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An IoT Low-Cost Smart Farming for Enhancing Irrigation Efficiency of Smallholders Farmers

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Abstract
Nowadays, agriculture faces several challenges in ensuring food safety. Water scarcity is one of the main challenges facing farmers in the rainfed agriculture sector, especially during the summer, leading to severe economic and farm losses. Internet of Things (IoT) has recently become a potentially revolutionary approach in smart farmingthat provides many innovative applications. In this research, we suggest an Edge-IoTCloud platform based on a deep learning methodology for monitoring and predicting farmers' ability to satisfy crop water demands when there is insufficient rainfall. The smart farming system allows collecting data about such important physical phenomena as soil moisture, air temperature, air humidity, water level, water flow, and luminous intensity. The latter is required for reliable and cost-efficient irrigation solutions that will be utilized to compute the necessary water quantity using Rawls and Turq formulas. Cloud services have been chosen for storing and processing significant amounts of data generated by sensors to produce a learning model that will be a basis for predicting future measurements using artificial intelligence and DL techniques. The preliminary results revelated that our proposal is a good starting point for developing low-cost smart farming for smallholder farmers to help them make better decisions.

Keywords Internet of things · Smart farming · Irrigation · Precision agriculture · LSTM · GRU

1 Introduction and Motivation

Farmers worldwide use 85% of the available freshwater resources, which will continue to be the dominant type of water consumption due to population growth and increased demand for food. In addition, with the skyrocketing advances in information,

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communication, and electronic devices, there is an ever-increasing interest in setting strategies based on information and communication technology (ICT) [1].

Wireless sensor networks (WSN) have become a requisite for agriculture applications and have become a reality today, going hand in hand with the success of theoretical research contributions that the field has witnessed during the last decade [2, 3]. The Internet of Things (IoT) concept was invented by Kevin Ashton in 1999. IoT aims to connect anything at any time in any place, and it has recently become more relevant due to the growth of mobile and tiny devices, the development of computing in the cloud, as well as data analytics. Billions of objects communicating and sharing information are interconnected via public or private IP networks. These interconnected objects collect data regularly and then analyze them to make decisions and initiate actions [4, 5].

According to the FAO, small-scale farming significantly contributes to food security and the rural economy. On the other hand, smallholders are frequently confronted with various limitations that limit their production, profitability, and capacity to contribute to economic progress. However, adopting solutions to improve irrigation efficiency has not reached small-holder farmers, owing to the high initial cost and high skills required to grasp the technology. Technological developments such as IoT, artificial intelligence (AI) and machine learning (ML), big data analysis, robotics, and cloud/Edge/Fog computing have paved the way for the new era of an agricultural revolution. These techniques have provided solutions to several problems that have been raised in what is now called smart farming. Among these problems, we can mention the identification of plant diseases, the prediction of agricultural yields, drought as well, and the efficient management of irrigation, which has a direct impact on agricultural production, especially if this water resource is scarce and in the case of insufficient rainfall. Irrigation water management in terms of quality and quantity is a challenging task that involves the consideration of several factors that can be classified into three categories, as illustrated in Fig. 1:

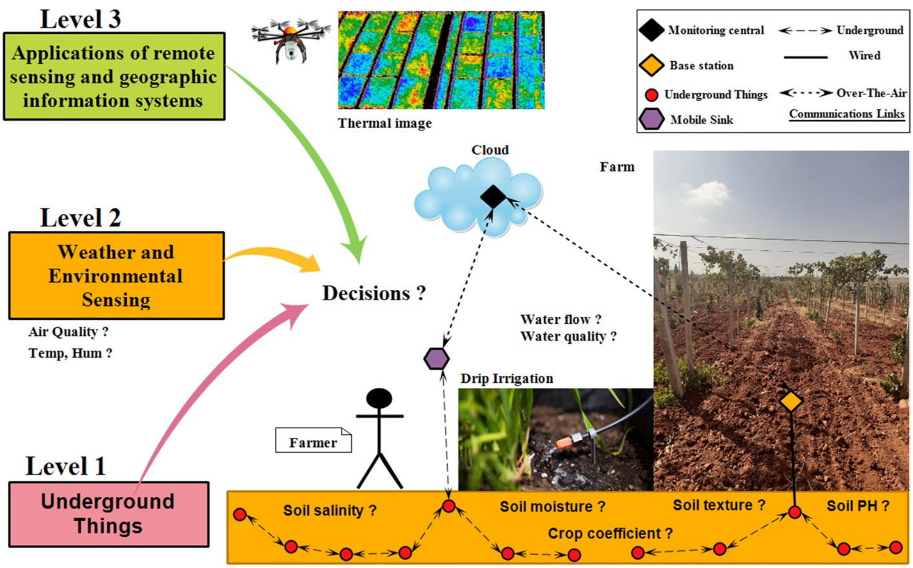


Fig. 1 Paradigm of factors that affect any selected methods of irrigation in precision agriculture

- The application of remote sensing and geographic information systems is a nonintrusive and noncontact technique; different studies have shown that thermal imaging is a suitable solution for identifying key parameters to schedule irrigation. Among the critical irrigation, features are water stress, evapotranspiration rate, stomatal conductance …etc. This technique could be used to assess the relationship between the water status of crop/field and radiation emission so it can be utilized as a measure for irrigation distribution and water stress [6–9]. However using the thermal imaging technique has many drawbacks that affect irrigation scheduling: different emissivities and reflections from surfaces obstruct precise temperature measurements, and most thermal imaging cameras have $\pm 2\%$ accuracy. Also, thermal images are difficult to interpret in specific objects eith erratic temperatures.
- Weather and environmental sensing are ranked as ground-level irrigation methods it directly affected by climate. Nodes of this level can cover a large geographic region. It is used to track important weather pattern changes, yet when combined with the internet of underground things (IOUT), sensing can provide real-time weather information that can be collected at the farm level [10–12].
- The IOUT is composed of sensors and networking systems. This need emerges from partially or fully submerged underground for real-time monitoring and soil sensing [13]. There are several critical features for irrigation, such as soil moisture, soil texture, soil salinity…etc. IOUT is protected by weatherproof enclosures and, in underground settings, water-tight containers [12, 14]. Unfortunately, energy consumption is a vital issue in IOUT because of the low power constraint for sensors to prolong the network's lifetime without a spare battery. Additionally, the soil's physical parameters greatly impact the channel quality in IOUG communications (e.g., soil moisture).

For more refined irrigation water management for agriculture, we found helpful to consider the influence of meteorological and environmental parameters and the underground measurement parameters of the agricultural plot to be studied. This paper proposes a decision support system (DSS) dedicated to smart agriculture that will allow small farm farmers to manage irrigation water best. We use concepts such as Edge computing, fog computing, and cloudlet [15] to bring computational and storage resources closer to the farmer and IoT to implement remote monitoring mechanisms through gateways between measurement devices and the cloud to perform computation and collaboration. Therefore, through the use of Long Short Term Memory Recurrence Networks (LSTM) and Gated Recurrent Units (GRU)-based models, we offer an Edge-IoT-Cloud intelligent irrigation framework with a DL approach to predict environmental factors from reaching further persuasive conclusions.

Specifically, we propose a sustainable, low-cost, autonomous, and easy-to-use irrigation control system to help smallholder farmers manage irrigation water for agriculture more efficiently. Using IoT-based sensing technology, the resulting platform is based on a DL approach by collecting fundamental physical quantities such as soil moisture, air temperature, humidity, water level, water flow, and light intensity. Furthermore, we consider an Edge-IoT-Cloud platform for storing , processing and exploitation a large amount of collected data. The contributions of this paper can be summarized as follows:

- Development of a low-cost, high-support smart agriculture platform to improve irrigation efficiency of small-scale farmers to save water in various crops that typically have a distinct water requirement profile at each stage of growth, and with high performance.
- Design of a smart IoT irrigation system based on the new Edge-IoT-Cloud platform.

- Water quantity calculation needed for irrigation depending on farm's soil texture and crop coefficient.
- Implementing edge-level infrastructure to predict the most important environmental factors (air temperature, air humidity, soil moisture) based on field sensory data and weather forecast data using Long-Term Memory Recurrent Network (LSTM) based models and Grid Recurrent Unit (GRU) based models.

The remainder of the paper is organized as follows: Sect. 2 presents a discussion on the application of IoT in smart agriculture. Section 3 introduces irrigation systems followed by Sect. 4, which briefly surveys the related works. Section 5 provides our proposed smart platform in precision agriculture, especially irrigation management systems. The experimental study and results analysis are discussed in Sect. 6 while Sect. 7 concludes the paper and outlines directions for future works.

2 IoT in Smart Agriculture

Smart farming technologies and precision agriculture (PA), they are becoming increasingly appealing due to their ability to meet such rising demand and meet global food supply demands [16]. PA is a farming method that uses data sensors, connected things, remote control equipment, and other advanced technology to provide more control over the field and the team to farmers. Data collection, cloud-based data analysis and decision-making, and IoT-assisted agricultural operations are the three types of IoT technology.

2.1 Benefits of IoT in Agriculture

Owing to recent advancements in sensor technology for implementing IoT-based smart farming, the growth of WSN and IoT technologies to improve these IoT systems plays a vital role in the agriculture digital revolution [17]. The benefits of IoT in agriculture are summarized in the following illustration.

- *Excelled efficiency*: Farmers can monitor their products and conditions in real-time using IoT-enabled agriculture. They can get insights quickly, foresee difficulties before they occur, and make well-informed judgments on how to prevent them. Agriculture IoT solutions also offer automation, such as demand-based watering, fertilization, and robot harvesting.
- *Agility*: Farmers can immediately respond to any significant change in weather, humidity, air quality, or the health of each crop or soil in the field thanks to real-time monitoring and forecast systems.
- *Improved product quality*: Farmers may better grasp the intricate connections between the environment and the quality of their crops by using soil and crop sensors, aerial drone surveillance, and farm mapping. They can reproduce the optimum circumstances and improve the nutritional content of the items by using linked systems.
- *Cleaner process*: IoT-based precision farming systems make farming more environmentally friendly but dramatically reduce pesticide and fertilizer consumption. This strategy yields a cleaner and more organic end product compared to standard farming practices.

Consequently, all of these factors might contribute to economic progress of any country and an enormous contribution to food security.

2.2 IoT Applications in Agriculture

According to the literature review, IoT applications in agriculture may be divided into six categories. As seen in Fig. 2, it is now possible to explore IoT applications in agriculture and gain a better understanding of the ability of IoT. In the following section, we highlight these six categories.

2.2.1 Irrigation Management System

Data collection through sensors aids in determining the precise irrigation period. About the fact that this is to be anticipated in many cases, IoT applications have been made easier in the timely water management. As a consequence, the misuse of water is decreasing day by day. Investigation in the field of irrigation systems were carried out to rationalize the use of water in diverse crops irrigation from basic ones to advanced ones. To achieve water saving, irrigation system frameworks have been proposed based on various techniques, e.g., thermal imaging, RGB (Red, Green, Blue) images [18], Crop Water Stress Index (CWSI), direct soil water measurements, etc. [19].

