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CREATION OF A CROP INFORMATION SYSTEM SUPPORTED BY ARTIFICIAL INTELLIGENCE AND IOT

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Abstract - Currently, not only Mexico but also many other countries face significant agricultural challenges resulting from climate change, the emergence of pests, and low automation in production processes. Against this backdrop, this research proposes the creation of an artificial intelligence-based crop information system with the aim of promoting rural innovation and strengthening food security through accessible and scalable technological solutions. Agricultural activity continues to rely on traditional methods that are not very sustainable, which limits the incorporation of modern tools and hinders the transition to more efficient practices. The study was developed methodologically in three phases: the first is the design of the IoT hardware, the second phase is the development of the artificial vision software, and finally, the last phase is the interpretation of the data for decision-making. The system proposes the development of an IoT transmitter-receiver device capable of transmitting analog and digital sensory data via LoRa radio communication, complemented by a YOLOv8-based computer vision system for crop health detection. The integration of these technologies seeks to optimize water use and advance agricultural sustainability. Python is also used in the implementation of artificial intelligence algorithms that identify plant diseases and activate irrigation systems only when soil moisture requires it, reducing the waste of water resources. This approach contributes to the construction of a more sustainable, efficient, and resilient agricultural model, capable of responding to the current and future needs of the sector, positioning technological innovation as a strategic axis for rural development and food security in Mexico.

Keywords: Agriculture 4.0, Sustainable Development, Artificial Intelligence, Internet of Things, LoRaWAN, Computer Vision.

Abstract - Currently, not only Mexico, but many other countries face significant agricultural challenges stemming from climate change, the emergence of pests, and low levels of automation in production processes. Given this scenario, this research proposes the creation of a crop information system supported by artificial intelligence, with the aim of promoting rural innovation and strengthening food security through accessible and scalable technological solutions. Agricultural activity continues to rely on traditional, unsustainable methods, which limits the adoption of modern tools and hinders the transition to more efficient practices.

The study was developed using a three-phase methodology: the first phase involves the design of the IoT hardware, the second phase the development of the machine vision software, and the final phase the interpretation of the data for decision-making. The system proposes the development of an IoT transmitter-receiver device capable of transmitting analog and digital sensor data via LoRa radio communication, complemented by a YOLOv8-based machine vision system for detecting crop health. The integration of these technologies aims to optimize water use and advance agricultural sustainability. Python is also used to implement artificial intelligence algorithms that identify plant diseases and activate irrigation systems only when soil moisture requires it, reducing water waste. This approach contributes to building a more sustainable, efficient, and resilient agricultural model, capable of responding to the sector's current and future needs, positioning technological innovation as a

strategic pillar for rural development and food security in Mexico.

Key words – Agriculture 4.0, Sustainable Development, Artificial Intelligence, Internet of Things, LoRaWAN, Computer Vision.

INTRODUCTION

Today's agriculture faces a challenging landscape characterized by the climate crisis, increased pests, and limited modernization in production processes. These factors affect not only Mexico but also many countries that depend on vulnerable and unsustainable agri-food systems. Technologies applied to the agricultural sector are rapidly advancing toward a new approach: Agriculture 4.0. In this model, digitization, automation, and artificial intelligence play a fundamental role in crop production, especially in tasks such as weed and pest management. **Error! Reference source not found.** These applications not only increase the efficiency and sustainability of agricultural systems, but also improve productivity and resilience to climate change.
This evolution presents both challenges and opportunities, such as the incorporation of emerging technologies: the Internet of Things (IoT) and artificial intelligence (AI) have become strategic alternatives for driving rural innovation and ensuring food security. The creation of a crop information system supported by artificial intelligence and IoT is becoming a fundamental axis for the transition to a more efficient and sustainable agricultural model, in which computer vision plays a key role by enabling the early identification of pests, diseases, and nutritional deficiencies in plants through the automated analysis of images captured in the field. Computer vision (CV) is a branch of artificial intelligence whose objective is to provide a computer or robot with the sense of sight so that they can interact more efficiently in complex environments (use of vision as an additional sensor). In general terms, it is a branch of artificial intelligence whose objective is to provide computer systems with the ability to "see" and process visual information in order to interact more efficiently in complex environments.

