Sprinkler Irrigation Automation System to Reduce the Frost Impact Using Machine Learning

Original Scientific Paper

Ricardo Yauri
Universidad Tecnológica del Perú,
Faculty of Engineering, Lima, Perú
boncer99@gmail.com
Universidad Nacional Mayor de San Marcos,
Faculty of Systems and Informatic Engineering,
Lima, Perú, ryaurir@unmsm.edu.pe

Oscar Llerena
Seoul National University of Science and Technology
Computer Science and Engineering
Seoul, South Korea
oscar.llerena.c@gmail.com

Jorge Santiago
Universidad Nacional Mayor de San Marcos
Faculty of Electronic and Electrical Engineering,
Lima, Perú
jorge.santiago3@unmsm.edu.pe

Jean Gonzales
Universidad Nacional Mayor de San Marcos
Faculty of Electronic and Electrical Engineering,
Lima, Perú
jean.gonzales2@unmsm.edu.pe

Abstract *– Frosts reduce the ambient temperature to the freezing point of water, affecting the agricultural sector and the integrity of plant tissues, severely damaged by freezing, destroying plant cells. In addition, losses are generated in the economy due to the death of cattle due to cold, hunger, diseases, etc. Latin America is a region that depends, to a considerable extent, on its crops for its consumption and export, so frost represents an urgent problem to solve, considering that in Perú the area of agriculture is not technical. Among the methods most used by farmers is anticipated irrigation, through automatic learning techniques, which allows predicting the behavior of a variable based on previous historical data. In this paper, sprinkler irrigation is implemented in crops exposed to frost, using an automated system with machine learning techniques and prediction models. Therefore, three types of models are evaluated (linear regression, random forests, and decision trees) to predict the occurrence of frosts, reducing damage to plants. The results show that the protection activation indicator from 1.1°C to 1.7°C was updated to decrease the number of false positives. On the three models evaluated, it is determined that the most accurate method is the Random Forest Regression method, which has 80.91% reliability, absolute mean error, and mean square error close to zero.*

Keywords*: Frost, machine learning, sprinkler irrigation, random forests, linear regression, decision trees*

1. INTRODUCTION

Frosts generate a drop in ambient temperature to levels below the freezing point of water, which a problem that affects the agricultural sector. When this phenomenon occurs, the environmental condition becomes critical for the integrity of plant tissues, severely damaged by freezing, generating ice inside the tissues and destroying plant cells [1, 2]. This problem usually occurred all over the world seriously affecting the economy. In our country, this negatively affects agriculture and livestock, causing loss of crop areas, and death of livestock due to cold, hunger, diseases, etc. [3]. Likewise, it affects the health of families due to the low temperature seasons that occur every year [4]. It is for this reason that it is necessary to implement a crop protection system against frost, especially due to climate change [5].

Latin America is a region that depends to a considerable extent on its crops for its consumption and export, so the frost problem represents a problem to be solved by the authorities currently, who have made little effort to mitigate this problem. Likewise, in Peru, agriculture is generally not technified, due to the lack of technical information and training from the state. It should be noted that the regions most affected in the country by frost are above 3000 meters above sea level [5, 6]. Likewise, despite the economic losses suffered by farmers in Peru, no government proposals have yet been put forward to solve this problem.

In the year 2022, the "Multisectoral Plan against Frost and Cold 2022-2024" was approved to reduce the vulnerability of the population to these phenomena recently. This plan seeks to reduce the damage, however, they leave aside the prevention policy to protect the population and their crops [7]. In the same way, different government and state agencies have identified 1,367 districts exposed to the occurrence of frost out of a total of 1,873 districts that exist in the country. To reduce the effect of frost, different techniques have been used (burning of weeds, use of hormonal products) [8] where early irrigation is the most used and with the best results. However, sprinkler irrigation is more efficient because it ensures frost protection down to -7°C [9]. Another widely used technique is hereditary mechanisms of resistance to water stress due to drought and frost, but, in developing countries, these techniques are complex and little known by farmers [10]. There are also proposals for the development of natural fibers that help mitigate frost which functions as thermal insulation [11].

