*sustainability*

MDPI

*Article*

# Smart Sensors and Artificial Intelligence Driven Alert System for Optimizing Red Peppers Drying in Southern Italy

**Costanza Fiorentino [1,*], Paola D'Antonio [1,*], Francesco Toscano [1], Nicola Capece [2], Luis Alcino Conceição [3], Emanuele Scalcione [4], Felice Modugno [1], Maura Sannino [5], Roberto Colonna [2,6], Emilia Lacetra [1] and Giovanni Di Mambro [7]**

1 Department of Agriculture, Forest, Food and Environmental Sciences, University of Basilicata, Via dell'Ateneo Lucano, 10, 85100 Potenza, Italy; francesco.toscano@unibas.it (F.T.); fely.mod@gmail.com (F.M.); emilialacetra@gmail.com (E.L.)
2 Department of Engineering, University of Basilicata, Via dell'Ateneo Lucano, 10, 85100 Potenza, Italy; nicola.capece@unibas.it (N.C.); roberto.colonna@unibas.it (R.C.))
3 VALORIZA—Research Center for Endogenous Resource Valorization, Polytechnic Institute of Portalegre, 7300-110 Portalegre, Portugal; luis_conceicao@ipportalegre.pt
4 Lucanian Agency of Innovation and Development in Agriculture (ALSIA), Via Annunziatella, 75100 Matera, Italy; emanuele.scalcione@alsia.it
5 Department of Agricultural Sciences, University of Naples Federico II, Via Università, 100, Portici, 80055 Naples, Italy; maura.sannino2@unina.it
6 Space Technologies and Applications Centre (STAC), Satellite Application Centre (SAC), 85100 Potenza, Italy
7 Elaisian SRL, Via Ostiense, 92, 00154 Roma, Italy; giovanni.dimambro@elaisian.com
* Correspondence: costanza.fiorentino@unibas.it (C.F.); paola.dantonio@unibas.it (P.D.)

**Abstract:** The Senise red pepper, known as peperone crusco, is a protected geographical indication (PGI) product from Basilicata, Italy, traditionally consumed dried. Producers use semi-open greenhouses to meet PGI standards, but significant losses are caused by rot from microorganisms thriving in high moisture, temperature, and humidity, which also encourage pest infestations. To minimize losses, a low-cost alert system was developed. The study, conducted in summer 2022 and 2023, used external parameters from the ALSIA Senise weather station and internal sensors monitoring the air temperature and humidity inside the greenhouse. Since rot is complex and difficult to model, an artificial intelligence (AI)-based approach was adopted. A feed forward neural network (FFNN) estimated greenhouse climate conditions as if it were empty, comparing them with actual values when peppers were present. This revealed the most critical period was the first 3–4 days after introduction and identified a critical air relative humidity threshold. The system could also predict microclimatic parameters inside the greenhouse with red peppers, issuing warnings one hour before risk conditions arose. In 2023, it was tested by comparing predicted values with previously identified thresholds. When critical levels were exceeded, greenhouse operators were alerted to adjust conditions. In 2023, pepper rot decreased.

**Keywords:** red pepper; weather station; machine learning; smart sensors; greenhouse



Academic Editors: Pawel Sobczak, Jacek Mazur, Piotr Markowski and Andrzej Anders

Received: 9 January 2025
Revised: 10 February 2025
Accepted: 12 February 2025
Published: 18 February 2025

**Citation:** Fiorentino, C.; D'Antonio, P.; Toscano, F.; Capece, N.; Conceição, L.A.; Scalcione, E.; Modugno, F.; Sannino, M.; Colonna, R.; Lacetra, E.; et al. Smart Sensors and Artificial Intelligence Driven Alert System for Optimizing Red Peppers Drying in Southern Italy. *Sustainability* **2025**, *17*, 1682. https://doi.org/10.3390/su17041682



## 1. Introduction

### 1.1. Problem Statement and Context

Since ancient times, humans have relied on solar drying as a natural and effective way to preserve agricultural and animal products. This method leverages the sun, a free and renewable energy source, to remove moisture and extend the life of these products. The Senise red pepper belongs to this category of products, and due to its characteristics and properties, it has obtained a PGI (protected geographical indication) designation from the Basilicata region. Traditionally, it was dried during the summer months by threading peppers into necklaces and hanging them under porticoes or balconies during the summer months. Today, Senise peppers are not only consumed locally but also distributed throughout Europe, with a growing local demand due to increased tourism. Consequently, producers cannot remain tied to traditional drying methods but must adapt their systems to meet today's business needs (quantity, quality, traceability, and healthiness of production). The economy of the Basilicata region, centered around its premium products, is founded on the high natural value of the territories, from which the stringent PGI regulations originate [1]. Current rules require that the peppers be dried in open-air environments, allowing only lightweight coverings that facilitate ventilation and can be easily removed. This effectively excludes the use of modern smart greenhouses equipped with automated systems to regulate the temperature, humidity, and ventilation. Many producers face significant challenges during the drying process, with some reporting losses exceeding 20% and, in extreme cases, up to 60% of the dry matter. Factors contributing to these losses include poor handling practices, suboptimal production methods, and inadequate storage facilities. Spoilage is primarily caused by microorganisms that thrive in the high moisture content of vegetables. Moreover, high temperature and relative humidity gradients can accelerate rot and create conditions conducive to pest and insect attacks [2]. The objective of the present study was to develop a low-cost monitoring system that complied with existing drying regulations while minimizing farmers' losses. The research focused on optimizing greenhouse production and drying methods, prioritizing sustainability and product quality. Technological advancements, such as the Internet of Things (IoT), cloud computing, and big data analytics, are increasingly integrated into agricultural practices. These tools enable the development of new process control systems, innovative services, and higher-quality products [3,4]. Real-time data analysis is critical for addressing complex challenges, such as complying with regulations, minimizing losses, optimizing timelines, and ensuring quality [5]. Advanced multivariate methodologies are necessary to achieve these objectives [6].

### *1.2. Current Advances and Relevance to the Problem*

Modeling the greenhouse microclimate depends on its intended application and can involve two main categories of models: physical models, which study the behavior and interactions of monitored parameters, and black-box models. Physical models analyze the relationships between variables and their behavior but can be challenging to develop due to the nonlinear dynamics involved [7–9]. Conversely, black-box models rely on input–output data to bypass these complexities and deliver reliable results without requiring detailed knowledge of the underlying physical processes [10]. To develop black-box models, a training and testing dataset is required, along with the appropriate model structure and parameterization [11]. Given the complex interactions between internal and external climatic variables, a black-box approach using AI and neural networks is the most suitable solution. The integration of artificial intelligence and Internet of Things technologies in smart greenhouses is transforming modern agriculture. These advanced systems enhance productivity, resource management, and sustainability [12]. Through AI-driven automation, environmental parameters such as air temperature and relative humidity can be controlled with remarkable precision [13]. Additionally, IoT-enabled wireless sensors allow for continuous, real-time data monitoring and analysis [14]. Smart greenhouses have demonstrated the ability to achieve targeted temperature settings with 90% accuracy and provide highly accurate humidity level estimations [15]. Data from multiple sensors are centralized and managed through cloud-based platforms, enabling remote monitoring and system adjustments [14,16]. Machine learning techniques, particularly artificial neural networks (ANNs), play a critical role in modeling complex drying processes and facilitating both real-time monitoring and process control [17]. These methods are also used to improve product quality metrics [18]. AI applications in smart greenhouses extend to various tasks, including automated pesticide spraying, efficient irrigation management, and pest identification using image processing technologies [12]. IoT-based monitoring systems further enhance efficiency by collecting temperature and humidity data in real time, enabling improved decision-making and operational optimization, particularly in industrial drying processes [19]. AI-powered systems are increasingly employed to refine greenhouse climate management and drying procedures. AI controllers can simulate and regulate complex variables, such as temperature and humidity, ensuring stable growing or drying environments [20]. For instance, in AI-enhanced greenhouses, temperature predictions achieve a 90% accuracy rate, while humidity levels are estimated with comparable precision [13]. By considering the enhancements in the farming system for tobacco crops [21], in the tobacco drying process, ANNs have been utilized to forecast temperature and humidity, with prediction errors consistently below 2% [22]. Choi et al. [23] developed an MLP neural network using external and internal greenhouse conditions as input variables. The model successfully predicted indoor temperature and relative humidity for intervals ranging from 10 to 120 min. The neural network employed four hidden layers and a variable number of nodes for predicting temperature and humidity separately. Similarly, Petrakis [24], in a 2022 study, introduced an ANN-based model capable of predicting indoor greenhouse conditions, including temperature and humidity, based on factors such as external temperature, wind speed, solar radiation, and prior internal conditions. The model provided accurate predictions up to 30 min in advance. Multiple studies have demonstrated the effectiveness of ANNs in estimating temperature and humidity within greenhouses [25–27]. Various ANN architectures, including multilayer perceptron (MLP), recurrent neural networks with long short-term memory (RNN-LSTM), and nonlinear autoregressive exogenous (NARX) models, have been employed for this purpose [25,27]. RNN-LSTM models have shown particularly high accuracy in predicting temperature and humidity over extended time periods [25]. Several studies have explored the use of artificial neural networks (ANNs) for predicting temperature and humidity in greenhouses. Feed forward neural networks (FFNNs) have shown promising results in estimating these parameters [28]. These findings suggest that ANNs can be valuable tools for precise greenhouse management and climate control.