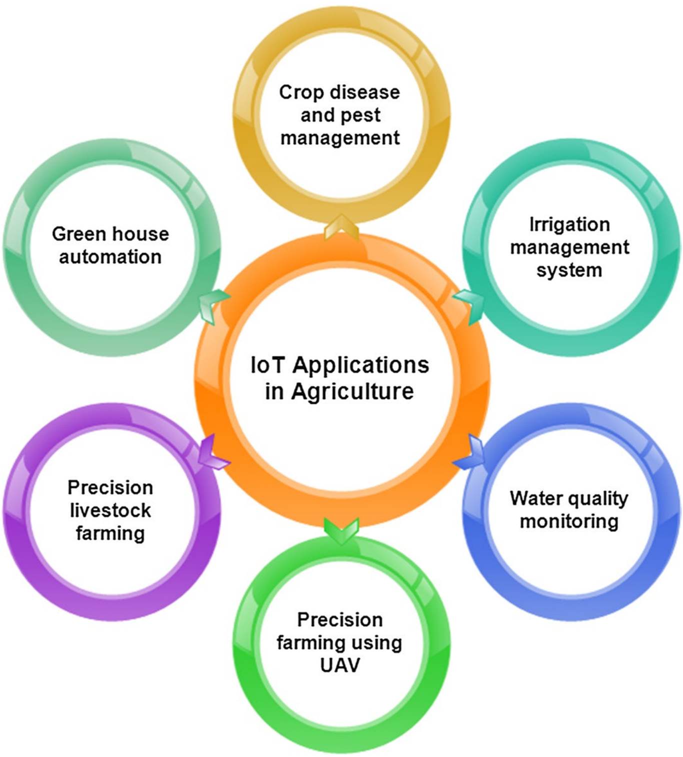


Fig. 2 IoT applications in precision agriculture

2.2.2 Water Quality Monitoring

Another problem that might impact crop health and limit harvest is water quality. Temperature, pH, conductivity, dissolved oxygen, and other variables all impact water quality. Water quality monitoring systems based on the Internet of Things are progressively emerging as a solution to this challenge. These devices may be used to remotely monitor and adjust the physical and chemical properties of the water.

2.2.3 Precision Farming Using UAV

Unmanned aerial vehicles (UAVs) and drones are also finding a position in agriculture in this modern era [17]. The agricultural drone is an interesting innovation in IoT-based agriculture field which is operated in practice according to two types [20]: Ground Drone and Aerial Drone, this can be programmed to detect details such as NDVI, water stress or lack of specific nutrients in crops. It benefits to the ease of use, time-saving, crop health imaging, integrated geographical information system (GIS) mapping and the ability to increase yields.

2.2.4 Precision Livestock Farming

In the livestock monitoring and management system [21, 22], IoT applications have a major impact. Here, the location trackers are implemented in the livestock so that they are tracked at grazing time. Therefore, the health conditions of all animals are recorded at the same time (supported by IoT technologies).

2.2.5 Green House Automation

Rapid climate change affects not only agriculture, but also the agricultural system in operation. In this situation, IoT applications play a key role in improving agriculture by installing sensors and actuators outside and inside the agricultural domain. Moreover, in the intelligent greenhouse system (IGS), IoT applications adjust the state of the climate according to the particular predefined instructions set. This can be done through sensors able to collect real-time data that help control the automatic irrigation system in IGS.

2.2.6 Crop Disease and Pest Management

From the birth of agriculture, crop diseases and pest have caused severe losses to farmers, IoT provides a solid platform for the development of successful agricultural disease and pest management strategies. It depends on three aspects: sensing, evaluation, and treatment, which is a difficult task in traditional farming practices.

3 Irrigation Systems

There are several ways to distribute water in farming operations that use water inputs, also known as watered farming. Different options have differing degrees of effectiveness, and in certain situations, a particular approach can be used for a specific crop.

The particular irrigation practice has several forms, which can be classified into several methods, as depicted in Fig. 3, according to water distribution way (WDS) and existence sensing systems (ESS) [2, 23]. In case of WDS, we found mainly four categories: (i) flood irrigation, (ii) shower water system, (iii) dribble water system, and (iv) nebulizer water system. Whereas in case of ESS, three categories can be considered: (i) water system without any thought, when the water sum isn't calculated or assessed, (ii) scheduled irrigation when the water is provided agreeing to the assessed needs in a period of the year, as well as (iii) Ad hoc water system when the water sum is calculated based on the sensors measurements or prediction using AI techniques. The majority of research on PA proposes using pumps and valves in order to convey the water in conjunction with sensors to degree natural parameters in arrange to calculate the water needs [2].

4 Related Works

In this section, we outline some irrigation system frameworks to save water based on different approaches, such as thermal imaging, Crop Water Stress Index (CWSI), direct soil water measurements, and so on, which have been developed. In addition, some of them have used AI techniques to enhance the prediction aspect. Researchers in [6] created an irrigation sensor mounted on a smartphone. The digital smartphone cameras were used to process RGB to grey for ratio determination between wet and dry soil areas to detect soil moisture. The wetness and dryness ratio are transmitted via a gateway to the water motor controller. In addition, a Mobile device (APP) is developed to regulate sensor activity (like ON/OFF) and to set a sensor in sleep mode. The bulk of the earlier proposed irrigation systems does not consider weather forecast information (e.g., precipitation) in the making of irrigation decisions. This engenders a waste of fresh water, energy, and crop quality (due

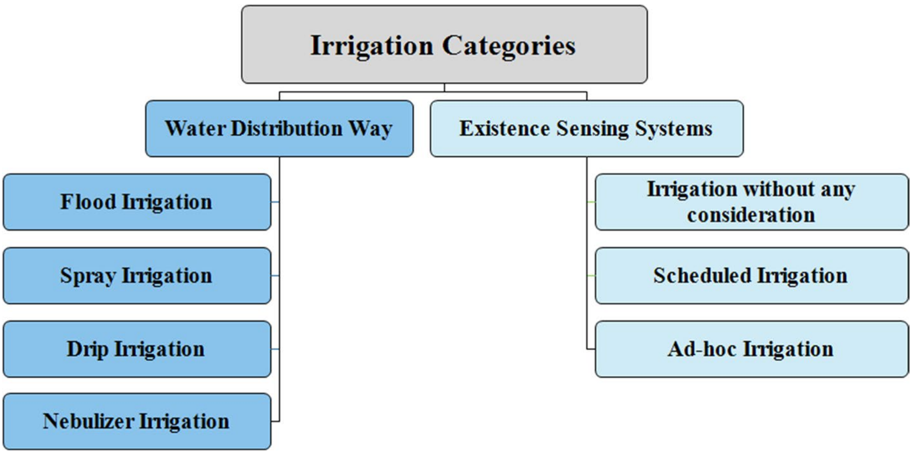


Fig. 3 Water management in precision agriculture

to excess in irrigation) like when rain immediately follows by the crop watering. To handle such cases, WSN-based solutions can provide more efficient decision support for such processes by using weather forecasting information (e.g., precipitation) from the Network. In prior works, the amount of water used was monitored and irrigation was scheduled on the basis of canopy temperature distribution of the plant, and data was collected by means of thermal imaging [6, 9]. Watering systems can also be mechanized using the soil volumetric water content information, using dielectric moisture sensors to regulate actuators and economize water, as an alternative to daily pre-determined and scheduled irrigation with a specific duration. For example, an irrigation controller opens a solenoid valve and irrigates bedding plants (impatiens, petunia, salvia, and vinca) when the substrate's water volume decreases below a given set point [1, 24]. Allen et al. [25] suggested the evapotranspiration (ET)-based method, which is a critical parameter in determining crop irrigation needs that are influenced by climate variables such as solar radiation, relative humidity, temperature, and wind velocity, as well as crop specificities such as growth phase, assortment and density, soil properties, hazards, and disease control. ET-based frameworks can reduce water consumption to 42% over time-based water irrigation scheduling [7, 10, 26]. Electromagnetic sensors for measuring soil moisture were the basic instruments for developing an irrigation system that can reach water savings of 53% compared with irrigation by sprinklers in a rural area of 1000 m^2 [1, 6]. Agriculture constitutes the greater part of the water used, and is therefore the first sector affected by water shortage, leading to in a decreased capacity of maintaining food production in its satisfactory level. Therefore, the efficient water use in agriculture remains one of the most important agricultural challenges that modern technologies are helping to resolve [27]. The author's goal in [28] was to gain a deeper understanding onsite-specific suitability of the Mid Elevation Spray Application (MESA) and Low Elevation Spray Application (LESA) sprinkler systems in corn irrigation, as well as future water and energy savings. The automated irrigation system has proven feasible and cost-effective in optimizing water resources for agricultural production [1]. A few scientific studies work on using data processing techniques for a stronger decision support framework for agricultural data. The authors in [10] propose a smart irrigation architecture based on IoT and hybrid approach that relies on DL to predict soil moisture. The proposed algorithm uses sensor data collected from recent and past weather forecasts to predict soil moisture. However, Environmental sensing is not sufficient to make a good irrigation scheduling, also authors don't take into consideration the crop coefficient and the soil texture. Due to the recent advances in the sensors industry for use in irrigation systems for agriculture, especially smart farming [26–29] and the progress in IoT technologies to be applied in improving these systems, IoT plays a major part in the digital revolution. Agana and Homaifar [30] discuss the issue of drought prediction using DL algorithms. The research focuses on the effectiveness of the suggested approach to traditional approaches such as support vector regression (SVM) and multi-layer perceptron (MLP) in forecasting various time scale drought conditions. The new solution showed an efficiency advantage over the classical approaches. Din et al. [31] an analysis of several IoT-based ML models were presented. The specific architecture and achievements in several areas include agriculture, climate and energy resources, IoT technologies, and ML techniques. A smart agriculture-based tracking system to track temperature and soil moisture have been implemented in [32]. The machine manages the sensed data and performs the necessary action based on temperature and soil moisture values stripped of human interference. Unfortunately, most of the earlier irrigation systems do not consider and combine the most important factors that affect any selected irrigation method in precision agriculture, as shown in Fig. 1 while making irrigation decisions.

This leads to a waste in fresh water, energy, and crop loss (due to the misuse of water), especially when by crop watering is immediately followed by rain or the vice versa. To handle such cases, we anticipate the IoT-based intelligent irrigation architecture proposal with a DL approach to predict (Soil-moisture, Air-temperature, Air-humidity) to reach more convincing conclusions. Table 1 compares various IoT systems for agricultural irrigation in terms of precision. The main difference between the present work and those available in the literature is that most of the schemes suggested focused only on one factor to compute the required water quantity. Unfortunately, few research works of literature discuss many factors simultaneously [1, 2, 10, 23]. The present work differs from previous research because it gathers four factors and combines them to enhance irrigation efficiency, productivity, quality, profitability, and agricultural production sustainability. In particular, we consider the following factors: i) the soil texture, ii) the crop coefficient, iii) sensed data with the weather forecast, and iv) sensing of the underground parameter, in our case soil moisture. The aim is to compute the required quantity of water according to these factors.

5 Smart Irrigation Platform

The platform presented above is based on the ideas proposed by [1, 10, 14, 33–40], by making appropriate modifications to our application. In this article, we propose a low-cost smart farming for enhancing irrigation efficiency of small-scale farming, however it will get more efficient. It will accomplish the following: (1) allows the deployment of a number of complementing low-cost sensors, (2) implements the concept of “intelligent irrigation in-the-box” with "plug-&-sense" approach, (3) utilizes edge computing technology to provide extremely creative methods that are simple to implement and appropriate for smallholders, (4) and uses technologies such as DSS and AI to predict the most important environmental factors (i) for a variety of crops, (ii) for a given farm’s soil texture and (iii) at a particular moment. As we can observe in Fig. 4, our platform’s devices in the first layer aim to collect data and transmit them for processing using the NRFL01 radio module and can be stored in a private database. The user (farmer) can analyze received data and monitor the crops in real-time. The system architecture is designed in three layers as depicted by Fig. 5: data layer (Box A) and (Box B) represents a Gateway node, data processing layer (Box C) at the edge level, and application layer (see Fig. 5). This distributed architecture represents a major extension of our previous works [5, 23, 39] on PA, where we calculated the useful reserve of water (RU) according to the texture of the soil (Clay, Limon, Sand, Organic Matter). For the second method, we used the (Rawls and Turq formulas) equations, which accurately estimating the required measurement of water according to the soil texture of the farm and the crop coefficient by merging Rawls linear regression equations.