It is necessary to take advantage of the great advances in the field of automatic learning, to predict the behavior of a variable based on previous historical data [12]. For this there are techniques based on embedded artificial intelligence using machine learning [13, 14]. This contributes to the design of an intelligent system to predict the occurrence of frosts. The model uses historical data of climatological input variables such as temperature, humidity, and pressure, which can be easily obtained from the SENAMHI website.

For all the above, this research proposes the following research question: How is it possible to implement an automated system to support the reduction of the impact of frost on crops?

For this reason, sprinkler irrigation is implemented in crops exposed to frost, using an automated system that will work together with machine learning techniques to predict the occurrence of frost in crops and reduce damage to plants and crops, avoiding great economic losses. As a contribution to the care of crops in agriculture, this system contributes to providing a solution to technical irrigation to improve efficiency in production and water savings [15, 16]. In addition, the application of the predictive system and irrigation by spraying will benefit the agricultural industry in Peru, by mitigating frost damage in crop fields.

This paper has several sections: Section 2 shows the related works. Section 3 describes the concepts and technologies used in automated sprinkler risk systems. Section 4 describes the implementation of the system. Finally, the results are shown in section 5, and the conclusions in section 6.

2. RELATED WORK

A flow of literature work was followed that started with the definition of the research objectives and then an exhaustive search of research papers using keywords related to sprinkler irrigation, frost, and machine learning. Studies were evaluated to identify key findings and gaps in the existing literature. Subsequently, the concepts, theories and results found were synthesized in the literature review, which provided the basis for the choice of methodology. Finally, the selected studies were cited, and included in the bibliography to support the statements and conclusions of this paper.

Frosts are a major problem in the agricultural sector in Peru and the world currently because each year thousands of hectares of crops are affected, which translates into millions of dollars in losses. However, there are different methods to mitigate this phenomenon, highlighting sprinkler irrigation. Vargas [17], shows the control of low temperatures in crops through sprinkler irrigation in the Bolivian altiplaNo. This research demonstrates how water, applied by spraying, allows crops to be protected from frost, taking advantage of the latent heat from freezing water, protecting the plant down to -8 °C. Likewise, the article presents a mathematical model to determine the value of the spray flow.

In the paper developed by Huayta [18] shows the efficiency of sprinkler irrigation is verified to reduce the effects of frost in two varieties of quinoa. The author used the Arduino platform to read the thermometer and turn on the electric pump. Likewise, parameters are considered to verify the protective effect, such as maximum leaf width, maximum leaf length, plant height, main stem diameter, panicle diameter, grain diameter, seed yield per plant, and days of physiological maturity. The results show that when quinoa crops are under the protection of sprinkler irrigation, they grow more than others.

Regarding review papers for frost monitoring, Zho [19], described that frost damage to crops generates economic losses for producers, making it necessary to use a digital infrastructure for the development of agriculture. In some papers, like Hansen et al. [20] and Lu et al.[21], an intermittent control strategy is used using a modified model that included the start and stop time of the system and the adjustment of the water application rate using a simulation with different values of airflow velocity, air temperature , air humidity and spray water temperature, being suitable for protection against frost, and automatically regulating the water application rate.

Some technologies used in the papers focus on the Internet of Things, cloud computing, Machine Learning, and the Soft Computing framework for designing sustainable agricultural systems. These technologies make it possible to obtain information in real time, process and analyze it, incorporate intelligence in decision-making, and use time series data as described in the Cadenas [22]. In addition, in Talsma [23], is used in machine learning techniques and deep neural network models for frost prediction. These technologies can be integrated to diagnose and quantify environmental stress in the winter wheat crop due to climate change through remote and proximal sensing, vegetation index analysis, and the use of statistical and machine learning techniques, to evaluate abiotic and biotic stress in winter wheat. They also allow for obtaining early and accurate information on the environmental impact on crops as described in the paper of Skendžić [24].