### *1.3. Research Challenges and Objective*

The research aimed to develop a low-cost alert system to monitor microclimatic variations inside the drying greenhouse and prevent spoilage. Due to the complexity of rot formation and the constraints imposed by PGI regulations, commercially available smart greenhouses are not suitable for drying Senise peppers. To address this, the study employed an FFNN, to analyze climate data from IoT sensors inside the greenhouse and external meteorological data from the ALSIA Senise weather station.

The primary objectives of this study were as follows:

(1) To design and implement an AI-based system capable of predicting the air temperature and relative humidity fluctuations inside the greenhouse;
(2) To identify critical humidity thresholds that contribute to pepper spoilage;
(3) To develop an early warning system that notifies operators one hour before critical conditions arise.

By achieving these objectives, the study sought to enhance the efficiency and sustainability of the drying process, reducing economic losses for producers.

The present study highlights the importance of AI-enhanced monitoring systems in addressing weather variability, a longstanding challenge in agro-food production. The developed warning system aligns with regulatory requirements while optimizing decision-making through real-time meteorological data and predictive models, enhancing both sustainability and efficiency. While no scientific evidence currently links the discussed issues to climate change, climatic variations in the Senise area are undeniable. In this context, the study demonstrates how an alert system can improve drying conditions without violating regulations, while future adjustments to guidelines may be necessary to adapt to evolving climatic conditions.

## 2. Materials and Methods

### *2.1. The Study Area*

Senise peppers are a traditional variety grown in the Pollino National Park in the Basilicata region (in southern Italy), predominantly in the Sinni and Agri valleys, an area encompassing several municipalities, including Senise, from which the pepper variety takes its name. The peppers are planted between February and March, transplanted in May, and harvested in mid-to-late summer, with August being the peak month. Harvesting is performed manually, with great care taken to avoid damaging the stems. The unique genetic characteristics of this pepper variety make it especially ideal for natural drying and the subsequent production of paprika. Senise red peppers can be pointed, trunked, or hooked. They are particularly known for their high vitamin C content and their ability to maintain their vibrant red color even after drying. The distinct taste and characteristics of these peppers, coupled with their strong regional identity, led to their recognition as a protected geographical indication (PGI) by the EU in 1996.

In the upper left corner of Figure 1, the drying infrastructure is shown; it was a rectangular greenhouse (48 m × 9 m) with a PVC roof. The ridge height was 4.00 m, while the sidewalls were 2.20 m high. Inside the greenhouse, a shading net was positioned around 2.00 m in height. Additionally, two large openings on the shorter sides of the greenhouse served as entry and exit points, as well as a natural ventilation system.

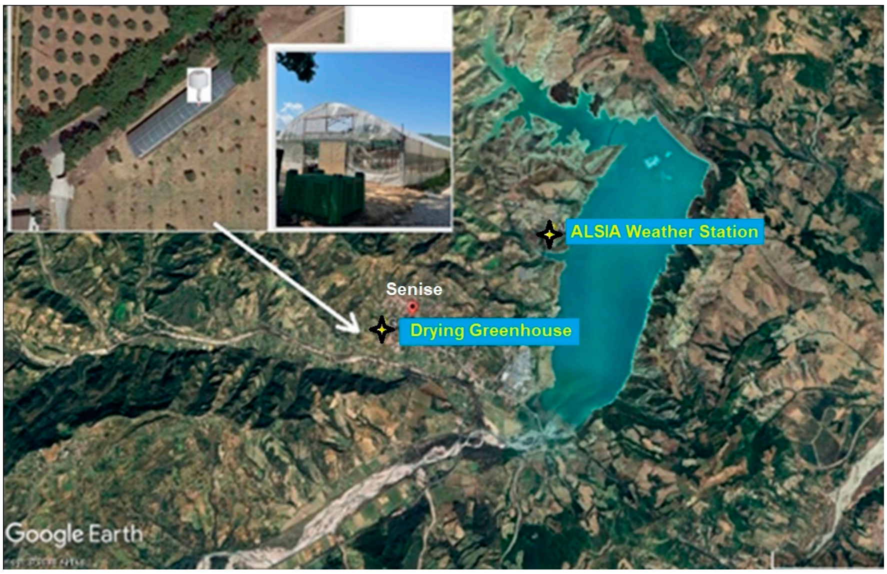



**Figure 1.** The drying greenhouse. The 2 yellow placeholders indicate the positions of the weather stations: the outdoor weather station was part of the regional monitoring network of the ALSIA agency, and the indoor sensors were from Elaisian SPA.

For monitoring outdoor agrometeorological variables, the Senise ALSIA weather station, located nearest to the greenhouse, was utilized, while temperature and humidity sensors were set up inside the drying greenhouse, approximately in the center of the structure (see Figure 1). The 2 yellow placeholders in Figure 1 indicate the positions of the weather stations.

The greenhouse was located approximately 2 km from the production area; the pepper harvest, in 2022 and 2023, took place from August to September, and the product was stored in the greenhouse in different stages, as shown in Table 1.

**Table 1.** Quantity and dates of storage of red peppers in the drying greenhouse.

| Time | Quantity (kg) |
|---|---|
| 17 August 2022 | 4500 |
| 26 August 2022 | 3800 |
| 12 September 2022 | 3700 |
| 24 September 2022 | 3900 |
| 5 August 2023 | 3300 |
| 20 August 2023 | 4700 |
| 8 September 2023 | 3800 |
| 16 September 2023 | 4100 |

### 2.2. The Climate Parameters

The data acquired by the ALSIA weather station of Senise are available online on the website of the agency. Elaisian provided the air temperature and humidity sensors positioned inside the greenhouse. The complete station "Enterprise" measured the air temperature (accuracy ±0.3 °C), relative humidity (±3%), precipitation (resolution 0.1 mm), and dew point (resolution 0.1 °C). The sensors were positioned at a height between 1.50 and 1.70 m to ensure representative measurements. Additionally, extra sensors were used: an ultrasonic anemometer to measure wind speed (sensitivity 0.12 m/s) and wind direction and a leaf wetness sensor to monitor the wetness hours. The parameters were acquired every 15 min and transmitted to the server every 60 min. This transmission interval was configurable to suit specific monitoring needs. In the event of mobile network connectivity problems, the station internally stored data from the last few days and restored the measured values to the cloud once the connection was re-established. The monitoring node was a Raspberry Pi (Raspberry Pi Foundation, Cambridge, UK). The primary programming language employed on the Raspberry Pi was Python 3.10, chosen for its versatility and extensive library support. The Raspberry Pi was a small but complete PC on a single board. The Raspberry Pi received data from the sensors and sent it to the Elaisian IoT platform, where parameter measurements were stored and displayed in real time. In case there was any sudden change in the air humidity value, the IoT-based device was able to send an autogenerated SMS alert to the owner's mobile phone.

From June to September 2021, relative humidity and temperature sensors were placed outside the greenhouse to evaluate whether the data acquired by the ALSIA station, located approximately 4 km away from the greenhouse, were representative of the study area. A correlation analysis was carried out on these data, and Pearson correlation coefficient values of 0.89 for temperature and 0.76 for relative humidity were found. The parameters were pre-processed to remove any outliers. In 2022 the sensors were placed inside the greenhouse.

The analysis procedure consisted of two steps:

(a) The first step aimed to highlight whether the variations in temperature and humidity inside the greenhouse, being a semi-open structure, were significantly influenced by the presence of the red peppers. For this purpose, a feed forward neural network (FFNN) trained on the climate parameters acquired in the greenhouse when it was empty and the data of the Alsia outdoor weather station were used to predict the humidity and temperature parameters inside the greenhouse when the product was present. The neural network was trained on a dataset comprising hourly temperature and humidity readings collected daily over a 50-day period, from late June to 16 August 2022. The parameters estimated, as if the greenhouse were empty, were compared with those acquired by the indoor sensors from 17 August to the end of September. From the comparison between the predicted and measured parameters, it was possible to identify the time intervals in which the values of humidity and temperature became higher to intervene by improving the natural ventilation of the greenhouse. The system was tested in August and September 2022, when the pepper was in the greenhouse for drying.

(b) In the ensuing phase, the neural network was trained from 17 August 2022 to 30 September 2022, when the peppers were dried in the greenhouse. Therefore, the system was also able to predict the values of the microclimatic parameters inside the greenhouse in the presence of red peppers, issuing warnings one hour before a risk condition arose. The alert system was tested during the 2023 experimental year by comparing the predicted values with the thresholds previously identified. When the critical level was exceeded, the greenhouse operators were alerted to improve conditions inside the drying structure.

