Precision Agriculture 4.0: Implementation of IoT, AI, and Sensor Networks for Tomato Crop Prediction

Miguel Ángel Giménez Pérez [1], Antonio Guerrero-González [2], Francisco Javier Cánovas Rodríguez [3], Inocencia María Martínez Leon [4], Francisco Antonio Lloret Abrisqueta [5]
[1,5] Master Industry 4.0 Study Program, Polytechnic University of Cartagena, Spain
[2,3] Department of Automation, Electrical Engineering, and Electronic Technology, Polytechnic University of Cartagena, Spain
[4] Department of Business Economics, Polytechnic University of Cartagena, Spain

ARTICLE INFORMATION

Article History:

Submitted 25 May 2024
Revised 04 July 2024
Accepted 09 July 2024

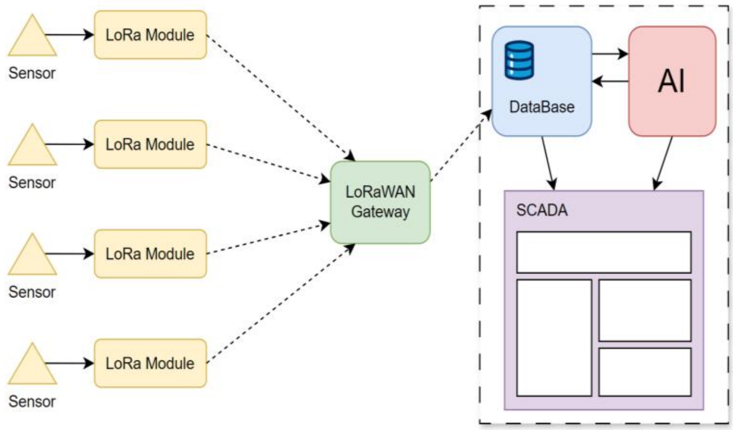
Keywords:

Agriculture;
Internet of Things;
Artificial Intelligence;
Sensor Networks;
Prediction

Corresponding Author:

Francisco Antonio Lloret Abrisqueta,
Master Industry 4.0 Study Program, Polytechnic University of Cartagena, Spain.
Email: francisco.lloret@edu.upct.es

ABSTRACT



Precision agriculture introduces an innovative approach to farm management by involving the use of technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and sensor networks to optimize resources and increase crop yields. In this context, the present study aimed to develop a tomato crop prediction system using IoT, AI, and sensor networks. A system architecture was designed, including distributed sensors, IoT gateways, and a cloud platform running AI models based on recurrent neural networks. These AI models were trained with environmental data and validated using actual harvest data. The results showed up that the model could predict weekly harvest volumes with an average error of 3.2% during the best 4-week period. The integration of IoT, AI, and sensor networks proved to be effective for accurate crop prediction and has potential for other applications in precision agriculture.

Document Citation:

M. Á. G. Pérez, A. G. -González, F. J. C. Rodríguez, I. M. M. Leon, and F. A. L. Abrisqueta, "Precision Agriculture 4.0: Implementation of IoT, AI, and Sensor Networks for Tomato Crop Prediction," *Buletin Ilmiah Sarjana Teknik Elektro*, vol. 6, no. 2, pp. 172-181, 2024, DOI: 10.12928/biste.v6i2.10954.

1. INTRODUCTION

Precision agriculture is an innovative approach to agricultural management that uses measurement and data analysis techniques to optimize resources and maximize crop yields [1]. This approach is based on providing plants with exactly what they need, at the right time and in precise quantities, by measuring and monitoring soil properties, climate, and crop conditions [2].

The adoption of precision agriculture has been driven by advances in technologies such as the Internet of Things (IoT), artificial intelligence (AI), and sensor networks [3]. These technologies allow substantial amounts of data to be collected and analyzed in real-time, facilitating informed decision-making and the implementation of specific agricultural practices for each area or even each plant [4].

IoT plays a critical role in enabling the connection and communication of devices and sensors in agricultural fields [5]. These sensors collect data on variables such as soil humidity, temperature, solar radiation, and the presence of pests or diseases. This data is transmitted over wireless networks to a cloud platform, where it is stored and processed [6].

AI analyzes collected data using techniques like machine learning and deep learning to identify patterns, make predictions, and inform decisions about irrigation, fertilizers, and pesticide application [7][8]. Furthermore, AI has also been used for image recognition and the detection of pests and diseases in crops [8].

Sensor networks play a crucial role in collecting real-time data from agricultural fields [9]. These networks are composed of multiple sensor nodes distributed around interest, which transmit the collected data to a central node or gateway. From there, the data is sent to the cloud for processing and analysis [10].

Big Data is crucial in precision agriculture, enabling the analysis of large volumes of data from IoT sensors, satellite imagery, and weather data [11][12]. This integration of massive data facilitates informed decision-making and optimization of agricultural processes, from planting to harvesting [13]. Big Data allows farmers to predict weather patterns, detect crop diseases early, and precisely adjust the use of resources such as water and fertilizers [14][15]. However, handling large-scale data also poses challenges in terms of privacy and security, requiring the implementation of robust data protection measures to ensure farmers' trust in adopting these advanced technologies [11][16].

Digital twins are emerging as a powerful tool in modern agriculture, offering a detailed virtual representation of physical agricultural systems [17][18]. These digital replicas allow farmers and scientists to simulate, monitor, and optimize agricultural processes in real-time, from crop growth to livestock management [19][20]. Digital twins integrate data from IoT sensors, satellite imagery, and predictive models to create a holistic view of the agricultural environment [18]. This technology facilitates yield prediction, early problem detection, and proactive decision-making to improve the efficiency and sustainability of agricultural operations [20][21]. Although its implementation still faces technical and adoption challenges, digital twins promise to revolutionize agriculture by providing accurate insights and enabling smarter and more sustainable management of agricultural resources [18][21].