Among these solutions are cyber-physical systems (CPS) that consist of sensors, intelligence (prediction), and actuators. In addition, prediction systems are mentioned in the paper of Zhou [25] and Kim [26], which describe how techniques with machine learning and neural networks contribute to the management, control, and prediction of frost. For integrated frost prediction systems, it is necessary to integrate distinct types of sensors.

3. SPRINKLER AND FROST IRRIGATION

3.1. FROST IN AGRICULTURE

In meteorological terms, frosts occur when the air temperature drops to 0ºC or less. However, there is agrometeorological frost, which is the drop in air temperature to critical levels of crops and kills plant tissues, with temperatures above 0ºC [27]. Frost causes damage when ice forms inside the tissues of plants, destroying of their cells. The damage is due to ice crystals that form in the protoplasm of cells, while indirect damage occurs with ice formed in the extracellular space. In both cases, cell damage affects the plants completely or part of it, reducing the quality of the product [1].

According to this paper [28], it is described that there are two types of frosts: radiative and advective. Radiative frosts are related to the leakage of heat accumulated during the day during the night. This happens when the night sky is clear, without wind and the air has a low temperature. This cooling generates thermal inversion due to height, depending on the local topography and weather conditions. Advective frosts occur due to the movement of cold air covering extensive areas of territory, which can last for several hours. These frosts are characterized by having drier and colder air, causing greater damage to plants. Fig. 1 shows the difference between these two types of frost, observing their variation with respect to temperature and altitude for each case.

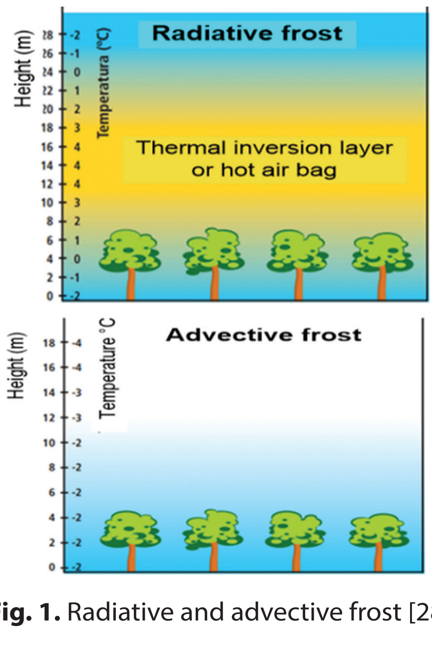

Fig. 1. Radiative and advective frost [28]

3.2. IRRIGATION BY ASPERSION

Sprinkler irrigation is an integral method to deliver pressurized water to the soil uniformly [15]. This method consists of applying intense and uniform rain on the crop, looking for a layer of water to cover each part of the plant. For this purpose, this system is made up of: the pumping group, pipes with hydrants, pipes carrying emitters (irrigation branches), and emitters [29].

The efficiency of the sprinklers is related to their quality, and they are mostly made of plastic. Modern sprinkler irrigation technologies have an innovation-oriented demand and are developing in the direction of high efficiency, energy saving, and enhanced intelligence. New sprinkler irrigation technology is combined with agricultural machinery today [15].

3.3. SENSORS

For the implementation of the irrigation system, it is necessary to add a series of sensor components.

- LM35. Analog sensor that measures temperature, is simple to use, economical, and has a small dimension. It is capable of measuring temperature in a range from -55 ºC to 150 ºC. [30] (Fig. 2).
- DHT11. It is a low-cost digital relative humidity and temperature sensor. It consists of a thermistor and a capacitive humidity sensor to measure the air. This component is used in applications related to monitoring in agriculture, etc. [31].
- BMP180. The BMP 180 barometric pressure sensor combines a wide pressure measurement range, a wide temperature range, high accuracy, and low power consumption [32] (Fig. 3).

