Smart Agriculture Using Real-Time IoT-LoRa: Wheat Crop Disease Prediction and Irrigation Management Based on Machine Learning Models

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Abstract: *This paper presents an innovative system for smart agriculture, combining the Internet of Things with Long Range technology (IoT LoRa) and Machine Learning (ML) to respond to two major challenges: 1) Real-time wheat disease detection and intelligent irrigation management. The system is designed to identify and classify three common wheat diseases in Algeria (yellow rust, brown rust, and powdery mildew) using the MobileNetV2 Deep Learning (DL) model implemented on a Raspberry Pi 4 with a camera. The model achieves a significant accuracy, precision, recall, and F1-score of 98%, which enables quick and accurate disease identification. 2) For better optimization of irrigation time, environmental parameters such as humidity, soil moisture, temperature, and light intensity are monitored using IoT sensors. The data of these parameters are transmitted via LoRa protocol for long-range and low-power communication. Then, the data are analyzed in real-time using ML algorithms such as k-Nearest Neighbors (k-NN), Support Vector Machine (SVM) and Random Forest (RF) which, have the best accuracy, precision, recall, and F1-score of 99.8%. Fuzzy logic is also used to facilitate calculations, ensuring efficient use of water in irrigation. Farmers can access this system remotely via a platform and receive real-time alerts on potential diseases and irrigation needs. This integrated approach improves crop health and yield while meeting the challenges of climate change and water scarcity, especially in semi-arid regions like Algeria.*

Keywords: *Smart agriculture, irrigation, IoT, LoRa, crop disease, deep learning, machine learning, fuzzy logic.*

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1. Introduction

Global food security faces significant threats caused by climate change and the rapid spread of plant diseases, which threaten the yield of agricultural production. With the rapid increase in the world population, the adoption of advanced technologies has become essential to ensure sustainable food production. Wheat is one of the most fundamental agricultural crops in the world. It represents a major foundation of food security. However, wheat is highly susceptible to diseases such as powdery mildew, yellow rust and brown rust, which can cause significant yield losses if not detected and managed promptly.

To face these challenges, it is important to develop accurate, rapid and reliable disease detection and irrigation management systems. In Algeria climate is semi-arid Mediterranean characterized by frequent droughts and limited rainfall further exacerbates the challenges faced by farmers. The country, in recent years (2018-2024), has a severe reduction in rainfall, making water scarcity a critical issue for agriculture. As a result, traditional irrigation methods are becoming insufficient, requiring the adoption of smart irrigation systems to optimize water use. In addition, the climatic conditions in Algeria create an environment conducive to the spread of wheat diseases, further threatening crop yields. To face these difficulties, we propose an innovative system that integrates Internet of Things with Long Range technology (IoT LoRa), Artificial Intelligence (AI) for advanced sensing technologies to monitor irrigation and predict crop diseases in real time. Our system consists of:

1. A neural network-based model MobileNetV2 Learning (DL) model for automated, real-time wheat disease recognition, implemented on a Raspberry Pi 4 equipped with a camera for image capture, and module LoRa to send alerts.
2. An irrigation system optimized via sensors

measuring soil moisture, temperature, ambient humidity and light intensity, the collected data by IoT LoRa is analyzed by Machine Learning (ML) algorithms (Random Forest (RF), k-Nearest Neighbors (k-NN), Support Vector Machine (SVM), logistic regression) and fuzzy logic, allowing to dynamically adjust and optimize irrigation. Farmers can monitor environmental conditions and receive alerts on potential diseases and irrigation timing, to ensure timely intervention, Figure 1.

Here is a structured distribution of the contributions:

1. Embedded disease detection: MobileNetV2 implemented on Raspberry Pi 4 connected by camera and a LoRa module, identifies rust and mildew in real time directly on the field.
2. For wheat disease prediction on a Raspberry Pi 4, computing and memory resources are often limited, which makes the use of lightweight models, such as MobileNetV2 is required.
3. Combines in a single system, a hybrid of ML, fuzzy logic and IoT LoRa, addressing both crop health and resource management. This integrated approach bridges the gap between distinct agricultural technologies.

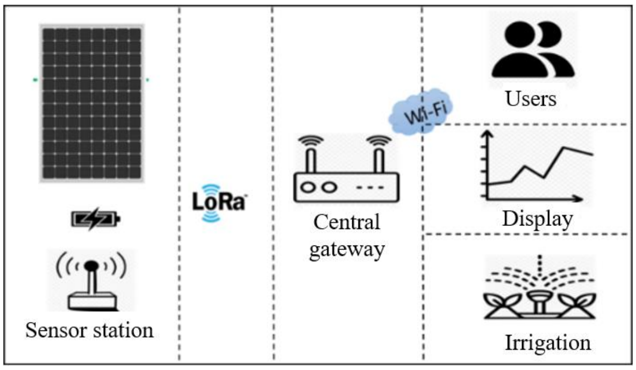


Figure 1. Schematic structure of the proposed IoT based system.

2. Related Works

2.1. Wheat Disease Prediction

Recent advances in IoT and AI have significantly improved disease forecasting and monitoring in smart agriculture. Researchers have developed an Artificial Intelligence of Things (AIoT) system for asparagus growth and disease monitoring, by deploying IoT and AI sensors to track environmental changes, their DL model has achieved high accuracy in pest detection and counting [8]. Bachhal *et al*. [4], on the integration of Pyramid Scene Parsing Network (PSPNet), ResNet-50 and Fuzzy SVM models improved the classification accuracy for corn fungal disease recognition. A hybrid Convolutional Neural Network (CNN) model was proposed in Kaur *et al*. [17] to detect leaf diseases, specifically targeting four grapevine diseases (black measles, black rot and leaf blight) using the EfficientNet B7 DL model by transfer learning. A two-stage system was developed for weather forecasting and disease monitoring [2]. First, the preprocessed data were fed into a Gated Recurrent Unit (GRU) for weather forecasting. Second, the crop images were preprocessed using an adaptive Gaussian filter and classified using ResNet50 for disease prediction. Dang *et al*. [10] compares the performance of different optimizers (Stochastic Gradient Descent (SGD), Adaptive Moment Estimation (Adam), Adamax) in an artificial neural network Artificial Neural Network (ANN) model applied to a dataset collected by a sensor system monitoring fires., the results indicate that the Adam optimizer achieves the highest prediction accuracy, confirming the effectiveness of the ANN model for this type of data. Kong [20], introduces an Unsupervised Video Object Segmentation (UVOS) technique using convolutional networks to improve traditional Video Object Segmentation (VOS) methods, it employs decomposition expressions for spatiotemporal relationships and a Single Linear Bottleneck Operator (SLBO) for feature extraction, optimized by pooling compensation.

