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Smart irrigation system based on IoT and machine learning

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Abstract

Traditional agriculture has been the pillar of development on the planet for centuries. But with exponential population growth and increasing demand, farmers will need water to irrigate the land to meet this demand. Because of the scarcity of this resource, farmers need a solution that changes the way they operate. With the advent of new technologies, the notion of Agriculture 4.0 has become a reality to keep up with and meet the demand. With the addition of artificial intelligence and IoT through the collection and processing of agricultural data, decisions have become more and more precise to facilitate decision-making. This paper proposes an intelligent and flexible irrigation approach with low consumption and cost that can be deployed in different contexts. This approach is based on machine learning algorithms for smart agriculture. For this, we used a set of sensors (soil humidity, temperature, and rain) in an environment that ensures better plant growth for months, from which we collected data based on an acquisition map using the Node-RED platform and MongoDB. We used many different models based on the collected data: KNN, Logistic Regression, Neural Networks, SVM, and Naïve Bayes. The results showed that K-Nearest Neighbors is better with a recognition rate of 98.3% and a root mean square error (RMSE) of 0.12, compared to other models (LR, NN, SVM, NB). and towards the end, we provided a web application that brings together the various data emitted by the sensors as well as the prediction of our models to allow better visualization and supervision of our environment.

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Keywords: Smart irrigation; Machine learning; Internet of Things; Agriculture 4.0; Web app

1. Introduction

Agriculture 4.0 or precision agriculture is a technology of agricultural supervision that detects, calculates, and reacts to inconsistencies within the same environment and other environmental yields. The main objective of the study of agriculture 4.0 is to provide a judgment support system to manage the whole field of agriculture to optimize

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the profits on the inputs as well as the conservation of the resources. . Predicting the pumping and effect of different fertilizers using remote sensing and crop health sensors are the first steps towards Agriculture 4.0 [1,2].

Agribusiness is the term used to see and calculate agricultural yields. The agricultural business blockchain includes animal husbandry, yield production, agrochemicals, agricultural implements, seed supply, and marketing and distribution strategy. Representatives and organizations that affect the food and fiber chain are part of this agri-food structure [3,4].

Water is a scarce and valuable natural resource and above all a necessary element, it must be planned, developed, conserved, managed, and above all used sustainably. Optimal management of available water resources at the farm level is necessary due to increasing demands and limited resources. It is important to increase crop yields under limited water sources for optimal crop production to meet future food production needs. The limited water supply should be used efficiently to irrigate more areas with the same amount of water [5,6].

In recent years several researchers have used artificial intelligence systems and the internet of things to deal with irrigation problems precisely using linear models.

In [7], the authors carried out an irrigation control model by detecting soil moisture deficit in root zones (RZSMD) using the notion of real-time, and for this, the authors used a system of identification of the water balance data to obtain a linear time series model. In [8], the authors proposed a soil moisture prediction system for a lychee orchard using the Deep Long Short-Term Memory (LSTM) model, which is a linear time series model that uses sequential processing over time. The authors in [9] proposed a support system for the automatic decision of intelligent irrigation (SIDSS) this system allows the estimation of the need for irrigation for one week and by using two models, the PLSR (Partial least Squares Regression) which is a linear model and the ANFIS (Adaptive Neuro-Fuzzy Inference System) which is a layered model.

However, these models allow better control of irrigation but combining it with data analysis techniques makes their sampling very slow and limited to the region where it is calibrated.

In this paper, we aim to propose an irrigation prediction approach to efficiently manage intelligent automatic irrigation. We proceeded in four steps:

i. Installing the sensors (soil moisture, temperature, and rain).
ii. Linking the set of sensors to an acquisition system,
iii. Using the Node-RED platform whose objective is to facilitate supervision, storage, and notification, and
iv. Processing the collected data using many algorithms namely: KNN, neural networks, support vector machine, Naive Bayes, and Logistic Regression. The results showed that the KNN algorithm has a better decision-making rate compared to the others, with a rate of 98.3%.

This approach will be of great use in the case of large-scale irrigation systems or domestic applications. This will make the heavy task of watering plants easier on the one hand, and better water management on the other.

The rest of the paper will be presented as follows: The second part will be devoted to the definition of agriculture 4.0, artificial intelligence, and the mathematical resolution of linear model treatment. The third part will present the creation of the database, the approach, the results, and finally a conclusion and perspectives.

