, and determines an operational state.

Based on this classification, an actionable insight consistent with the identified condition is generated, displayed to the user with its priority level, and stored in the event history. The flow can therefore be summarized as follows: measurement, interpretation, state, and actionable insight.

The third step comprises the development and general integration of the IoT system. The technical implementation was structured around four main components: the acquisition module, backend, database, and frontend. The DDDM engine was incorporated into the backend and serves as the core of the proposal by comparing measurements with the configured ranges and transforming them into operational states and actionable insights. Figure 1 shows the general flow of information among these components.

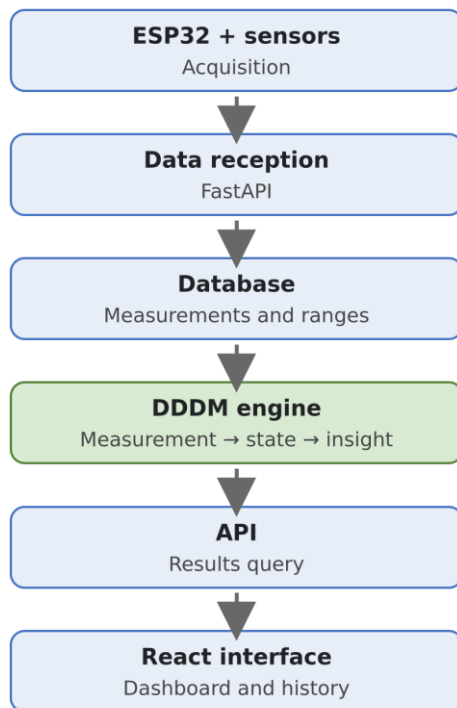


Figure 1. Information flow among the components of the DDDM-oriented IoT system

Under this structure, the acquisition module gathers the records corresponding to crop and postharvest monitoring, after which the backend receives, validates, and processes them. The database stores the measurements, ranges, and resulting outputs, while the frontend

presents the generated states and insights to the user. The function of each component is described below, along with the DDDM engine integrated into the backend, given its importance to the study's contribution.

Acquisition module. ESP32 nodes connected to soil moisture, pH, NPK, and temperature sensors were considered. Within the pilot, these nodes represent the source and structure of the measurements subsequently sent to the backend.

Backend. This component was implemented with FastAPI to receive records, validate their structure, manage their storage, and respond through an API to queries submitted from the interface.

Database. A relational structure was used to organize the measurements, configured ranges, states, insights, and events produced during scenario execution.

DDDM engine. This component represents the functional core of the proposal. For each measurement, the engine retrieves the corresponding operational range and compares it with the received value. Based on the result, it determines a state and generates an insight consistent with the identified condition. The flow is therefore expressed as the sequence measurement, comparison with ranges, state, and insight.

Frontend. The interface was implemented with React and Vite to display a dashboard organized by zones and nodes, together with the event history and recommendations produced by the architecture.

To represent the measurements processed by the architecture during the functional pilot, a controlled scenario generator was implemented. This component creates plausible synthetic datasets for the variables included in the system while preserving the record structure, contextual information, and variability associated with each operational condition. The DDDM architecture then processes the measurements using the same interpretation flow established for the platform, making it possible to reproduce suitable, warning, critical, and communication-loss scenarios under repeatable conditions.

The fourth step is directed toward preparing the evaluation in a controlled environment. For this reason, plausible synthetic inputs replace the physical connection to the sensors. This measure makes it possible to examine the complete data flow and isolate the software response to previously defined conditions. Table 4 summarizes the treatment assigned to the inputs and the DDDM outputs associated with each pilot component.

Table 4. Treatment of variables within the functional pilot

Component	Input variables	Treatment within the pilot	Expected DDDM output
Crop	Soil moisture, pH, and NPK.	Plausible synthetic series and parameters defined according to the crop, stage, and zone.	Operational state and insight directed toward reviewing irrigation or the conditions associated with pH and NPK, according to the activated rule.
Postharvest	Temperature corresponding to the minimum thermal node.	Synthetic thermal series with values inside and outside the established range.	Thermal state and indication of whether the temperature is inside or outside the configured range.
Context	Timestamp, zone, stage, and range configuration.	Metadata linked to and preserved with each reading.	Traceability of the rule applied and the recommendation produced.

Before the scenarios were executed, the operational intervals that the

DDDM architecture would use to interpret the synthetic

measurements were established to maintain pilot repeatability. These intervals were defined as pilot-specific parameters rather than universal agronomic thresholds, since moisture conditions and readings obtained from NPK sensors vary according to sensor type,

calibration, and soil characteristics. For pH and temperature, the intervals were adapted from the available technical evidence on tomato cultivation and storage.