2.2. Irrigation Management and Monitoring Systems

Smart irrigation systems have gained popularity as a solution to optimize water usage and improve crop yield. An irrigation system developed to determine water requirements based on EvapoTranspiration (ET) rates [5, 36]. Dahane *et al*. [9] proposed in an edge-IoT cloud platform using DL to monitor, predict, and calculate water requirements. Davide *et al*. [11], presents a multifunctional irrigation system comprising drip emitters and mini-sprinklers was tested in a vineyard, Italy. Kishorebabu and Sravanthi [18], an IoT-based system was proposed to monitor environmental parameters in the Hyderabad region. Kodali and Mandal [19], sensors were used to monitor temperature, precipitation, light intensity, humidity, and pressure, with data being communicated via SMS, email, and Twitter. Benyezza *et al*. [6] presents, an IoT-based zonal irrigation system was designed to improve plant growth conditions while minimizing water and energy consumption. A wireless sensor network was installed in a greenhouse to transmit soil moisture and temperature data to a Raspberry Pi server via radio frequency communication. Elsherbiny *et al*. [14], a hybrid DL approach integrating CNNs with IoT sensor data was proposed for precise irrigation and water status identification of wheat. Talaat [30], the Crop Yield Prediction Algorithm (CYPA), exploiting IoT techniques for precision agriculture. Manikandan *et al*. [22] proposed edge-IoT cloud platform using DL to monitor and predict crop water demands under insufficient rainfall. Dahane *et al*. [9], presents a smart control system integrating IoT sensors and an automatic irrigation system was developed for smart farming.

Finally, Riskiawan *et al*. [25], the integration of IoT and AI was explored for automated environmental control in greenhouses, showcasing the potential of modern technologies in agricultural management.

3. Methodology

This section describes the overall methodology and the main principals of the proposed system. This approach is divided into two parts:

a) An IoT and ML irrigation monitoring and automation system.
b) DL plant disease prediction system.

Figure 2 presents the general scheme of this methodology, illustrating how each system interacts with the other modules to constitute the whole system, system-a) integrates several sensors for measuring plant environmental parameters, connected to an Arduino, and a LoRa SX1278 module to transmit the data to the gateway composed by an author Raspberry Pi for irrigation monitoring via a ML model and Fuzzy Logic, thus allowing their processing and the activation of the remote monitoring function. In addition, system-b) comprises a camera module associated with a Raspberry Pi for disease classification via a DL model, as well as a LoRa SX1278 module for sending alerts to the cloud.

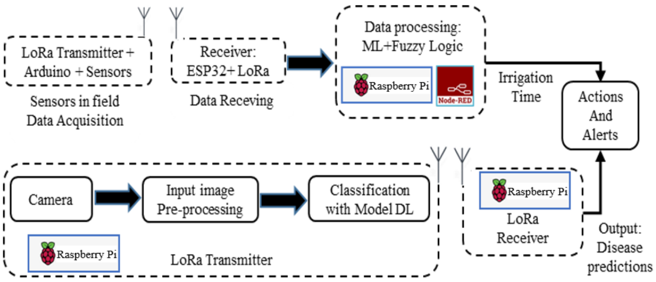


Figure 2. Architecture of the proposed irrigation and disease prediction system.

3.1. Plant Disease Prediction System

To predict wheat diseases in real time we used a Raspberry Pi 4 equipped with a camera. LoRa technology is used to transmit alerts to users. The implementation of the system is illustrated in Figure 2. In order to identify and classify the three wheat diseases, a MobileNetV2 DL model was implemented the Raspberry Pi 4, for in field practical use.

Figure 3. Proposed device for detecting plant diseases.

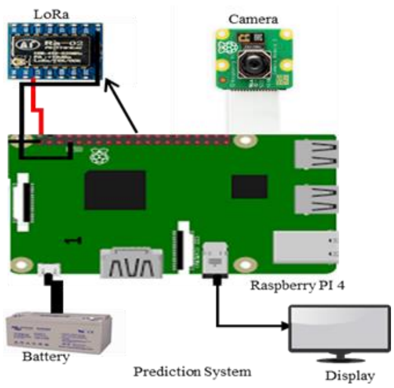


Figure 4. Proposed device for detecting plant diseases plan.

The MobileNetV2 model was trained using Python in a Jupyter environment in Anaconda. Once trained, the model is implemented on the Raspberry Pi 4. The camera connected to the Raspberry Pi 4 is configured to capture images of wheat plants in real time, Figures 3 and 4. These images are processed to detect disease and sends alerts. These alerts are transmitted via a LoRa module connected to the Raspberry Pi 4, Figure 2. This solution provides a flexible, low-power for disease detection in agricultural settings, particularly in remote.

- **Model Used**

In literature, many models used for wheat disease prediction, such as VGG16, GoogleNet, ResNet50 and MobileNetV2. Table 1 compares and summarizes the performance of these models, the trade-offs between accuracy, complexity, and inference speed of CNN architectures. Heavyweight models like VGG16 and ResNet50 achieve very high accuracy (99.77% and 98.67%, respectively) but require substantial computational resources, making them better suited for cloud computing environments, and GoogleNet represents a balanced compromise in terms of performance and efficiency. In contrast, lightweight models such as MobileNetV2 with a much lower number of parameters, allow for very fast execution, making them ideal for field applications, especially when deployed on embedded devices like drones or IoT systems.

Table 1. Comparison table of CNN models.

Model	Accuracy	Parameters	Speed	Reference
VGG16	99.77%	Very heavy	Slow	Tufa *et al.* [31]
ResNet50	98.67%	heavy	Moderate	Demmese *et al.* [12]
GoogleNet	99.58%	medium	Moderate	Yang *et al.* [34]
MobileNetV2	99.53%	light	Very Fast	Lu *et al.* [21]

In the proposed system, an application is required on the Raspberry Pi for image classification. The Raspberry Pi is chosen for its low power consumption, which is essential for our case. However, due to its limited memory and processing speed, MobileNetV2 is an excellent choice because of its simplicity, speed, and acceptable accuracy.

The model is evaluated using a loss function and metrics such as accuracy. In our case, we use the categorical cross-entropy loss function, the equation this function is as follows:

$$Loss = -\sum_{i=1}^{N} y_i log(p_i) \quad (1)$$

Where:

N: is the number of classes.
Yi: is the true label (0 or 1, one-hot encoded).
pi: represents the predicted probability for class i.

- Metrics: to assess the model's performance. they provide information about the quality of the model. In our case, the metric used is accuracy, which calculates the proportion of accurate prediction.

The equation for *Accuracy* is 003A

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ Number\ of\ Predictions} \quad (2)$$

Where:

- True positives represent the model predicts positive.
- True negatives represent the model predicts negative.