2. Related works

2.1. Agriculture 4.0

Agriculture 4.0 is a term that encompasses general agriculture but this time with precision in the entire value chain of a food product starting with the type of soil, climate, irrigation methods, amount of water used, and crop recovery. To ensure this, we will need the different tools available to have an agriculture 4.0 or agriculture of the future. In recent years, the industry ecosystem has invested in innovation in terms of technological development, focusing mainly on low-cost and highly efficient actions in terms of production with knowledge-based development acquired through years of visualization and data collection that has paid off in developing an IoT system based on smart irrigation and water reuse that has saved 5.5 billion m3 each year as well as an energy-saving of 44% of total water withdrawal. China has about 20% of the world's population with a very limited water rate of 6%, this data has prompted the Chinese government to develop and create tools to promote Water-Saving Irrigation (WSA) and move towards Agriculture 4.0 by creating solutions based on cloud computing and the Internet of Things (IoT) as well as SOA technology to solve the problem of scarcity of an important element for agricultural production, namely water [10,11].

2.2. Artificial intelligence for agriculture

Artificial Intelligence for Agricultural Innovation (AI4AI) is a new principle that is beginning to gain the confidence of the scientific community. Agriculture is experiencing rapid adoption of artificial intelligence (AI) and machine learning (ML) in terms of both agricultural products and agricultural techniques in the field. Cognitive computing is becoming the most disruptive technology in agricultural services, as it can understand, learn, and respond to different situations (based on learning) to increase accuracy. Currently, Microsoft is working with 175 farmers in Andhra Pradesh, India, to provide advisory services for seedlings, land, fertilizer, etc. This initiative has already resulted in an average 30% higher yield per hectare compared to last year [12].

Support Vector Machine

SVM is a discriminative classifier formally defined by a separation hyperplane. Thus, using labeled training data, SVMs can produce a hyperplane that categorizes the new unlabeled data. Then, a training set (yi; xi); i=1,2..., n where xi ∈ R n represents the itch vector and yi ∈ R n, represents the target element. Many types of SVMs have been developed to accommodate different types and more importantly complexity of problems. The linear SVM, used in this study, produces the optimal hyperplane in the form:

$$f(x) = w^T * x + b \tag{1}$$

Where: $yi\left(w^T * x + b\right) \geq 1 - \xi_i; \xi \geq 0$; or each $i = 1, 2, \ldots, n$

SVM models can be used with different kernels: linear, polynomial, radial basis function, and sigmoid. The kernel function is a point product of input data points mapped into a higher dimensional feature space by ξ transformation [8]

Naïve Bayes

Naïve Bayesian is a probabilistic machine learning algorithm that is based on Bayes' theorem developed by Thomas Bayes (1702–1761) [13]. This theorem can be expressed as the probability of A occurring given that B has already occurred. Considering $X = (x_1, \ldots, x_n)$ as the features and Y as the class variable. The specificity of the NB algorithm is that it considers that the features are independent and that changing one feature does not affect any other. Although it seems simple, NB has proven to be an effective classifier [9].

Neural Network

The neural network [10] can perform an arbitrary mapping from one vector space to another vector space. These neural networks can use a priori unknown information hidden in the data, but they are not able to extract it. It should be noted that in mathematical formalism [14], learning means adjusting the weighting coefficients so that certain conditions are met. To define a neural network, we first introduce the linear model defined as:

$$g(x, w) = \sum_{i=1}^{P} w_i f_i(x) \tag{2}$$

Where the vector w is the parameter vector of the model, and the functions f (x) are non-parametric functions for the variable x. Neural networks are included in the category of models that are non-linear in their parameters. The most common form of static neural network is a simple extension of the previous relationship:

$$g(x, w) = \sum_{i=1}^{p} w_i f_i(x, w') \tag{3}$$

Where $f_i(x, w^i)$ are parameterized functions, called "neurons". The output of a neuron is given by the equation

$$y = f[w_0 + \sum_{i=1}^{n} w_i x_i] \tag{4}$$

Logistic regression

Logistic regression is a model used when the dependent variable is categorical either (0 or 1), (True or False), or (On or Off) [11].

The logistic function is in the form:

$$p(x) = \frac{1}{1 + e^{-(x-\mu)/s}} \tag{5}$$

where μ is a location parameter (the midpoint of the curve, where $p(\mu) = \frac{1}{2}$ and s is a scale parameter [15].

K-Nearest Neighbors

K-Nearest Neighbors [12] is a simple algorithm that stores all available cases and ranks new cases based on a similarity measure.