5.1 Edge Network Description

The data processing and intelligence layer are more than a simple pipe where your data is transiting. iIt can process everything, at the edge level (Box C). As a result, the Raspberry Pi 3 B + (RPI3) boards-based edge network will be able to conduct complex and intensive AI data analyses locally, enabling the so-called Edge-AI architecture to deliver intelligence closer to end-users. Edge-AI allows for complete management of IoT data and AI processing, creating a completely autonomous and intelligent system with plug-and-sense and predict characteristics for implementing sophisticated IoT applications

Table 1 A comparative analysis between the proposed work and existing platforms

Factors:	Goap et al. [10]	Gutiérrez et al. [1]	Vuran et al. [14]	Rezk et al. [33]	Roopaei et al. [9]	Proposed platform
Soil texture	No	No	No	No	No	Yes
Crop coefficient	No	No	No	No	No	Yes
Underground sensing	Yes	Yes	Yes		No	Yes
Environmental sensing	Yes	Yes	Yes	Yes	No	Yes
GIS (Thermal image)	No	No	No	No	Yes	No
Crop productivity	No	No	No	Yes	No	No
Advantages	**1.** An open-source technology based smart system to predict the irrigation requirements of a field using the sensing of ground parameter like soil moisture, soil temperature, and environmental conditions using K-means and SVR	**1.** The automated device was put to the test for 136 days in a sage crop area, and water savings of up to 90% were obtained as compared to conventional agricultural irrigation activities **2.** energy autonomy and low cost of the system	**1.** Underlying sensing technology and communication mechanisms for IOUT **2.** Sensors are buried at different depths in soil depending on the crop type and root depth **3.** Other soil properties can be measured to populate the soil map such as the organic matter present in the soil, acidity (pH), percentage of sand, clay and and silt particles, and nutrients such as magnesium (Mg), potassium(P)… etc	**1.** Outperforms existing platforms for the five datasets for drought classification, and crop productivity respectively	**1.** Thermal imaging has the advantage of providing a temperature value for all of the pixels within the sensor's field of view	**1.** Development of a low cost, an open-source high-level support smart farming for enhancing irrigation efficiency of smallholder farmers to achieve water savings in diverse crops, and great performance **2**. Computation of the required quantity of water according to the soil texture of the farm and the crop coefficient **3.** Development of an operational architecture at the edge level to predict (Air-Temperature, Air-Humidity, Soil-Moisture) using LSTM-based models and GRU-based models

Table 1 (continued)

Factors:	Goap et al. [10]	Gutiérrez et al. [1]	Vuran et al. [14]	Rezk et al. [33]	Roopaei et al. [9]	Proposed platform
Disadvantages	**1.** They don't monitor stress variations with thermal images **2.** Environmental sensing is not sufficient to make a good irrigation scheduling	**1.** Don't based on the soil texture and crop coefficient to enhance irrigation also they don't monitor stress variations with thermal images **2.** A decision support based on IA techniques which actually very crucial in smart farming systems	**1.** Focus only on the underground factors however environmental sensing and SIG play very important role in precision agriculture **2.** Unfortunately, in IOUT energy consumption is a vital issue because of the low power requirement for sensors in order to extend the lifespan of the network without battery replacement **3.** Moreover, the channel quality in IOUG is impacted by physical parameters of the soil	**1.** Don't focus on using (Soil texture, Crop coefficient, Underground sensing, GIS) what is not enough to make decisions for the farmer **2.** Unfortunately the platform does not allow the computation of the required quantity of water	**1.** Different emissivities and reflections from surfaces obstruct precise temperature measurements **2.** In specific objects having erratic temperatures thermal images are difficult to interpret	**1.** Don't monitor stress variations with thermal images which can beef up the irrigation system **2.** Don't monitor other soil properties such us: acidity (pH), soil salinity and nutrients such as magnesium (Mg), potassium(P)

across a wide range of IoT verticals. ML models developed in the central cloud and deployed on the edge layer are typically used in prediction services. The three design steps of the proposed architecture are described in Fig. 6 and explained with sufficient detail in the following.

5.2 Step 1: Remote Sensing DATA

The smart farming system architecture, as illustrated in Fig. 5, has been proposed to collect, transmit and process the physical collected parameters (Soil-Moisture, Air- Temperature, Air-Humidity, Water-level, Water-flow, Luminous intensity, Combustible Gas (vapours) for the security of crops) of farming land along with the weather forecast information to manage the irrigation efficiently, the field data collection device is depicted in Fig. 9. It summarizes details of the sensors that are included in this box. The programming of the irrigation scheduling algorithm by the language (Merely C/C++). We configure the NRF24L01 module in write mode, and we specify the address of the destination, then we read the sensor values using the "analogRead ()" function on the pins data, then we apply a calculation to normalize the captured data. If there is a frequent change in the data, then we send 6 successive packets, separated by a small interval; these packets are necessary for detecting an anomaly in the Fog layer; otherwise after each one-hour duration, we send a packet. Before sending a packet with this module, you must switch to the sending mode, then choose a common communication channel and define the destination address.

5.3 Step 2: DATA Processing and Intelligence Layer

We begin this step by using the library Pandas [41] to load the datasets, then pick the target columns (Soil-Moisture, Air-Temperature, Air-Humidity) then we locate and delete the missing values since we can't go through the learning process with the inclusion of the last ones. This step includes manipulation libraries, and pre-processing of data (Numpy, Pandas …etc.), and other learning (Keras, Tensorflow, Pytorch …etc.). Selecting a library that meets our needs presents a challenge, as each of them has its own advantages and disadvantages. The libraries we have used throughout our work are highlighted in Fig. 7. In this phase, the input data of the learning model is prepared, Table 2 illustrate the different steps of pre-treatment. Preparation and cleaning step is started by using the "Pandas" library, to load the datasets, then select the target columns (Temperature, humidity …), then we identify and we would eliminate the missing values, because we cannot pass to the training phase with the presence of its last, the results obtained are shown in Table 2. In this research work, we used free datasets from different sources, which contain values measured at an interval of one hour (the prediction of future measurements), and other in real time (detection of anomalies) which are not treated in this paper. We are interested in creating prediction models, to predict future measurements ("Hours" and "Days"). Scaling of inputs variables is a critical step in the use of neural networks, the difference in the scales between the input variables may increase the difficulty of the problem to be modelled), so it is advantageous to apply pre-processing transformations to the input data, the outputs are post processed forgive the required output values. In our case, we used the "MinMaxScaler" method, which is included in the "sklearn" library, this

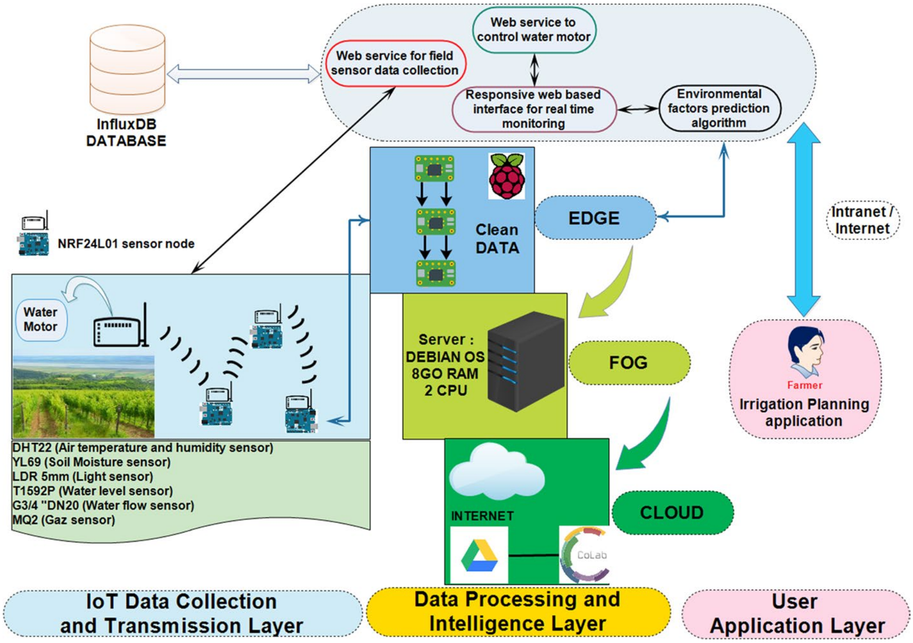
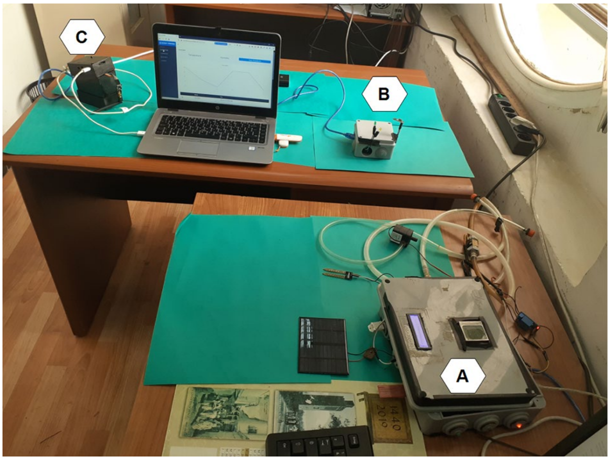


Fig. 4 Proposed IoT-based smart farming system architecture

Fig. 5 Global View of our proposed operational architecture



estimator allows to reduce the scale between ("0" and "1"), depending on the function (1). In the last step, we will structure the data in the form of a sequence as shown in Fig. 8.