In summary, compiling a model with these parameters defines how the model will be trained and evaluated. The Adam optimizer adjusts the weights, the categorical cross-entropy loss function measures errors for multi-class classifications, and accuracy is used to track overall model performance during training and evaluation.

- Precision: among the images predicted as belonging to a given class, this measures the proportion of them that are actually correct:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (3)$$

- Recall: among the images actually belonging to a given class, this is the proportion correctly detected:

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (4)$$

- F1-score: harmonic mean of precision and recall, particularly useful for imbalanced or multi-class datasets, as it balances the two:

$$F1 = \frac{Precision * Recall}{Precision + Recall} \quad (5)$$

- Shannon entropy: to assess the balance of the dataset, we used Shannon entropy *H*, calculated as follows:

$$H = -\sum_{i=1}^{k} p_i log(p_i) \quad (6)$$

p_i is the proportion of samples in class *i* among the *k* classes. This measure reaches its maximum value (*log k*) when all classes are equally likely, and tends to zero when one or a few classes dominate the distribution. To facilitate comparisons between datasets with different numbers of classes, we normalize this value by *log k*, thus obtaining an index between 0 (unbalanced) and 1 (perfectly balanced).

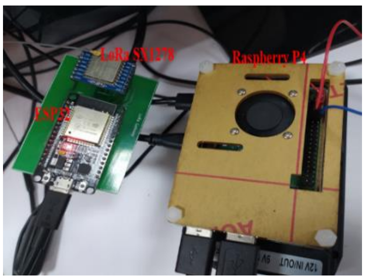
3.2. IoT System for Smart Irrigation

For real-time irrigation monitoring, we used plant parameter measurement sensors, connected to an Arduino, and a LoRa SX1278 module. The implementation of the system is illustrated in Figure 2. In order to calculate the irrigation time, a Machine Learning model was chosen and implemented on the Raspberry Pi 4. Soil moisture, gives a direct indication of the amount of soil water available to plants. Meanwhile, ET, which represents the loss of water through evaporation from the soil and transpiration from plants, is calculated from climatic variables such as temperature, air humidity, wind and sunshine. By integrating these two parameters into the machine learning model, with the assistance of fuzzy logic, we can predict the irrigation duration needed.

3.2.1. Hardware and Methods

This study utilizes cutting-edge IoT technology integrated with the LoRa protocol. The system employs an SX1278 LoRa module connected to an Arduino mega board, powered by 20W solar panels with 12V batteries Table 2. The station contains three sensor nodes: Node-Sensor1 detects ambient temperature, humidity, and soil moisture, Node-Sensor2 measures soil temperature and pH levels and Node-Sensor3 measures wind speed, direction, and rainfall across the agricultural field, as illustrated in Figures 5-a) and 6. These configurations are illustrated in Figures 5 and 6. The gateway, consisting of an ESP32, a Raspberry Pi 4, and a LoRa module, receives and processes data, as depicted in Figures 5 and 6 [23, 24, 26, 28].

a) Sensor's station (Arduino+LoRa SX1278+sensors).



b) Gateway (RaspberryP4+ESP32+ LoRa SX1278).

Figure 5. IoT system for smart irrigation.

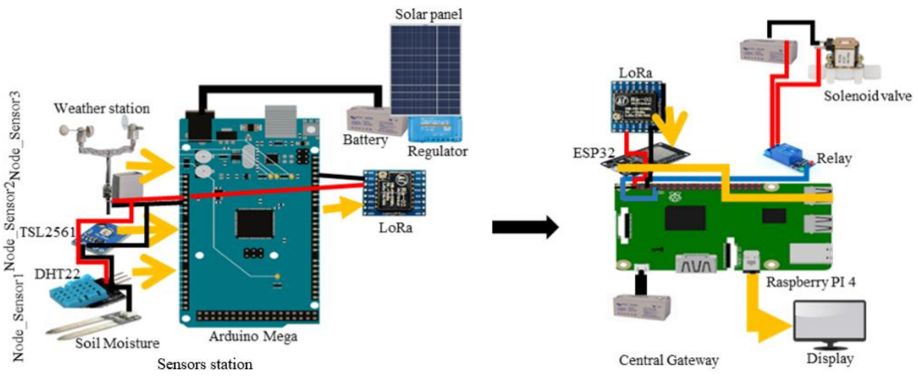


Figure 6. Irrigation system monitoring plan.

Table 2. Hardware specification.

Component/Sensor	Operating voltage (V)	Mode/Function
Raspberry Pi 4 (4GB)	5 V	Full linux computer
ESP32	3.3 V	Microcontroller with Wi-Fi
Arduino mega	5 V	Microcontroller with many I/O ports
SX1278 LoRa modules	1.8-3.7 V	LoRa communication: RX/TX/sleep/range of up to 2 km in open terrain
DHT22 (AM2302)	3.3-6 V	Temperature and Humidity sensing
Soil moisture sensor (FC-28)	3.3-5 V	Analog/Digital soil moisture sensing
Soil temperature sensor (DS18B20)	3.0-5.5 V	Measures soil temperature
Raspberry Pi camera module Rev 1.3	3.3 V	Image and video capture
Weather meter kit	5 V	Weather monitoring (wind, rain, etc.)
pH Sensor	5 V	pH measurement
Water flow sensor (12V)	12 V	Measures water flow rate
TSL2561 (light sensor)	2.7-3.6 V	Ambient light sensing (I²C)
Solenoid valve	12 V	Controls water (ON /OFF)
Relay module 12V	12 V	Switch high-power devices
Solar panel 20W	12 V	Converts sunlight into electrical energy
Charge controller 12 V	12 V (input/output)	Regulates battery charging from solar panel
Batteries	12/9/5V	Stores energy for powering the system

3.2.2. Data Processing

The data received by the gateway node (ESP32, Raspberry Pi 4, LoRa), as shown in Figure 5-b), is processed via the Node-RED platform. The data processing environment in Node-RED uses node functions to separate the different data values, organizes their structure and sequence. Node-RED is the main environment to manage operations in the gateway Figure 7.

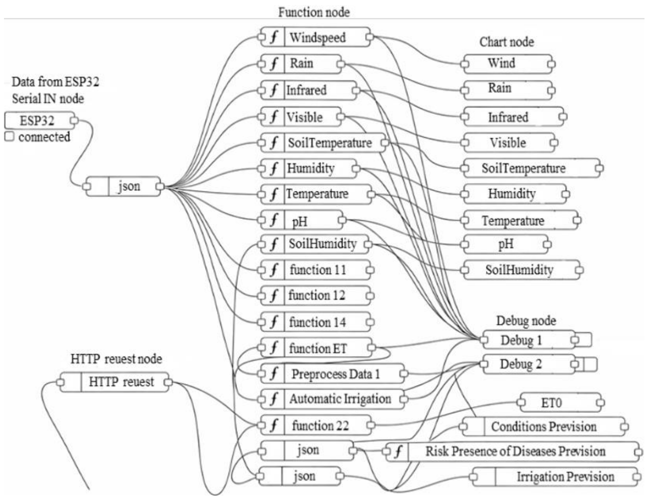


Figure 7. Node-red environment in Raspberry Pi 4.