If we want to classify a case using the KNN approach the case is classified by a majority vote of its neighbors, and the case is assigned to the nearest class among its k nearest neighbors measured by a distance function [16].

Among the on-site distance functions:

- ✔ Euclidean: $$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{6}$$
- ✔ Manhattan $$\sum_{i=1}^{k}|x_i - y_i| \tag{7}$$
- ✔ Minkowski: $$(\sum_{i=1}^{k}(|x_i - y_i|)^q)^{\frac{1}{q}} \tag{8}$$

2.3. Compared previous work on supervised machine learning

Table 1 presents different previous works with machine learning models used, features, experimental, and simulation:

Table 1. Previous work on supervised machine learning models.

Reference	Supervised model	Features	Experimental		Simulation
			Edge	Cloud	
[17]	Linear regression	This paper allows the prediction of required irrigation water and this using a database collected through several detection sensors	✔	✔	✔
[18]	KNN, SVM, Logistic regression	This paper model presents a system for forecasting the amount of water required in real-time by plants for irrigation and using several sensors	✔	✔	×
[19]	SVM, KNN, Naïve Bayes	These models enable threshold-based classification using sensor data in a cloud database “ThingSpeak”. • Accuracy SVM:87%, Naïve bayes: 76%, KNN:71%	✔	×	✔
[20]	KNN, SVM	This model is used for the detection of infection on several plant samples without forgetting the real-time monitoring of temperature and soil humidity. • Accuracy: 96%	✔	×	✔
[21]	KNN	The algorithm used here is dedicated to the analysis and monitoring of agricultural images taken by drones	✔	×	✔
[22]	SVM	This model allows the adjustment of the amount of irrigation automatically in a domestic plant environment	×	✔	✔

3. Discussions

3.1. Context

In this paper, we present all the steps we followed to realize the irrigation system. Fig. 1 shows the different steps followed for the realization of this smart irrigation system. To do this, we started with the first step which consists of choosing the sensors necessary for the realization of the model starting with the soil moisture sensor

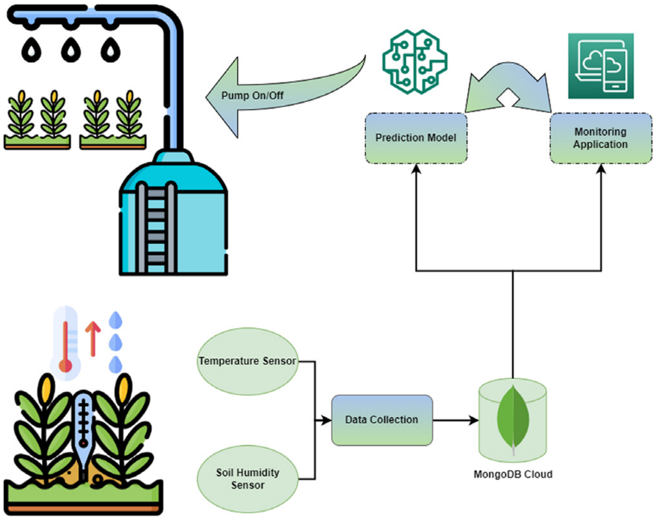


Fig. 1. Proposed irrigation system.

which is used to present the level of soil moisture, and then the temperature/humidity and rain sensors. Once the sensors are connected to the Arduino board, we start programming the board to operate the sensors in such a way as to have the different data grouped and transmitted in real-time. After that, we ensured the storage of the data using Node-Red and MongoDB, we grouped months of data which allowed us to train these data to be able to predict the start or stop pumping.

3.2. Data collection and storage

Afterward, we used the Node-RED platform to facilitate the creation of the connected object, but especially to connect a system to supervision and storage platforms. It is with the same objectives that we have preceded, that we began to retrieve and visualize data from sensors. This step consists of connecting our card with the Node-Red environment and making a system based on the data flow received from the sensors and making a preprocessing for each data (see Fig. 2).