Table 5. Operational intervals defined for the pilot

Variable	Lower critical limit	Lower warning limit	Suitable interval	Upper warning limit	Upper critical limit
Soil moisture	0–19%	20–39%	40–70%	71–85%	86–100%
pH	<5.5	5.5–5.9	6.0–7.0	7.1–7.5	>7.5
Normalized nitrogen	0–19%	20–39%	40–70%	71–85%	86–100%
Normalized phosphorus	0–19%	20–39%	40–70%	71–85%	86–100%
Normalized potassium	0–19%	20–39%	40–70%	71–85%	86–100%
Storage temperature	<8 °C	8–9.9 °C	10–15 °C	15.1–18 °C	>18 °C

The variables included in the pilot were selected based on literature addressing crop monitoring, soil physicochemical properties, efficient water use, nutrition, and postharvest tomato storage conditions (Instituto Nacional de Investigaciones Forestales, Agrícolas y Pecuarias [INIFAP], 2020, 2023, 2025, n.d.). However, these sources present general agronomic criteria and do not provide universal thresholds applicable to moisture or NPK sensors. For this reason, the intervals used in the validation were established as

operational ranges for the prototype and were intended solely to assess the functional behavior of the DDDM architecture.

Based on the established intervals, the evaluation is organized into eight controlled scenarios representing suitable, warning, critical, and communication-loss conditions. Before each scenario, the variable to be evaluated, the expected state, and the expected insight are determined, as shown in Table 6.

Table 6. Controlled scenarios and expected evaluation outputs

Scenario	Variable evaluated	Expected state	Expected insight
E01	All	Suitable	Continue monitoring the operational condition.
E02	Moisture	Warning	Review the moisture condition or irrigation in the zone.
E03	pH	Critical	Give priority attention to the soil pH condition.
E04	Nitrogen	Warning	Review nitrogen availability.
E05	Phosphorus	Warning	Review phosphorus availability.
E06	Potassium	Warning	Review potassium availability.
E07	Temperature	Critical	Give priority attention to the elevated storage temperature.
E08	Communication	No communication	Check node availability or connection.

To support functional validation, a controlled scenario generator was implemented to produce plausible synthetic measurements with controlled variation within the interval assigned to each scenario. Each execution automatically records the generated measurements, the expected and obtained states, the expected and obtained priorities, and the expected and generated insights. The generator is used solely to provide repeatable inputs for assessing the system's functional behavior and therefore does not replace sensor calibration or physical sensor evaluation.

The fifth step corresponds to the orderly execution of the experimental procedure. First, the zones, variables, and ranges required for each test case will be registered in the system. The scenario will then be defined, and the expected state, priority, and insight will be documented before the test begins. Third, the generator will produce the synthetic measurements associated with the selected scenario, which will be processed by the DDDM engine to determine the operational state and corresponding insight. Next, the state, priority, insight, and traceability evidence presented by the application will be retrieved. Finally, the generated outputs will be compared with the expected outputs, and the result of each case will

be documented to allow it to be repeated using the same configuration.

The sixth step comprises the analysis of functional agreement and traceability. For each execution, the expected and obtained states, the expected and obtained priorities, and the expected and generated insights will be documented. State agreement will be established when the category produced is the same as the one expected for the scenario. Priority agreement will be established when the generated level corresponds to the expected level, and insight agreement will exist when the suggested action follows the rule defined for the variable and condition being evaluated. An execution will demonstrate functional agreement only if all three elements match and maintain their relationship with the source measurement, applied range, zone or node, and timestamp.

The seventh and final step focuses on presenting the results through the execution records and the table summarizing the pilot. In each execution, the results will be stored automatically to compare the expected state with the obtained state, along with the priority and insight produced by the DDDM engine. Agreement among these elements will make it possible to assess the functional behavior of

the proposed architecture in each scenario. Since the inputs, rules, and expected outputs will be established in advance, the functional acceptance criterion will be 100% agreement in the controlled cases.

Within this scope, the proposal will be evaluated according to its ability to transform the measurements representing the controlled scenarios into operational states, priority levels, and actionable insights consistent with the rules of the DDDM architecture. Therefore, the results are limited to the functional validation of the interpretation process and do not extend to loss reduction, product quality improvement, or system performance under actual production conditions.

RESULTS OR FINDING

The design and implementation process described in the methodology resulted in the proposed DDDM-oriented IoT architecture for the intelligent monitoring of tomato cultivation and postharvest.

The implementation resulted in an IoT platform that integrates data acquisition, DDDM processing, and result visualization (Figure 2). The interface organizes the information by zones or nodes and displays the received measurement, operational state, priority level, and corresponding actionable insight for each monitored variable. The condition shown represents normal operation because all variables are within the configured ranges and are classified as suitable.