In our work, we chose to use the Node-RED environment with the Application Programming Interface (API) interface in the Raspberry gateway, a powerful approach that combines two technologies for a robust and flexible IoT. Node-RED is a tool in the environment that simplifies the management of data flows between IoT devices. FastAPI serves as a robust backend to manage API requests and process data, while Node-RED coordinates these data flows, automates processes, and seamlessly integrates multiple systems, Figure 8.

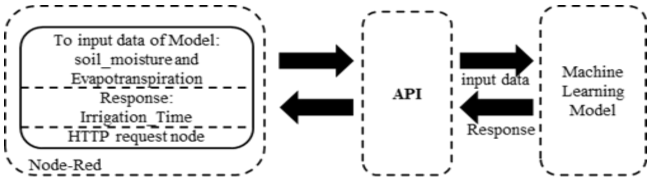


Figure 8. Schema illustrating the integration of node-red, API block, and our model for automated irrigation.

3.2.3. Evapotranspiration Equation

ET is the result of two processes: [3, 5, 32, 35, 36], Evaporation represents water loss from the soil, and transpiration represents water loss from the crop. To calculate ET, the penman-monteith equation is used to determine the amount of water lost through both evaporation and plant transpiration. The Food and Agriculture Organization (FAO) recommends this method for the daily estimation of reference evapotranspiration ET_p, according the FAO-56 PM method, taking into account the different climatic variations, as shown in Equation (7) [3, 5, 7, 15, 32, 35]:

$$ET_p = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (7)$$

Where:

ET_p: represents the penman-monteith reference evapotranspiration (mm day-1).
Rn: represents the net solar radiation (MJ/m2/day).
G: represents the ground heat flux in (MJ/m2/day) can be ignored.
T: represents the average air temperature in degrees Celsius (°C).
u_2: represents the wind speed at a height of 2 meters, measured in meters per second (m/s).
(es-ea): represents the saturation vapor pressure (kPa).
Δ: represents the slope of the saturated vapor pressure curve (kPa/°C).
γ: represents the psychrometric constant (kPa/°C) is equal to 0,66.

3.2.4. Models Used in Machine Learning for Irrigation

For precise irrigation management, the illustrated in Figure 9, to analyzes various environmental parameters collected by the sensors, in addition to monitoring soil moisture thresholds, then calculates the daily water losses through evapotranspiration (ET_P) to optimize the irrigation, using the ML model with Fuzzy logic. Through this approach, water use efficiency is improved, thereby reducing costs and increasing crop yield.

The model calculates irrigation based exclusively on soil moisture and reference evapotranspiration (ET_o) estimated according to the penman-monteith method (FAO-56), without applying a coefficient specific to wheat.

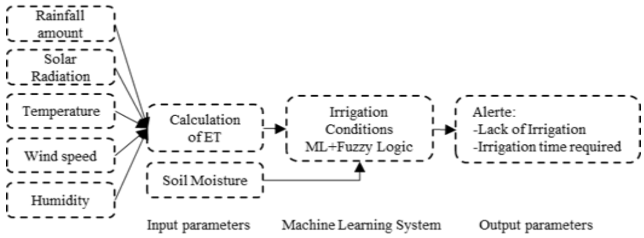


Figure 9. Precision irrigation management.

To get access to ML models, Scikit-learn is the most powerful library for ML in Python with Jupiter, providing a range of effective ML tools for modeling, notably in classification. The models used are as follows:

1. Logistic regression: a supervised linear classification algorithm widely popular in ML. Architecture and key functions:

Linear combination of inputs

$$z = w.x + b \quad (8)$$

where w denotes the weight vector and b represents the bias term.

Sigmoid function to obtain the probability

$$P(Y = 1 \mid x) = \sigma(z) = \frac{1}{1 + e^{-z}} \quad (9)$$

Cost function to measure the performance of the model

$$Cost(y, \hat{y}) = \frac{1}{m}\sum_{i=1}^{m}[y^{(i)} \, log(\hat{y}^{(i)}) + (1 - y^{(i)}) \, log(1 - \hat{y}^{(i)})] \quad (10)$$

where

$y^{(i)}$ is the true label and $\hat{y}^{(i)}$ is the predicted probability.

2. Optimization (gradient descent): update the weights to minimize the cost function.

$$w := w - \alpha \frac{\partial \text{Cost}}{\partial \text{w}} \quad (11)$$

where α is the learning rate.

3. Thresholding: convert the probability output into a binary classification

$$Class = \left\{ \begin{cases} 1 \text{ if } \sigma(z) \geq 0.5 \\ 0 \; if \; \sigma(z) < 0.5 \end{cases} \right. \quad (12)$$

4. RF: ML algorithm primarily used for solving classification problems, the working principle presented as follows:
5. Gini impurity or entropy (for Classification): these measures are used to decide the best split at each node in a decision tree.

Gini impurity:

$$G = 1 - \sum_{i=1}^{C} p_i^2 \quad (13)$$

where pi represents the probability of class i.

Entropy:

$$H = -\sum_{i=1}^{C} p_i \log(p_i) \quad (14)$$

6. Majority voting, classification: final class label is determined by the majority vote among the predictions from individual trees.
7. Out-Of-Bag (OOB) error estimation: is an estimate of the model's prediction error, calculated using the data not included in the bootstrap sample for each tree.
8. SVM: ML algorithms capable of solving classification, regression, and anomaly detection problems.
9. Hyperplane selection: a linear SVM identifies the optimal hyperplane that maximizes the margin while effectively separating the classes.

Equation of the hyperplane:

$$w.x + b = 0 \quad (15)$$

where

w: weight vector
b: bias term.

10. Common kernels: polynomial, linear, and Radial Basis Function (RBF).

$$K(x,y) = exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \tag{16}$$

11. k-NN algorithm: an algorithm falling under the supervised learning class.
12. Distance calculation: commonly used distance functions include Euclidean, Manhattan, and Mankowski distances, Euclidean distance [16, 29].

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{17}$$

Where: x_i and y_i are data points.

13. Finding neighbors: based on the smallest distances calculated to Identify the 'k' nearest neighbors.
14. Mean Squared Error (MSE): for regression, to evaluate quality of a split in regression tasks.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{18}$$

y_i: represents the real value.
$\hat{y}$: represents predicted value.
N: represents number of samples.