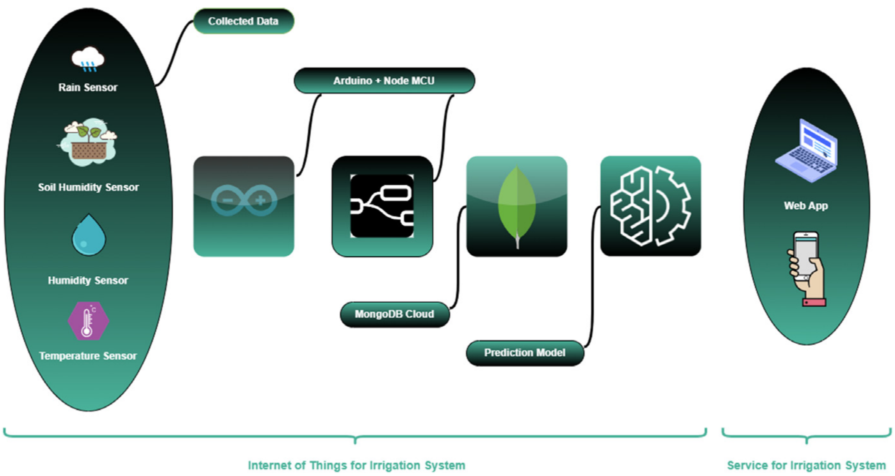


Fig. 2. Irrigation System from Dashboard to Services.

Among the data processed through several algorithms and with the help of experts in the field of agriculture, we were able to collect different types of data:

✓ Data collected through the sensors: Temperature, air humidity, soil humidity, and rainfall data.
✓ Data collected through water pumps: Pumping data (On/Off)

Fig. 3 shows the flow used for data acquisition and storage:

✓ Arduino node: This node allows the connection between the node-red server and our Arduino card.
✓ Preprocessing node: This node is used to allow the splitting of data emitted by the sensors.
✓ Soil Humidity, Air humidity, Temperature, and Rain nodes: These nodes are used for the extraction of specific data emitted by the preprocessing node.
✓ Notify node & Mail node: These nodes allow the sending of a set of notifications by email to allow good monitoring of our sensors.
✓ MongoDB nodes: This allows the storage of data emitted by the sensors directly on MongoDB storage.
✓ Local data node: Allows local data storage.
✓ Dashboard nodes: Allows real-time data visualization as mentioned in Fig. 4

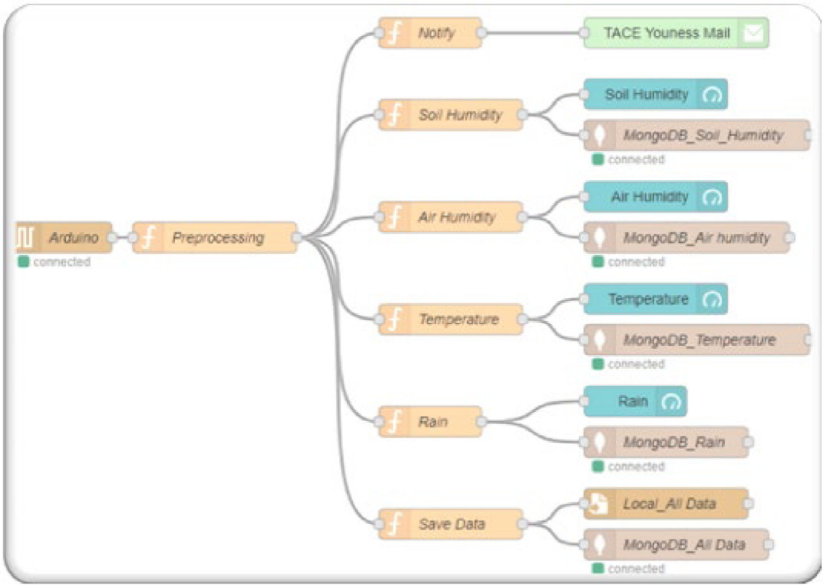


Fig. 3. Node-Red flow is used to split, store, notify and visualize data.

In our system, two storage methods have been proposed, both using the MongoDB solution:

- Local MongoDB: Through the Node-Red flow connectivity shown in Fig. 5 with a local MongoDB server to train data through multiple prediction models.
- MongoDB Cloud Fig. 6: This storage part sends data to the cloud through a python function, and it is dedicated to the application to allow the reception of data and the prediction of pumping in real-time and allows visualization in time actual state of the environment.