$$X_{sc} = \frac{\mathrm{X} - X_{min}}{X_{max} - X_{min}} \tag{1}$$

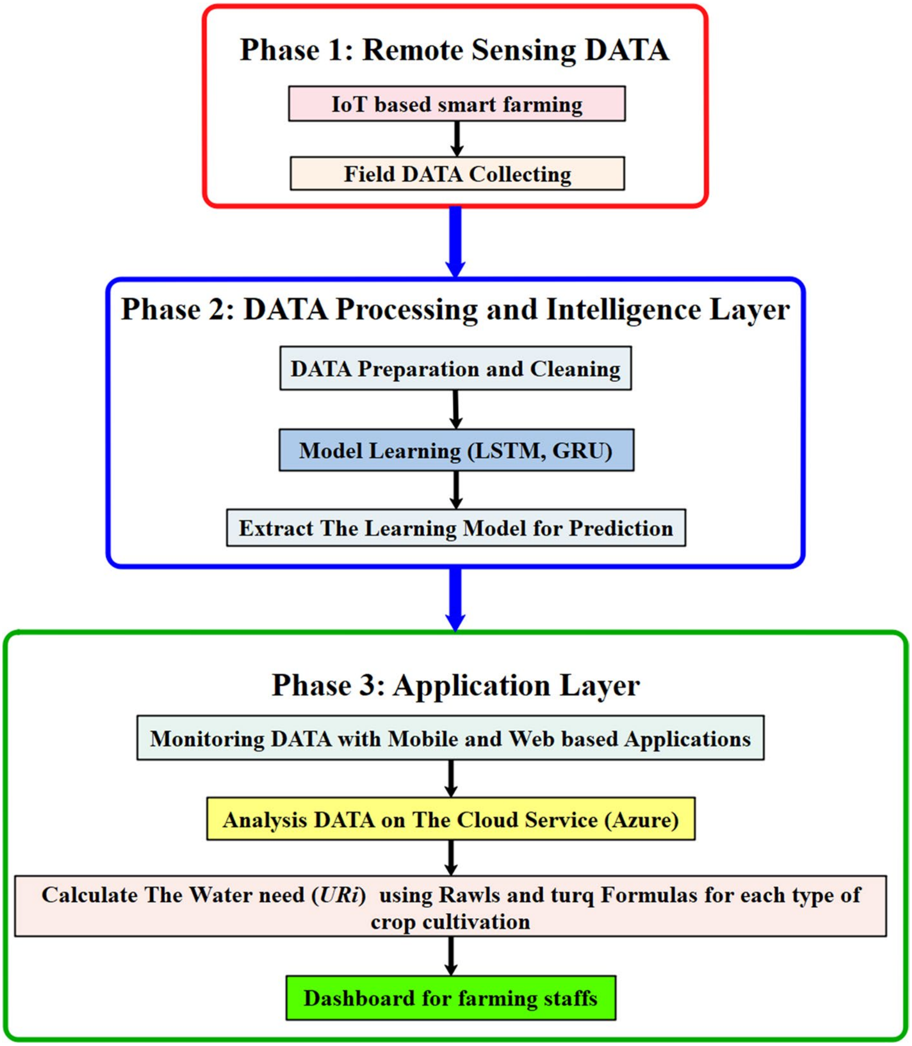


Fig. 6 Main steps of IoT-based smart farming decision support system

$$X_i = X_0 \ldots X_n \tag{2}$$

$$Y_i = X_{n+1} \tag{3}$$

The operational architecture illustrates information about soil moisture for the upcoming days; it also suggests irrigation plans based on the level of soil moisture and precipitation predicted by the system. To save water and energy, the generated information by algorithm and device is stored in InfluxDB database at the server as given in Fig. 11. The Edge system is placed between IoT sensors Network and the Cloud as an intermediate layer. It comprises three primary modules: data acquisition module, prediction module, and visualization module. Data collected by networked sensors are sent using different transmission network protocols. Data is stored closely to the Edge to provide quick access to data for the farmer during interventions. Moreover, farming data remains available even if the internet connection is temporarily interrupted. Processing and validating data at the edge level reduce the amount of data transmitted to the cloud and conserves the global energy of the architecture and network bandwidth. we have planned a (RPI3) boards as an Edge level because it includes sufficient hardware resources for processing, at the software level it is based on the Linux kernel, so it is compatible with most languages and AI libraries. Each sensor in our IoT system has a range of measurements that must be evaluated at Edge's level to serve as a baseline for detecting abnormal behavior. For instance, if we consider a temperature ranging from − 40 to + 80 °C for the DHT22 sensor, such imprecise data must also be corrected according to each sensor's behavior and take into consideration historical data to prevent the system from triggering false alerts and adapt the frequency of data collection and sensing to obtain more reliable data. After the preparation and cleaning of the data, the learning phase is performed. This phase is costly in terms of resources, so we have chosen to use the "Google Colab"(GC) platform [42], which offers "CPU" and Free "GPU", as well as the "Google Drive" (GD) [43] storage service to save the model as a file (*. h5) after each epoch.

5.4 Step 3: Application DATA

Data are collected and processed by a web service based on NodeJS before being sent periodically to the cloud architecture. All data streams are stored in GD before they are transmitted to GC to execute AI techniques used for training, testing, and prediction.

NodeJS listens on the serial port "/dev/ tty0", with a baud rate of 115,200; when new data is written to the port, we extract the measurements (they are in the form of a character string separated by commas), then we check if all the sensors work perfectly. These data are stored in the InfluxDB database temporarily; after that, we form a structured package with the last six measurements of each sensor because they must correspond to the entries of the detection models anomalies phase that will be presented in our future works. The MQTT client then sends a request to the MQTT broker, which is in the local server or in a Virtual Machine (VM) at the Cloud level. All the operations are displayed on the active page (written in HTML with JavaScript, which has listener's events compatible with messages generated by the SocketIO module to display all changes in real time). To start irrigation planning, we need to calculate the useful reserve of water UR parameter in mm. There are multiple functions for quantifying UR from soil texture data. The linear regression equations have the advantage of being simple

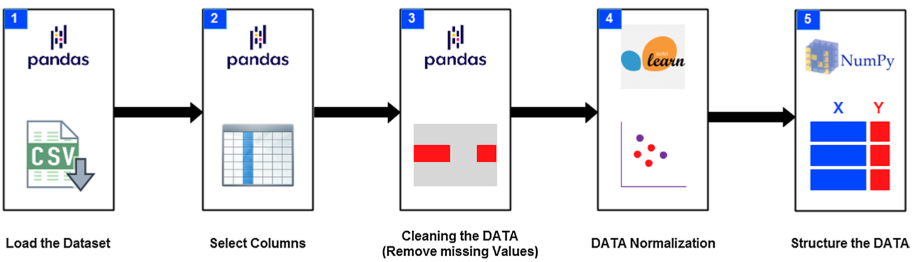


Fig. 7 Data preparation and cleaning steps

Table 2 Datasets used

Datasets	Selected measures	Interval	Rows	Number of empty rows
Eleven years of mountain weather, snow, soil moisture and stream flow data from the rain-snow transition zone [44]	Soil moisture	1 h	35,064	3002
Historical Hourly Weather Data 2012–2017 Hourly weather data for 30 USA, V1.1 [45]	Temperature, Humidity	1 h	45,254	3152
Sensor readings with temperature light humidity 2014–2015 [46]	Temperature, Humidity	5 min	56,571	0
Soil moisture dataset [47]	Soil moisture	1 min	10,290	0

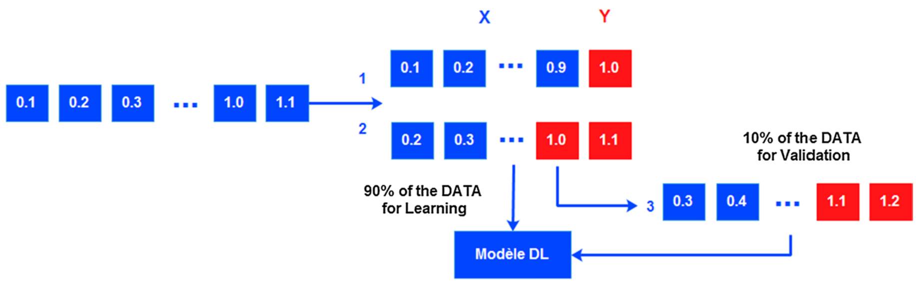


Fig. 8 Example of an input data structure as a sequence for a learning model

and have been tested on a large sample of US soils (2,500 horizons taken from 32 states of the United States), their validation offered correlation coefficients of 0.80 and 0.87 for water content estimation at − 15,000 hPa and − 330 hPa respectively. To start irrigation planning, we need to calculate the useful reserve of water UR parameter in mm. There are multiple functions for quantifying UR from soil texture data. The linear regression equations have the advantage of being simple and have been tested on a large sample of US soils (2500 horizons taken from 32 states of the United States), their validation offered correlation coefficients of 0.80 and 0.87 for water content estimation at − 15,000 hPa and − 330 hPa respectively.

6 Rawls Linear Regression Equations:

The Useful reserve (*URi*) of a farm *i* is a key metric in our contribution. Initially, we calculate the field capacity using formulas (4) and (5) with:

- W330 water content at −330 hPa (mm/m).
- W15000 water content at - 15.000 hPa (mm/m).
- Ar: Clay content (%).
- Sa: Sand content (%).
- MO: Organic matter content.
- h: the thickness of the horizon(mm).

$$W330 = 257.6 - (2 * \text{Sa}) + (3.6 * \text{Ar}) + (29.9 * \text{MO}) \tag{4}$$

$$W15,000 = 26 + (5 * Ar) + (15.8 * MO) \tag{5}$$

The useful reserve (UR) in mm is calculated for each horizon by the following function (6):

$$UR = (W330 - W15000) * h \tag{6}$$

- Wilting point: W1500 without irreversible dieback of plants.
- Field capacity: W330 after saturation and drying for 48 h.

This reserve determination depends on the soil characteristics and the plant nature, more details on the irrigation scheduling algorithm steps are given below.

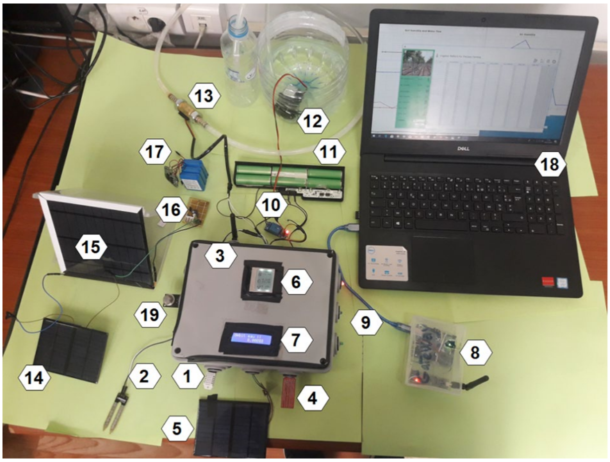


Fig. 9 Field data collection device. [Legends 1: DHT22 Sensor, 2: Soil moisture Sensor, 3: NRF24L01 module, 4: Water level Sensor, 5: Light sensor, 6: LCD display nokia, 7: LCD display I2C, 8: Gateway node, 9: LEDs notification, 10: Relay Switch, 11: Power supply 12 V, 12: Water pump, 13: Water flow sensor, 14: Solar panel ZW85X115-12, 15: Solar panel 6 V, 16: amplifier, 17: Power supply 9 V, 18: PC] The mega Arduino card and NRF module are in the Box

6.1 Turq formula:

In our application, we have proposed three calculation methods, the first method calculates the RU according to the soil texture thanks to the soil structure knowledge (Clay, Limon, Sand, Organic Matter), the soil texture table that directly estimates the RU, and for the second method, we used the Rawls linear regression equations. Besides, for the calculation of potential evapotranspiration ETP, we use the third method, it's Turq formula: The formula (7) is valid for relative humidity (hr) ≥ 50% (on the month), the formula (8) for hr < 50%. Furthermore, an operational architecture at the edge level to predict environmental factors based on field sensory data and weather forecasting data using (LSTM)-based models and (GRU)-based models.

$$ETP = 0.013\mathrm{j}\ (\mathrm{Rg} + 50)\left(\frac{\mathrm{T}}{\mathrm{T} + 15}\right) \tag{7}$$

$$ETP = 0.013\ \mathrm{j}\ \ (\mathrm{Rg} + 50)\left(\frac{\mathrm{T}}{\mathrm{T} + 15}\right)\left(1 + \frac{50 - \mathrm{hr}}{70}\right) \tag{8}$$

$$B = \mathrm{ETR} - (\mathrm{Peff} + \mathrm{RFU}) \tag{9}$$

$$Peff = 0.6 * \mathrm{Pmoy} - 10\ \ \mathrm{ifPmoy} \le 70\ \mathrm{mm} \tag{10}$$

$$Peff = 0.6 * \mathrm{Pmoy} - 25\ \ \mathrm{if\ Pmoy} > 70\ \mathrm{mm} \tag{11}$$

$$ETR = \ \mathrm{ETP} * \mathrm{Kc} \tag{12}$$

With: ETP: evapotranspiration in mm/month. J: number of days in the month. T: average temperature over the month (°C). hr: average relative humidity (%). Rg: average solar radiation (here measured) in cal/cm^2/day. ETR: the actual evapotranspiration. RFU: it's easy reserve useful RFU. Peff: effective rain. KC: is a cultural coefficient.