This visual recognition capability, combined with deep learning algorithms, provides producers with accurate decision-making tools, reducing the indiscriminate use of agrochemicals and promoting sustainable development that prioritizes the conservation of natural resources and the protection of the environment [3]. Likewise, the integration of IoT sensors with artificial intelligence systems enables the continuous collection of data on soil moisture, temperature, and quality, creating a digital ecosystem that promotes precision agriculture and strengthens food security in rural communities [4]. In this sense, artificial intelligence is not only a technological resource, but also a catalyst for innovation that drives agricultural productivity and contributes to the resilience of cropping systems in the face of the challenges of climate change, thus consolidating a paradigm where technology becomes a strategic ally in ensuring the sustainability and competitiveness of the agricultural sector.

The greatest challenge facing the agricultural sector is considered to be the integration of technologies from various areas of knowledge, enabling a true digital transformation in products, services, processes, and new business models [5] [6].

This revolutionary new paradigm has spread to the agricultural sector with the creation of agriculture 4.0, which appropriates knowledge and prepares for the future by adopting new technologies such as the Internet of Things, big data, cloud computing, advanced robotics, and artificial intelligence in the agribusiness production chain [7].

Agriculture 4.0 has demonstrated its potential to transform production through the use of sensors, computer vision algorithms, and communication systems that optimize resources and improve crop health [8]. Some research claims that AI information systems and machine learning (ML) algorithms are emerging technologies for analyzing large amounts of data applied to the agricultural sector [9].

Building AI-based models, such as artificial neural networks, convolutional neural networks, and reinforcement learning, are very demanding tasks, but parametric estimates are useful for solving forward-looking problems [10][11]. ML has been used to control pesticide application repetitions in agriculture [12], soil fertility, and productivity [13].

Another representative technological resource in the agricultural field is the Internet of Things (IoT), which highlights the potential of wireless sensors in the various stages of cultivation, from the beginning of soil preparation to the transport of the harvest. It is a technology used in this type of study also known as cloud computing. This term is relevant in agriculture because of its operability with IoT, as it is not only a technology but also integrates many things[11]. It is an Internet-based computer system that provides hardware, software, services platform for storage of various

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applications, texts, images, and videos of agricultural information [14].

However, it also poses challenges due to the integration of technologies with agricultural practices [15]. LoRa technology is emerging as a promising and efficient alternative for long-distance transmission in rural areas for agricultural monitoring [16].

This study focuses on the development of an agricultural information system that integrates an IoT transceiver device capable of transmitting analog and digital sensor data via LoRa radio communication, complemented by a YOLOv8-based computer vision system.
According to [17], these tools allow real-time monitoring of crop health, optimization of agricultural resource use, and strengthening of response capacity to phytosanitary threats, all through accessible and scalable solutions for the rural environment.

This proposal seeks to respond to the need to modernize agricultural practices, reducing dependence on traditional methods and promoting a more efficient and sustainable model. The implementation of algorithms in Python will make it possible to identify plant diseases and activate irrigation systems only when soil moisture requires it, which contributes to reducing water waste and advancing toward sustainability.

This study contributes to sustainable agricultural development by integrating IoT-LoRa technologies and computer vision, enabling more efficient use of resources, reducing environmental impacts, and strengthening food security.

DEVELOPMENT

Methodology

The system was developed using an iterative approach with an engineering design (Prototype, Test, and Repeat), which allowed for continuous adjustment of the hardware and software components based on the results obtained in the field, ensuring their relevance and applicability in real agricultural scenarios. In the first phase, the design of the IoT hardware focused on the selection of humidity, temperature, and air quality sensors, whose accuracy and low energy consumption are essential for the sustainability of the system. Subsequently, the second phase focused on the development of computer vision software, using artificial intelligence algorithms capable of identifying pests and anomalies in crops by analyzing images captured in real time, which is in line with current trends in digital agriculture[19].

Finally, the third phase consisted of interpreting the data for decision-making, where machine learning techniques were applied to generate predictive models that support the efficient management of water and nutritional resources, contributing directly to sustainable development and food security. This methodology, by combining prototyping, testing, and repetition, not only ensures continuous improvement of the system but also strengthens producers' resilience to the challenges and needs of climate variability in crops.