The integration of these technologies in precision agriculture has proven to be beneficial in various aspects, such as increasing yields, reducing resource waste (water, fertilizers, pesticides), improving crop quality, and reducing environmental impact [22].

In tomato agriculture, the implementation of Industry 4.0 technologies has become crucial to optimize production and face the current challenges of the sector [1]. Tomato cultivation, being one of the most important crops worldwide, requires precise management of resources such as water, nutrients and protection against pests and diseases [2]. Technologies such as IoT, AI and sensor networks allow continuous and accurate monitoring of crop conditions, facilitating informed decision making in real time [3][5]. For example, soil moisture sensors can optimize irrigation, while AI cameras can detect diseases or nutritional deficiencies early [6][7]. The use of drones and Big Data analysis allows a holistic vision of the crop, improving the planning and execution of tasks [13]. These innovations not only increase the yield and quality of tomatoes, but also reduce the use of inputs, reducing costs and environmental impact [23]. In an increasingly competitive market and with growing concerns about sustainability, the adoption of these technologies in tomato production becomes essential to ensure the efficiency, profitability and long-term sustainability of this important crop [24].

1.1. Comprehensive Theoretical Base and Proposed Method

This article proposes a precision agriculture system for tomato crops that integrates IoT, AI, and sensor networks to predict harvests. The system consists of the following main components:

- Sensor Network: A network of sensors distributed in the agricultural field collects data on key variables, such as soil moisture, temperature, solar radiation, relative humidity, and other relevant environmental factors [23]. The sensor nodes are equipped with rechargeable batteries and wireless communication to transmit the collected data to a central node or gateway.

- IoT Gateway: The IoT gateway receives data from sensor nodes and transmits it to a cloud platform over a network connection (such as Wi-Fi, cellular, or satellite). The gateway may also include local processing capabilities to perform basic analysis and make real-time decisions [25].
- Cloud Platform: The data collected by the sensors is stored and processed on a cloud platform. This platform uses AI techniques, such as machine learning and deep learning, to analyze data and extract valuable insights [26]. AI models are trained with historical data and continually updated with new data collected to improve their accuracy.
- Visualization and Control System: The results of data analysis and recommendations generated by AI models are presented to farmers through a visualization and control system. This system can take the form of a web or mobile application, or a SCADA (Supervision, Control and Data Acquisition) system [27]. Farmers can monitor the status of their crops, receive alerts, and adjust farming practices, as necessary.
- Smart Actuators: Based on the results of data analysis and system recommendations, smart actuators can be activated, such as automated irrigation systems, application of fertilizers or pesticides, and temperature, and humidity control in greenhouses, among others [28]. These actuators can be controlled remotely or through instructions based on predefined rules.

The workflow of the proposed system can be summarized as follows:

1. Sensors collect real-time data from the field.
2. Data is transmitted through the sensor network to the IoT gateway.
3. The IoT gateway sends the data to the cloud platform.
4. AI models in the cloud analyze data and generate recommendations.
5. Recommendations and analysis results are displayed in the control and monitoring system.
6. Smart actuators are activated based on farmers' recommendations and instructions.

This integrated approach of IoT, AI, and sensor networks allows highly automated and data-driven precision agriculture, leading to more efficient management of resources and increased yields.

2. METHODS

The development of the crop forecasting system was conducted through a systematic approach that included several phases, from the conception and design of the system architecture to the implementation and evaluation of the predictive models. Each phase was crucial to ensure the system met the specific requirements of the greenhouse environment and provided accurate and useful forecasts. Each of the steps followed in this process is detailed below.

2.1. System Architecture Design

The first step involved a thorough system requirements analysis, identifying critical environmental variables for growing tomatoes, such as temperature, relative humidity, and solar lighting. Different sensor models were evaluated to ensure they met the requirements for accuracy, durability, and ease of integration. Based on the requirements analysis, the Dragino LHT65N-E5 sensors were selected for their ability to measure multiple environmental variables and their compatibility with LoRa communication. The selection methods included a thorough evaluation of the options available on the market, considering criteria such as measurement accuracy, durability, energy consumption, and ease of integration with other system components.

To determine the most appropriate type of communication, several protocols within the Internet of Things technology were evaluated, considering the specific conditions of the installation and the requirements of the project. LoRa technology was selected for its ability to provide ultra-long range spread spectrum communication and high immunity to interference, in addition to its low power consumption. In the proposed solution, each greenhouse that is monitored will have a node equipped with three sensors that measure temperature, humidity and solar radiation. It was decided to use the Dragino LHT65N-E5 LoRa WAN sensors, which measure temperature, humidity and illuminance, and are ideal for agricultural applications and smart cities. These sensors allow users to send data over extremely long distances, minimizing current consumption. In addition, its design aimed at efficient use in energy terms, with a 2400 mAh battery that can last up to 10 years, facilitates maintenance, since the batteries are easily replaceable.

The resolution of the temperature sensor is 0.01ºC, a tolerance of ±0.3ºC and a long-term loss of less than 0.02ºC/year, with the measurement range being -40ºC to 80ºC. In reference to the humidity sensor, its resolution is 0.04%RH, with a precision of ±3%RH and a long-term loss of less than 0.02ºC/year. Its measurement range is between 0 and 96%RH. The external illuminance sensor is based on a BH1750 sensor, the cable length is 50cm, sufficient for installation in an area in which it captures the data with the greatest similarity to that of the plants, without being affected by the shadows in measurements. Its precision is 1lx and measures in a range of 0 to 65535lx, its operating temperature is between -40ºC and 85ºC.