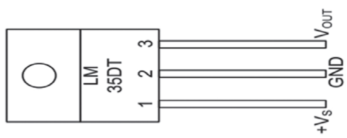

Fig. 2. LM35 Sensor [30]

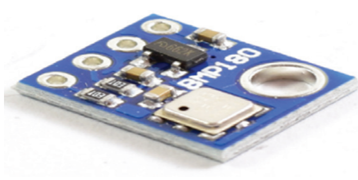

Fig. 3. Sensor BPM180

4. PROPOSED SYSTEM

The system performs the acquisition of the readings of the meteorological sensors and controls the performance of the sprinklers. The hardware development stage was through a V-methodology while the CRISP methodology was used for the implementation and evaluation of the learning algorithms. Likewise, to have an easy monitoring of the crop and a reliable response of the system, it is proposed to divide the project into two parts: end-devices and base station as shown in Fig. 4:

- End Devices. It is composed of weather sensors connected to the Arduino module with LoraWan data transmission, to send the information to the base station. In addition, it has a protection stage, for its deployment in a crop field. The power part of the system, it has a solar panel and a DC battery for 24-hour operation.
- Base station. It is built based on a Raspberry micro-computer with the Ubuntu operating system. The prediction algorithm will be implemented using three different machine learning techniques. These models will have data received by the base station as inputs and perform the frost prediction, determining the moment in which the protection system will be deployed in the end-devices.

The proposed system is divided into two stages. The first stage is responsible for making the prediction and the second stage does the monitoring and activation. Each of these will be detailed below.

4.1. PREDICTIVE STAGES

In this stage, a series of steps are followed to develop the frost prediction algorithm as shown in Fig. 5, which are: Data cleaning, Training, input of variables, Model construction, and Evaluation. In the Training stage, a previously cleaned data set is used to use regression techniques, decision trees, and random forests. During training, the models learn to recognize patterns and relationships between input variables and frost occurrence using Python's Scikit-Learn tool. In the variable entry stage, the temperature data is provided, and the probability of frost occurrence is estimated. This involves calculating specific thresholds or limits to determine when a frost is considered likely. Finally, in the Evaluation stage, the model's predictions are analyzed using performance metrics, such as the hit rate. This allows you to evaluate the effectiveness of the prediction algorithm and adjust or improvements.