Design of the IoT Sensor Network and LoRa Communication

To ensure operability in rural areas lacking conventional telecommunications infrastructure, a long-range network architecture (LPWAN) based on LoRa technology was designed. The network operates under a star topology, where multiple sensor nodes (transmitters) transmit telemetry to a central node (Gateway/Receiver) responsible for processing and acting.

Figure 1. *Node architecture* **Source:** *Own elaboration*.

The hardware architecture of the transmitter nodes and monitoring nodes was designed as an autonomous embedded system. The processing core is the ESP32-S3 microcontroller, selected for its 32-bit Xtensa® LX7 dual-core architecture, which offers the computing power necessary for edge computing and energy efficiency.

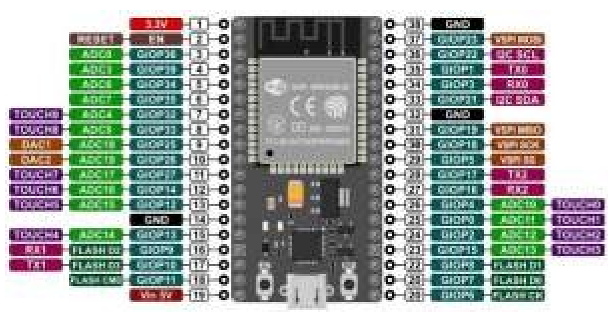

Figure 2. *Esp32 architecture*.

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Source: *Own elaboration.*

Capacitive v1.2 soil moisture sensors were implemented for the acquisition of physical variables. Unlike traditional resistive sensors, capacitive technology prevents electrolysis and corrosion of the electrodes, extending the device's useful life in high salinity and humidity environments, a critical factor for the sustainability of industrial maintenance.

Figure 3. *Soil moisture sensor.*
Source: *Own elaboration.*

Data transmission is carried out using the Reyax RYLR998 LoRa transceiver module, which operates via a UART interface. This module was configured to operate in the 915 MHz frequency band, optimizing signal penetration in environments with dense vegetation.

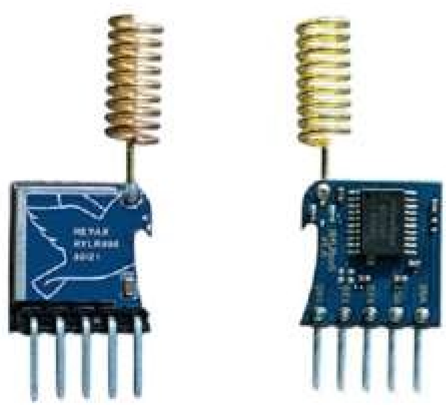

Figure 4. *Reyax 998 LoRa antennas.*
Source: *Own work.*

Energy management and autonomy for nodes operating in remote locations were achieved by implementing a self-sustaining power supply system consisting of photovoltaic panels and recycled lithium battery banks. To maximize autonomy, the microcontroller was programmed under a "Deep Sleep" routine. In this mode, the system remains inactive, consuming minimal energy (in the order of microamperes), and "wakes up" only at programmed intervals to take sensor readings, transmit the data packet via LoRa, and go back to sleep. This energy management strategy solved the initial autonomy problems detected in the pilot phases.

The receiving node acts as the gateway between the local LoRa network and the cloud. Upon receiving data frames from the transmitters, this device performs two critical functions:

IoT Telemetry: Through a WiFi connection (when available) or mobile data, it uploads the records to the ThingSpeak platform for historical visualization and trend analysis.

Actuator Control: The system integrates a 4-channel relay module (5V-120/220V, 10A). Based on programmed control logic, if the reported humidity is below the critical threshold of 40%, the Gateway activates the irrigation pump contactors in a sectorized manner, ensuring that water is supplied only to areas that physiologically require it.

Artificial Vision System for Crop Quality Control

To ensure crop quality and early detection of biotic stress, modular computer vision software was developed using the Python 3.11 programming language. The software architecture integrates specialized libraries: OpenCV for pre-processing images in the BGR to RGB color space, Ultralytics for deep learning model inference, and Tkinter for the graphical user interface (GUI), allowing intuitive interaction for agricultural operators.