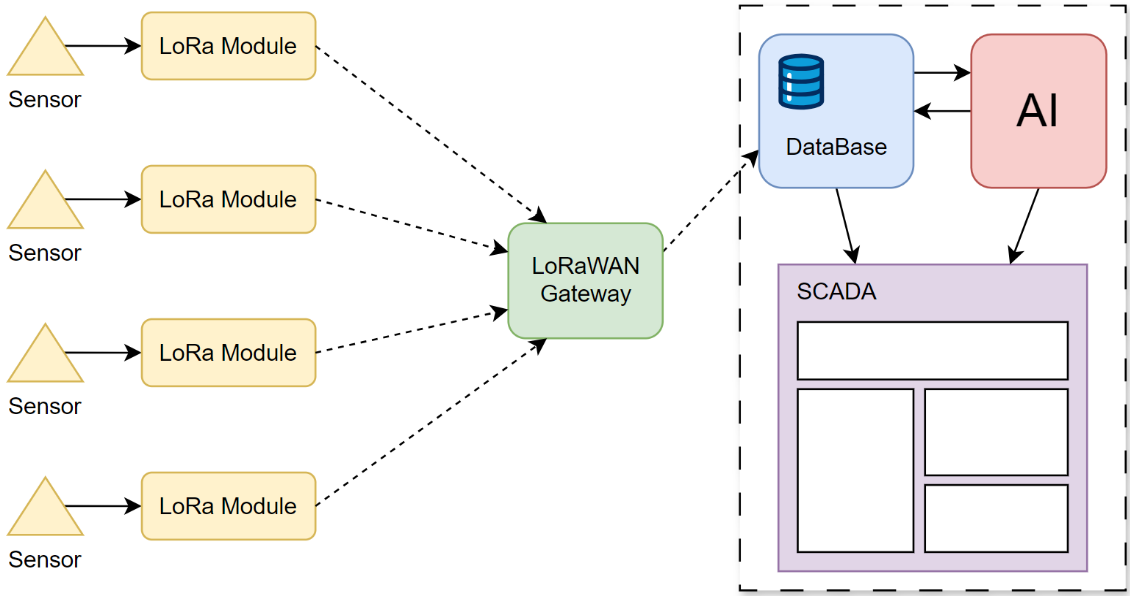


Figure 1. Application diagram

2.2. Deployment of Sensors and Gateways

Before deployment, greenhouse inspections were conducted to determine optimal locations for sensors and gateways. Factors such as space layout, sources of interference, and accessibility for maintenance were considered. Dragino LHT65N-E5 sensors were installed in the selected greenhouses. Sensors were strategically distributed to cover all critical areas, ensuring that the data collected was representative of the overall greenhouse conditions. Each sensor was calibrated before installation to ensure measurement accuracy. The TTN gateways were installed in central locations on the agricultural sites to maximize coverage. Accounts were set up on The Things Network (TTN) and gateways were registered, allowing the LoRa sensors to automatically connect and start transmitting data.

2.3. Data Collection and Storage

Node-RED was utilized to build data pipelines, integrating sensors, gateways, and cloud infrastructure. This facilitated the creation of data streams from sensors to Google Cloud InfluxDB, enabling real-time processing and efficient data storage. The data transmitted by the sensors was received by the gateways and sent to the Google Cloud Platform. Node-RED processed this data, performing cleaning and transformation tasks before storing it in Google Cloud InfluxDB, a database optimized for time series. Retention and downsampling policies were implemented to manage storage costs without losing relevant data. To send data from TTN to Node-RED via MQTT, the following steps must be followed:

1. Configure the inbound MQTT node to Node-RED: Start Node-RED and drag an inbound MQTT node to the work tab. Configure the node with the connection details provided by TTN, including the MQTT server URL, port, and login credentials. Specifies the MQTT topic that TTN uses to send sensor data.
2. Configure packet decoding node: Add a Function node to the work tab and write the JavaScript code required to decode data packets received from TTN. Connect the input MQTT node to the function node so that the received data is automatically decoded.
3. Connect to database: Drag the node corresponding to the database you are going to use (for example, "MySQL" or "MongoDB") to the work tab and configure the connection details, including the server address, the port, username, password, and database name.
4. Store the data: Add a database insert node (for example, "MySQL insert" or "MongoDB insert") and specify the table or collection where the data will be stored. Connects the function node (which decodes the data) to the database insert node. Evaluate the configuration by sending test data from TTN to verify that it is received, decoded, and stored correctly in the database.

These steps ensure that sensor data is efficiently transmitted from TTN to Node-RED, decoded and stored in the corresponding database for further analysis and use.

2.4. Development of Predictive Models

Recurrent neural networks (RNN), specifically LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Units), were selected for their capability to handle sequential data and make long-term predictions. These models are especially suitable for analyzing time series, such as environmental data collected in greenhouses. The collected data was structured in input/output pairs, where environmental conditions and meteorological data in a specific time window were associated with the expected harvest quantities for the following week. The data were divided into training and validation sets to evaluate the performance of the model. Initially, models were trained using simulated data to establish a performance baseline. Later, they were retrained with real data collected from the sensors. Training was conducted on Google Colab, using GPU acceleration to improve efficiency and reduce processing time.