3.3. Dataset

With the help of IoT technologies, made up of a multitude of autonomous devices in the form of sensors capable of self-organization and working to collect information, we began to implement these devices in various environments containing several domestic plants in the mass collection process for the absolute need of information,

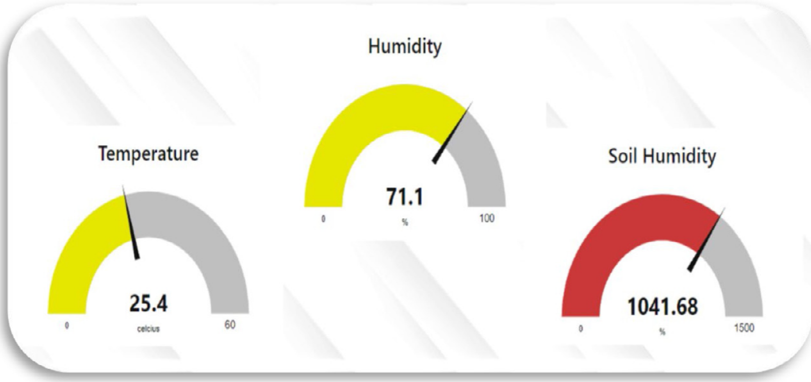


Fig. 4. Node-red Supervision system.

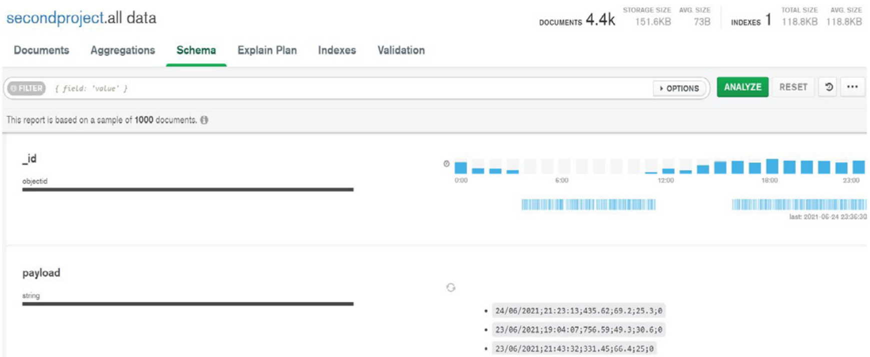


Fig. 5. Scheme of data collected in MongoDB Local.

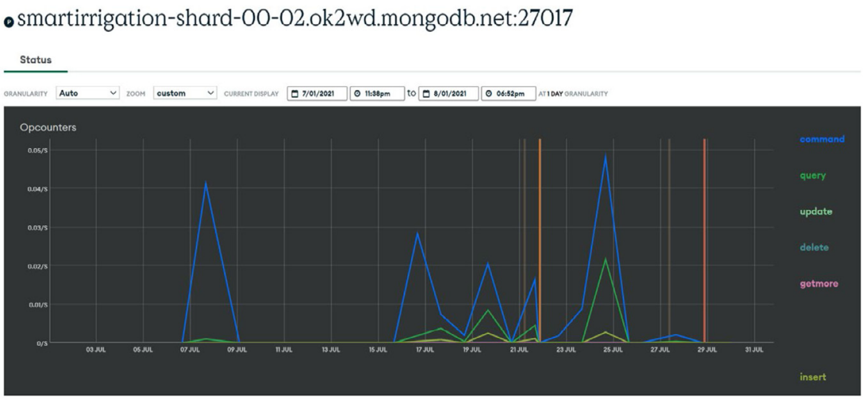


Fig. 6. Charts presented all used commands in MongoDB Cloud.

which was a near-total implementation of our Dataset implemented to deploy the data using an algorithm to generate a very important console during the expansion of our system.

At the crossroads, we find the incoming data from the centralized sensors on the timestamping data, and digital data, accompanying this expansion we find:

- Soil moisture data: This data is emitted by an analog sensor in a data interval between the value 0 and the value 1023, which is illustrated in the table, we notice that the minimum value is 314.47 and the maximum value is 987.83, so the average value is 384.5.
- Temperature data: These data are becoming more and more important, and they have been collected thanks to a temperature sensor which presents the state of the temperature in Celsius, we see that the average temperature during these months of the collection is 26, 34 °C and the minimum value is 18 °C without forgetting the maximum value is 39 °C, to subsequently overcome its limits proof of expectations.
- Air humidity data: With the same sensor that ensured the collection of temperature values, we managed to collect humidity data, for an analysis passage of these data which is as follows: the average is 66.4%, and the minimum value is 38% and the maximum value is 81.3%, while collects the massive data pass.

In the race for computerization, we find the Output data: For this, we have proposed an architecture based on the peer-to-peer principle which resides in categorical data between a value “0” which means that pumping must be stopped, and a value “1” which means that pumping must be activated.