3.2.5. Fuzzy Logic for Irrigation Scheduling

Fuzzy logic modeling is essential in the IoT for handling uncertainty and inaccuracies in data generated by IoT sensors and devices. In an IoT system, sensors collect data on various parameters such as humidity, temperature, brightness, etc. This data is often fuzzy due to natural variations and measurement errors. Fuzzy logic can be used to model these uncertainties and provide appropriate responses.

A fuzzy logic model comprises three key components: fuzzification, inference, and defuzzification [33]. The fuzzification process transforms precise sensor readings into fuzzy values. Inference uses a set of fuzzy rules to evaluate these values and make decisions. Finally, defuzzification converts fuzzy results into concrete actions for IoT devices. The application of fuzzy logic in IoT thus makes it possible to improve the robustness and reliability of systems, particularly in the fields of precision agriculture.
specifically:

Fuzzy sets are defined on input variables (e.g., soil moisture, evapotranspiration ET_o) and represent agronomic concepts such as dry soil, high ET_o.

Fuzzy rules such as (If the soil is dry and ET_o is high, then irrigation should be strong) allow these sets to be combined to evaluate the appropriate response levels.

The obtained fuzzy result is then defuzzified to produce a precise value, such as the irrigation duration to be applied in the real actions of the irrigation system, such as the opening time of the solenoid valve, illustrated in black in Figure 16.

Example of fuzzy logic rules (to be adapted according to the farmer's request):

- **Rule 1**: soil moisture ['low'] and evapotranspiration ['high'], then irrigation ['high'].
- **Rule 2**: soil moisture ['medium'] and evapotranspiration ['medium'], then irrigation level ['medium'].
- **Rule 3**: soil moisture ['high'] and evapotranspiration ['low'], then irrigation level ['NO irrigation'].
- **Rule 4**: soil moisture ['low'] or evapotranspiration ['high'], then irrigation level ['high'].
- **Rule 5**: soil moisture ['high'] or evapotranspiration ['low'], then irrigation level ['low'].

In our case, we apply fuzzy logic to datasets to train the model ML by taking into account the uncertainty and subtle variations present in the data. Thus, during the training phase, the model learns to interpret these degrees of belonging and to manage ambiguous situations. Subsequently, when the model is deployed, it generates a fuzzy logic-based result, offering a nuanced prediction that better reflects the complexity of the phenomena studied, Figure 9.

4. Results

4.1. Dataset for Diseases Prediction of Wheat and Smart Irrigation

- **Dataset 1**: wheat disease prediction: images of wheat crops are acquired from Kaggle website. The wheat disease dataset contains: total of 3661 images, of which 1110 images of wheat affected by brown rust disease, 1156 images of wheat affected by yellow rust disease, and the remaining 1395 images are healthy [13], we add dataset of 1081 images of wheat affected by powdery mildew [27]. The wheat diseases composing the dataset 1 are illustrated in the Figure 10.

Healthy Brown_rust Yallow_rust Powdery_Mildew

Figure 10. Example images dataset 1.

The images used in this study come from the public Kaggle dataset "wheat plant diseases," which includes images taken under various environmental conditions. The dataset includes images from agricultural fields with natural diversity in terms of lighting, leaf orientation, wheat varieties, and disease stages. This variability improves the generalization of the model.

Wheat brown rust, also called leaf rust, is a common wheat disease caused by Puccinia triticina, it can significantly impact wheat yields and quality. Wheat yellow rust, called stripe rust, is caused by Puccinia striiformis f. sp. tritici, this disease is one of the most significant threats to wheat production worldwide, leading to severe yield losses. Wheat powdery mildew results from an infection by the fungus Blumeria graminis f. sp. tritici. This disease appears as white, powdery spots primarily on the leaves, but can also affect stems, flowers, and even the grain.

- **Dataset 2**: this dataset is composed by open-meteo website [1] data. This website provides access to a complete dataset of weather data and offers a range of weather information, collected from various reliable sources, such as current weather data, and real-time data on humidity, temperature, wind speed, air pressure, precipitation, and other weather conditions. Historical weather data, archived information covering past weather conditions, allowing access and analysis of weather patterns over long periods.

The integrated data on Open-Meteo is used as dataset to train our ML model to predict irrigation needs in agriculture.

Dataset 2 collected meteorological information from Open-Meteo for the specific area of the test field 36.62 °N, 3.12 °E. These general variables temperature, humidity, radiation, evapotranspiration covering the wheat growing season (in Algeria, from October to May) were used to train the Machine Learning model during the first phase. Then, the local measurements collected by our weather station in real conditions were used as input to the pre-trained model, allowing irrigation needs to be predicted in real time based on site specific conditions.

4.2. Results of Disease Prediction of Wheat

In this study, the detection of wheat leaf diseases was investigated using a dataset consisting of images of wheat plant leaves. The acquired images underwent preprocessing before being fed into our MobileNetV2 model for classification.

In the dataset 1, the class proportions in our dataset fall within a narrow range (approximately 23% to 29%) as illustrated in the Figure 11, indicating a balanced distribution that mitigates the immediate need for imbalance correction. Nevertheless, we recognize the importance of detailing the corrective strategies we would employ if the class distribution becomes skewed in future scenarios.

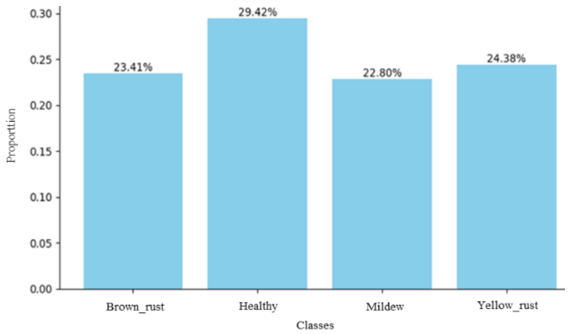


Figure 11. Class distribution with proportions, using shannon entropy.

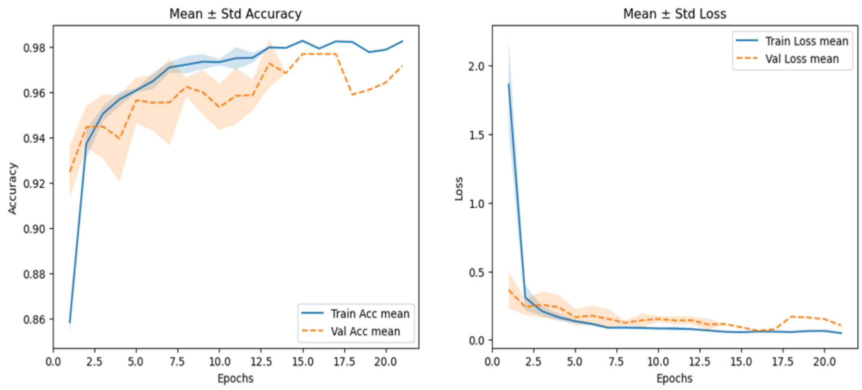


Figure 12. Evaluation of MobileNetV2, with changes in training, validation accuracy and training, validation loss data, for fold 5.