3. RESULTS AND DISCUSSION

3.1. Study Results

The model was first trained and evaluated on simulated data, achieving a mean absolute error of 12%. The model was then retrained using real sensor data collected from the greenhouses. With these test data, the model achieved a mean absolute error of 8.5%. It was decided to use simulated data initially due to the high temporal and financial costs associated with collecting real data. Collecting data over a year involves expensive deployment of nodes and the purchase and installation of equipment and without obtaining a production forecast. Therefore, using simulated data allows you to train the AI model from the beginning, ensuring performance within the admissible margins now of launch. As more empirical data is collected, the model will be retrained, progressively improving its accuracy without the need to wait a full year to obtain a working model.

After validation, the system was deployed in real-time to assess the accuracy of ongoing harvest predictions. Over 16 weeks of the current crop cycle, the model showed an average error of 6.7% compared to actual harvest quantities. At that time, monitoring was expanded to cover 50% of the farm area, increasing from 29 to 43 greenhouses. With the increase in available data, precision improved markedly, reaching a mean error of 5.3% over 14 weeks. The best performance was achieved over 4 weeks with a mean error of only 3.2%. Thanks to these analyses it was possible to reduce the error of the predictions to a significant extent.

Figure 2 shows the differences between manually estimated production and actual production data (X axis the week of the year and Y axis the difference between the estimate and the actual production). A significant improvement was observed, going from peaks in Figure 2 of more than seventy-five tons to not reaching four tons as a maximum in the differences between estimates on Figure 3.

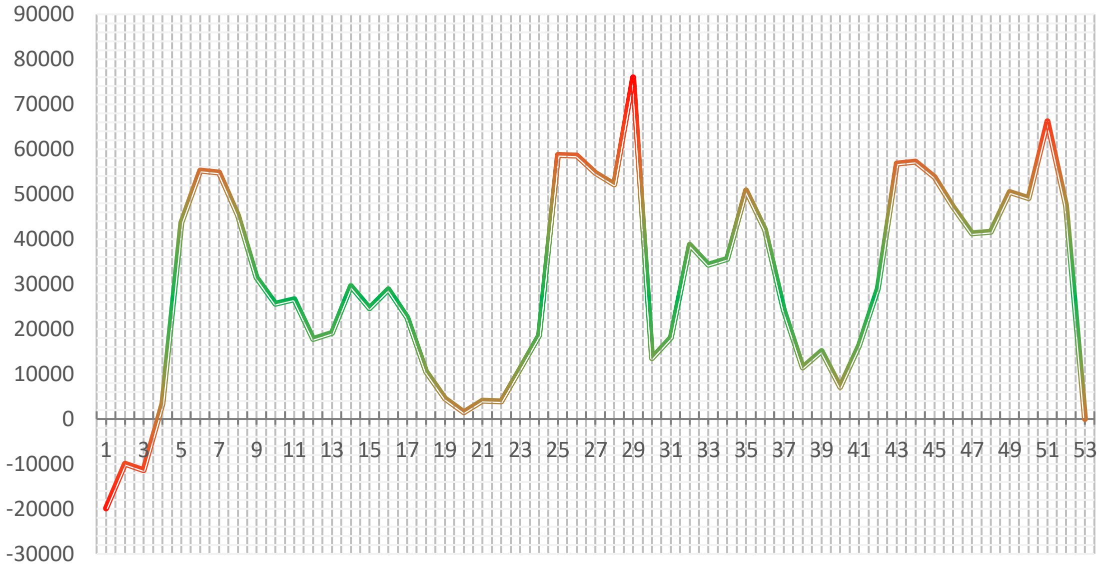


Figure 2. Graph the difference between manually estimated production and actual production

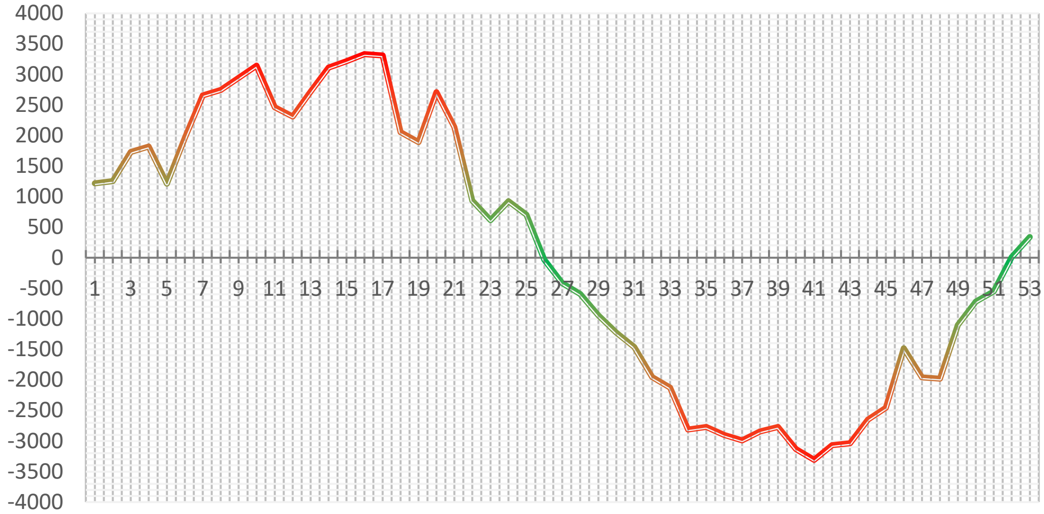


Figure 3. Graph the difference between estimated production with the described application and actual production

Therefore, it is observed that the error committed with the developed application is much smaller than that committed by manual estimation. To know how different these data are empirically and not by observations of the graphs, the mean square error (1) will be calculated to be able to know empirically which one has the best result.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}\left(\widehat{Y}_t - Y_t\right)^2}{n}} \tag{1}$$

With this we obtain that the error in the manual estimation is 37139.56 and the error in the estimation with the developed application is 2204.78. Thus obtaining that the application greatly improves the estimation of production.