For crop quality control, the YOLOv8 (You Only Look Once, version 8) model was also considered because it represents a recent advance in the field of CNNs, designed to perform fast and accurate detections in real time. Its optimized architecture allows it to tackle complex classification and detection problems with an efficient balance between accuracy and speed, even under conditions of limited computational resources. This makes it an ideal tool for application in agricultural environments, where the availability of specialized hardware is often restricted.

The model architecture and training implemented the YOLOv8 (You Only Look Once, version 8) algorithm, selected for its single-stage convolutional neural network (CNN) architecture, which offers an optimal balance between accuracy (mAP) and inference speed, crucial for real-time processing on edge devices. This technology becomes an ideal tool for application in agricultural environments

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where the availability of specialized hardware is often limited.

The model was trained using a hybrid dataset, composed of images collected from crops in the southern region of Tabasco and synthetically augmented using the Roboflow platform to improve generalization. The training process consisted of 50 epochs, achieving convergence of the box loss and classification loss functions to stable minimum values, indicating effective learning of the morphological characteristics of the pathologies.

Figure 5. *Data segmentation in Roboflow*.
Source: *Own elaboration*.

The implemented algorithm processes images and video in real time. The inference process uses an adjustable confidence threshold to filter false positives. The system tags detections and generates count statistics by class, allowing the user to visualize the incidence of diseases in the inspected batch.

Ec. (1) Detection and inference logic (code snippet): results = model(img, stream=False, conf=confidence_threshold)

The algorithm operates under sequential automated inspection logic:
Acquisition: The system captures the video stream from CCTV cameras or static files.
Inference: The image is processed by the neural network, which predicts the coordinates of the bounding boxes and the class probability.
Statistical filtering: An adjustable confidence threshold (initially set to = 0.20) is applied to discard false positives. Only detections with a confidence C>a are processed.
Ec. (2) Validation criterion: $D_{valid} = \{d \in D \mid Conf(d) > 0.20\}$
Taxonomic Classification: The system maps the detected class indices to their scientific and common names using an internal translation dictionary. **Visualization and Counting:** Bounding boxes and labels are rendered on the original image and statistical counters are updated on the dashboard in real time, allowing the disease incidence rate in the inspected batch to be calculated.

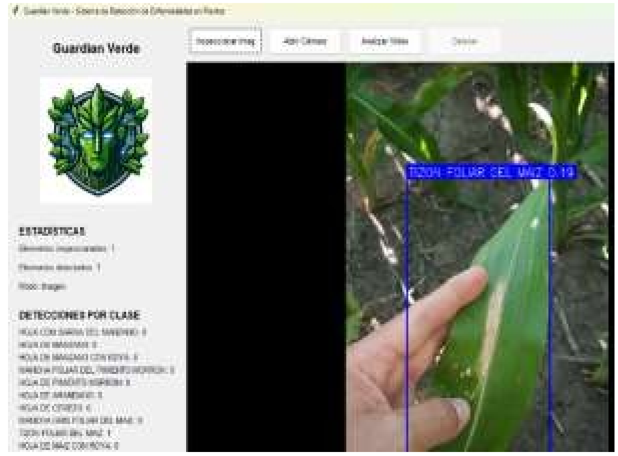

Figure 6. *User interface*.
Source: *Own elaboration*.

This methodology allows not only to identify the presence of pathogens such as rust (Puccinia sorghi) or blight, but also to quantify the severity of the infection based on the density of detections per leaf, providing hard data for agronomic decision-making.

Standardization of the Irrigation Process

From an industrial engineering perspective, traditional irrigation is a non-standardized process, subject to high variability introduced by the human factor and empirical evaluation. To mitigate this, a closed-loop control algorithm was designed that transforms irrigation into a deterministic process based on quantitative data.

Control Logic and Algorithm
The system operates under an On-Off control logic with hysteresis to protect the actuators. A critical soil moisture setpoint (H_min) of 40% was defined, determined as the safe lower limit before the crop enters water stress.