To ensure the maximum reliability of the data, specific measures were implemented during the pre-processing phase. In particular, we found that the readings from the Elaisian station and the ALSIA platform contained no missing data. However, for gaps shorter than two hours, a linear interpolation algorithm was applied to maintain the system's ability to make reliable predictions. Outliers were identified using a criterion based on the standard deviation (3σ) and confirmed with the Grubbs test. The detected outliers were then replaced with the weighted average of the surrounding values. These strategies enhanced the data quality and neural network accuracy, ensuring greater model reproducibility.

### *2.3. The Neural Network*

Feed forward neural networks (FFNNs) [29] are a class of artificial neural networks in which the connections between nodes do not form loops. The use of a neural network allows the extraction and analysis of complex characteristics among the multiple variables offered by the sensors used to collect agrometeorological data. To predict the temperature and humidity inside the greenhouse, an FFNN was implemented.

The FFNN architecture was selected due to the following advantages:

- The prediction of internal temperature and humidity was influenced by multiple climate variables with complex interdependencies. FFNNs are well suited for modeling such nonlinear relationships, whereas traditional statistical models may struggle to capture them effectively.
- The input features included time-lagged climate variables ($t-1$ and $t-2$), making FFNNs a suitable choice for learning temporal dependencies without requiring explicit time-series models like recurrent neural networks (RNNs), which can be more computationally expensive and prone to vanishing gradient issues.
- Compared with more complex deep learning models (e.g., LSTMs or GRUs), FFNNs require fewer computational resources while still providing high prediction accuracy. This makes them a practical choice for real-time applications in greenhouse monitoring.
- Through careful architecture design (e.g., reducing neurons in the second hidden layer and applying K-Fold cross-validation), the FFNN was optimized to generalize

well to unseen data while minimizing overfitting. Other machine learning models, such as decision trees or support vector machines (SVMs), may require extensive feature engineering.

This FFNN network was trained using the data collected from the climate variables inside and outside the greenhouse, also considering the temporal correlations detected by the preliminary statistical analysis. The inputs used for prediction at time "t" were based on data collected over the previous two hours (t − 1 and t − 2), both outside and inside the greenhouse:

- Internal temperature and internal humidity: T_OUT(t − 1) and H_OUT(t − 1); T_OUT(t − 2) and H_OUT(t − 2).
- External temperature and external humidity: T_IN(t − 1) and H_IN (t − 1); T_IN (t − 2) and H_IN (t − 2).

The model predicted the following outputs:

- Predicted internal temperature: T_IN_E(t).
- Predicted internal humidity: H_IN_E(t).

The neural network was designed with the following outputs:

(1) Input layer: 8 input features representing the past two hours of both internal and external temperature and humidity values.
(2) Hidden layers:
    - First hidden layer: 64 neurons with ReLU (rectified linear unit) activation function. The number of neurons was chosen based on empirical studies and the complexity of the problem. The number of neurons in the FFNN was determined based on preliminary experiments to achieve an optimal trade-off between the predictive accuracy and the computational efficiency.
    - Second hidden layer: 32 neurons with ReLU activation. This layer reduced the number of parameters to prevent overfitting and helped in extracting higher-order features.
(3) Output layer:
    - The output layer consisted of 2 neurons, one for predicting the internal temperature and the other for predicting the internal humidity for the next hour.
    - Activation: Since the problem was a regression task and the forecasts were continuous values, the output layer used a linear trigger function. It was chosen for its effectiveness in handling vanishing gradient problems and for its ability to introduce non-linearity into the model.

The schematic diagram of the architecture of the feed forward neural network (FFNN) used in this study is shown in Figure 2.

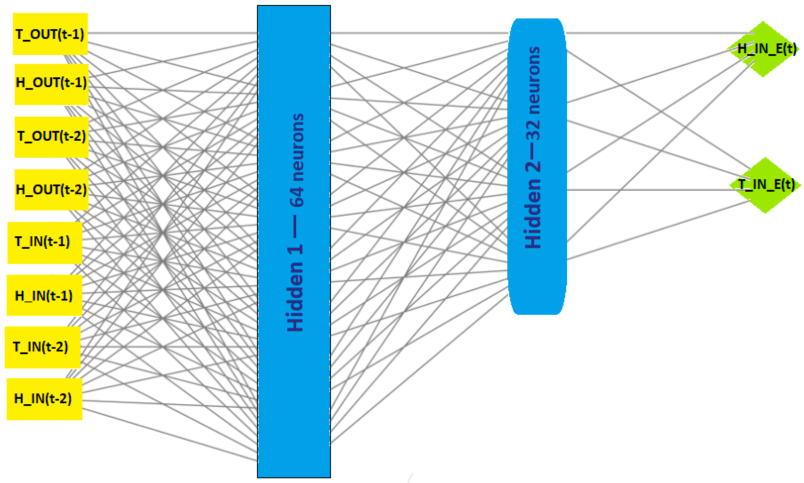



**Figure 2.** Schematic diagram of the feed forward neural network (FFNN). The diagram illustrates the structure of the neural network used to predict the internal air temperature and relative humidity inside the greenhouse.

The neural network was trained using the stochastic gradient descent (SGD) optimizer. The model was trained for 10,000 epochs to ensure adequate learning while monitoring the validation loss to prevent overfitting. Since MATLAB R2023a's Deep Learning Toolbox was employed, the batch size was automatically optimized based on the available computational resources and dataset size, ensuring efficient memory management during training. Hyperparameters such as weight initialization, activation functions, and dropout rates were set based on preliminary experiments to maximize model generalization and predictive accuracy.

During the training process, input data were propagated through the network. Each neuron, by summing the weighted inputs, adding a bias term, and applying the ReLU activation function in the hidden layers, calculated its activation function. The network predictions were compared with the actual values of the target variables T_IN and H_IN, and the error was calculated with the mean squared error (MSE) loss function. The error was subsequently backpropagated through the network to adjust the weights and biases. The backpropagation algorithm calculated the gradients of the loss function with respect to the weights and updated them to minimize the error.

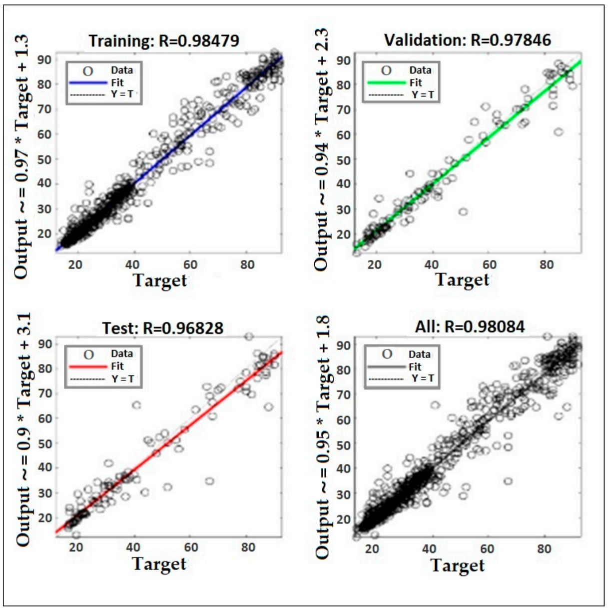
### *2.4. The Neural Network Training and Validation*

After training, the model was evaluated on a test set to assess its performance. The following metrics were used:

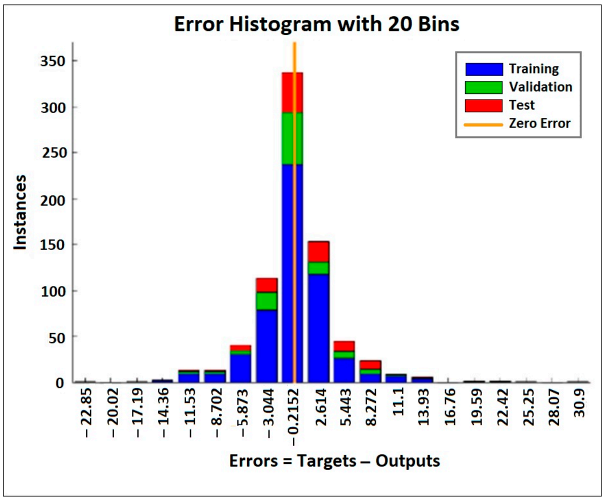
- Mean squared error (MSE): This was the main metric for evaluating the prediction accuracy. A lower MSE indicated better performance.
- Mean absolute error (MAE): The MAE was also tracked to assess the model's performance in terms of the absolute error in the predicted temperature and humidity.
- Cross-validation: The model's generalization ability was assessed using K-Fold cross-validation. This approach split the dataset into K subsets, training the model K times on different training/validation splits. This reduced the likelihood of overfitting to any single subset of data.

The dataset used in the training phase of the neural network was divided into three subsets: 70% for training, 20% for validation, and 10% for testing.

In Figure 3 the results of the neural network reliability analysis are shown; the plots are related to case (a) described in Section 2.2. In the scatter plots for training, validation, and testing (Figure 3a, along with the corresponding root mean square errors), the network demonstrated a strong ability to predict humidity and temperature conditions inside the drying structure. The error histogram (Figure 3b) clearly showed that most of the air relative humidity predictions deviated by only ±0.215%, a low measurement in relation to the drying characteristics of the fresh peppers. Furthermore, only a very small percentage of the predictions showed errors greater than ±3%, making the system particularly efficient in predicting relative humidity values at practically any time of day or night.