At the same time, an analysis of the annual costs associated with the implementation of the system was conducted. This analysis demonstrated that, despite initial and operational costs, investment in IoT, AI, and sensor network technologies results in a significant net benefit due to improved prediction accuracy and resource optimization. In turn, it was considered that the first year would not generate income due to the time required to train the models. The evolution of income and expenses for this solution is presented in the following Figure 4.

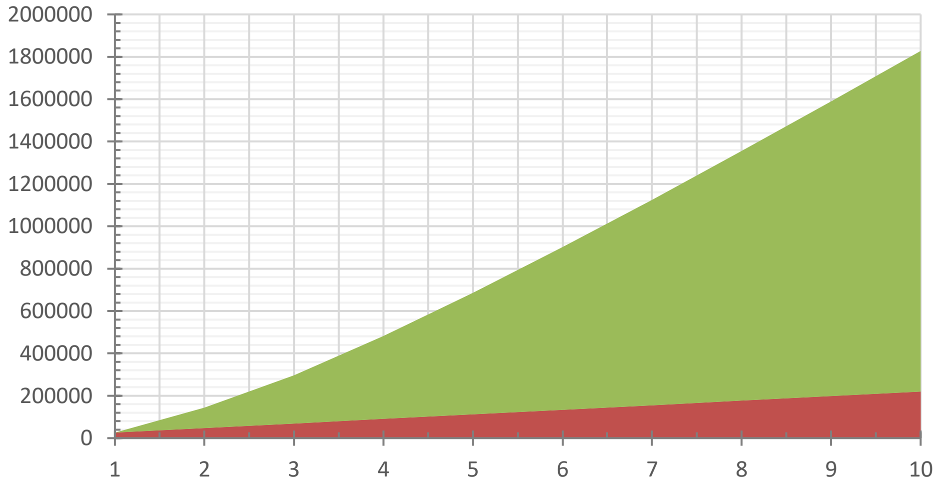


Figure 4. The comparative graph between system expenses and income generated thanks to this

The graph indicates that profits begin to exceed expenses from the second year onwards, with accumulated income of €1.608.000 and expenses of €219.523, resulting in a profit of €1.388.477. This projection is based on the following assumptions: the initial and annual cost of the solution, which is estimated at €30.500 in the first year and €29.000 in subsequent years. Furthermore, it is estimated that the proprietary solution, once implemented and refined, will achieve a success rate comparable to that of a much more expensive commercial solution, but with the additional advantage of being personalized and scalable according to the specific needs of the company.

3.2. Cost analysis

Regarding the costs of the project, these are associated with several key factors, including the number of sensors necessary to install in each of the greenhouses and the number of Gateways required. In an installation of 86 greenhouses of varied sizes, after a detailed analysis, it was concluded that one sensor for every three greenhouses would be sufficient. This decision was based on the proximity of the greenhouses to each other and a field analysis that showed that the data from the different sensors were remarkably similar. This approach allows you to significantly reduce costs by minimizing the number of sensors used. The installation of Gateways was also optimized due to the proximity of the greenhouses. It was determined that a single Gateway, located in the centre of the facility, would be sufficient to cover communication for all sensors, representing another significant savings in infrastructure costs.

Furthermore, it is essential to consider the costs associated with computing the prediction model. These costs are estimated at approximately 3000 euros due to the influence of data quality and this cost cannot be given a fixed value. Added to this amount are the expenses generated by the human inspection necessary to supervise, control and analyse the predictive models. This monitoring is crucial to guarantee the accuracy and effectiveness of the system, ensuring that the models are adjusted correctly and that any anomalies are detected and corrected in a timely manner can be seen in Table 1.

Table 1. All this resulted in costs

Item	Description	Quantity	Cost per Unit (€)	Total Cost (€)
Sensor	Sensors for monitoring temperature, humidity, and solar radiation	29	50	1.450
Gateway	Centralized gateway for data collection	1	363	363
Computational Cost	Cloud computing for data processing and model training	-	-	3.000
Human Inspection	Manual inspection and control of predictive models (5h/day)	-	-	20.000
Total				**24.813**

3.3. Discussion

The results obtained in this study demonstrate the potential of integrating technologies such as the Internet of Things (IoT), artificial intelligence (AI), and sensor networks for the successful implementation of precision agriculture, which is in line with previous research [1],[5],[7],[29]. By leveraging real-time data collected by IoT sensors and analyzing it using machine learning techniques such as recurrent neural networks (RNN), the system was able to generate accurate predictions on weekly harvest volumes. This approach allows informed decision-making and the implementation of tailored agricultural practices for each greenhouse or growing zone, aligning with benefits reported in other studies [2],[9],[30]. By having reliable forecasts, farmers can optimize production planning, resource management, and marketing strategies, thereby reducing the risks of over- or under-supply.

In addition to crop forecasting, the system architecture based on IoT, AI, and sensor networks lays the foundation for exploring other innovative applications in precision agriculture, such as yield optimization, automated irrigation, and pest detection [3],[4],[22],[27],[31]. For example, fine-tuning factors such as irrigation, fertilization, and pesticide application could be achieved by analyzing sensor data and implementing machine learning algorithms, as has been demonstrated in previous studies [32][33]. Integrating computer vision and deep learning techniques could significantly enhance early detection of pests and diseases in crops [6],[31]. By identifying and addressing these issues promptly, yield losses can be minimized, and pesticide use reduced, benefiting both productivity and environmental sustainability, in line with previous research findings [8],[34].