The algorithm, executed on the Gateway node, periodically queries the telemetry from the distributed sensors. The decision logic follows the following standardized pseudocode:

1. Reading: Obtain the average moisture value (H_actual) for sector i.
2. Decision:
   a. If H_current < 40: Activate Relay K (Turn on Pump).
   b. If H_current > 60%: Deactivate Relay K (Turn off Pump).

Artificial Vision Training Results

The YOLOv8 model was trained for 50 epochs. The training behavior, visible in the loss and metrics graphs, shows stable convergence. The classification loss (cls_loss) decreased progressively from 3.75 to approximately 2.25, indicating that the model effectively learned to distinguish between the 27 available classes.

The overall performance of the model was evaluated using the Precision-Recall (PR) curve, obtaining a Mean Average Precision (mAP) at 50% intersection over union (IoU) of 0.346 for all classes. Although the maximum overall F1 score was 0.31 with a confidence threshold of 0.155, detailed analysis by class reveals superior performance in the crops targeted by this research.

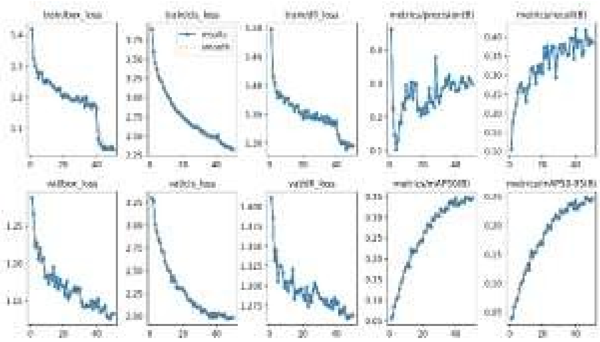

Figure 7. *Training results*.
Source: *Own elaboration*.

DISCUSSION AND ANALYSIS OF RESULTS

The results obtained from the implementation of the prototype are discussed below, evaluating technical performance against the sustainability and operational optimization objectives set. The analysis is divided into three fundamental tests: telemetry network efficiency, computer vision model validation, and water savings quantification.

Test 1: Scope and Reliability of the IoT Network. The transmission capacity of the Reyax 998 LoRa module was evaluated in a rural environment with medium vegetation. Field tests confirmed a stable data transmission link up to a distance of 14 km in line of sight. This validates the technical feasibility of the proposed LPWAN architecture to overcome the connectivity gap in agricultural areas without internet infrastructure, meeting the objective of technological accessibility. In addition, the implementation of the "deep sleep" mode in the ESP32 microcontroller proved to be effective for energy autonomy, allowing continuous operation with recycled batteries and solar panels, eliminating dependence on the conventional power grid.

Test 2: Accuracy of the Computer Vision Model. Analysis of the YOLOv8 algorithm training reveals stable convergence of box and classification losses during the 50 epochs executed, indicating effective learning of morphological characteristics. Although the overall Mean Accuracy (mAP 0.5) was 0.346, a breakdown analysis using the normalized confusion matrix demonstrates high effectiveness in the region's target crops. Specifically, the system correctly identified 75% of cases of corn leaf blight.

From an industrial engineering perspective applied to quality control, these values are acceptable for an early warning system, as they allow farmers to segregate affected batches and apply targeted corrective measures, reducing crop loss, which, according to preliminary tests, improved yield by 20%. However, significant cross-confusion is observed in visually similar tomato pathologies, suggesting a future need to balance the dataset to strengthen the model's generalization.

Test 3: Irrigation Standardization and Water Savings The implementation of the control algorithm based on the 40% moisture threshold transformed the irrigation process from an empirical activity to a standardized operation. Monitoring through the ThingSpeak platform allowed us to verify the direct correlation between ambient temperature and soil moisture, validating the automatic response of the actuators.

When comparing volumetric consumption, the automated system reduced water use by 50% compared to the traditional flood irrigation or fixed schedule method previously used in the test area. This result directly responds to the sustainability objective, demonstrating that low-cost technification can significantly mitigate water stress without compromising crop health.

