Alert System to prevent damage during drying of PGI peppers in southern Italy: preliminary results

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Abstract. The Pepper of Senise PGI is a typical product of Basilicata region in southern Italy. Historically, the drying process of 'Peperone Crusco' took place during the summer months, in the wind and under the porches of rural buildings. This method is not in line with today's business needs (quantity, quality, traceability and healthiness of production) but it is necessary to follow the strict requirements of the production specification to maintain the PGI denomination. The objective is to develop a low-cost monitoring system suitable for the regulation that reduces product losses during the drying phase due to invasive rotting phenomena (losses exceeding 20% of dry matter). To monitor outdoor agrometeorological variables, the Senise ALSIA weather station, the closest to the greenhouse, was use, while, another equipped with air humidity and temperature sensors was positioned inside the drying greenhouse. A feedforward neural network (FFNN) was trained using climate parameters collected from the empty greenhouse and data from the Alsia outdoor weather station, employing a multivariate approach. The goal was to predict in advance humidity and temperature inside the greenhouse, as it was empty, also when the pepper was introduced in the greenhouse. To evaluate the impact of the presence of the peppers on environmental conditions, the predicted parameters were compared with the measured values recorded in the greenhouse after the peppers were introduced.

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 trained and tested during 2022 year. The developed neural network can predict with a good accuracy level ($R^2 = 0.96$) the microclimate variables inside the greenhouse during the drying period.

Keywords: Pepper, Machine Learning, Smart Agriculture, greenhouse.

1 Introduction

Internet of Things (IoT) technology is used in smart greenhouses as a monitoring system, resulting in digital matching or even digital twins on the Internet [1]. The IGP Senise (Basilicata, Italy) pepper is a typical product, historically the peppers were sewn into necklaces and hung to dry in the summer months, under the porticoes or balconies. Today the Senise pepper is exported throughout Italy, and the local demand has also increased due to tourism. Therefore, producers need to increase production, so the traditional drying method must give way to larger-scale systems, such as greenhouses. The Basilicata region, however, has very strict regulations on the drying of peppers as it is a PGI product, which does not allow the use of smart greenhouses. The pepper can be dried in greenhouses that must be opened or at most covered by sheets that allow ventilation and can be easily removed. Many producers complain of serious product losses during the drying phase due to invasive rotting phenomena (losses exceeding 20% of dry matter). Generally, high gradient of relative humidity and temperature can be decisive factors for the spread of rot and also predispose the environment to the propagation of insects and pests [2]. The need for sustainable management strategies based on careful scientific processing of the multiple data that can be acquired in real time with new technologies [3] together with the need to answer complex production questions (compliance with production specifications, minimizing product losses, production times, product quality) requires the development and prototyping of highly efficient and effective multivariate methodology of analysis [4]. Modeling the microclimate of a greenhouse differs depending on the purpose. There are two main categories of models, the physical ones, based on the study of the behavior of the monitored parameters and their interactions, and the black-box models [5]. The development of a physical model can be very difficult due to the non-linear dynamics in the interactions between the involved parameters [6] [7]. On the other hand, the black-box models are based on the system identification process, it depends on the on experimental input and output data. The use of such models allows obtaining reliable results, without having detailed knowledge of the physical phenomena involved in the process [8] [9]. Choi et al. (2022) [10] trained an MLP neural network using the data of both the external and internal greenhouse conditions as the input variables, to predict the indoor temperature and relative humidity for 10 to 120 min later. Petrakis et al., in 2022, [11] developed a model using artificial neural networks (ANN), which can predict temperature and relative humidity inside the greenhouse, based on outside temperature and relative humidity, wind speed, solar irradiance, as well as internal temperature and relative humidity up to half an hour before.