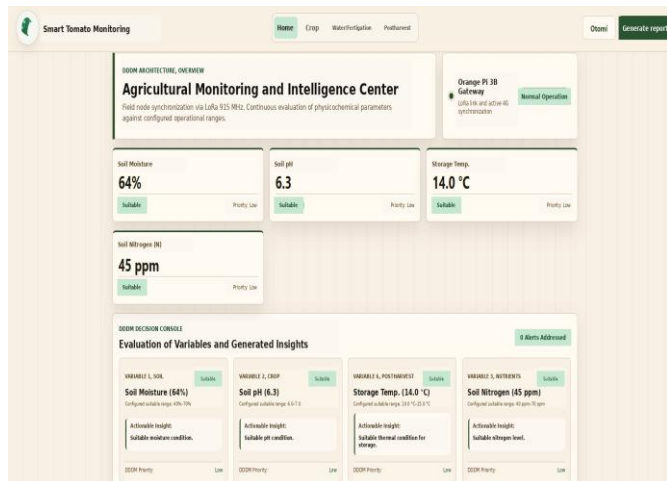


Figure 2. Overview of the DDDM-oriented IoT platform

The functional pilot included eight predefined scenarios, each evaluated twenty times, for a total of 160 executions. In every case, the controlled scenario generator produced the measurements, and the DDDM engine processed them according to the ranges and rules established before testing began.

Table 7. Scenarios included in the functional pilot.

Scenario	Variable evaluated	Executions
E01	Normal condition	20
E02	Moisture	20
E03	pH	20
E04	Nitrogen	20
E05	Phosphorus	20
E06	Potassium	20
E07	Temperature	20
E08	Communication	20

Each scenario had the same number of executions. E01 corresponded to an operation in which all variables remained within the suitable intervals; E02 and E04–E06 assessed lower warning conditions; E03 and E07 examined upper critical conditions; and E08 verified the expected response to a communication loss. This distribution made it possible to evaluate the output categories included in the architecture without changing the configuration between repetitions of the same scenario.

The interpretation process performed by the DDDM engine is illustrated through a critical temperature scenario (Figure 3). Once the measurement is received, the architecture retrieves the corresponding operational range, calculates the deviation from the configured limit, determines the operational state and priority level, and generates the associated actionable insight. The same procedure was performed automatically for each measurement produced during the pilot. The figure therefore shows the traceability between the input data and the resulting decision according to the flow established in the methodology.

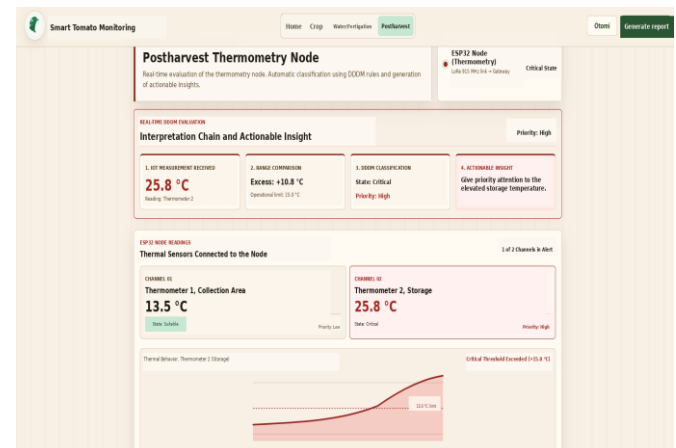


Figure 3. Representative example of the DDDM interpretation process for a critical temperature condition.

Table 8 presents the results of the 160 executions. In each scenario, the generated state, priority, and insight were compared with the predefined expected outputs. An execution was considered to have achieved full agreement only when all three elements matched.

Table 8. Functional pilot results by scenario

Scenario	Generated interval	Expected state	Executions	Correct state	Correct priority	Correct insight	Agreement
E01	All variables within their suitable ranges	Suitable	20	20/20	20/20	20/20	100%
Normal operation							
E02	20.3–38.5%	Warning	20	20/20	20/20	20/20	100%
Low moisture							
E03	7.52–8.15 pH	Critical	20	20/20	20/20	20/20	100%
High pH							
E04	20.0–37.9%	Warning	20	20/20	20/20	20/20	100%
Low nitrogen							
E05	20.1–38.7%	Warning	20	20/20	20/20	20/20	100%
Low phosphorus							
E06	20.4–38.7%	Warning	20	20/20	20/20	20/20	100%
Low potassium							
E07	18.2–22.0 °C	Critical	20	20/20	20/20	20/20	100%
High temperature							
E08	Not applicable	No communication	20	20/20	20/20	20/20	100%
Communication loss							

Overall, the architecture behaved consistently across the eight scenarios, reproducing the expected outputs throughout the 160 executions.