Algorithm Steps: Algorithm of irrigation scheduling

Result: Calculate required water quantity (*RU*) with different methods;
The variables used in the algorithm for irrigation planning:

- **Threshupper**: selection of maximum threshold soil- moisture required to stop irrigation.
- **Threshlower**: selection of minimum threshold soil- moisture required to start irrigation.
- **C_Date**: read precipitation information of upcoming days and select the nearest precipitation date.
- **D_Irrigation**: irrigation at a specific date.
- **C_SM:** current soil moisture.

Step 1. Initialize soil texture of the farm and the crop coefficient to compute precisely the required water quantity of each crop.
Step 2. Initialize minimum threshold (Threshlower) of soil moisture to start irrigation and maximum threshold (Threshupper) of soil moisture to stop irrigation
Step 3. Set mode (manual/auto) for irrigation
Step 4. **If** (mode = auto) {
Read and check current soil moisture (C_SM)
  If (C_SM< = Threshlower)
    // condition check of current soil moisture from its set threshold value by user
{
Step 5. Set mode (1: Texture of the soil, 2: Rawls, 3: Turq, 4: Prediction with LSTM, GRU) for calculating RU
    If choice == 1{
Calculate required water quantity (*RU*) using soil texture triangle to estimate the RU.
    }
    Else If choice == 2 {
Calculate required water quantity (*RU*) using Rawls linear regression equations.
    }
    Else If choice == 3 {
Calculate required water quantity (*RU*) using Turq formula.
    }
    Else If choice == 4 {
Calculate required water quantity (*RU*) by extracting the learning model for prediction (Air-Temperature, Air-Humidity, Soil-Moisture) and using the predicted DATA in Turq formula.
    }
  While (Threshupper > C_SM)
    // condition for watering until soil moisture reaches its minimum required value.
      {
        Send 1 to relay switch to start irrigation; //*Signal to Start Water motor*
      }
      Send 0 to relay switch to stop irrigation; *//Signal to stop the water motor*
      }
    Else
      {
        Send 0 to relay to stop irrigation; *//Signal to stop the water motor*
      }
 }
Else
{
Step 6. Select date to start irrigation
    If (current_date> = irrigation_date) **Then**
      // condition to start the irrigation at specify date
      {
        While (Threshupper>C_SM)
        {
          Send 1 to relay to start irrigation; *//Signal to start the water motor*
        }
      }
  Else
      {
        Send 0 to stop irrigation; *//Signal to stop the water motor*
      }
 }
End

7 Experimental Study and Analysis

This section presents the proposed platform implementation and the analysis of the results. We use low-cost, open-source hardware platforms such as Arduino boards and Raspberry because commercial IoT devices are maturing, but they are still prohibitively expensive for low-income nations. The main objective of this experimental study is to create our own wireless network under the Arduino environment to transmit data from one or more sensors at any time of the day. Along with weather forecast information for developing an algorithm for predicting the upcoming day's environmental factors for enhancing irrigation efficiency of smallholder farmers to achieve water savings in various crops and great performance. The system was tested in our laboratory (RIIR) in the Oran1 University, and we plan to test the platform ion a real farm of the vineyard in El-Malah city, close to Oran city (Algeria).

A Decision Support System (DSS) has been developed (see Fig. 8) to predict the soil moisture based on field sensors as highlighted in Fig. 9 data and weather forecasting data, using LSTM-based-models and GRU-based models. The algorithm displays data about the upcoming days with regard to the three parameters. It also suggests irrigation schemes, based on the level of soil moisture and on anticipated precipitation. In order to save water and energy, the generated information by algorithm and device is stored in InfluxDB Database at the server. The smart DSS in detail is shown in Fig. 8. To get a better understanding of how our platform works, we model it by representing conceptually all communications involved in its operation. To do this, we use the UML (*Unified Modeling Language)* modeling approach to model configuration tasks and the information exchange between different communicating objects that are involved in the test environment used in our project context. Sequence diagrams allow us modeling these exchanges. This diagram (see Fig. 10) depicts the various data collection exchange, storage and display messages that can take place between communicating objects: platform, gateway, Edge, Fog, Cloud and the intermediary (the farmer). Our objective remains the development of an autonomous platform for environmental data measurements, such as air temperature, air humidity, solar radiation, soil humidity …etc., in real time. In this work, a sensor/actuator node has the collecting data role and sending them to the gateway, which is connected to a serial port on the PC. A desktop application developed with Java allows us reading received data via this serial port, and storing them in a InfluxDB database, then visualizing them through graphical curves and calculating the need for soil water with the different defined methods. After that, the application sends this need to the sensor/actuator node to perform the irrigation process. The main steps related to the operation of the platform are highlighted in Fig. 8.

7.1 Remote sensing DATA

These results are preliminaries because the test was made inside the laboratory, so we plan to test the platform on a real vine farm r to demonstrate the proposed platform performance. All data were uploaded each hour to the web server for remote supervision. For instance, real-time experimentation details are shown in Fig. 11. We suggest cloud services solution for storing the large amounts of data generated by sensors, then we used them in the prediction of future measurements; Azure Cloud was chosen to ensure the accessibility and availability of our platform (it can be accessed anywhere and anytime), thus guaranteeing scalability and increasing resources in the case of overload (elasticity). We received a free student offer, which we will use it to create a virtual machine (VM) linked to a public IP address, and then we access this machine with the Remote desktop protocol (RDP). InfluxDB offers a limited free cloud service, but it allows users to customize their dashboard for monitoring and data analysis, as presented in Fig. 11.

In order to increase computing power and load balancing; it is necessary to think of adding slave nodes which take care of the resource-intensive processing, the communication on this cluster is carried out by a wireless network produced by the WIFI card integrated into the (RPI3) as illustrated in Fig. 12. Figure 13 represents the number of packets where the edge cannot process them according to several scenarios, according to the results the gateway can process 6 packets per second without loss, although the case of several nodes represents a better gain because most of the packets are lost because of the NRF24L01 module which fails to receive them. In Fig. 14, we evaluate the irrigation planning algorithm for real-time monitoring and DSS, which shows the current soil moisture recorded by the sensor. Precipitation information will help users/farmers in planning/scheduling optimum irrigation by calculating the real useful reserve (UR) by different modes. If the moisture has increased to 20%, irrigation will start automatically. The vertical bars indicate automated irrigation periods triggered by temperature when soil-humidity was below the threshold value (20%), the water flow increased until the soil-humidity was above 20%, than the water flow decreased to 0 at 17:28.

7.2 Experiment for Tomato Irrigation

Growth-stage-specific K_C for potato and tomato used in this study are mentioned above the Table 3 according to the food and agriculture organization of the United Nations [48]. Figure 15 depicts water requirement calculation for tomato crop with rooting of 30 cm.

The estimation of the reserve of soil from the texture triangle is: RFU = 12.20, for a visual representation of the dependence, the texture class was: silty clay loam with a red dot as described in Fig. 16, we have used the soil texture calculator of united states agriculture department [49]. The estimated reserve of a soil from Rawls formulas is: RFU = 12.0. One can also predict the actual ETR evapotranspiration for the month 2019-03-22 to 2019-04-22. T: refers to the average monthly temperature = 20 (° C). Hr is the monthly average relative humidity = 46 (%). With the surface of 10 hectares and Kc ini = 0.8. Hence, the monthly water required equals 76.33, and the need for daily water amounts to 2.46. The growth-stage-specific K_C is also considered in the calculation of the UR, it has been noticed that for a growth-stage-specific K_C fin = 0.8, the actual evapotranspiration ETR equals 9.83. Similarly, ETR is computed for the K_C ini = 0.2 and K_C mid = 0.9. The results obtained are ETR = 2.45 and ETR = 11.06 successively.

7.3 Experiment for Potato Irrigation

Notably, in Fig. 17 shows the estimated reserve of soil from the texture triangle. It can have observed that the value of RFU = 36.0, as shown in Fig. 16, the texture class was: slit loam with a blue dot. The estimated reserve of soil from Rawls formulas is: RFU = 39.04. We can also estimate the actual ETR evapotranspiration for the month 2019-03-22 until 2019-04-22 so that the data is collected from InfluxDB database. T refers to average temperature over the month = 20 (°C). Hr is the average relative humidity = 46 (%). With a surface of 10 hectares and Kc ini = 0.4. Hence, the monthly water required equals − 241.21, and the daily need for water is − 7.78. The growth-stage-specific K_C has also been considered to

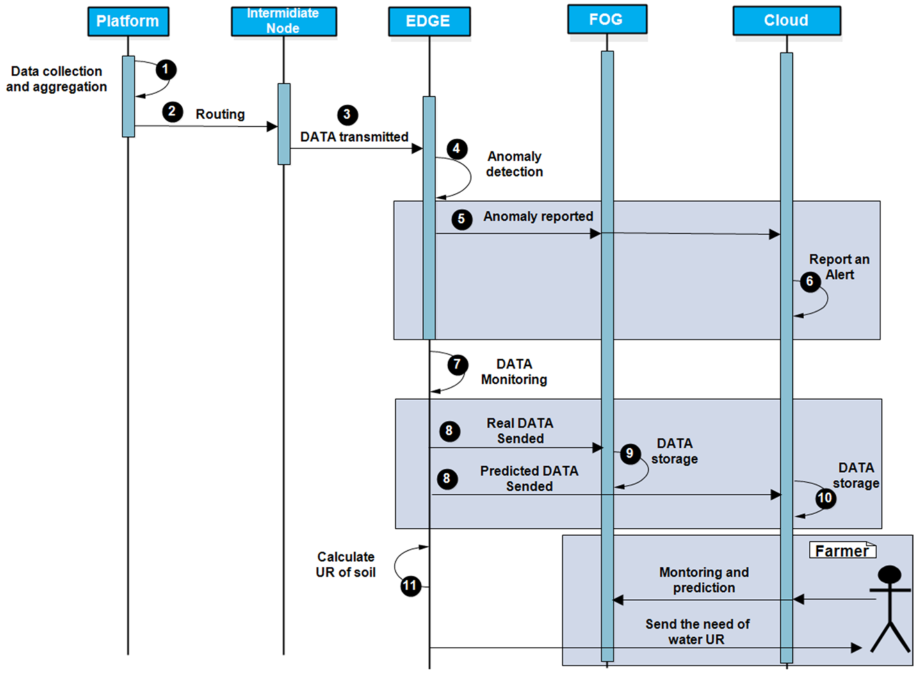


Fig. 10 Sequence diagram of the irrigation system

calculate the UR. As a result, for a growth-stage-specific K_C fin = 0.75, the actual evapotranspiration ETR equals 9.22. Correspondingly, ETR is calculated for the K_C ini = 0.4 and K_C mid = 1.15 and the results attained are ETR = 4.91 and ETR = 14.14 successively.

7.4 Prediction DATA Using LSTM-Based Models and GRU-Based Models

This section presents the implementation of the new Edge-IoT-Cloud based architecture dedicated to smart farming and the obtained results analysis.