In the present work, a Feedforward neural networks (FFNNs) was trained on the outdoor and indoor temperature and relative humidity data. The comparison between the data acquired in the greenhouse in the presence of the product and those estimated (at the same time) in the hypothesis of product absence, highlighted the presence of some temperature and humidity gradients which can be managed with appropriate structural modifications to the greenhouse The objective of the present work is to develop a low-cost monitoring system suitable for the expected drying regulation that reduces farmers' losses.

2 Material and Methods

2.1 The Study Area

Senise peppers are a local ecotype grown in the Pollino national park in Basilicata, mainly in the Sinni and Agri valleys, an area that includes several municipalities, including Senise, from which the ecotype takes its name. It is sown between February and March and buried in May, and is harvested in midsummer, especially in August. Harvesting must be done by hand with particular attention not to damage the stalks. The genetic properties of this pepper make it particularly suitable for natural drying and for the subsequent production of paprika. Senise red peppers have various shapes: pointed, trunk and hook. It is characterized by a high content of vitamin C and has the ability to retain its characteristic bright red color even after drying. The peculiar organoleptic characteristics of the red peppers and the undisputed typicality that follows led to the recognition of the Protected Geographical Indication (PGI) by the EU in 1996. To monitor outdoor agrometeorological variables, the Senise ALSIA weather station, the closest to the greenhouse, was use while another equipped with air humidity and temperature sensors was positioned inside the drying greenhouse, approximately in the center of the structure. In figure 1 are shown the location of both weather station. In the upper-left section of the figure is shown the infrastructure intended for drying the product, located in a farm about 2 km from the production area. It is a rectangular structure (48 m x 9 m) whose construction characteristics are attributable to those of a greenhouse, with a PVC roof, whose height at the ridge is 4.00 m and at the sides 2.20 m.

Fig. 1. Location of the Alsia and the greenhouse “Elaisian” weather station.

Inside the greenhouse, approximately at the height of 2.00 m, there is a shading net, furthermore there are two large openings on the shorter sides which, in addition to representing the access and exit route within the infrastructure, are used as natural ventilation system. The pepper harvest occurred in August, on 17 August 4500 kg of product was deposited in the greenhouse, while on 26 August approximately another 3500 kg were deposited

2.2 The Climate Parameters

Elaisian provided a weather station equipped with air humidity and temperature sensors which were positioned inside the greenhouse as shown in figure 2. The parameters were acquired every 15 minutes. The Elaisian Iot platform stores and displays the real-time data. In case if there is any sudden change in the air humidity value the IoT based device will send an autogenerated SMS alert to owner's mobile phone. The data measured by the ALSIA weather station of Senise are available online on the web-site of the agency. The data acquired from the weather stations were pre-processed to remove any out-layers. In July 2022, 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 a Pearson correlation coefficient value of 0.89 for temperature, and 0.76 for relative humidity, was found. Furthermore, after pre-processing, the data were analyzed by using multivariate neural network trained on the climate parameters acquired in the greenhouse when it was empty in correlation with the data acquired from the Alsia outdoor weather station, in order to predict humidity and temperature inside the greenhouse when the product was present. The neural network begins to predict the parameters when the product is introduced into the greenhouse. The parameters estimated, as if the greenhouse was empty, were compared with those acquired by the indoor sensors. 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 2022, when the pepper was in the greenhouse for drying.

2.3 The neural network

Feedforward neural networks (FFNNs) [12], are a class of artificial neural networks in which the connections between nodes do not form loops. The use of a neural network allows you to extract and analyze complex characteristics among the multiple variables offered by the sensors used to collect agrometeorological data. To predict the temperature and humidity inside the greenhouse, a FFNN was implemented. This 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 structure of the neural network:

The input level receives the following variables

1. Air humidity inside the greenhouse at time i-2 = $U_{int}(i-2)$;
2. Outdoor Air humidity at time i-2 = $U_{ext}(i-2)$;
3. Air temperature inside the greenhouse at time i-2 = $T_{int}(i-2)$:
4. Outdoor Air temperature at time i-2 = $T_{ext}(i-2)$.