(**a**)




(**b**)

**Figure 3.** (**a**) Scatter plots of training, validation, and test dataset with the related root square errors of the neural network prediction of humidity and temperature conditions inside the drying structure. (**b**) Histogram of errors of predicted and measured air relative humidity.

When the neural network was trained to predict air temperature and humidity inside the greenhouse in the presence of the red peppers (case (b) in Section 2.2), the error histogram showed that most of the air relative humidity predictions deviated by only ±0.25%, a low measurement in relation to the drying characteristics of the fresh product, and also, in this case, a very small percentage of the predictions showed errors greater than ±3%.

## 3. Results and Discussion

The main objective of the present work was to identify the conditions that determine the onset of pepper rot phenomena and to develop an alert system to limit its occurrence, compatibly with the restrictions imposed by the PGI directive. It is crucial to emphasize the importance of designing a low-cost monitoring system due to the low profit margins that this crop often generates for farmers. These challenges arise both from the damage peppers can suffer during the growing phase (adverse weather conditions, pest attacks, diseases, etc.) and from losses caused by rotting during the drying phase. From this perspective, leveraging free data provided by the regional weather station is highly advantageous both for the reliability of the data, periodically validated by ALSIA operators, and for the presence in the Senise area of numerous drying greenhouses for peppers owned by producers organized into a consortium. The system was, therefore, designed to be easily applied also to other greenhouses in the area without the need to install external weather stations at each site, thereby avoiding additional costs.

In 2022, the FFNN was used to predict air temperature and humidity values inside the greenhouse in the absence of the red peppers. A comparison was conducted between the values measured in the presence of the product and those estimated by the neural network to evaluate the impact of the pepper's presence inside the greenhouse. This analysis aimed to assess the significance of these variations and their evolution over time and to calculate critical threshold values during the red pepper drying phase.

In 2023, the neural network was trained using data acquired in the previous year (17 August to 30 September) to predict relative humidity and temperature values inside the greenhouse in the presence of the product, with a one-hour lead time. By comparing the estimated relative humidity in the absence of the stored red peppers with that in its presence and applying the thresholds established in the prior year's study, it became possible to generate alerts and prompt timely interventions by farm operators.

Additionally, as the greenhouse was semi-open, excessive relative humidity could negatively impact the pepper drying process. As a result, the system was designed to alert producers whenever the relative humidity measured by the weather station outside the greenhouse exceeded 85% for more than two consecutive days. Studies have shown that to prevent fungal growth and mycotoxin production, it is essential to control drying and storage conditions using hazard analysis and critical control point systems. This is crucial as mycotoxin-producing fungi can thrive at relative humidity levels above 85–91% [30,31].

### *3.1. Analysis of Air Humidity and Temperature Patterns*

Figure 4 shows the average daily values of temperature and relative humidity, inside and outside the greenhouse in the period from 1 August to 30 September 2022. The pepper began to be placed in the greenhouse for drying on 17 August, as shown in Table 1.

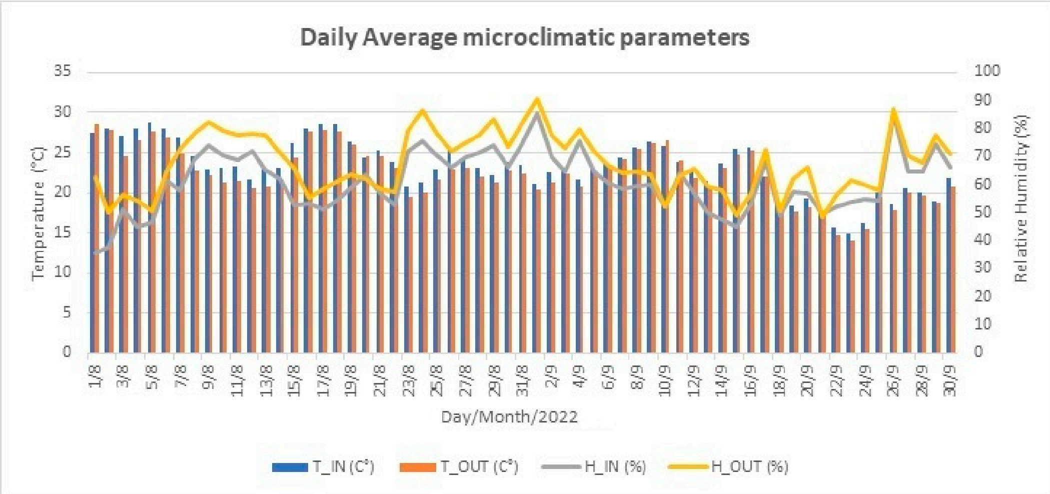



**Figure 4.** Mean daily values of temperature and relative humidity measured from the Senise Alsia weather station and the sensors located inside the greenhouse in August and September 2022.

Both measured parameters, outside and inside the greenhouse (Figure 4), showed very similar patterns when the Senise pepper was not present in the greenhouse (1–16 August). The relative humidity measured inside the greenhouse always showed lower values compared with the external measurements (ALSIA), while the temperature inside the greenhouse was higher than the corresponding values recorded outside. Under ideal ventilation conditions, humidity levels inside and outside the greenhouse should be the same. However, due to the presence of protective sheets and the positioning of the openings, this equilibrium was not achieved [32]. The dynamics between indoor and outdoor parameters were complex, and the indoor values at time t were influenced by external ones also relating to previous time steps. Figure 5 shows the hourly curves of the estimated and measured relative air humidity. The estimated and measured relative humidity curves in the greenhouse overlapped very well in the period in which the red peppers were not present in the greenhouse, while the former shifted toward lower values in the subsequent period. An ANOVA analysis was performed on the measured and estimated datasets by confirming the null hypothesis, i.e., that there was no significant difference between the means of the two datasets, in the period when the red pepper was not present in the greenhouse (1–16 August) and rejecting it in the period in which the pepper was present in the greenhouse. Both tests were performed with a significance level ($p$-value) of 0.05. A similar analysis was performed on the estimated and measured temperature data, yielding results closely aligned with those observed for relative humidity. However, since the most pronounced differences were found in the relative humidity data, the neural network was trained to incorporate both parameters (relative humidity and temperature). Nevertheless, for the development of the alert system, the analysis prioritized relative humidity measurements due to their greater significance.

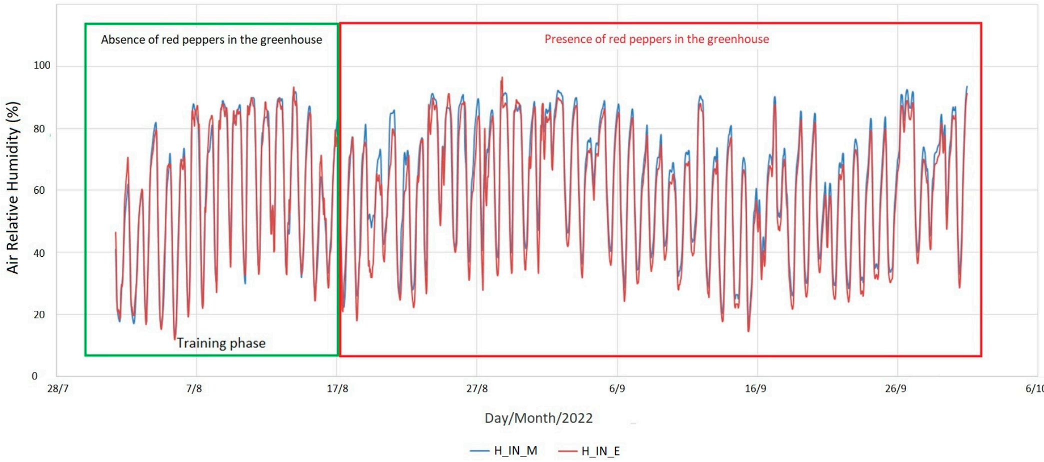
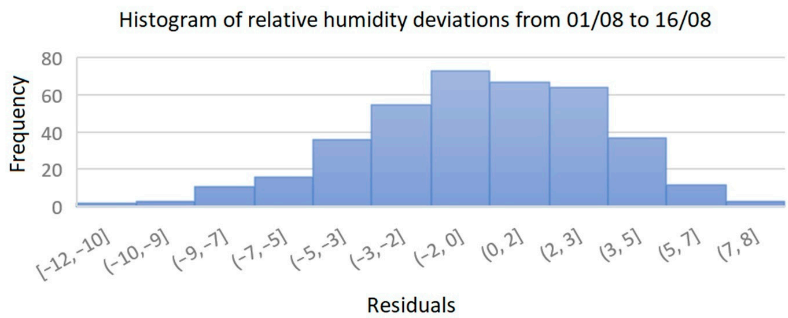
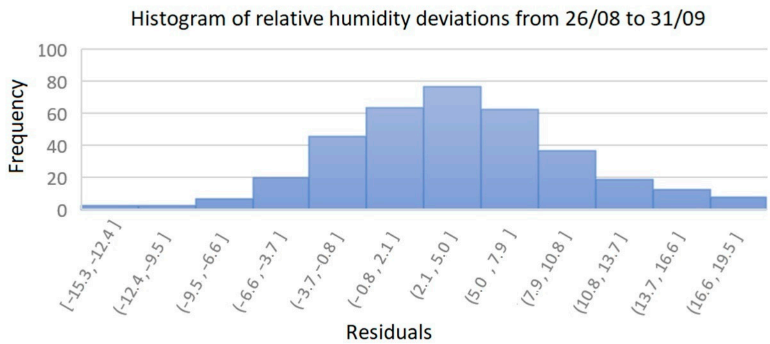



**Figure 5.** The measured (H_IN_M, blue line) and estimated (H_IN_E, red line) relative humidity inside the greenhouse. The graph shows the data starting from 1 August to 30 September; the period in which the neural network was tested is highlighted in green, while the period in which the peppers were present in the greenhouse is highlighted in red.