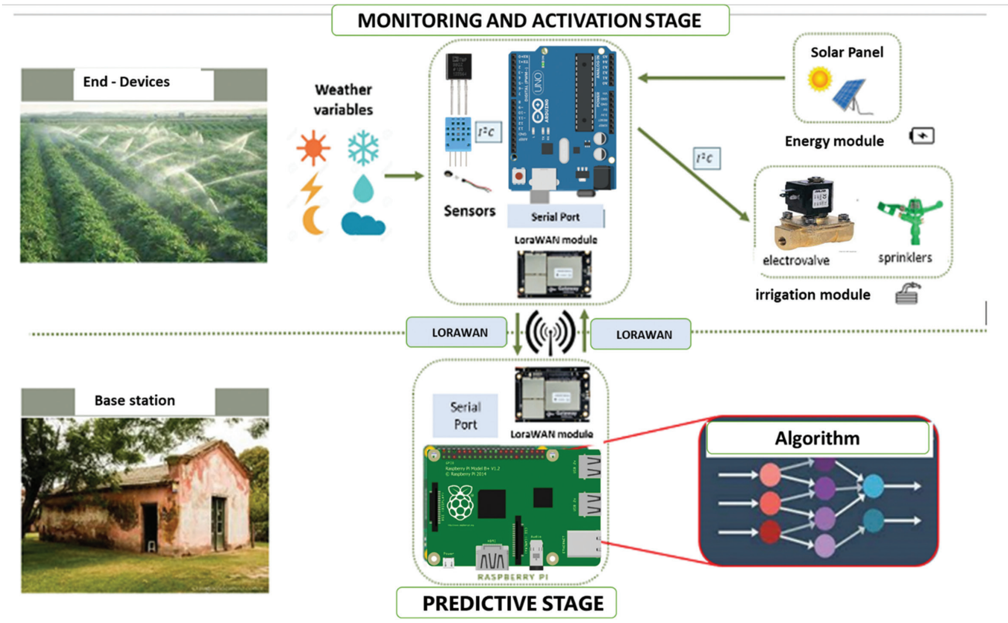

Fig. 4. Frost protection system design

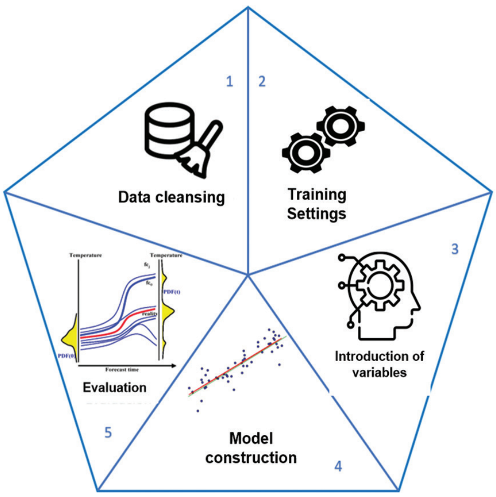

Fig. 5. Predictive Stage Processes

4.2. MONITORING AND ACTIVATION STAGE

This section describes the process of transmission of weather variables to reach the Raspberry module and its input to the prediction models. For this, the following steps are followed:

- The data of the climatological variables are acquired through the sensors, and they are used for the frost and climate forecast.
- The variables are stored in the Arduino hardware for later transmission.
- The data is sent to the Raspberry PI to enter the predictive models.
- Subsequently, a drive stage is implemented, and the response of the frost predictive models is graphically displayed, to activate the actuators

controlled by the Arduino module (Fig. 6). The drive stage performs the following steps:

- Using the algorithm based on the trained predictive models, frosts are predicted, sending data from the Raspberry to the Arduino module using a LoraWAN network.
- The Arduino drives the actuator to deploy the protection system.
- The electrovalve is activated so that it can allow the passage of water towards the sprinklers, starting the irrigation.

Finally, Fig. 7 shows the stages described above integrated into the system. The interaction between the base station and the end-devices is observed through a LoraWAN communication system, and the specific location of the prediction algorithm (base station) and actuators in the Arduino (end-device).

4.3. ALGORITHM DEVELOPMENT

Meteorological data were obtained from the NASA service (Data Access Viewer), which was subjected to a preparation process through filtering. In the first stage, the parameter values of the model are adjusted (number of epochs, number of layers, etc.) for training. Then a validation process is carried out with different data, entering, for example, information for May and June 2022, and frosts are predicted in July. This result can be verified with the real data of the occurrence of frost, obtaining the precision of the prediction. After this, the algorithm is implemented in a Raspberry, which has a low computational load, because it only performs the inference process. Fig. 8 shows the flowchart that indicates the conditions to be met to display the predicted data.