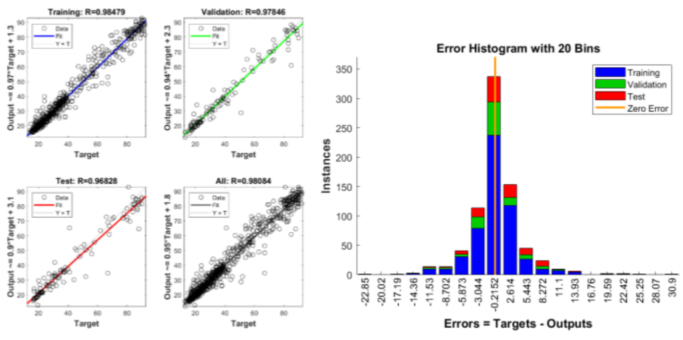
The output level is composed of two neurons, each responsible for predicting a target variable:

1. Air temperature inside the greenhouse at time i = $T_{int}(i)$
2. Air humidity inside the greenhouse at time i = $U_{int}(i)$

The network includes 2 hidden layers, the first composed of 60 neurons and the second composed of 30 neurons. Each neuron in the hidden layers uses the ReLU (Rectified Linear Unit) activation function, chosen for its effectiveness in handling vanishing gradient problems and for its ability to introduce non-linearity into the model.
During *the Training Process*, the input data is propagated across the network. Each neuron calculates its activation by summing the products of the weights and the received inputs, adding a bias term and applying the ReLU activation function in the hidden layers. The error between the network predictions and the actual values of the target variables $T\mathrm{int}(i)$ and $U\mathrm{int}(\mathrm{i})$ is calculated using the mean square error (MSE) loss function. The calculated error is back-propagated through the network to update the weights and biases. This update is done using the backpropagation algorithm, which calculates the error gradients with respect to the weights.

2.4 The neural network validation

The neural network, described in the previous paragraph, was trained on a dataset comprising hourly temperature and humidity readings collected daily over a 50-day period, from late June to August 16th 2022. The dataset was divided into three subsets: 70% for training, 20% for validation, and 10% for testing. As shown in the scatter plots for training, validation, and testing (Figure 2a, 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 (fig. 2b) clearly shows that most of the air relative humidity predictions deviate by only ± 0.215%, a low measurement in relation to the drying characteristics of the fresh product. Furthermore, only a very small percentage of the predictions show errors greater than ±3%, making the system particularly efficient in predicting relative humidity values at practically any time of day or night.



(a) (b)

Fig. 2. (a) Scatter-plots of training, validation and test data-set 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.

3 Results and discussion

The main objective is to identify the conditions that determine the onset of pepper rot phenomena in order to limit its occurrence. Figure 3 shows the average daily values of temperature and relative humidity, as well as the values of the relative humidity estimated (blue line) by the neural network inside the greenhouse. In the period from 17 to 31 August, i.e. when the pepper was placed in the greenhouse to dry, from the comparison between the hourly values of the parameters estimated inside the greenhouse, as if the product were not present, and those actually measured, a threshold value will be defined. If thresholds are exceeded, an alert will be sent to farmers. The alert system will be able to send an alert one hour in advance of the onset of a risk condition, thus activating the appropriate preventive measures to improve the microclimate inside the greenhouse itself. However, these will be interventions aimed at improving the natural ventilation or solar irradiance of the greenhouse, given the restrictions imposed by EU legislation which gives the Senise pepper the PGI designation.