To conclude, we have carried out a partial implementation of the final architecture while demonstrating the feasibility to be far from a generalized failure.

3.4. Model result

This graph in Fig. 7 presents a schematic manipulation of data consisting in creating considered modeling of the results obtained in a way that allows reporting on the dentition plan to concretize it as a certain result, in connection with this practice, the prognoses remain in many respects since they are by nature inductive, then we find the empirical observations which are universally summed up by peer-to-peer identification which categorizes two different colors, the first is the color red as a synonym of knowledge at category “0” judged by the pumping that relies on a temperature versus and with a humidity deviated towards deactivation. While a green color manifests category “1” which is based on temperature pumping versus influenced at the same time by active humidity.

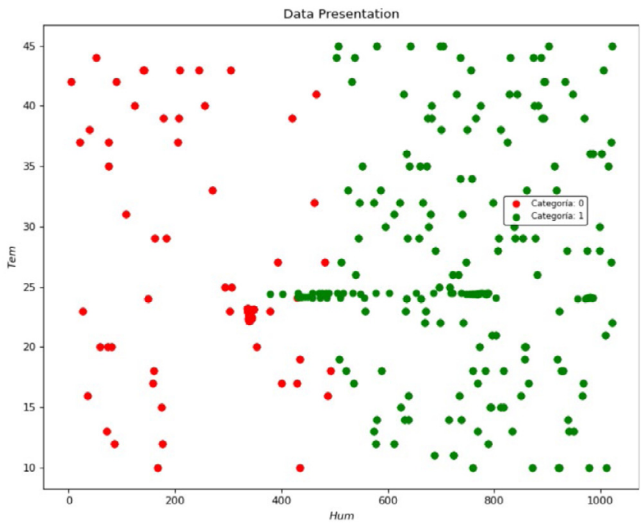


Fig. 7. Data presentation.

The presentation of the Predefined sections of the plants consists in using massive data and training it using a multitude of methods and algorithms to be able to extrapolate it from the events that have occurred to better predict future events and deduce the forecasts of our irrigation system, to promote future trends that will necessarily materialize. The likelihood is then possible depending on the algorithms chosen as to the actual occurrence of the output data, therefore the use of the following algorithms: neural network, support vector machine (SVM), logistic regression, Naïve Bayes, and K-Nearest Neighbors (K-NN).

Table 2. Present analysis data.

	Incoming data			Outgoing data
	Soil moisture data	Temperature data	Air humidity data	Pump data
Mean	384.50	26.34 °C	66.4%	–
Min	314.47	18 °C	38%	0
Max	984.83	39 °C	81.3%	1

Table 3. Results data training model.

Models	Parameter	Accuracy	(RMSE)
K-Nearest Neighbors	K = 3	98.3%	0.12
Neural Network	Sequential, Epochs = 50	97,2%	0.16
Naïve Bayes	GaussianNB	97%	0.17
Support Vector Machine	Linear SVC	96,7%	0.17
Logistic Regression	Logistic Regression	96.2%	0.19

Specifically, the following table (Table 3) uses the various tests carried out to train the predictions, in a framework of exploration of the relevant data from a pre-sorting which reveals the following results, then we can note that the K-NN model signed a rate of 98.3% in a training set and (RMSE) of 0.12, comparing with Neural Network, Gaussian Naive Bayes, SVM and logistic regression with successive result warehouse : (97,2%/ 0,16), (97%/ 0,17), (96,7%/ 0,17) and (96,2%/ 0,19). All this is to assess the potential benefits to properly determine the data that arises (see Table 4). .

Before applying models, we decided to standardize the data and then separate the data between the test data and the training data to have a better application of our model and to come out with better accuracy. We used a neural network classification based on a precise number of periods, and in each period, we will be able to visualize the accuracy of the data as well as the lost data.