The objective of these experiments is to demonstrate how to create our wireless network under an Arduino environment to transmit data from one or more sensors at any time of the day, simultaneously with information about meteorological conditions to develop an algorithm to predict environmental factors during the few days to come. The system was first tested in our laboratory, and we plan to test it on a vine farm near El-Malah city, located in western Algeria. Figure 6 presents an IoT-based smart farming DSS for to execute the models. A functional architecture within the Edge's level has been developed (see Fig. 5) to predict the environmental factors based on field sensors and weather forecasting data using LSTM-based models and GRU-based models. In this research work, two diverse information sources are considered, each featuring complementary and characteristic features suitable to design and test LSTM and GRU approaches: In [44], historical hourly weather data (2012–2017) have been collected from 30 American and Canadian cities, as well as six Palestinian ones. The dataset covers ~ 5 years of high temporal resolution (hourly measurements) data of numerous weather attributes, such as temperature and

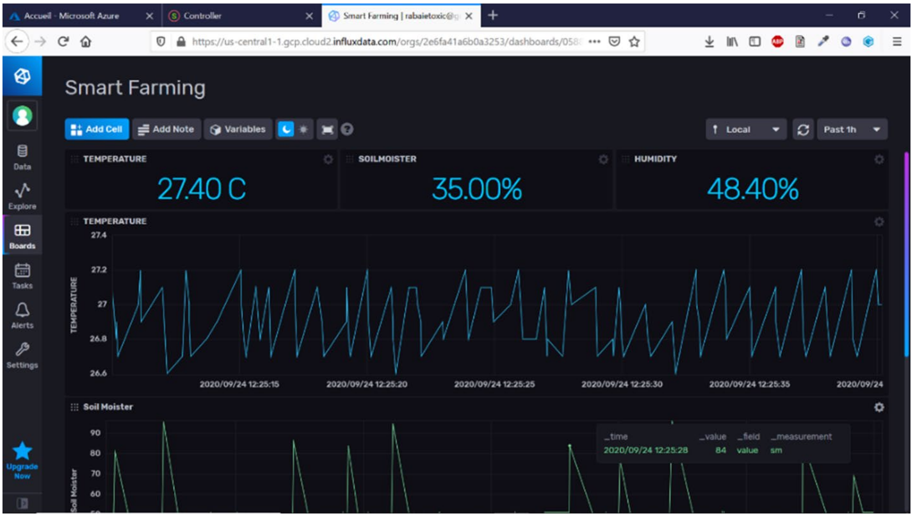


Fig. 11 Monitoring and analysis of data on the cloud service

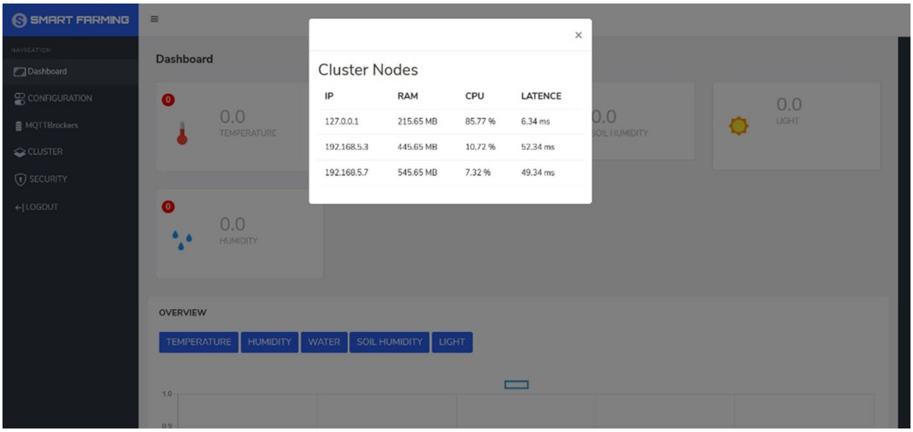


Fig. 12 List of nodes that make up the cluster at the edge level

humidity that make the overall interest of our study. Detailed hydro-meteorological data from the mountain rain-to-snow transition area are available from 2004 to 2014 (Historical Hourly Weather Data 2012–2017) [45]: we are exclusively interested in soil moisture calculations in the progress of this study. This data version resolves errors in all data files and replaces the earlier datasets. In our study, we treated the learning time on a dataset of 1191 lines, for an epoch, and with a size of batch (batch-size) of 512, with several architectures (32,64,128,256), thus with the two calculation units' "CPU" and "GPU", the results are represented in Fig. 18. From the results of the graph, we generally observe that the learning time increases, when the number of units in the layer increases (more units mean more operations), as well as GRU and faster than LSTM (the unit is only made up of two doors, instead of three doors), also GPU usage is efficient (LSTM is 30 times faster with GPU), the implementation of both algorithms with "Pytorch" library is better than "Tensorflow

/ Keras" with the CPU, and vice versa with the use of GPUs. The models built must be implemented, so optimizing the time necessary to carry out a prediction is also necessary. For this, we switch to a lighter version of our model using "Tensorflow Lite" the conversion reduces their file sizes and introduces optimizations that do not affect accuracy. As shown in Fig. 19, the comparative results between LSTM and GRU on the prediction time (512 lines as inputs) using the different libraries (with the CPU). We notice that "GRU" is faster than "LSTM", and the models with "Tensorlow Lite" are the fastest, then "Pytorch", and at the bottom of the classification "Tensorflow / Keras”. In conclusion, we will use the GPU with the "Tensorflow" library in the learning phase, and for the deployment, we convert to "Tensorflow / Lite" if the accuracy of the two models (LSTM and GRU) is close, then we choose the one from GRU because it is the fastest. In this study, the LSTM cell architecture as defined by Zaremba et al. [11] used in TensorFlow 2.0 has been utilized for the experiments. Several factors might enable speeding-up the training time, comprising the dataset size, the platform development (e.g., Tensorflow, Pytorch, Keras, Caffe, MXNet), the hardware platform (e.g., CPU, GPU, TPU) and the AI/ML hyper-parameters mode (e.g., the hidden layer’s number, the neurons number in each layer, the learning rate, in addition to the batch size and the periods number). GC is a suitable area provided by Google for the training of models.

We used a laptop (Laptop PC) with a processor in all experiments: Intel Core i5-6300U @ 2.40 GHz, Memory: 8GO RAM, Disk: 256 GO SSD. In addition, a comparison between the LSTM-based and GRU-based models’ performances over the two test sets, is described in Figs. 20, 21 and 22, through a comparison of the results of both training and validation datasets, respectively. Results analysis has shown some key insights: (1) the training time can be reduced by if the model size is reduced and the batch size is increased; (2) CPU outperforms GPU in terms of speed in the of small-sized models training time. It could be justified that with small models, the CPU-GPU data transfer overhead surpasses the computation acceleration benefit; (3) LSTM-based models require la ong training time compared to GRU-based models.

Even LSTM and GRU involve 1 input layer and 2 hidden layers, with 128 neurons for the first and 64 for the second. The loss plot shows that the model has comparable performance on both training and validation datasets. If these parallel plots start to depart consistently, it might be a sign to stop training at an earlier epoch, as given in Figs. 20, 21 and 22. We also discovered the importance of collecting and reviewing metrics during our DL models training. Indeed, we observe that the training time for each epoch with LSTM-based models is around 200 s. However, it could be calculated around 300 s with GRU-based models. We proposed Adam,a method for efficient stochastic optimization to train our models that only requiresfirst-order gradients with little memory requirement. To avoid the overfitting issue,we used a callback technique in order to use the model that performed better on thevalidation set.

According to the recent research results, it even surpasses LSTM-based models in many applications. The experiments were conducted to predict the Air-Temperature, Air-Humidity and Soil-Moisture to predict these parameters of the upcoming days. Figures 20 (a) and (b) illustrate that the model has comparable performance for Air-temperature, and gives the best results on both training and validation, especially with LSTM-based models. Even the Mean Squared Error (MSE) is higher than in GRU-based models. Table 4 compares the results of the two models, LSTM and GRU. The error is almost the same, while LSTM is more precise and converges faster, while the error increases as the number of steps increases; when in advance of one step forward, we rely more on predicted values, so we lose precision. Figures 21 (a) and (b) depict that the model with GRU-based models outperforms LSTM-based models slightly. Table 5 confirms that the GRU model is more accurate, whereas the error increases as the number of steps increases also show that the models obtained are accurate, even with several steps forward. Figures 22a and b show that the parallel plots start departing consistently after 10 epochs. At the start of the 60th epoch, stopping training at an earlier epoch might be a sign. According to the results of Table 6, we notice that the error is large from the first step for both models; in the case of underfitting, the model has not learned enough from the data, so it has a weak generalization.

ReLU is the inner activation to avoid local minima issues. The experiments are repeated 5 times, and the median Mean Absolute Error (MAE), the (MSE) and Root Mean Squared Error (RMSE) on both test sets are presented in Table 7. Despite all this, the model was well trained on testing and validation datasets recognizing that the graph size was too tiny. The findings show that the GRU-based models will improve performance for Soil-Moisture and Air-Temperature predictions. However, the LSTM-based model outperforms GRU-based models for Air-Humidity forecasts. Experiments were performed to determine the most reliable neural network topology, in terms of accuracy. MSE, RMSE, and MAE values for each technique are reported in Tables 8,9 respectively. The results are very superior in our prediction model with the ones found in previous studies by [10] and [50] where the values drop slightly; however, a significant decrease in RMSE, MAE and MSE values is observed in both the training and validation of both LSTM and GRU based-model's predictions, they minimize the error between the actual data and the predictions. In comparison to a hybrid method (SVR + Kmeans), we found that SVR predicts soil moisture with higher MSE. Furthermore, ANN forecasts are unstable since they are based on averages from multiple network initializations, which can result in a different result each time a model is learned. The SVM results, on the other hand, are consistent and special. Regardless, it was shown that the LSTM and GRU-based models outperformed other methods in all situations.

8 Conclusions and Future Scope

In this work, we suggested an IoT-based intelligent irrigation system founded on a new Edge-IoT-Cloud platform with DL approaches and open sources technologies to predict the environmental factors in our smart farming system (Air-temperature, Air-Humidity, Soil-moisture) in order to reach more conclusions that have proven to be convincing. Then, this irrigation system was implemented and presented. As a result, it has been deemed feasible and cost-effective to optimize water resources for agricultural production. Moreover, this irrigation system allows cultivation in places with water scarcity, thereby improving sustainability. Besides the monetary savings in water use, the importance of this natural resource preservation justifies the use of this kind of irrigation system.