Figure 13 shows the confusion matrix, the vertical and horizontal axes represent the true label and the predicted label, respectively, we present the average confusion matrix (averaging the different matrices across folds). The resulting confusion matrix shows that MobileNetV2 model demonstrates high classification accuracy for valid data.

ROC-AUCs curves, associated with each class Figure 14, the average Receiver Operating Characteristic (ROC) curve per class, along with the corresponding average Area Under the Curves (AUCs). Precision, recall, and F1-score all range between 0.93 and 0.98, as summarized in Table 3, indicating excellent ability to correctly detect each class and a good balance between false positives and false negatives. These results reflect high performance and limited variability across folds. The average confusion matrix shows marginal interclass confusion, while the average AUC values, close to 1 for each class, confirm excellent discrimination ability. To evaluate the performance of our MobileNetV2 model, we used k-fold cross-validation (k=5), and was fine-tuned over 50 epochs. We summarize the accuracy and loss values resulting from the training and validation steps for this model in the graphs shown in Figure 12. In this study, the MobileNetV2 model demonstrated high accuracy while maintaining minimal loss. Indeed, the training accuracy was measured at 98.00%.

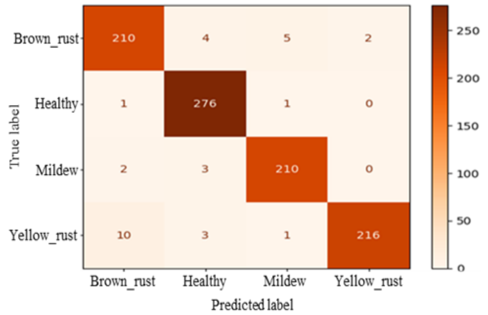


Figure 13. Average confusion matrix of MobileNetV2 for all folds.

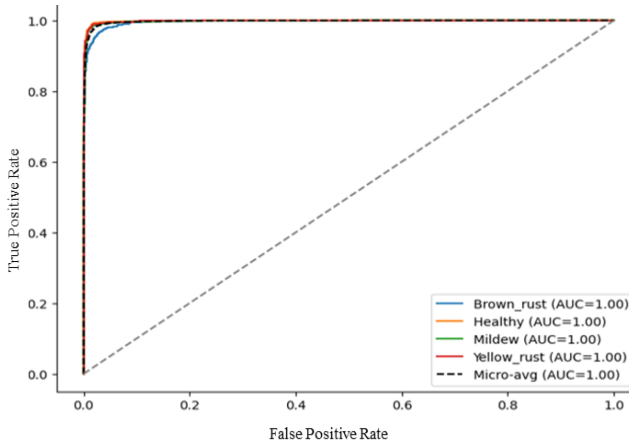


Figure 14. ROC curves by class of MobileNetV2 model.

Table 3. Results of our MobileNetV2 model using k-fold (k=5) cross-validation.

Algorithm	kNN	RF	SVM	Logistic regression
Accuracy	0.9880	0.9985	0.9880	0.9791
Precision	0.9880	0.9985	0.9883	0.9791
Recall	0.9880	0.9985	0.9880	0.9791
F1-Score	0.9880	0.9985	0.9881	0.9791

This methodology demonstrates high performance, remarkable stability across folds, and high reliability in estimating the model's generalization ability. And these results indicate that the model effectively generalizes to unseen data without overfitting.

Healthy-plant Brown-rust-plant Powdery-Mildew-plant

Figure 15. Prediction results for real plants: real images captured by Raspberry Pi camera on wheat field.

Figure 15 depicts three real images of: healthy plant, brown rust affected plant and powdery mildew affected plant, with their equivalent prediction results, the obtained results are accurate which confirms the accuracy of our system. In this latter, when a prediction is made for a disease, the model analyzes the captured image, and saves the result in a file organized according to the disease classification, and it was accompanied by the date and time of treatment. In parallel, the result can be sent as an alert if there is a disease.

4.3. Results for Smart Irrigation

The raw data in Excel format shown in Figure 16-a) of sensors and dataset 2, is often unreliable and incomplete, which can generate erroneous results when used for modeling. To resolve these issues, it is essential to preprocess and clean the missing data using the Pandas library, the preprocessing results are shown in Figure 16-b). These critical tasks should be performed both on the dataset intended for model training and on the raw sensors data.

Ph	Temperature	SoilTemperature	Humidity	Soilhumidity
NaN	NaN	NaN	NaN	NaN
8.17	NaN	22.25	NaN	NaN
NaN	23.2	NaN	57.0	164.0
NaN	NaN	NaN	NaN	NaN
NaN	NaN	NaN	NaN	NaN

a) Raw data of sensors and dataset 2.

Ph	Temperature	SoilTemperature	Humidity	Soilhumidity
182.000000	341.000000	182.000000	341.000000	341.0
8.131593	23.692669	23.736044	57.346041	164.0
0.069100	0.459449	4.481136	3.414143	0.0
8.010000	23.100000	19.940000	55.000000	164.0
8.070000	23.200000	20.515000	56.000000	164.0
8.140000	23.700000	22.310000	57.000000	164.0
8.190000	24.100000	24.967500	57.000000	164.0
8.250000	24.600000	46.500000	75.000000	164.0

b) Preprocessing raw data results.

Figure 16. Preprocess data.

To best select the model for our system, RF algorithm, kNN, SVM, and logistic regression algorithms were applied on dataset 2 to evaluate the performance of each classifier. The Model accuracy, precision, recall and F1-score results are summarized in Table 4, and ROC Curves associated with each model Figure 17. The analysis revealed that the radio frequency Model achieved the highest overall accuracy. kNN, SVM, and logistic regression algorithms also demonstrated strong performance.

Table 4. Results of the machine learning application.

Fold	Accuracy	Precision	Recall	F1-score
1	0.94	0.94	0.93	0.93
2	0.96	0.96	0.95	0.96
3	0.97	0.97	0.97	0.97
4	0.98	0.98	0.97	0.98
5	0.98	0.98	0.98	0.98

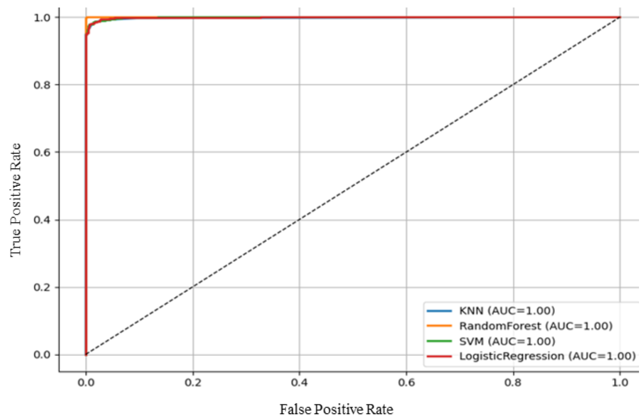


Figure 17. ROC Curves of kNN, RF, SVM and logistic regression models.