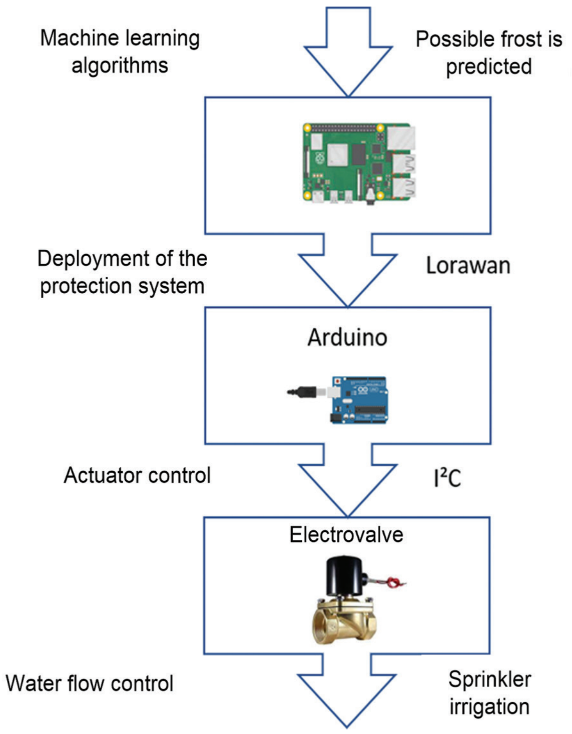

Fig. 6. Drive Stage Steps

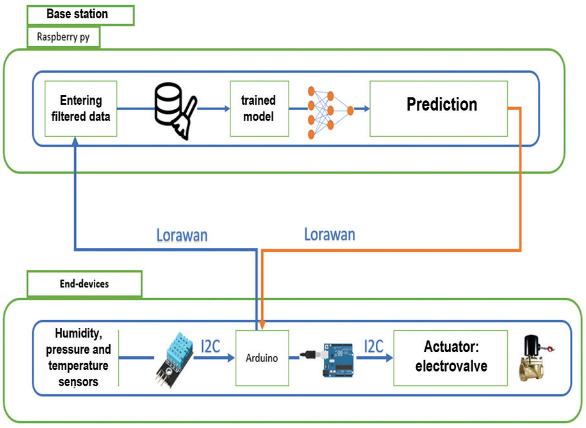

Fig. 7. Integrated system

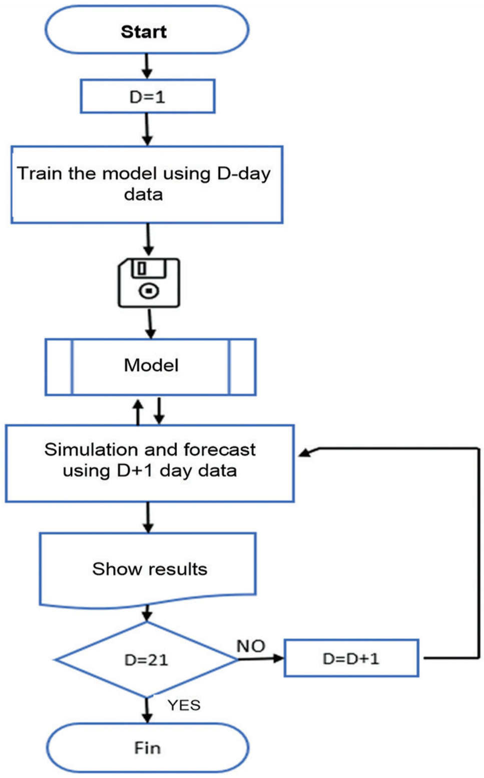

Fig. 8. Inference Process Flowchart

5. RESULTS

The end-devices need more protection because the red lights, the solar panel and the pressure, temperature, and humidity sensors are exposed, as well as the Arduino module and the power stage of the system. In this prototype, a heat-resistant, hermetic-sealable plastic box is used as the casing as shown in Fig. 9.

To obtain the temperature history in the region, the NASA tool that offers historical temperature data for a large part of the planet Earth was used. In this case, a marker was placed in the town of Ataura, where climatological variables were analyzed for their subsequent treatment. Fig. 10 shows the NASA tool used to obtain historical climate data (maximum temperature, minimum temperature, humidity, precipitation, pressure, and wind speed).

With the support of computational tools, such as Python and its sklearn library, the algorithm necessary to predict temperatures was developed. This temperature prediction system is related to frost, establishing that if the temperature drops below 1.1°C, the protection system is activated.