To highlight the significance of these differences, a targeted analysis was conducted [33]. Figure 6 shows the histograms of the differences between the estimated and measured relative humidity, relating to the period of absence of product (Figure 6a) in the greenhouse and to the following two weeks in which the peppers were introduced in the greenhouse (Figure 6b). While in Figure 6a, the distribution of deviations is almost symmetrical around the value 0, in the other graph, it moves toward positive values.




(**a**)




(**b**)

**Figure 6.** Histograms of the differences between the estimated and measured air relative humidity relating to the period of absence of red peppers (**a**) and in the presence of drying peppers in the greenhouse (**b**).

In Table 2, the coefficient of determination ($R^2$) and the root mean square error (RMSE) of the measured and estimated relative humidity were reported in relation to the different periods. The $R^2$ values, relating to the period in which the pepper was not present in the greenhouse, was very high, equal to 0.98, while it dropped to 0.88 when the product was present in the greenhouse. The coefficient of determination of the estimated and measured relative humidity values significantly reduced in the 4 days following the introduction of the Senise pepper in the greenhouse.

**Table 2.** $R^2$ and RMSE values for linear regression of measured and estimated datasets. The ID number is associated to the different periods following the date when the pepper was placed in the greenhouse.

| ID | 2022 | $R^2$ | RMSE |
|---|---|---|---|
| | 1–16 August | 0.98 | 3.4 |
| | 17 August to 30 September | 0.89 | 6.9 |
| 1 | 17–19 August | 0.86 | 7.4 |
| | 17–25 August | 0.9 | 6.9 |
| 2 | 26–29 August | 0.89 | 7.3 |
| | 26 August to 3 September | 0.94 | 5.4 |
| 3 | 12–15 September | 0.85 | 7.6 |
| | 12–20 September | 0.91 | 6.7 |
| 4 | 24–28 September | 0.88 | 7.4 |
| | 24–30 September | 0.94 | 5.5 |

The climatic dynamics during the four periods when peppers were introduced into the greenhouse were different. From 17 to 20 August, higher average temperatures (25–28 °C) and lower relative humidity (51–62%) were recorded both inside and outside the greenhouse (Figure 4). In contrast, during the period from 26 to 29 August, the average temperatures decreased (22–25 °C), while the relative humidity increased (66–74%). From 12 to 15 September, the average temperatures were even lower (21–24 °C), with relative humidity ranging between 45% and 57%. Finally, from 24 to 27 September, the average temperatures further declined (15–20 °C), and the relative humidity ranged from 57% to 64%, peaking at 87% on 26 September, when 9.8 mm of rain was recorded.

Figure 7 shows the RMSE of the estimated and measured air relative humidity in the day following the placement of the red pepper in the drying greenhouse at four different times in the 2022 study year (as reported in Table 1).

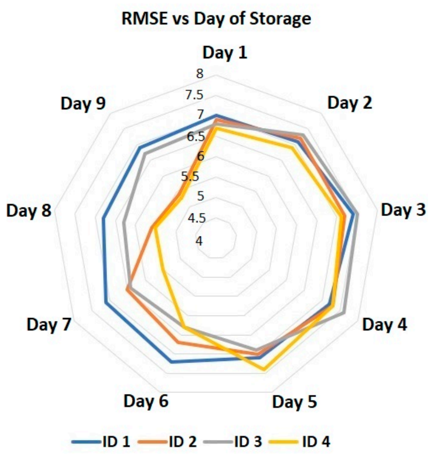



**Figure 7.** RMSE values for linear regression of measured and estimated datasets evaluated from the first to the ninth day after the red pepper was placed in the greenhouse at the different dates (ID number).

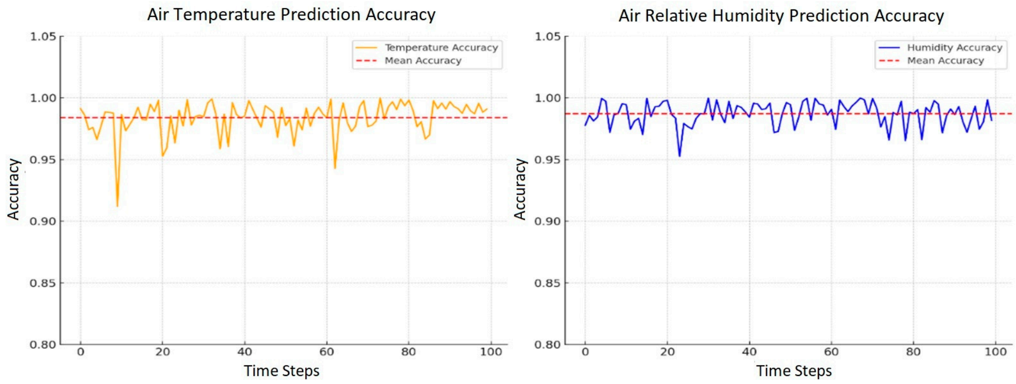
Temperature and relative humidity were the two most effective microclimatic variables in triggering sudden deterioration processes [34] of the peppers during the drying period. The RMSE values confirmed the highlights of the previous analysis. The drying process and storage conditions of the peppers were critical factors affecting their quality and safety. Moisture content and water activity played crucial roles in fungal growth and mycotoxin production during paprika processing [30]. The drying process typically involved three stages: a short induction phase, a linear drying rate period, and a slower diffusion-controlled phase [35].

During period ID-1 (Table 2), the correlation between the relative humidity values measured inside the greenhouse and those estimated as if the greenhouse were empty showed the lowest $R^2$ values during the first three days after the peppers were placed in the drying greenhouse. The increase in humidity inside the greenhouse, due to the presence of the product, occurred more rapidly because of higher external temperatures and lower relative humidity levels, in perfect agreement with the literature. Research on pepper drying has examined various factors affecting the process. The temperature directly influences the evaporation rate of water within the peppers [36], thus determining the drying rate. High temperatures can accelerate evaporation but may also cause thermal damage to the Senise red pepper, compromising its structural and nutritional quality [37]. Low relative humidity, while typically resulting in faster drying rates, can lead to excessively rapid and non-uniform drying. This creates moisture gradients within the pepper, compromising its integrity and causing cracking or breakage [38].

During periods ID-2 and ID-3, the minimum correlation between the two parameters occurred during the four days following the placement of the product in the greenhouse. In both cases, the temperatures were lower than in ID-1, and only in the case of ID-2 were the air humidity levels higher. Finally, during period ID-4, which occurred at the end of September, there was a further drop in temperatures along with higher external air humidity. In this case, the minimum correlation between the estimated and measured relative humidity inside the greenhouse was observed in the five days following the introduction of red peppers. This was the period during which the highest product losses occurred. Relative humidity plays a crucial role in maintaining an optimal hygroscopic balance. High relative humidity can reduce drying efficiency as water-saturated air impedes evaporation from the product [39,40]. This can lead to inadequate storage conditions, encouraging the growth of pathogenic microorganisms and increasing the risk of spoilage. Excessively low temperatures slow the drying process, increasing the risk of microbial proliferation and mold formation [38,41]. Air temperature and relative humidity, which regulate the rate of moisture evaporation and the risk of microbial growth, have a significant impact on the drying process of PGI Senise peppers. A noticeable increase in relative humidity was observed during the first three to four days after the peppers were placed in the greenhouse. This occurred because moisture from the fresh product was released into the surrounding air, temporarily altering the greenhouse microclimate. The results indicated that when external humidity levels remained high for several consecutive days, the drying process slowed down, increasing the risk of fungal contamination. However, sudden temperature fluctuations can accelerate moisture loss while simultaneously compromising the structural integrity of the peppers, potentially leading to uneven drying and quality deterioration.