In the meantime, we have illustrated the efficiency of AI strategies used in this article, especially regarding training speed and accuracy control. However, our practical realization is still relevant today and does not stop there. This platform does, in reality, have multiple viewpoints open to it: Introduce recognition models for fruits and vegetables and protection protocols. Indeed, we plan to use a computer vision system based on IoT using DL models to improve the quality of crops. Design and deployment of a precision agriculture-based (LPWAN) Low Power Wide Area Networks technologies such as Lora and Sigfox, which

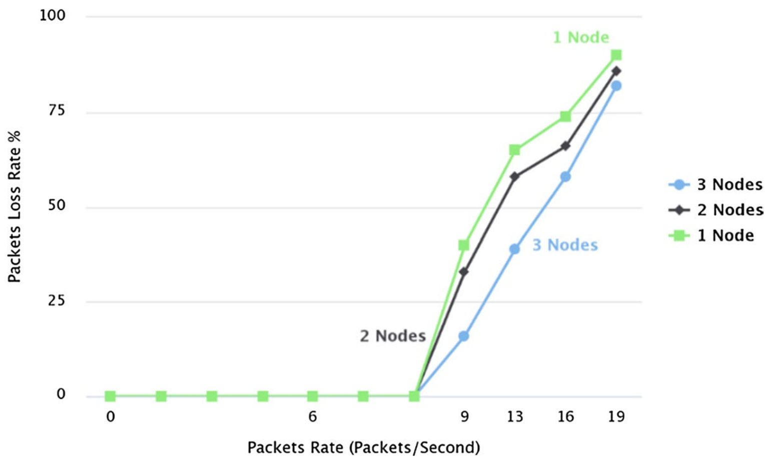


Fig. 13 The rate of packets loss under several scenarios

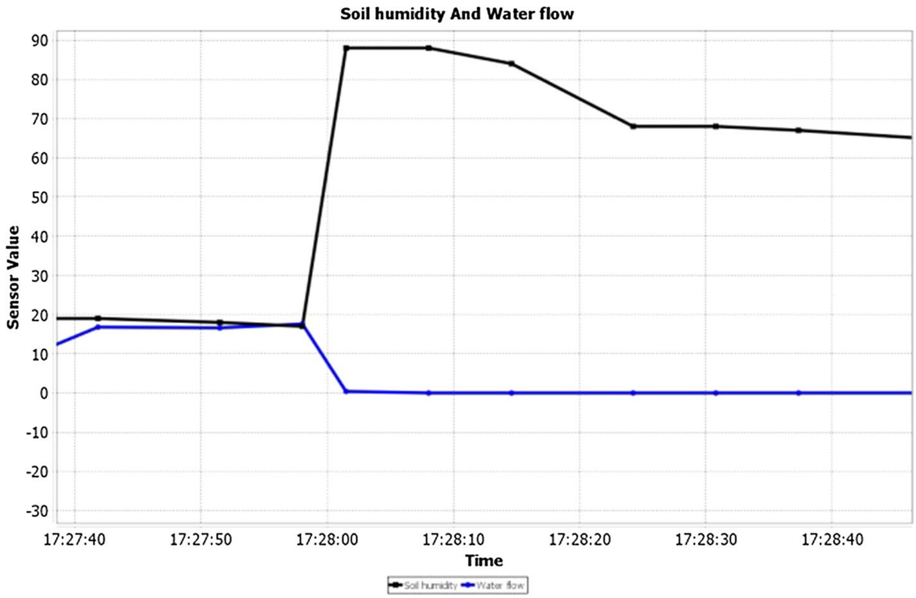


Fig. 14 Analysis of irrigation launching

Table 3 Growth-stage-specific K_C for tomato

Crop	Clay %	Silt %	Sand %	Organic matter %	Rooting depth cm	Crop coefficients (K_C)		
						K_c ini	K_c mid	K_c fin
Tomato	28,0	55,0	17,0	1,75	30–60	0.2	0.8–0.9	0.8–0.7
Potato	17,80	47,0	25,90	2,65	< 30	0.4–0.5	1.1–1.15	0.75–0.8

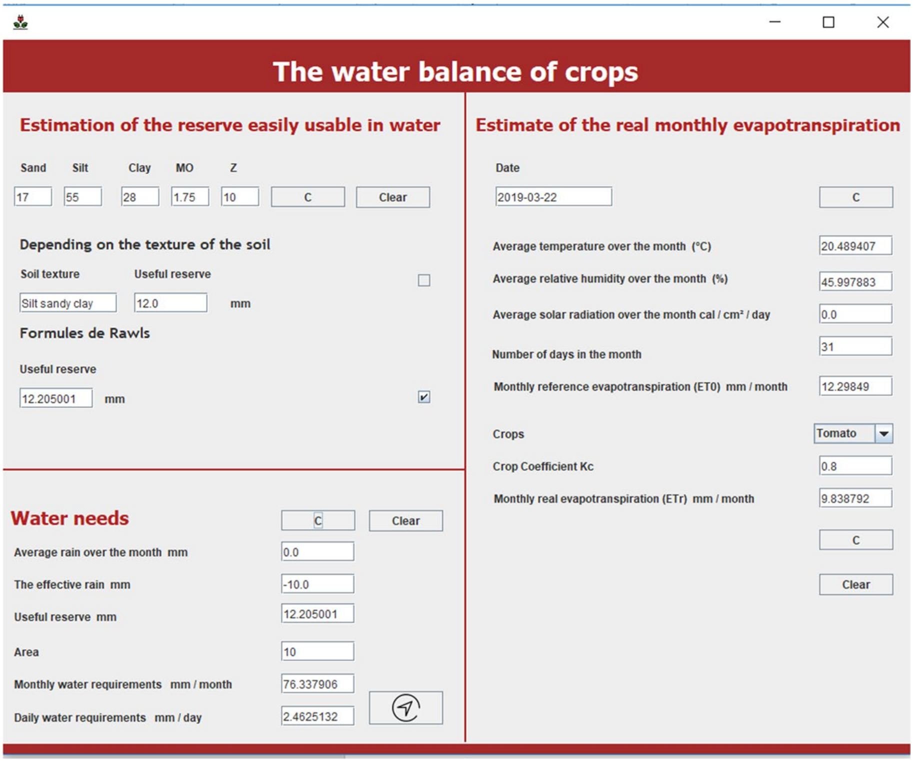


Fig. 15 Calculation of water needs for tomato cultivation with rooting depth of 10 cm

are energy-saving techniques similar to Long Range Wide Area Networks (LoRaWAN), for improving irrigation performance of large-holder farmers.

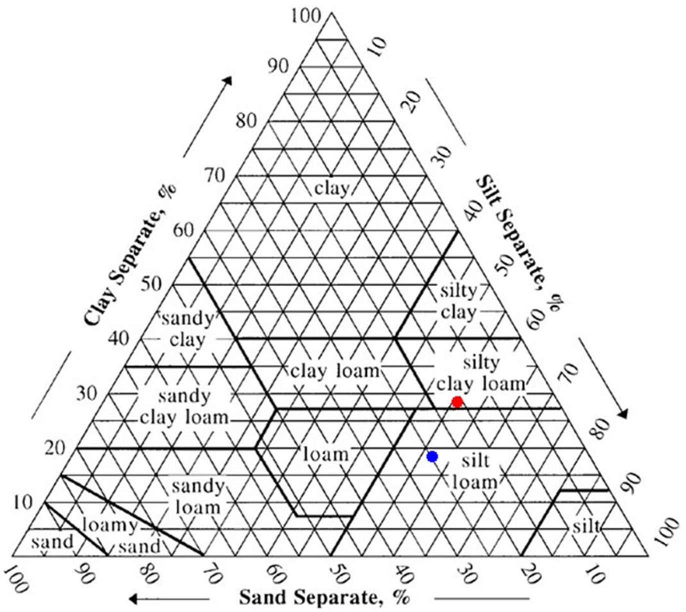


Fig. 16 The soil texture triangle generated by soil texture calculator of USDA

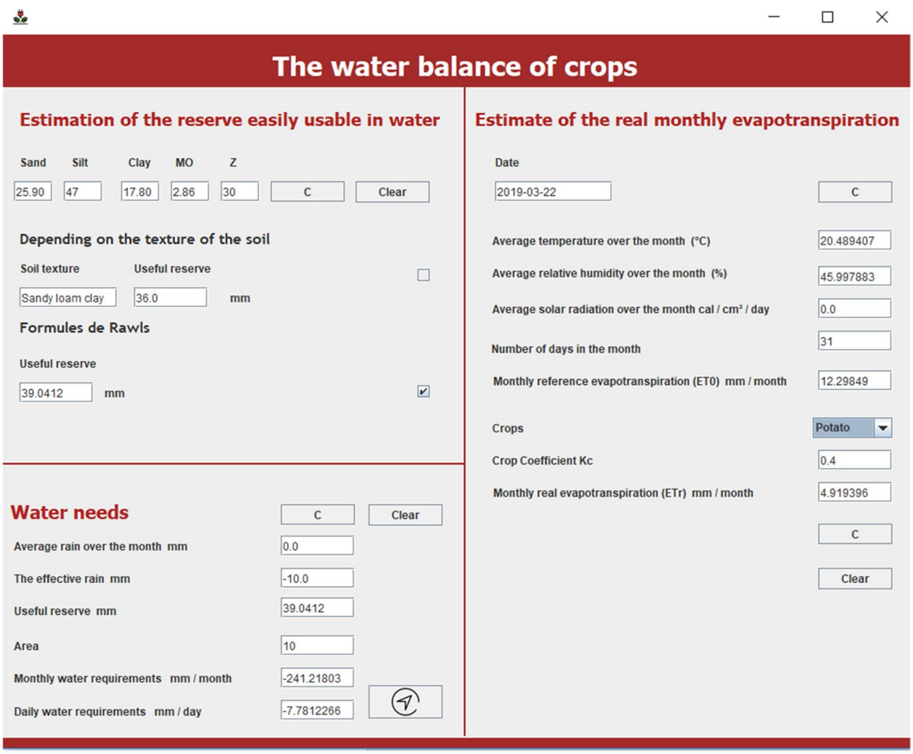


Fig. 17 Calculation of water needs for potato cultivation with rooting depth of 30 cm

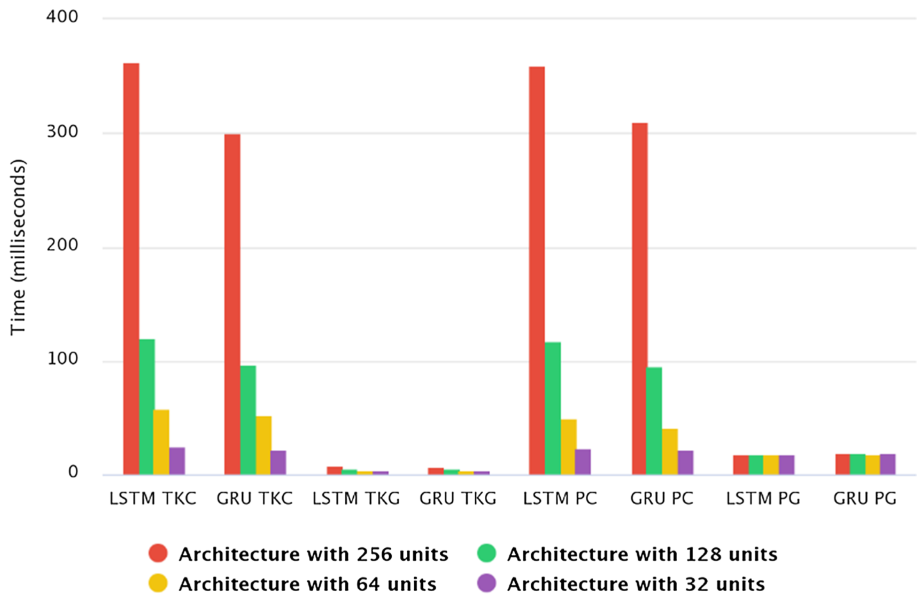


Fig. 18 Comparative results between LSTM and GRU on training speed (*TK* Tensoflow/Keras, *C* CPU, *G* GPU, *P* Pytorch)