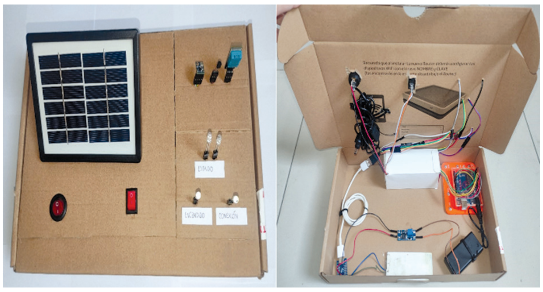

Fig. 9. End Device Prototype

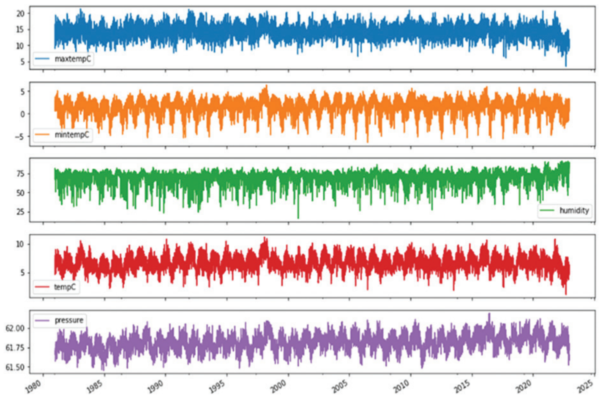

Fig. 10. Meteorological data (1981-2022)

The results compare the behavior of the three types of machine learning algorithms (linear regression, Decision Tree Regression, and Random Forest Regression). The first evaluation is conducted with the linear regression method to predict the temperature values as observed in Table 1, where there are date values, environmental variables, and the activation of the frost control system.

Table 1. Linear Regression Temperature Data

DATE	TEMP. Real (°C)	TEMP. Forecast (°C)	Difference	Activate
2022-06-16	-2.31	-1.88	-0.43	YES
2022-06-24	-2.47	-0.65	-1.82	YES
2022-06-27	-1.59	-2.41	0.82	YES
2022-07-08	-1.81	-0.93	-0.88	YES
2022-07-18	-0.64	0.74	-1.38	YES
2022-07-27	1.1	1.59	-0.49	NO
2022-07-29	-2.92	-1.58	-1.34	YES
2022-08-02	1.26	1.5	-0.24	NO
2022-08-10	-1.01	0.72	-1.73	YES
2022-08-14	-1.35	0.92	-2.27	YES
2022-08-24	0.23	1.22	-0.99	NO
2022-08-25	-1.57	0.22	-1.79	YES
2022-08-28	0.36	0.44	-0.08	YES
2022-09-01	-1.63	0.67	-2.3	YES
2022-09-08	0.54	0.7	-0.16	YES
2022-09-17	-0.27	0.85	-1.12	YES
2022-09-19	1.6	0.3	1.3	YES
2022-09-27	1.58	2.36	-0.78	NO
2022-10-03	0.6	1.63	-1.03	NO
2022-10-06	1.2	2.23	-1.03	NO
2022-10-12	1.62	2.15	-0.53	NO
2022-10-20	-0.6	0.98	-1.58	YES
2022-10-25	1.87	2.64	-0.77	NO

For the evaluation of the models, the average value of the absolute error (MAE) is used, which is a measure of the average discrepancy between the predicted values and the real values in a data set. This evaluation metric is efficient in regression problems through the following equation, where the calculation for "n" real and predicted values is observed:

$$MAE = \sum_{i=0}^{n} \frac{|real\ value_i - predict\ value_i|}{n} \quad (1)$$

While the MAE calculates the mean of the absolute differences, the ECM Mean Squared Error calculates the mean of the squared differences and penalizes the largest errors more, as observed in equation 2:

$$ECM = \sum_{i=0}^{n} \frac{(real\ value_i - predict\ value_i)^2}{n} \quad (2)$$

The absolute error value and square error are calculated for three types of algorithms. Subsequently, these values are averaged, obtaining the results in Table 2. Of the three methods used, the Decision Tree Regression method is the most accurate since its mean absolute error and its mean square error are closer to zero.