Overall, the results obtained in this study support the adoption of precision agriculture approaches driven by technologies such as IoT, AI, and sensor networks, which is consistent with the trends and perspectives reported in the literature [1],[5],[30]. These technologies allow for the collection and analysis of substantial amounts of data, facilitating informed decision-making and the implementation of situation-specific agricultural practices. As these technologies continue to advance and become further integrated into agriculture, it is expected that significant improvements in productivity, resource use efficiency, and environmental sustainability will be achieved, as has been suggested in other studies [2],[7],[23],[35],[36].

4. Conclusion

The study presented demonstrates that the integration of technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and sensor networks, as expected in the introduction, resulted in an effective system for crop prediction in tomato crops. The results obtained in the "Results and Discussion" chapter validate the ability of the proposed approach to generate accurate predictions on weekly harvest volumes, with a mean error of only 3.2% in the best four-week period.

These findings confirm the potential of precision agriculture driven by real-time data and machine learning techniques, which is in line with the expectations initially raised. In addition to harvest predictions, the developed system lays the foundation for exploring other innovative applications, such as yield optimization, automated irrigation, and early detection of pests and diseases.

Regarding future development prospects, it is anticipated that as IoT, AI, and sensor network technologies continue to advance and become further integrated into agriculture, a greater impact will be achieved on productivity, efficiency in the use of resources, and environmental sustainability. These technological advances will allow for more informed decision-making and the implementation of highly personalized agricultural practices for each specific situation.

Furthermore, the results obtained in this study open new opportunities for future research, Such as the exploration of deep learning techniques for image analysis and pest detection. By utilizing convolutional neural networks (CNNs) and other sophisticated models, it is possible to develop systems that can automatically identify and classify pests and diseases in crops from images. This approach could lead to faster and more accurate detection, enabling farmers to take timely actions to protect their crops, thereby increasing yields and reducing losses. The integration of artificial vision systems for crop monitoring. Artificial vision systems can revolutionize crop monitoring by providing continuous and automated surveillance of agricultural fields. These systems can be integrated with drones or fixed cameras to capture high-resolution images and videos of crops. By analyzing these visuals, artificial vision systems can monitor plant growth, health, and detect any abnormalities or stress factors. This integration can provide real-time insights and data-driven decisions, leading to better crop management and optimized use of resources. The development of optimization algorithms for the efficient management of resources such as water and fertilizers. Efficient management of resources such as water, fertilizers, and pesticides are crucial for sustainable agriculture. Future research could develop advanced optimization algorithms that utilize data from various sensors and environmental conditions to create precise and efficient resource management plans. These algorithms can help in determining the optimal amount and timing of resource application, reducing waste, and enhancing crop productivity. By integrating these algorithms with IoT systems, farmers can achieve significant cost savings and promote environmentally friendly practices.

Precision agriculture holds significant potential for improving the sustainability and efficiency of farming practices. Environmentally, it promotes resource conservation, soil health, biodiversity, carbon footprint reduction, and climate adaptation. By optimizing the use of resources such as water, fertilizers, and pesticides, precision agriculture minimizes waste and reduces chemical runoff, preserving natural ecosystems. Additionally, the use of advanced monitoring and forecasting systems allows farmers to better adapt to changing climate conditions, enhancing resilience and reducing crop losses due to extreme weather events.

Socially, precision agriculture offers economic benefits, requires new skills and knowledge, impacts employment, raises issues of social equity, and contributes to rural development. It can increase farm profitability by improving crop yields and reducing input costs, particularly benefiting small and medium-sized farmers. However, the implementation of these technologies necessitates training and education, presenting both a barrier and an opportunity for agricultural education. While automation may reduce the demand for manual labor, it creates new job opportunities in technology-related fields. Ensuring equitable access to precision agriculture technologies and managing the transition in the labor market are crucial for maximizing the benefits and supporting the development of rural communities.

In summary, the research presented demonstrates the transformative potential of precision agriculture driven by technologies such as IoT, AI, and sensor networks, and lays the foundation for future research and applications in this constantly evolving field. Since, this type of agriculture allows for better production forecasts, which allows for less food waste since the amount produced by a facility is known in advance.

5. Challenges and Limitations

Despite the promising results and future research opportunities, this study also presents several challenges and limitations that must be considered:

- Data Availability Limitations. The quality and quantity of available data are crucial for training AI models and making accurate decisions. However, obtaining high-quality data in sufficient quantities can be challenging. Data availability limitations can result from restrictions on sensor access, technical issues, and environmental variability that can affect consistent data collection.
- Implementation and Maintenance Costs. The cost of implementing and maintaining monitoring systems and optimization algorithms can be significant. Sensors, gateways, and cloud infrastructure have high initial costs, along with recurring maintenance and upgrade expenses. These costs can be prohibitive for small agricultural operations, limiting the widespread adoption of these technologies.
- Technical and Integration Challenges. Integrating diverse technologies like IoT, AI, and computer vision systems presents considerable technical challenges. Ensuring the interoperability of different devices and platforms, managing large volumes of data, and requiring a robust network infrastructure are some of the technical obstacles that need to be overcome. Additionally, implementing these technologies requires specialized skills and may face resistance due to unfamiliarity with new technologies.
- Sensor Sensitivity and Precision. The accuracy and reliability of sensors used in crop monitoring can vary, affecting the quality of collected data. Factors such as extreme weather conditions, equipment wear, and improper calibration can impact sensor performance. Developing robust, high-precision sensors is crucial to ensure that the data is dependable and useful for decision-making.
- Ethical and Privacy Considerations. Using advanced technologies in agriculture also raises ethical and privacy concerns. Data collection and usage must be conducted ethically, ensuring farmers' data privacy and preventing misuse of information. Establishing clear and transparent data management policies and ensuring farmers understand and consent to the use of their data is essential.