### 3.2. The Alert System

In 2023, the FFNN was trained using data collected during the previous year (17 August 2022 to 30 September 2022) to predict relative humidity and temperature values when the peppers were stored inside the greenhouse, with a one-hour lead time. A comparison between the measured and predicted values of temperature and relative humidity was performed. Statistical analysis of the output revealed that the RMSE and mean absolute error (MAE) for temperature predictions were 0.81 °C and 0.54 °C, respectively, while the RMSE and MAE for relative humidity predictions were 2.6% and 1.88%, respectively—results that can be considered satisfactory. Figure 8 illustrates the accuracy of the predicted versus measured parameters within the greenhouse in the presence of the product over a four-day sample period. The system remained operational throughout the entire pepper drying period in the greenhouse, from August to September 2023.




(**a**) (**b**)

**Figure 8.** (**a**) Graph showing the accuracy between estimated and measured temperatures in the presence of peppers inside the greenhouse over four consecutive days. (**b**) Accuracy between estimated and measured relative humidities in the presence of peppers inside the greenhouse.

The threshold system was developed on the data acquired in 2022, and it was based on comparing the hourly values of parameters estimated inside the greenhouse as if the peppers were not present, H_IN_E_WP, with those estimated when the product was present inside the greenhouse, H_IN_E_P. The threshold value was defined by referring to the histogram in Figure 6b, setting it equal to two standard deviations, as follows:

$$\text{Alert} \rightarrow \Delta H = \text{H\_IN\_E\_P} - \text{H\_IN\_E\_WP} > 12\%. \quad (1)$$

By applying the thresholds established in the 2022 study, it became possible to generate alerts and prompt timely interventions by farm operators. In fact, the developed alert system could issue a warning one hour before a risk condition arose, allowing the activation of appropriate preventive measures to improve the greenhouse microclimate. However, these interventions were focused on enhancing natural ventilation or solar irradiance due to the restrictions imposed by EU legislation, which grants the Senise pepper its PGI designation.

Figure 9 shows the graph of residuals between the estimated air relative humidity inside the greenhouse in the presence and absence of red peppers (ΔH), from 5 August to 30 September 2023. The outliers were removed from the graph.

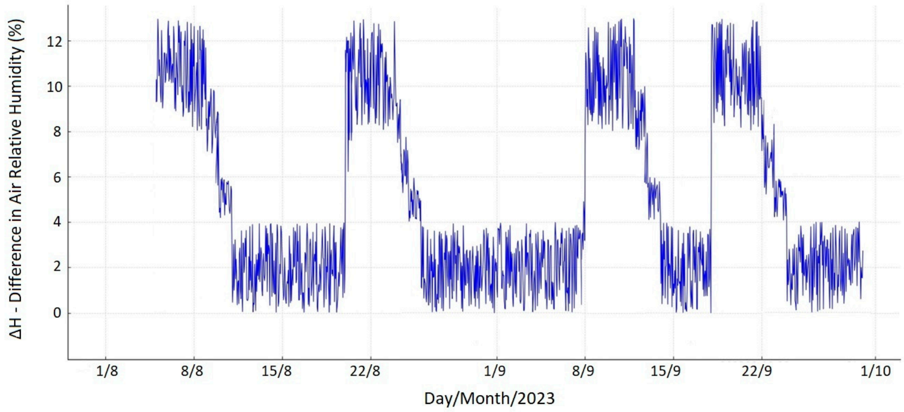



**Figure 9.** Residuals of estimated air relative humidity inside the greenhouse in the presence of the red pepper compared with its absence (ΔH) in summer 2023.

During this period, patterns influenced by both the presence of products and changes in environmental conditions were evident. Until 5 August 2023, the greenhouse was empty. On 5 August, the first batch of red peppers was placed inside the greenhouse (Table 1). From 5 to 9 August, external temperatures ranged between a minimum of 18 °C and a maximum of 28 °C. During this period, ΔH reached values of 13%. Subsequently, from 20 to 24 August, when additional peppers were placed in the greenhouse for drying, ΔH values increased again, while the external temperatures fluctuated between 22 °C and 35.5 °C, which probably contributed to amplify the observed humidity differences. A similar pattern was observed from 8 to 12 September, when temperatures moderated slightly, with averages ranging between 18.5 °C and 31 °C. The final highlighted period, from 16 to 20 September, showed temperatures stabilizing again at higher levels, between 22 °C and 34 °C. Following each of these highlighted periods, the graph indicates a gradual reduction in ΔH during the 2 days afterward, with differences dropping below 4–10%. For the remaining periods, when no significant events occurred, ΔH consistently remained below 4%. During the study period the alert system was activated several times, highlighting that the interventions carried out to improve natural ventilation inside the greenhouse were likely still insufficient to fully meet the intended objectives. Nevertheless, during 2023, product losses during the drying process were reduced.

Compared with studies on the use of predictive neural networks to predict microclimate conditions inside drying facilities currently in the literature, the present experimental approach has some key differences. Choi in 2019 [23] proposed an MLP model to predict the microclimate inside fully enclosed greenhouses, achieving 90% accuracy in predicting air humidity. The proposed model, however, addresses an even more complex and intriguing challenge, namely, the estimation—and relative management—of humidity and temperature in a semi-open environment. Compared with other studies, such as the one carried out by Petrakis in 2022 [24], which implemented a prediction system based on ANNs for smart greenhouses, the present study stands out due to the specificity of the application in a context characterized by extremely stringent regulations, which prevent complete automation, defining extremely critical or complex management challenges. Further studies are underway to refine the threshold system. Additionally, ongoing investigations aim to examine the presence of in-field infestations that could contribute to rot during the red pepper drying phase. To further improve this study, we acknowledge certain limitations. First, the system's applicability to other geographical regions with different environmental conditions may be affected by its reliance on the specific climate of the Basilicata region. Second, the dependence on IoT-based monitoring requires a stable data transmission infrastructure, which may not be available in all agricultural settings. Finally, although the model accurately predicts temperature and humidity variations, it does not yet account for other critical factors that could enhance the accuracy of the alert system, such as air circulation patterns and potential external contamination. Future developments will aim to integrate these additional variables to improve predictive reliability and ensure wider applicability of the proposed method.

### *3.3. Potential Solutions to Optimize Red Pepper Drying Process*

One potential solution to these challenges lies in the development of smart greenhouses as part of the Industry 4.0 framework. The focus of this industrial revolution is not merely on automation but on creating intelligent production systems that integrate data, making it easily accessible, analyzable, and actionable [42]. For instance, digital twin technologies can optimize production processes, energy consumption, and operational costs, all while accounting for key factors that influence the product quality and yield [22,43,44].

One potential approach could involve solar greenhouses, which offer an efficient and eco-friendly drying method for agricultural products. Compared with traditional sun-drying methods, solar greenhouses offer better quality by protecting crops from external contaminants [45]. They can function using either natural or forced convection systems, with the latter offering reduced drying times and improved control over humidity levels. Moreover, the incorporation of thermal storage solutions ensures consistent heat distribution throughout the drying cycle [46]. Unfortunately, current regional regulations prevent the use of this method, despite its potential compatibility with many of the guidelines already in place.

Growtronix is a modular system that monitors and controls greenhouse parameters like temperature, humidity, and lighting, allowing precise environmental customization. Monnit Greenhouse Monitoring is a solution that provides real-time monitoring and alerts for temperature, humidity, and other conditions to maintain optimal growth environments. Intel Edison-Based DIY Systems are projects using microcontrollers for smaller-scale or custom greenhouse solutions, showcasing flexibility and adaptability. Such systems are difficult to adapt to the specific case of Senise red peppers because the structural design of the greenhouse used for peppers may not align with the operational requirements of off-the-shelf smart systems, necessitating a tailored approach. Additionally, the requirements for maintaining the peppers' quality and preserving their geographical designation often involve specific drying directives imposed by the PGI protocol.

Drying technologies have undergone significant evolution [47], shifting from traditional methods like sun drying to modern techniques such as solar, convective, infrared, ultrasound, radio-frequency, microwave, and freeze drying [48]. While these innovations have improved efficiency, their positive impact on maintaining the sensory and bioactive qualities of chili peppers, such as color, texture, capsaicinoids, and antioxidants, should not be viewed as an unquestioned advantage. Advanced techniques often involve high energy costs and operational complexities that must be carefully weighed against the benefits in terms of product quality. Recent trends highlight the optimization of processes to improve product quality while minimizing energy consumption, raising questions about the long-term sustainability of these solutions. Although pre-treatment techniques, like blanching and cold plasma, have shown promising potential in preserving bioactive compounds, their actual scalability and economic impact remain to be fully established. Furthermore, hybrid methods that combine drying and pre-treatment strategies seem to promise an optimal balance between efficiency and quality, but a critical examination of the synergies and limitations of these solutions is necessary. Future research should focus on comparative analyses of different drying methods, considering not only product quality but also energy efficiency, to guide researchers, policymakers, and industry stakeholders toward more sustainable and effective drying technologies.