Table 2. Mean absolute error and mean square error

	Lineal regression	Decision Tree Regression	Random Forest Regression
Mean absolute error	1.08	1.12	0.87
Root mean square error	4.55	2.08	1.09

Furthermore, we can use the mathematical indicators to obtain the experimental results based on the parameters of the confusion matrix using false positives (FP) where the model incorrectly classifies an instance as positive when it is negative. False negatives (FN) correspond to an erroneous classification of an instance as negative when it is positive. From this we can calculate the Total False Positives (FPR) using the Total Negatives (TN) parameter with the following relationship: FPR = FP/(FP+TN). And on the other hand, we can have the false negative rate (FNR) using the true positives (TP) to obtain the relationship: FNR = FN/(TP+FN).

The number of false positives and false negatives activates the frost protection system. (The critical temperature for ignition is 1.1°C). As can be seen in Table 3, there are four protection failures in linear regression, 7 in the Decision Tree Regression method, and 4 in the Random Forest Regression method.

False positives are less harmful than false negatives since in the case of false negatives they do not activate the protection against frost, therefore the crop would be damaged. For this reason, the value of the protection activation indicator was increased to 1.7°C, reducing the prediction errors (Table 4).

Table 3. False positives and false negatives with 1.1°C indicator

	false positive	false negative
Regression lineal	1	3
Decision tree regression	2	5
Random forest regression	2	2

Table 4. False positives and false negatives with 1.7°C indicator

	false positive	false negative
Regression lineal	1	0
Decision tree regression	2	2
Random forest regression	1	0

Fig. 11 shows the difference between the actual value and the predicted value with the Random Forest Regression method. Finally, to monitor the operation of the system, the efficiency of the prediction algorithm, and the predictions of frost occurrence, an Android application was developed. This application allows you to display updated data in real time (Fig. 12).

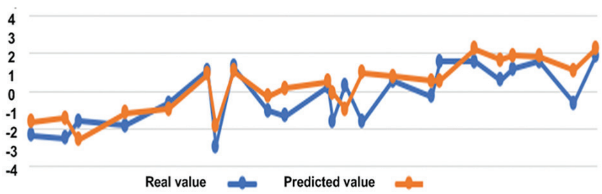

Fig. 11. Comparison between actual and predicted value.

Fig. 12. WARU application (frost monitoring)

6. CONCLUSIONS

The automation of the deployment of the frost protection system was successfully implemented, starting with the reading of the sensors in end-devices and then analyzing the data in the base station. This station issues an order to activate the solenoid valve to activate sprinkler irrigation. In addition, the deployment of the protection system is conducted by turning on a led, to indicate the activation of the opening of the solenoid valve that allows the passage of water towards the sprinklers.

The results of this research provide a specific approach for the deployment of the frost protection system, describing the sensor reading process until the activation of the solenoid valve, while researchers such as Skendžić [24] only broadly describe the impact of climate change on crops and offers a more general vision of monitoring techniques in agriculture. In addition, this paper focuses on practical and technical aspects, unlike works such as Talsma [23], which only show prediction models and algorithms without practical integration in the field or an overview of the benefits of sprinkler irrigation in the case of Yan [15].

The frost detection algorithm was successfully developed, entering historical meteorological data which influences the accuracy of the different models, for which a greater amount of meteorological data is needed to improve the prediction system. The results of the prediction algorithm have an acceptable error range, where the protection activation indicator is increased from 1.1°C to 1.7°C to reduce it. These changes turn out to be positive, as they decrease false negatives from 3 to 0 in the linear regression method, from 5 to 2 in the Decision Tree Regression method, and from 3 to 0 in the Random Forest Regression method.

On the three models evaluated, the Random Forest Regression method has better reliability with 80.91% accuracy and mean absolute error and mean square error close to zero. In addition, it has zero incidences of false negatives, avoiding damaging crops in the event of a frost.

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