Addressing these challenges and limitations is essential to maximize the positive impact of advanced technologies in agriculture. Overcoming data, cost, technical, sensor precision, and ethical barriers will allow more effective and widespread implementation of these innovations, leading to more sustainable and efficient agriculture.

REFERENCES

[1] R. Akhter and S. A. Sofi, “Precision agriculture using IoT data analytics and machine learning,” *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 8, pp. 5602–5618, 2022, https://doi.org/10.1016/j.jksuci.2021.05.013.

[2] A. O. da Silva *et al.*, “Irrigation in the age of agriculture 4.0: management, monitoring and precision,” *Revista Ciencia Agronomica*, vol. 51, no. 5, pp. 1–17, 2020, https://doi.org/10.5935/1806-6690.20200090.

[3] T. J. Esau, P. J. Hennessy, C. B. MacEachern, A. A. Farooque, Q. U. Zaman, and A. W. Schumann, “Artificial intelligence and deep learning applications for agriculture,” *Precision Agriculture: Evolution, Insights and Emerging Trends*, pp. 141–167, 2023, https://doi.org/10.1016/B978-0-443-18953-1.00003-9.

[4] S. Ghatrehsamani *et al.*, “Artificial Intelligence Tools and Techniques to Combat Herbicide Resistant Weeds—A Review,” *Sustainability 2023*, vol. 15, no. 3, p. 1843, 2023, https://doi.org/10.3390/su15031843.

[5] L. Gupta, S. Malhotra and A. Kumar, "Study of applications of Internet of Things and Machine Learning for Smart Agriculture," *2022 IEEE International Conference on Current Development in Engineering and Technology (CCET)*, pp. 1-5, 2022, https://doi.org/10.1109/CCET56606.2022.10080342.

[6] M. M. Islam *et al*., “DeepCrop: Deep learning-based crop disease prediction with web application,” *J Agric Food Res*, vol. 14, p. 100764, 2023, https://doi.org/10.1016/j.jafr.2023.100764.

[7] J. Jung, M. Maeda, A. Chang, M. Bhandari, A. Ashapure, and J. Landivar-Bowles, “The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems,” *Curr Opin Biotechnol*, vol. 70, pp. 15–22, 2021, https://doi.org/10.1016/j.copbio.2020.09.003.

[8] W. Ji, D. Zhao, F. Cheng, B. Xu, Y. Zhang, and J. Wang, “Automatic recognition vision system guided for apple harvesting robot,” *Computers & Electrical Engineering*, vol. 38, no. 5, pp. 1186–1195, 2012, https://doi.org/10.1016/j.compeleceng.2011.11.005.

[9] L. Klerkx, E. Jakku, and P. Labarthe, “A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda,” *NJAS - Wageningen Journal of Life Sciences*, vol. 90–91, p. 100315, 2019, https://doi.org/10.1016/j.njas.2019.100315.

[10] M.-H. Liang, Y.-F. He, L.-J. Chen, and S.-F. Du, “Greenhouse Environment dynamic Monitoring system based on WIFI,” *IFAC-PapersOnLine*, vol. 51, no. 17, pp. 736–740, 2018, https://doi.org/10.1016/j.ifacol.2018.08.108.

[11] M. Amiri-Zarandi, R. A. Dara, E. Duncan, and E. D. G. Fraser, “Big Data Privacy in Smart Farming: A Review,” *Sustainability (Switzerland)*, vol. 14, no. 15. 2022, https://doi.org/10.3390/su14159120.

[12] J. Iaksch, E. Fernandes, and M. Borsato, “Digitalization and Big data in smart farming – a review,” *Journal of Management Analytics*, vol. 8, no. 2, pp. 333–349, 2021, https://doi.org/10.1080/23270012.2021.1897957.

[13] S. Wolfert, L. Ge, C. Verdouw, and M. J. Bogaardt, "Big Data in Smart Farming – A review," *Agric Syst*, vol. 153, pp. 69–80, 2017, https://doi.org/10.1016/j.agsy.2017.01.023.

[14] S. Neethirajan, "The role of sensors, big data and machine learning in modern animal farming," *Sens Biosensing Res*, vol. 29, p. 100367, 2020, https://doi.org/10.1016/j.sbsr.2020.100367.

[15] D. S. Paraforos and H. W. Griepentrog, "Digital farming and field robotics: Internet of things, cloud computing, and big data," *Fundamentals of Agricultural and Field Robotics*, pp. 365-385, 2021, https://doi.org/10.1007/978-3-030-70400-1_14.

[16] A. Roukh, F. N. Fote, S. A. Mahmoudi, and S. Mahmoudi, "Big Data Processing Architecture for Smart Farming," *Procedia Comput Sci*, vol. 177, pp. 78–85, 2020, https://doi.org/10.1016/j.procs.2020.10.014.

[17] A. Nasirahmadi and O. Hensel, "Toward the Next Generation of Digitalization in Agriculture Based on Digital Twin Paradigm," *Sensors (Basel)*, vol. 22, no. 2, 2022, https://doi.org/10.3390/s22020498.

[18] C. Pylianidis, S. Osinga, and I. N. Athanasiadis, "Introducing digital twins to agriculture," *Comput Electron Agric*, vol. 184, p. 105942, 2021, https://doi.org/10.1016/j.compag.2020.105942.