## 4. Conclusions

While the alert system developed in this study is specifically designed for the Senise pepper drying process, with appropriate adjustments, it can be adapted to other contexts with similar management requirements. In fact, the Senise pepper is representative of other Italian realities subject to strict regulations in order to maintain the PGI status. In particular, the use of low-cost IoT sensors and publicly available meteorological data makes this technology highly accessible, even for small-scale producers, minimizing the need for complex and costly installations. This approach, based on AI algorithms, enables seamless integration into environments with varying microclimatic conditions, enhancing the efficiency of the drying process. Although smart greenhouses represent a promising solution for sustainable food production in the face of global challenges, they are often not applicable in such contexts. One of the main causes of Senise red pepper loss occurs in the greenhouse during the drying phase. Monitoring the microclimatic conditions in the greenhouse analyzing the data by using AI applications to enable targeted interventions has proven to be a very promising approach in reducing production losses. Further research is needed, including field monitoring of the crops, to assess potential nutritional deficiencies or the presence of pest attacks and diseases during the growing season of the peppers, which could also impact the drying phase. To address complex production challenges—such as meeting production standards, minimizing product loss, optimizing lead times, and ensuring product quality—there is a clear need for sustainable management strategies. These strategies must be based on the careful scientific analysis of real-time data, made possible by new technologies [49]. This underscores the importance of developing and prototyping decision support systems (DSSs) that are both effective and cost-efficient. As highlighted by Maraveas in 2023 [12], while these artificial intelligence applications show potential in improving agricultural sustainability and resource use efficiency, challenges remain, including cost, technology commercialization, and disparities between developed and developing regions. The adoption of these technologies represents a significant step toward more efficient and sustainable agricultural practices.

**Author Contributions:** Conceptualization, C.F., P.D., F.T., N.C., L.A.C., M.S. and R.C.; data curation, C.F., P.D., F.T., N.C., L.A.C., E.S., F.M., M.S., R.C., E.L. and G.D.M.; formal analysis, C.F., P.D., F.T., N.C., L.A.C., E.S., F.M., M.S., R.C., E.L. and G.D.M.; funding acquisition, C.F., P.D., F.T., L.A.C., E.S. and F.M.; investigation, C.F., P.D., F.T., N.C., L.A.C., E.S., F.M., M.S., R.C., E.L. and G.D.M.; methodology, C.F., P.D., F.T., N.C., L.A.C., E.S., F.M., M.S., R.C., E.L. and G.D.M.; project administration, C.F. and P.D.; resources, C.F., P.D., F.T., N.C., L.A.C., E.S., F.M., M.S., R.C., E.L. and G.D.M.; software, C.F., P.D., F.T., N.C., L.A.C., F.M., M.S. and R.C.; supervision, C.F., P.D., F.T., N.C., L.A.C., E.S., F.M., M.S., R.C. and E.L.; validation, C.F., P.D., F.T., N.C., L.A.C., E.S., F.M., M.S., R.C., E.L. and G.D.M.; visualization, C.F., P.D., F.T., N.C., L.A.C., E.S., F.M., M.S., R.C., E.L. and G.D.M.; writing—original draft, C.F., P.D., M.S. and R.C.; writing—review and editing, C.F., P.D., F.T., N.C., L.A.C., E.S., F.M., M.S., R.C., E.L. and G.D.M. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported by the University of Basilicata and "Casa delle Tecnologie Emergenti" of Matera, "Laboratorio del Giardino delle tecnologie emergenti"—CTEMT; Smart@Irrifert Project PSR Basilicata 2014–2020—Sottomisura 16.2, CUP G19J21004870006; and "Vertical gaRdens with Digital twin of plants" Viridiis Project, PRIN 2022, Cup C53D23000480006.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data presented in this study are available on request from the corresponding author.

**Conflicts of Interest:** Author Giovanni Di Mambro was employed by the company Elaisian SRL. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## References

1. Fiorentino, C.; D'Antonio, P.; Toscano, F.; Donvito, A.; Modugno, F. New Technique for Monitoring High Nature Value Farmland (HNVF) in Basilicata. *Sustainability* **2023**, *15*, 8377. [CrossRef]
2. Esper, A.; Mühlbauer, W. Solar Drying—An Effective Means of Food Preservation. *Renew. Energy* **1998**, *15*, 95–100. [CrossRef]
3. Akyazi, T.; Goti, A.; Oyarbide, A.; Alberdi, E.; Bayon, F. A Guide for the Food Industry to Meet the Future Skills Requirements Emerging with Industry 4.0. *Foods* **2020**, *9*, 492. [CrossRef] [PubMed]
4. Babiceanu, R.F.; Seker, R. Manufacturing Operations, Internet of Things, and Big Data: Towards Predictive Manufacturing Systems. In *Service Orientation in Holonic and Multi-Agent Manufacturing*; Borangiu, T., Thomas, A., Trentesaux, D., Eds.; Springer: Cham, Switzerland, 2015; pp. 157–164. [CrossRef]
5. Hu, G.; You, F. Renewable Energy-Powered Semi-Closed Greenhouse for Sustainable Crop Production Using Model Predictive Control and Machine Learning for Energy Management. *Renew. Sustain. Energy Rev.* **2022**, *168*, 112790. [CrossRef]
6. Gautron, R.; Maillard, O.A.; Preux, P.; Corbeels, M.; Sabbadin, R. Reinforcement Learning for Crop Management Support: Review, Prospects and Challenges. *Comput. Electron. Agric.* **2022**, *200*, 107182. [CrossRef]
7. Lopez-Cruz, I.L.; Fitz-Rodríguez, E.; Salazar-Moreno, R.; Rojano-Aguilar, A.; Kacira, M. Development and Analysis of Dynamical Mathematical Models of Greenhouse Climate: A Review. *Eur. J. Hortic. Sci.* **2018**, *83*, 269–279. [CrossRef]
8. Su, Y.; Xu, L. Towards Discrete Time Model for Greenhouse Climate Control. *Eng. Agric. Environ. Food* **2017**, *10*, 157–170. [CrossRef]
9. Fiorentino, C.; AbdelRahman, M.A.E.; D'Antonio, P.; Toscano, F.; Sannino, M.; Abate, N.; Conte, D.; Lasaponara, R.; Masini, N. Space-to-tree: Architectural Framework for Real-time Monitoring of Pines in Natural and Historical Park. *Internet Technol. Lett.* **2024**, *7*, e574. [CrossRef]
10. Zhang, P. Industrial Control System Simulation Routines. In *Advanced Industrial Control Technology*, 1st ed.; Elsevier Inc.: Amsterdam, The Netherlands, 2010; pp. 781–810. [CrossRef]
11. Esteves, M.S.; Perdicoúlis, T.P.A.; dos Santos, P.L. System Identification Methods for Identification of State Models. In Proceedings of the 11th Portuguese Conference on Automatic Control (CONTROLO'2014), Porto, Portugal, 21–23 July 2014; Volume 321. [CrossRef]
12. Maraveas, C. Incorporating Artificial Intelligence Technology in Smart Greenhouses: Current State of the Art. *Appl. Sci.* **2023**, *13*, 14. [CrossRef]
13. González-Vidal, A.; Mendoza-Bernal, J.; Ramallo, A.P.; Zamora, M.Á.; Martínez, V.; Skarmeta, A.F. Smart Operation of Climatic Systems in a Greenhouse. *Agriculture* **2022**, *12*, 1729. [CrossRef]
14. Shamshiri, R.R.; Hameed, I.A.; Thorp, K.; Balasundram, S.K.; Shafian, S.; Fatemieh, M.; Sultan, M.; Mahns, B.; Samiei, S. Greenhouse Automation Using Wireless Sensors and IoT Instruments Integrated with Artificial Intelligence. In *Next-Generation Greenhouses for Food Security*; Intech: London, UK, 2021. [CrossRef]
15. López-Aguilar, K.; Benavides-Mendoza, A.; González-Morales, S.; Juárez-Maldonado, A.; Chiñas-Sánchez, P.; Morelos-Moreno, A. Artificial Neural Network Modeling of Greenhouse Tomato Yield and Aerial Dry Matter. *Agriculture* **2020**, *10*, 97. [CrossRef]
16. Kodali, R.K.; Jain, V.; Karagwal, S. IoT Based Smart Greenhouse. In Proceedings of the 2016 IEEE Region 10, Humanitarian Technology Conference (R10-HTC), Agra, India, 21–23 December 2016. [CrossRef]
17. Miraei Ashtiani, S.H.; Martynenko, A. Toward Intelligent Food Drying: Integrating Artificial Intelligence into Drying Systems. *Dry. Technol.* **2024**, *42*, 1240–1269. [CrossRef]
18. Sun, Q.; Zhang, M.; Mujumdar, A.S. Recent developments of artificial intelligence in drying of fresh food: A review. *Crit. Rev. Food Sci. Nutr.* **2018**, *59*, 2258–2275. [CrossRef]
19. Spagnuolo, A.; Vetromile, C.; Masiello, A.; De Santo, G.; Suriano, M.; Mercuri, G.; Pellegrino, M.; Piccolo, G.; Lubritto, C.; Di Cicco, M.R. Industrial Drying of Fruit and Vegetable Products: Customized Smart Monitoring and Analytical Characterization of Process Variables in the OTTORTO Project. *Processes* **2023**, *11*, 1635. [CrossRef]
20. Caponetto, R.; Fortuna, L.; Nunnari, G.; Occhipinti, L.; Xibilia, M.G. Soft Computing for Greenhouse Climate Control. *IEEE Trans. Fuzzy Syst.* **2000**, *8*, 753–760. [CrossRef]
21. Sifola, M.I.; del Piano, L.; Todisco, D.; Graziani, G.; Faugno, S.; Sannino, M.; Piscopo, R.; Salluzzo, A.; Cozzolino, E. A Multipurpose Sustainable Farming System for Tobacco Crops in the Mediterranean Area. *Sustainability* **2023**, *15*, 16636. [CrossRef]