The results discussed show that the integration of IoT, computer vision, and artificial intelligence in the developed prototype is a viable alternative for advancing agricultural sustainability and operational optimization. The reliability of the telemetry network, the predictive capacity of the computer vision model, and the standardization of irrigation demonstrate that the system not only meets the technical objectives set, but also provides tangible benefits in terms of energy efficiency, loss reduction, and rational water use.

These findings confirm the potential of the proposal as a decision-making support tool in rural environments, while also pointing to areas for improvement, such as the balance of datasets to strengthen the generalization of the model, which should be addressed in future research to consolidate its impact on food security and sustainable development.

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1) Connectivity and energy autonomy in rural environments (IoT-LoRa).

The results in terms of range (≈14 km line of sight) and self-sustaining operation confirm that a LoRa-based LPWAN architecture is technically feasible for agricultural telemetry where conventional infrastructure is limited. This finding is consistent with evidence that LoRa/LPWAN enables monitoring of large areas with low power consumption and stable links, even in scenarios with complex vegetation and terrain [15][16]. The deep sleep and photovoltaic power supply strategy used in the prototype reinforces the literature that highlights energy efficiency as a critical factor for scalability and sustainability in agricultural IoT deployments [14][15].

2) Computer vision and YOLOv8 performance for early warning.

Although the overall mAP obtained (≈0.35 @IoU 0.5) could be improved, its specific performance on target crops (e.g., corn leaf blight) positions it as a functional early warning system. This pattern of practical utility with room for refinement is consistent with reviews reporting that deep learning in agriculture achieves solid results when local data and dataset curation are available [3][9]. Recent studies with YOLOv8 in fruit tree phytosanitation show significant gains after balancing and augmenting the dataset, which supports prioritizing data curation and difficult classes as the next step [20][1].

3) Standardization of irrigation and water savings through data-based control.

The reduction in water consumption (~50%) compared to empirical irrigation coincides with evidence that integrating moisture sensors, AI models, and automation can optimize irrigation volumes, frequency, and timing, directly impacting sustainability and production resilience [10][18]. The transition from simple rules (on-off with hysteresis) to predictive schemes is in line with precision agriculture trends, where forecasting and the integration of soil and climate variables increase crop efficiency and stability [9][10].

4) Agriculture 4.0 integration: data, adoption, and scalability.

The convergence of IoT, AI, and communication has resulted in actionable decisions (batch segmentation, sectorized irrigation), which is consistent with the Agriculture 4.0 paradigm that emphasizes data-intensive value chains, traceability, and digital services [11][4]. However, the literature warns that adoption depends on socio-technical factors—availability of quality data, local capabilities, and governance models—so scalability requires data protocols, cybersecurity, and training strategies to ensure that the technical benefits to be sustained in real implementations [5] [19].

CONCLUSIONS

This research achieved its overall objective of developing and implementing a comprehensive agricultural monitoring system that combines the Internet of Things (IoT) and Artificial Intelligence to optimize processes in rural areas with low infrastructure. The technical feasibility of using LoRa technology for telemetry transmission over distances of up to 14 km without dependence on local internet was demonstrated, validating a robust and accessible communication architecture for the Mexican countryside.

In relation to the objectives of sustainability and resource optimization, the standardization of the irrigation process through automatic control logic allowed for a 50% reduction in water waste compared to traditional methods.

Overall, the results confirm that the convergence of IoT, AI, and process control enables affordable, scalable, and contextualized precision agriculture, capable of translating data into timely interventions that improve resource use efficiency, reduce operational uncertainty, and strengthen food security in rural environments.

Future lines of research that will complement further development of the system are:

1.- Improving model performance and multimodal dataset robustness: furthering class balancing, incorporating multispectral and hyperspectral images, and self-supervised learning to increase generalization, reduce confusion between visually similar pathologies, and strengthen detection in variable lighting conditions and occlusions; complementarily, exploring active learning techniques in the field to efficiently annotate difficult cases and accelerate continuous improvement cycles.

2.- Intelligent irrigation and fertigation control with prediction: evolve from an on-off scheme with hysteresis to model-based predictive control (MPC) that integrates weather forecasts, soil moisture dynamics, and crop phenology in order to optimize the volume, timing, and sectorization of irrigation and fertigation, maximizing water savings and production stability under scenarios of climate variability.

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