After creating, testing, and selecting the best model RF, we deployed it on the Raspberry Pi and applied it to sensor data. The sensor station continuously collects data and sends it to Node-RED on the Raspberry Pi as illustrated in Figure 18. Once received, a function node in Node-RED processes and formats the data as required by the model. The formatted data is then transmitted via an API that utilizes Python's FastAPI, through an HTTP request node in Node-RED. The API interface receives the input data, passes it to the model for prediction, and finally returns the results, the process is illustrated in Figure 19. This integrated setup enables seamless and real-time communication between the sensor station and the gateway (Node-RED, and the machine learning model), facilitating decision-making based on real-time weather data.

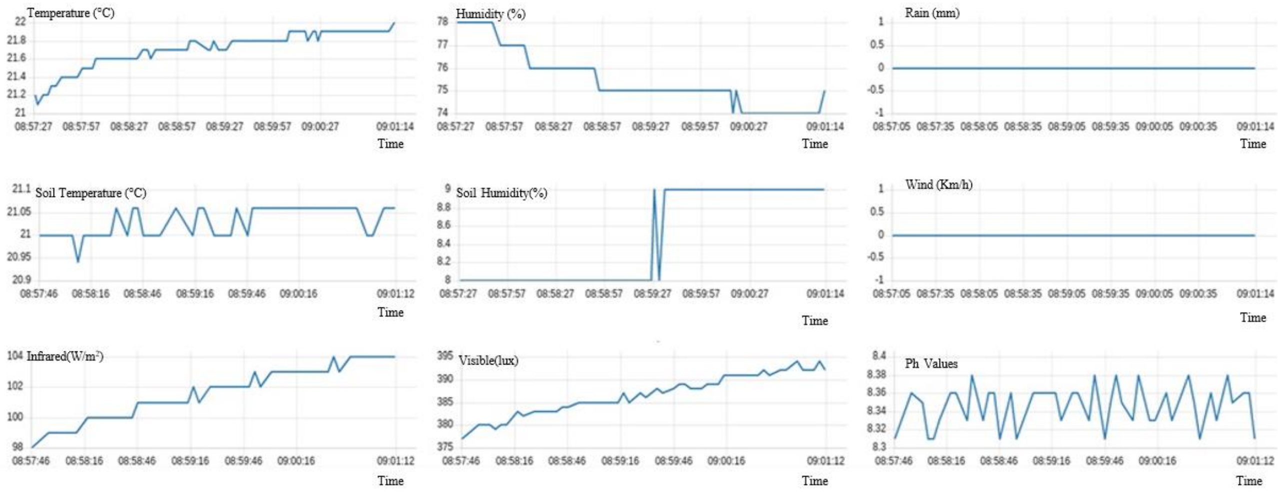


Figure 18. Graphs of parameter values in Node-Red for data collected by the weather station.

Figure 19 illustrate un example of both the input data and the response from the RF model. The input data, formatted in JavaScript Object Notation (JSON), includes sensor measurements: temperature (10°C), relative humidity (91%), soil moisture 0.31, soil temperature 18°C, and evapotranspiration 0.31 as per the FAO method. In response, the model returns a JSON format (Figure 20), object with the class3, which represents the time of predicted irrigation to control the status of the water solenoid valve (ON/OFF).

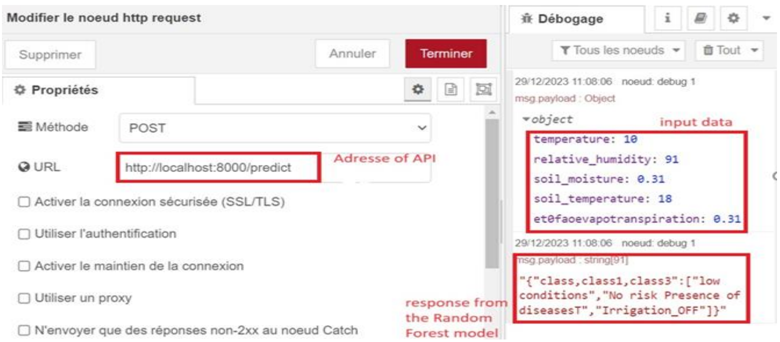


Figure 19. Steps on node-red to API.

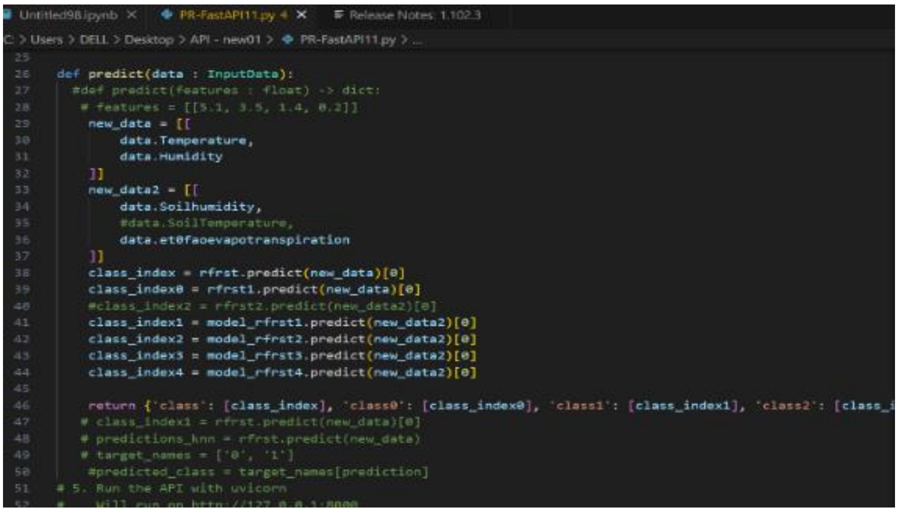


Figure 20. Response from our model API on visual studio.

The prediction of the required irrigation duration based on soil moisture and ET, is shown in Figure 21. Soil moisture, gives a direct indication of the amount of soil water available to plants. Meanwhile, ET represents the loss of water through soil evaporation and plant transpiration, is calculated from climatic variables such as temperature, air humidity, wind and sunshine. By integrating these two parameters into the machine learning model, with the assistance of Fuzzy logic, we can predict the irrigation duration needed as shown in Figure 21.