22. Martínez-Martínez, V.; Baladrón, C.; Gomez-Gil, J.; Ruiz-Ruiz, G.; Navas-Gracia, L.M.; Aguiar, J.M.; Carro, B. Temperature and Relative Humidity Estimation and Prediction in the Tobacco Drying Process Using Artificial Neural Networks. *Sensors* **2012**, *12*, 14004–14021. [CrossRef] [PubMed]
23. Choi, H.; Moon, T.; Jung, D.H.; Son, J.E. Prediction of Air Temperature and Relative Humidity in Greenhouse via a Mutlilayer Perceptron Using Environmental Factors. *Prot. Hortic. Plant Fact.* **2019**, *28*, 95–103. [CrossRef]
24. Petrakis, T.; Kavga, A.; Thomopoulos, V.; Argiriou, A.A. Neural Network Model for Greenhouse Microclimate Predictions. *Agriculture* **2022**, *12*, 780. [CrossRef]
25. Jung, D.; Kim, H.S.; Jhin, C.; Kim, H.J.; Park, S.H. Time-series analysis of deep neural network models for prediction of climatic conditions inside a greenhouse. *Comput. Electron. Agric.* **2020**, *173*, 105402. [CrossRef]
26. Outanoute, M.; Lachhab, A.; Selmani, A.; Oubehar, H.; Guerbaoui, M. Neural network based models for estimating the temperature and humidity under greenhouse. *Int. J. Multi Discip. Sci.* **2016**, *3*, 26–33.
27. Taki, M.; Ajabshirchi, Y.; Ranjbar, S.F.; Matloobi, M. Application of Neural Networks and Multiple Regression Models in Greenhouse Climate Estimation. *Agric. Eng. Int. CIGR J.* **2016**, *18*, 29–43.
28. Singh, V.K.; Tiwari, K.N. Prediction of Greenhouse Micro-Climate Using Artificial Neural Network. *Appl. Ecol. Environ. Res.* **2017**, *15*, 767–778. [CrossRef]
29. Hornik, K.; Stinchcombe, M.; White, H. Multilayer feedforward networks are universal approximators. *Neural Netw.* **1989**, *2*, 359–366. [CrossRef]
30. Casquete, R.; Rodríguez, A.; Hernández, A.; Martín, A.; Bartolomé, T.; Córdoba, J.J.; Córdoba, M.G. Occurrence of Toxigenic Fungi and Mycotoxins during Smoked Paprika Production. *J. Food Prot.* **2017**, *80*, 2068–2077. [CrossRef]
31. Carbonell, J.V.; Piñaga, F.; Yusá, V.; Peña, J.L. The dehydration of paprika with ambient and heated air and the kinetics of colour degradation during storage. *J. Food Eng.* **1986**, *5*, 179–193. [CrossRef]
32. Mistriotis, A.; Bot, G.P.A.; Picuno, P.; Scarascia-Mugnozza, G. Analysis of the efficiency of greenhouse ventilation using computational fluid dynamics. *Agric. For. Meteorol.* **1997**, *85*, 217–228. [CrossRef]
33. Adhitya, R.Y.; Ramadhan, M.A.; Kautsar, S.; Rinanto, N.; Sarena, S.T.; Munadhif, I.; Syai'In, M.; Soelistijono, R.T.; Soeprijanto, A. Comparison methods of Fuzzy Logic Control and Feed Forward Neural Network in automatic operating temperature and humidity control system (Oyster Mushroom Farm House) using microcontroller. In Proceedings of the 2016 International Symposium on Electronics and Smart Devices (ISESD), Bandung, Indonesia, 29–30 November 2016; pp. 168–173. [CrossRef]
34. Mahmood, M.H.; Sultan, M.; Miyazaki, T. Significance of Temperature and Humidity Control for Agricultural Products Storage: Overview of Conventional and Advanced Options. *Int. J. Food Eng.* **2019**, *15*, 20190063. [CrossRef]
35. Vega-Gálvez, A.; Lemus-Mondaca, R.; Bilbao-Sáinz, C.; Fito, P.; Andrés, A. Effect of air drying temperature on the quality of rehydrated dried red bell pepper (var. Lamuyo). *J. Food Eng.* **2008**, *85*, 42–50. [CrossRef]
36. Sigge, G.O.; Hansmann, C.F.; Joubert, E. Effect of Temperature and Relative Humidity on the Drying Rates and Drying Times of Green Bell Peppers (*Capsicum annuum* L). *Dry. Technol.* **1998**, *16*, 1703–1714. [CrossRef]
37. Nouri, N.M.; Abbood, H.M.; Riahi, M.; Alagheband, S.H. A review of technological developments in modern farming: Intelligent greenhouse systems. *AIP Conf. Proc.* **2023**, *2631*, 030012. [CrossRef]
38. Sabudin, S.; Hakimi Remlee, M.Z.; Mohideen Batcha, M.F. Effect of relative humidity on drying kinetics of agricultural products. *Appl. Mech. Mater.* **2014**, *699*, 257–262. [CrossRef]
39. Tsafaras, I.; Campen, J.B.; Stanghellini, C.; de Zwart, H.F.; Voogt, W.; Scheffers, K.; Al Harbi, A.; Al Assaf, K. Intelligent greenhouse design decreases water use for evaporative cooling in arid regions. *Agric. Water Manag.* **2021**, *250*, 106807. [CrossRef]
40. Soussi, M.; Chaibi, M.T.; Buchholz, M.; Saghrouni, Z. Comprehensive Review on Climate Control and Cooling Systems in Greenhouses under Hot and Arid Conditions. *Agronomy* **2022**, *12*, 626. [CrossRef]
41. Mishra, S.; Verma, S.; Chowdhury, S.; Dwivedi, G. Analysis of recent developments in greenhouse dryer on various parameters—A review. *Mater. Today Proc.* **2021**, *38 Pt 1*, 371–377. [CrossRef]
42. Jamwal, A.; Agrawal, R.; Sharma, M.; Giallanza, A. Industry 4.0 Technologies for Manufacturing Sustainability: A Systematic Review and Future Research Directions. *Appl. Sci.* **2021**, *11*, 5725. [CrossRef]
43. Howard, D.A.; Ma, Z.; Veje, C.; Clausen, A.; Aaslyng, J.M.; Jørgensen, B.N. Greenhouse Industry 4.0–Digital Twin Technology for Commercial Greenhouses. *Energy Inform.* **2021**, *4*, 37. [CrossRef]
44. D'Antonio, P.; Fiorentino, C.; Abdelrahman, M.A.E.; Sannino, M.; Scalcione, E.; Lacertosa, G.; Modugno, F.; Marsico, A.; Donvito, A.R.; Conceição, L.A.; et al. Modeling Climatic, Terrain and Soil Factors Using AHP in GIS for Grapevines Suitability Assessment. *Sustain. Dev.* **2024**, *33*, 970–991. [CrossRef]
45. Nidhi, D.; Verma, P. A Review Paper on Solar Greenhouse. In Proceedings of the 3rd National Conference on Advances in Engineering, Technology & Management (AETM'16), Ambala, India, 9 April 2016; pp. 43–48. [CrossRef]
46. Ahmad, A.; Prakash, O.; Kumar, A.; Chatterjee, R.; Sharma, S.; Kumar, V.; Kulshreshtha, K.; Li, C.; Eldin, E.M.T. A Comprehensive State-of-the-Art Review on the Recent Developments in Greenhouse Drying. *Energies* **2022**, *15*, 9493. [CrossRef]

47. Burchi, G.; Chessa, S.; Gambineri, F.; Kocian, A.; Massa, D.; Milazzo, P.; Rimediotti, L.; Ruggeri, A. Information Technology Controlled Greenhouse: A System Architecture. In Proceedings of the 2018 IoT Vertical and Topical Summit on Agriculture—Tuscany (IOT Tuscany), Tuscany, Italy, 8–9 May 2018; pp. 1–6. [CrossRef]
48. Elmatsani, H.; Munarso, S.; Benyamin, B.; Budiyanto, A.; Yohanes, H.; Djafar, M.; Sjafrina, N.; Koeslulat, E.; Lukas, A.; Lanjar, L.; et al. Global perspective on red chili drying: Insights from two decades of research (2004–2023). *Front. Sustain. Food Syst.* **2024**, *8*, 1456938. [CrossRef]
49. Sannino, M.; Faugno, S.; Maresca, G.; Suardi, A.; Fiorentino, C.; Assirelli, A.; Panico, T. Olive growing in the Sorrento Peninsula: Operative, economic, and environmental evaluation trough LCA of mechanical harvesting. *Heliyon* **2024**, *10*, e40461. [CrossRef]