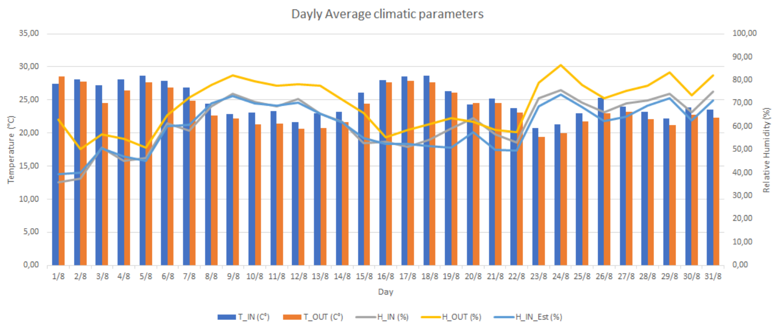


Fig. 3. Mean daily values of temperature and relative humidity measured from the Senise Alsia weather station and the sensors located inside the greenhouse in August 2022.

Both measured parameters, outside and inside the greenhouse (figure 3), shows very similar patterns when the Senise pepper is not present in the greenhouse (1-16 August). The relative humidity and temperature measured inside the greenhouse always show lower values than the external one (ALSIA). In ideal ventilation conditions the humidity values outside and inside the greenhouse should be the same, but due to the presence of the protective sheets and the position of the openings, this does not happen [12]. The dynamics between indoor and outdoor parameters are complex and the indoor values at time t are influenced by external ones also relating to previous time steps.

The hourly curves of the estimated and measured relative humidity [13] in the greenhouse overlap very well in the period in which the product was not present in the greenhouse, while the former shifts towards lower values in the subsequent period.

To ensure that these differences are significant, a targeted analysis was conducted [14]. There were analyzed the differences between the estimated and measured variables relating respectively to the period of absence of product in the greenhouse and to the following two weeks in which approximately 4000 kg of peppers are brought in at a time on 17 and 26 August. The Histogram of the differences between the estimated and measured variables relating to the period of absence of product in the greenhouse was almost symmetrical around the value 0, in the other two cases it moves significantly towards positive values.

A regression analysis was performed on the data in relation to the different periods, in table 1, the coefficient of determination (R^2). The R^2 values, relating to the period in which the pepper was not present in the greenhouse is very high, equal to 0.96, while it drops to 0.85 in the two periods in which the product was present in the greenhouse. The coefficient of determination of estimated and measured relative humidity values significantly reduce in the 4 days following the introduction the Senise pepper in the greenhouse. The climatic dynamics of these two periods are different: from 17 to 20 of August we have higher temperature values and lower relative humidity both inside and outside the greenhouse (figure 3), while in the period from 26 to 29 of August average temperatures are lower with a higher degree of humidity. Temperature and relative humidity are the two most effective microclimatic variables in triggering sudden deterioration processes [15] of the product during the drying period.

Table 1. Coefficient of determination for linear regression of measured and estimated data sets.

August 2022	01-31	01-16	17-31	17-20	26-31	26-29
R^2	0.88	0.96	0.85	0.82	0.83	0.8

Currently, the threshold values for air temperature and humidity have been set to exceed by at least 10% those predicted in the absence of the product. However, further experimentation is necessary to better refine and establish these values. There are many examples of smart greenhouses equipped with IoT sensors, automated systems, and data analytics, that ensure precise environmental management: Growtronix - A modular system that monitors and controls greenhouse parameters like temperature, humidity, and lighting, allowing precise environmental customization; Monnit Greenhouse Monitoring - 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 - 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 due to 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, and the requirements for maintaining the peppers' quality and preserving their geographical designation often involve specific drying directives imposed by the PGI protocol.

4 Conclusion

To date, one of the major factors in product loss for Senise peppers is rot in the greenhouse. It will be necessary to conduct further investigations, including monitoring the crop in the field [16]. The need for sustainable management strategies based on careful scientific processing of the multiple data that can be acquired in real time with new technologies, together with the need to respond to complex production questions (compliance with production specifications, minimization of product losses, lead times production, product quality) requires the development and prototyping of effective, but also inexpensive, decision support systems (DSS). The monitoring of microclimatic parameters of the greenhouse, in order to carry out targeted interventions, has proven to be a winning strategy in reducing production losses.

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