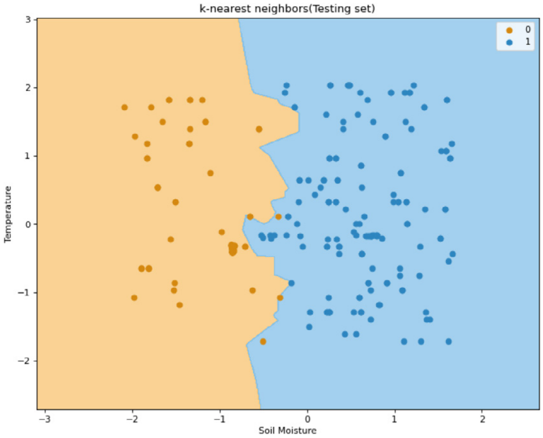
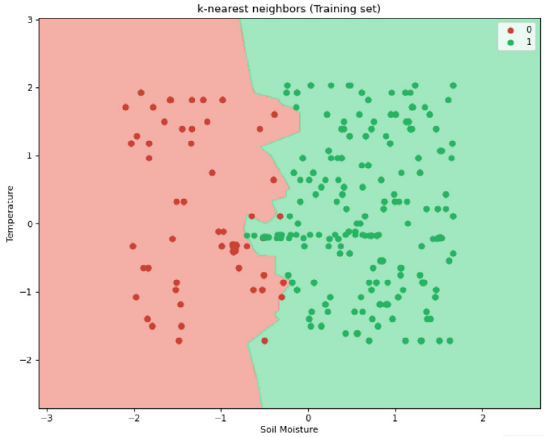
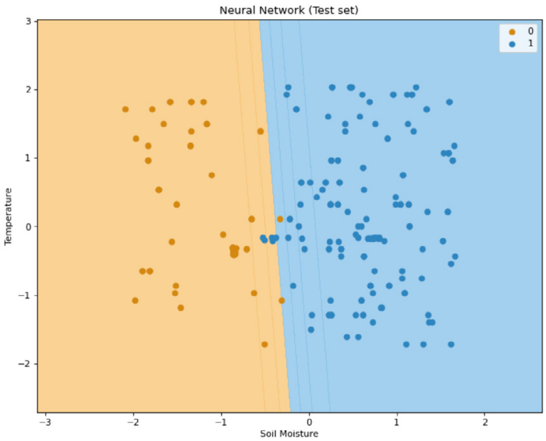
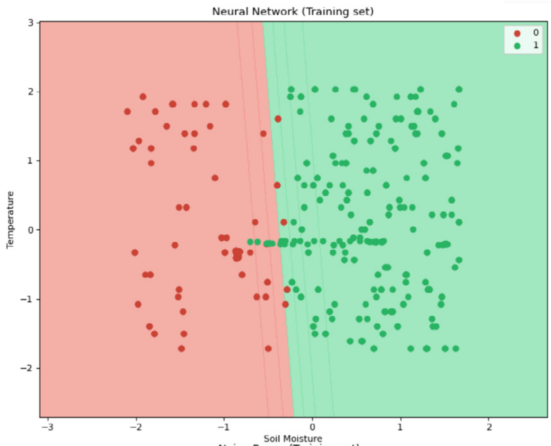
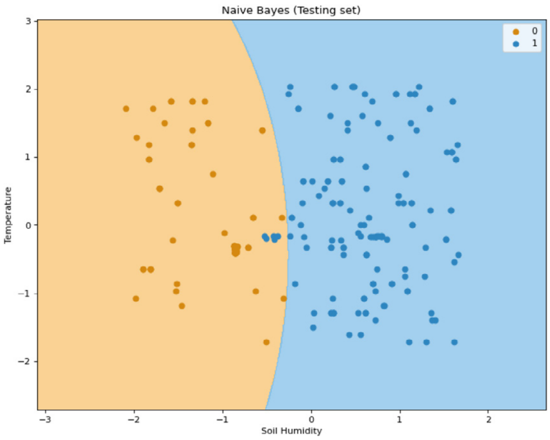
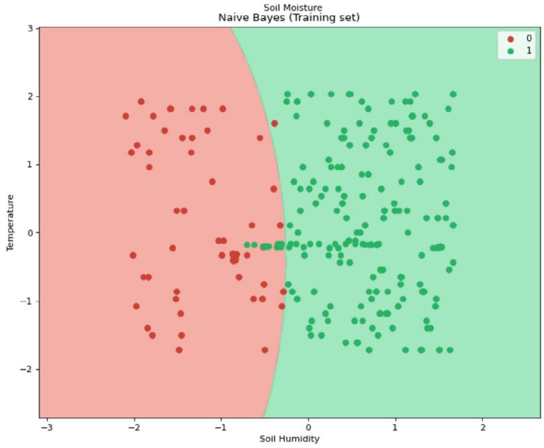
In Table 1 we present the result of the models used in this paper with her parameter, accuracy, and RMSE. Table 2 presents the same result as a graph:

- Line 1 presents the result of the KNN model: we can see the pumping points between "0" presented with orange color in the testing set and red color in the training set and "1" presented with blue in the testing set and green color in the training set. In this line, we see that the model integrates all the data (points) presented in red in their environment and vice versa for data presented in green, which explains the results of this model with a rate of 98.3%.
- Line 2 characterizes a sequential neural network model with 50 epochs, the presented rate is 97.2% and the root-means-square error is 0.16.
- Line 3 shows the results of the Naive Bayes model. We notice a non-linear classification where we have introduced more points in their category between category "0" and category "1". We can see an improvement over the SVM model, with a rate of 97%.
- In Line 4 we illustrate the results of the SVM model where we can see that we have a linear classification that separates the "0" and "1" categories and we see some points that are not in their specific category which is why we have a lower rate of 100% more precisely 96.7%.
- Finally, we have a logistic regression model with the rate of 96.2% and the root-mean-square error a bit close to 0.2

4. Conclusion

Intelligent irrigation is an important step to increasing production to meet the world's food needs, which are expected to increase by more than 70% by the year 2050. It is also about managing the use of water for irrigation. In this paper, we propose an irrigation prediction that starts with the creation of a database using a data acquisition card with multiple sensors (Soil humidity sensor, temperature and humidity sensor, rain sensors) and the Node-RED platform. This allowed us to collect multiple data to be able to use it in our decision support models using machine

Table 4. Graph represents the result of our models.

Model	Graph of Testing set	Graph of the Training set
K-NN		
Neural Network		
Naïve Bayes		

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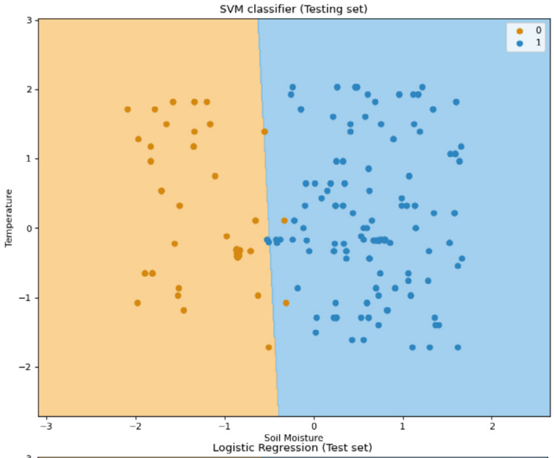
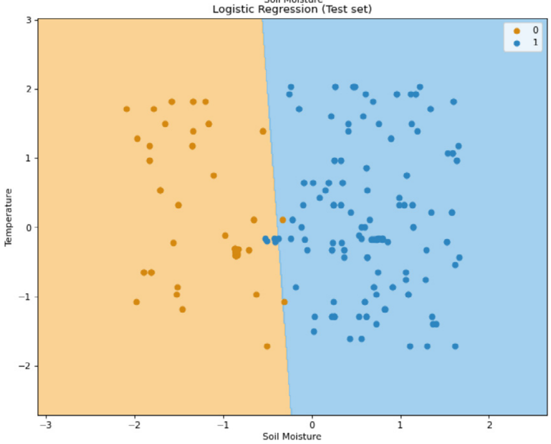
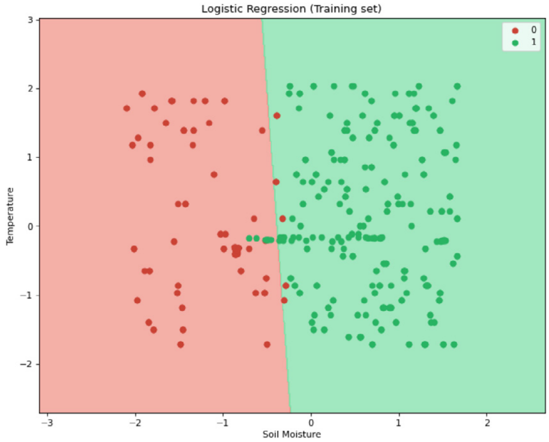
learning. The results showed that K-Nearest Neighbors has a recognition rate of 98.3% compared to other models, and finally present a web application to group all functions carried out throughout this course to facilitate the visualization and supervision of the environment through a simple telephone or laptop. As for the future, we would like to expand the database by integrating other data on the one hand, and on the other hand, use other algorithms but especially semi-supervised learning to ensure accuracy in decision making.

Table 4 (*continued*).

Model	Graph of Testing set	Graph of the Training set
SVM		
Logistic Regression		

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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