The eight scenarios achieved 100% agreement. In E01, all variables maintained the suitable classification throughout the twenty executions.

The pH values in E03 exceeded 7.5, and the temperatures in E07 were above 18.0 °C. As a result, the respective critical rules were activated in all twenty repetitions of both scenarios. In E08, the absence of a measurement was recognized as a communication loss and produced the expected output in every execution.

When the results were combined, 160 matches were recorded for the state, 160 for the priority, and 160 for the insight. All 160 executions simultaneously met the three elements and, consequently, the functional acceptance criterion established in the methodology. Within the scenarios analyzed, this result reflects the consistency among the controlled inputs, configured rules, and outputs produced by the DDDM engine.

The implemented architecture is consistent with the trend observed in agricultural IoT solutions, where acquisition, storage, processing, and visualization are integrated as connected functions. Navarro et al. (2020) describe the evolution of data-processing approaches in smart farming solutions, while Ibarra-Cabrera et al. (2024) present the integration of an IoT system with an application designed for tomato monitoring. In the architecture developed in this study, this integration focused on preserving the relationship between each measurement and its operational interpretation within the platform.

The main contribution identified during the functional pilot lies in the reproducible transformation of measurements into states,

priorities, and insights, rather than in their visualization alone. This characteristic is related to the work of Araújo et al. (2023), who integrate data acquisition, storage, and runtime reasoning to support data-driven agricultural decisions. Similarly, Sharma and Shivandu (2024) recognize data integration and real-time decision-making as relevant elements in developing IoT-based agricultural solutions. Compared with these studies, the pilot provides functional evidence of an explicit and traceable interpretation chain within a scope that does not include predictive models or action automation.

The 100% agreement value should be interpreted according to the study design because the inputs, operational intervals, and expected outputs were established before the executions. The architecture interprets the measurements using decision rules configured from the operational ranges defined for the pilot. In this sense, the result confirms that the implemented logic reproduced the expected responses in the 160 controlled executions, but it does not represent an estimate of agronomic accuracy, predictive capability, or generalizability to conditions not considered in the study. Likewise, the twenty repetitions of each scenario made it possible to assess functional stability under the synthetic variation incorporated into each interval, although they do not replace an evaluation with physical sensors or reproduce the variability of a production environment.

Within the defined scope, the results support the operation of the DDDM interpretation process. Measurements representing suitable, warning, critical, and communication-loss conditions were consistently converted into operational states, priorities, and actionable insights. However, the use of synthetic data and ranges configured specifically for the pilot constitutes the main limitation. Consequently, the results cannot be extrapolated to loss reduction, improved tomato quality, or system performance under actual

cultivation and postharvest conditions. A subsequent evaluation should incorporate calibrated sensors, actual production conditions, and agronomic criteria adapted to the implementation context.

CONCLUSION

The aim of this study was to develop and functionally validate an IoT architecture intended for the intelligent monitoring of tomato harvest and postharvest through data-driven decision-making. Based on this purpose, the proposal connected the received measurements with their operational interpretation and the generation of useful information to support decision-making.

To achieve this objective, the architecture was implemented through a platform that integrates data acquisition, processing, storage, and visualization. The incorporation of the DDDM approach made it possible to convert contextualized measurements into operational states, priority levels, and actionable insights while maintaining traceability between the received value, the configured range, and the output shown to the user.

To verify the behavior of the implemented architecture, a functional pilot comprising eight scenarios and 160 executions was conducted. In each execution, the generated state, priority, and insight matched the expected outputs, resulting in full agreement of 100%. Within the scope of the controlled scenarios, this result demonstrated consistent functional behavior under suitable, warning, critical, and communication-loss conditions.

However, the main limitation of the study is the use of synthetic measurements and operational ranges established for the pilot. Accordingly, the results are limited to the functional validation of the interpretation process and do not verify sensor accuracy, the agronomic validity of the ranges, or system performance under actual production conditions.

Based on this limitation, future work should evaluate the already implemented architecture under actual cultivation and postharvest conditions using calibrated sensors and measurements collected directly from the production process. This stage would make it possible to analyze the platform's behavior in response to the variability inherent in the environment, as well as to verify and adjust the operational ranges used during the pilot according to agronomic criteria and the specific implementation conditions. This would allow the performance of the DDDM architecture to be evaluated during continuous operation and strengthen the representativeness of the parameters used to interpret the measurements.

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