[19] S. Neethirajan and B. Kemp, "Digital Twins in Livestock Farming," *Animals 2021*, vol. 11, no. 4, p. 1008, 2021, https://doi.org/10.3390/ani11041008.

[20] J. Nie, Y. Wang, Y. Li, and X. Chao, "Artificial intelligence and digital twins in sustainable agriculture and forestry: a survey," *Turkish Journal of Agriculture and Forestry*, vol. 46, no. 5, pp. 642–661, 2022, https://doi.org/10.55730/1300-011X.3033.

[21] W. Purcell, T. Neubauer, and K. Mallinger, "Digital Twins in agriculture: challenges and opportunities for environmental sustainability," *Curr Opin Environ Sustain*, vol. 61, p. 101252, 2023, https://doi.org/10.1016/j.cosust.2022.101252.

[22] C. Maraveas, D. Piromalis, K. G. Arvanitis, T. Bartzanas, and D. Loukatos, "Applications of IoT for optimized greenhouse environment and resources management," *Comput Electron Agric*, vol. 198, p. 106993, 2022, https://doi.org/10.1016/j.compag.2022.106993.

[23] M. J. Masud Cheema, T. Iqbal, A. Daccache, S. Hussain, and M. Awais, "Precision agriculture technologies: present adoption and future strategies," *Precision Agriculture: Evolution, Insights and Emerging Trends*, pp. 231–250, 2023, https://doi.org/10.1016/B978-0-443-18953-1.00011-8.

[24] M. Bacco, P. Barsocchi, E. Ferro, A. Gotta, and M. Ruggeri, "The Digitisation of Agriculture: a Survey of Research Activities on Smart Farming," *Array*, vol. 3–4, p. 100009, 2019, https://doi.org/10.1016/j.array.2019.100009.

[25] M. Padhiary, D. Saha, R. Kumar, L. N. Sethi, and A. Kumar, "Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation," *Smart Agricultural Technology*, vol. 8, p. 100483, 2024, https://doi.org/10.1016/j.atech.2024.100483.

[26] B. Petrović, R. Bumbálek, T. Zoubek, R. Kuneš, L. Smutný, and P. Bartoš, "Application of precision agriculture technologies in Central Europe-review," *J Agric Food Res*, vol. 15, p. 101048, 2024, https://doi.org/10.1016/j.jafr.2024.101048.

[27] C. Prakash, L. P. Singh, A. Gupta, and S. K. Lohan, "Advancements in smart farming: A comprehensive review of IoT, wireless communication, sensors, and hardware for agricultural automation," *Sens Actuators A Phys*, vol. 362, p. 114605, 2023, https://doi.org/10.1016/j.sna.2023.114605.

[28] P. Saha, V. Kumar, S. Kathuria, A. Gehlot, V. Pachouri, and A. S. Duggal, "Precision Agriculture Using Internet of Things and Wireless Sensor Networks," *2023 International Conference on Disruptive Technologies, ICDT 2023*, pp. 519–522, 2023, https://doi.org/10.1109/ICDT57929.2023.10150678.

[29] M. A. Zamir and R. M. Sonar, "Application of Internet of Things (IoT) in Agriculture: A Review," *Proceedings of the 8th International Conference on Communication and Electronics Systems, ICCES 2023*, pp. 425–431, 2023, https://doi.org/10.1109/ICCES57224.2023.10192761.

[30] U. Shafi, R. Mumtaz, J. García-Nieto, S. A. Hassan, S. A. R. Zaidi, and N. Iqbal, "Precision Agriculture Techniques and Practices: From Considerations to Applications," *Sensors 2019*, vol. 19, no. 17, p. 3796, 2019, https://doi.org/10.3390/s19173796.

[31] A. Khan, A. D. Vibhute, S. Mali, and C. H. Patil, "A systematic review on hyperspectral imaging technology with a machine and deep learning methodology for agricultural applications," *Ecol Inform*, vol. 69, p. 101678, 2022, https://doi.org/10.1016/j.ecoinf.2022.101678.

[32] T. Talaviya, D. Shah, N. Patel, H. Yagnik, and M. Shah, "Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides," *Artificial Intelligence in Agriculture*, vol. 4, pp. 58–73, 2020, https://doi.org/10.1016/j.aiia.2020.04.002.

[33] I. Ullah, M. Fayaz, M. Aman, and D. Kim, "Toward Autonomous Farming - A Novel Scheme Based on Learning to Prediction and Optimization for Smart Greenhouse Environment Control," *IEEE Internet Things J*, vol. 9, no. 24, pp. 25300–25323, 2022, https://doi.org/10.1109/JIOT.2022.3196053.

[34] A. Yazdinejad *et al*., "A Review on Security of Smart Farming and Precision Agriculture: Security Aspects, Attacks, Threats and Countermeasures," *Applied Sciences 2021*, vol. 11, no. 16, p. 7518, 2021, https://doi.org/10.3390/app11167518.

[35] V. Kaliannan and F. K. S. Al Saidi, "Intelligent Computing with Drones and Robotics for Precision Agriculture," *Signals and Communication Technology*, pp. 1–17, 2024, https://doi.org/10.1007/978-3-031-51195-0_1.

[36] X. Zheng, S. Shao, L. Li, and Y. Wang, "Research and Design of Monitoring System for Greenhouse Based on Internet of Things," *Proceedings - 2022 4th International Symposium on Smart and Healthy Cities, ISHC 2022*, pp. 59–63, 2022, https://doi.org/10.1109/ISHC56805.2022.00021.