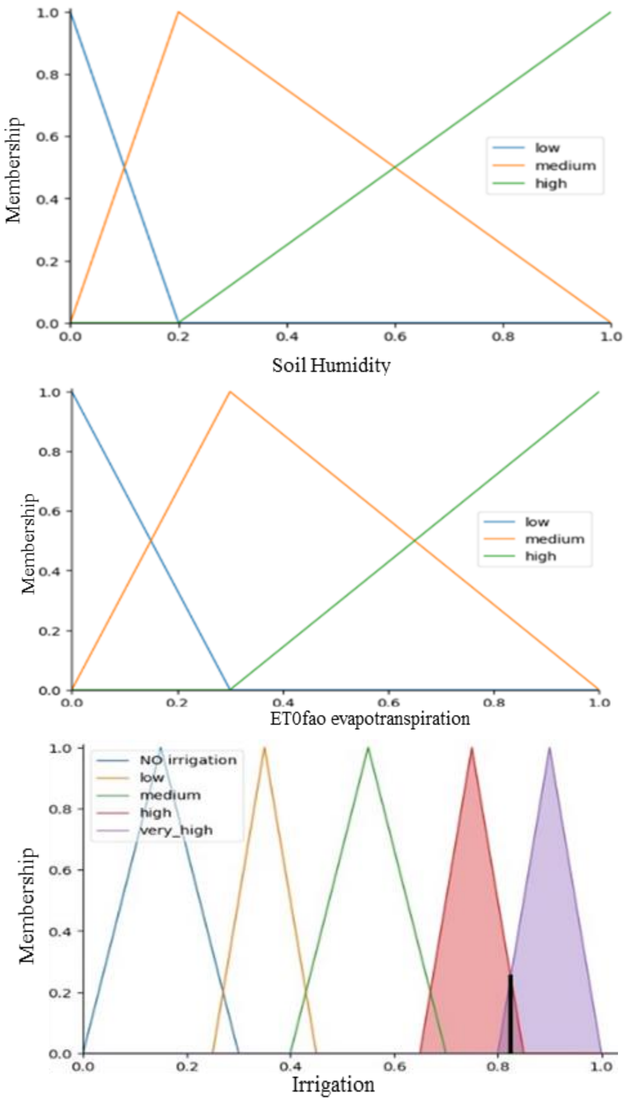


Figure 21. Making irrigation decisions based on soil moisture and evaporation using fuzzy logic.

Figure 21 visualizes how input measurements of soil moisture and ET are converted into an irrigation decision (duration) via a fuzzy logic system.

Figure 22 illustrates a concrete experimental scenario:

- Observed inputs: hourly changes in soil moisture and ET_0 during the test.
- Calculated irrigation duration: for each interval.

Comparing the two, the figures demonstrate the good convergence between calculated and applied duration, verifying the reliability of the fuzzy controller in the field.

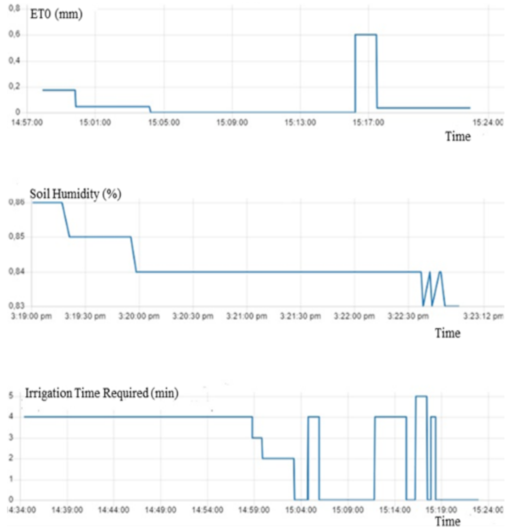


Figure 22. Test to predict and calculate the required irrigation duration based on soil moisture and ET.

The model analyzes current soil moisture and ET values and calculates the flow rate and amount of water consumed during this predicted duration as shown in Figure 23, avoiding plant water stress and water waste. This data-driven approach improves irrigation management efficiency, promotes crop growth, and contributes to sustainable water resource management.

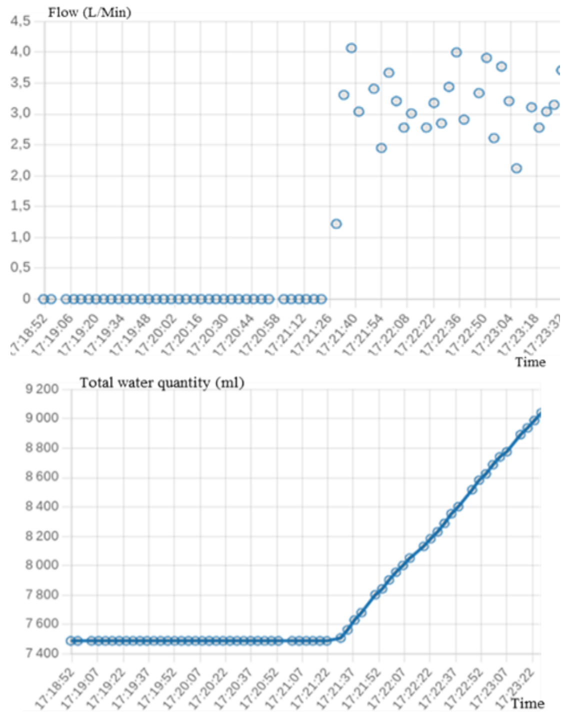


Figure 23. Water flow rate and total water quantity during the predicted irrigation duration.

5. Conclusions

In this study, agricultural images captured in real-time by cameras integrated into a Raspberry Pi4 are preprocessed and analyzed to predict the presence of diseases. The proposed MobileNetV2 model achieves an optimal accuracy, precision, recall, and F1-score of 98%, with using k-fold. These results highlight that the DL techniques employed in this approach are a wise choice for field monitoring, thus promoting precision agriculture.

Furthermore, this study presents a prototype irrigation system capable of automating irrigation and optimizing water use. The system collects critical data such as soil moisture, temperature and humidity, precipitation, wind speed, and light intensity from the sensor station. This system leverages LoRa IoT technology to enable real-time data conversion and remote control, thus improving its efficiency and applicability to irrigation management. The RF machine learning algorithm achieves an optimal accuracy, precision, recall, and F1-score of 99.8%. Fuzzy logic is used to facilitate and ensure efficient water use in irrigation.

In summary, this work combines different technologies: IoT, LoRa technology, DL for disease detection, and ML using fuzzy logic for irrigation management, to address major agricultural challenges. The proposed system predicts the presence of diseases and ensures efficient use of water for irrigation.

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