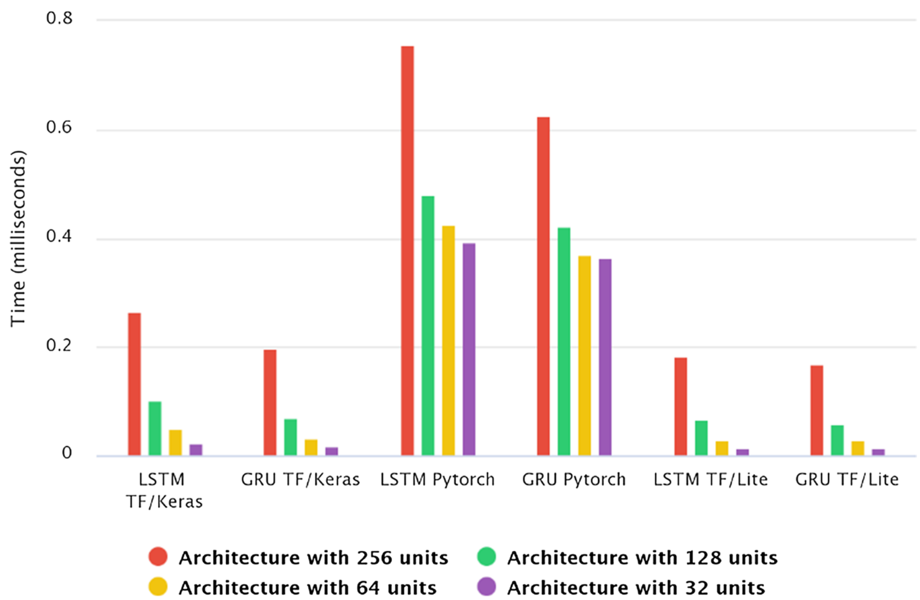
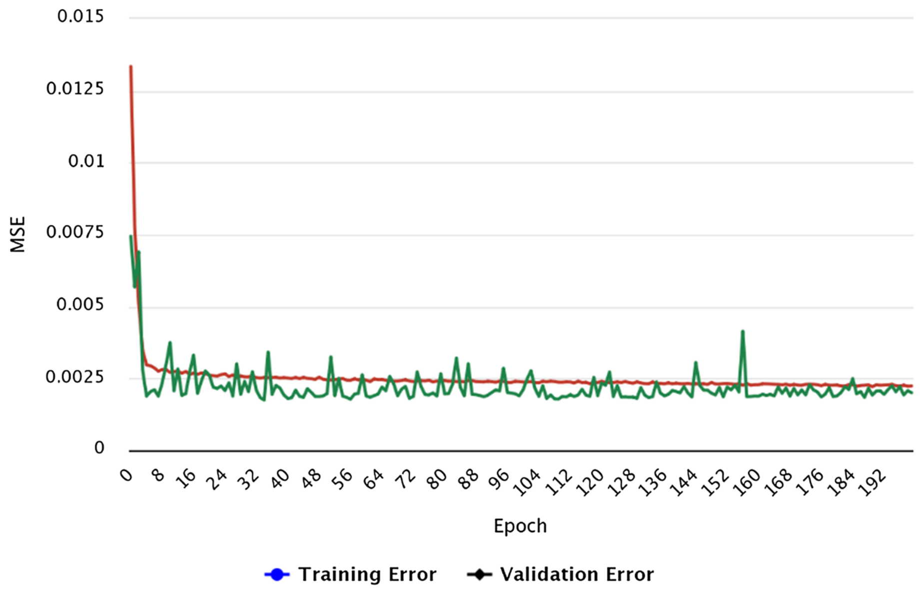
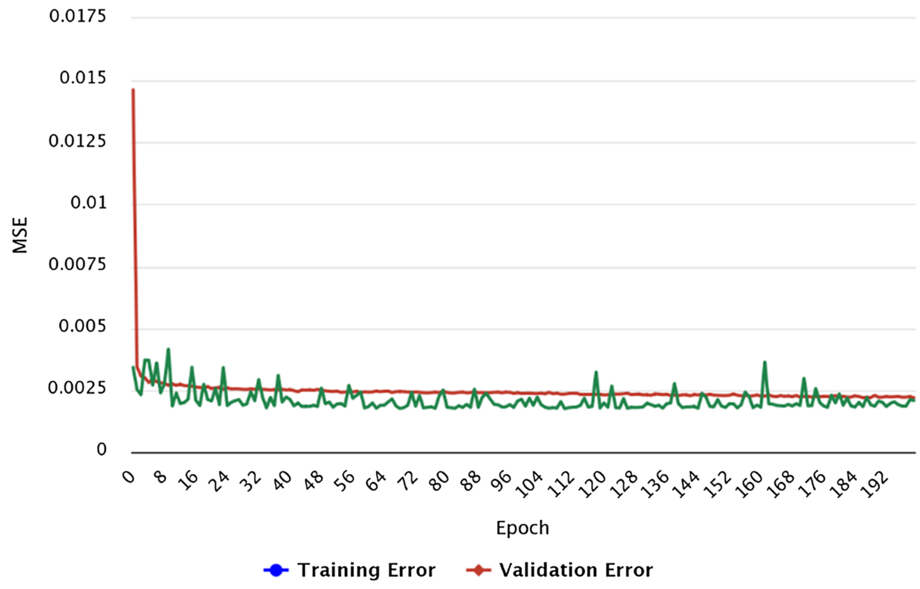


Fig. 19 Comparative results between LSTM and GRU on the prediction time (*TF* Tensorflow)

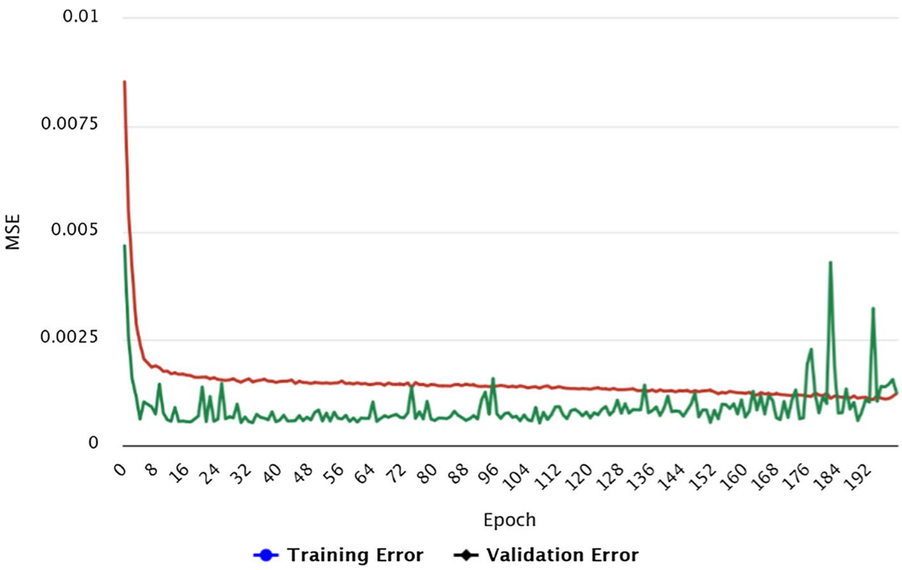


(a)

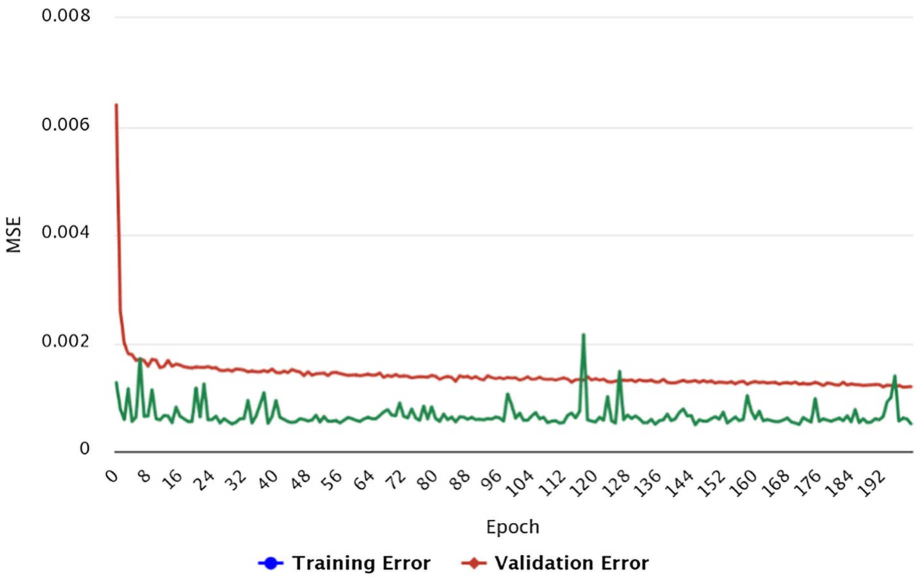


(b)

Fig. 20 **a** Plot of Model Loss on Training and Validation of Air-Temperature using LSTM-based models. **b** Plot of Model Loss on Training and Validation of Air-Temperature using GRU-based models

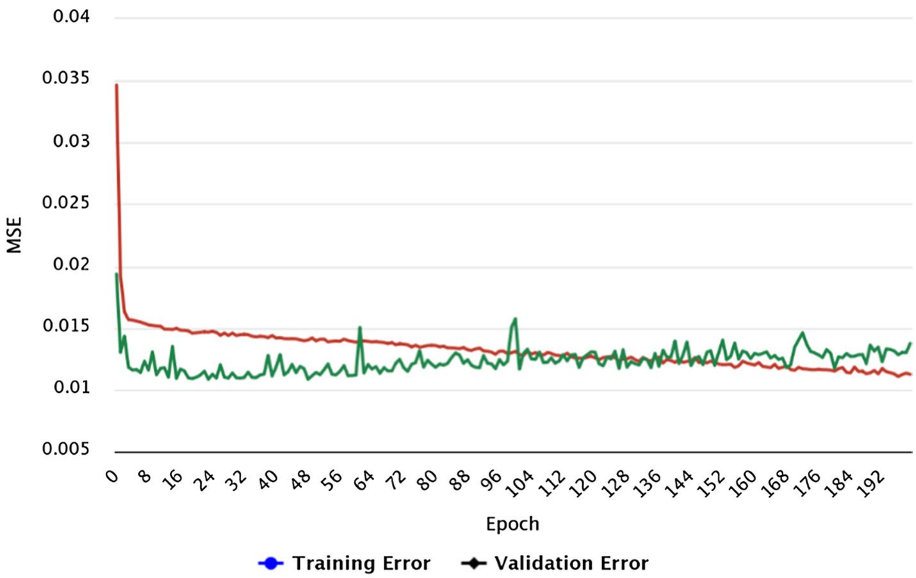


(a)

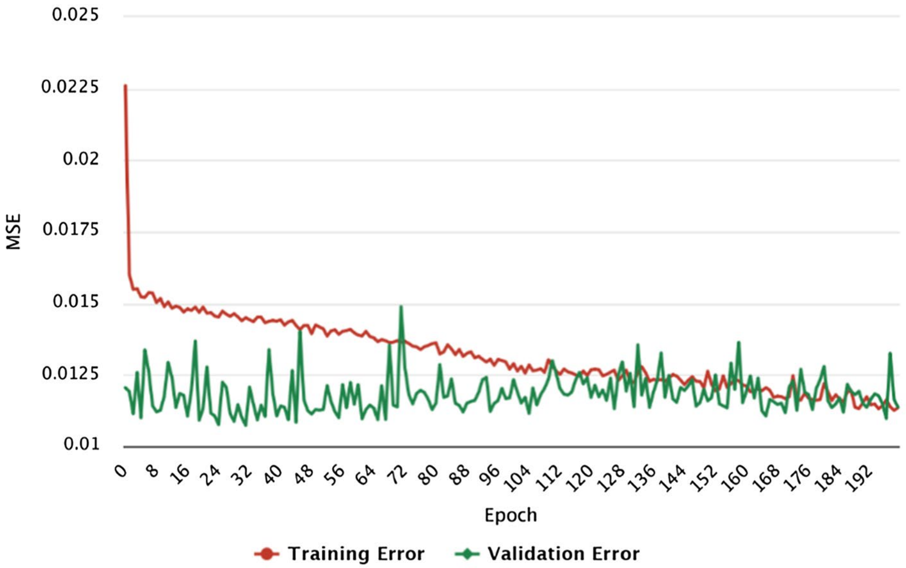


(b)

Fig. 21 **a** Plot of Model Loss on Training and Validation of Soil-Moisture using LSTM-based models. **b** Plot of Model Loss on Training and Validation of Soil-Moisture using GRU-based models



(a)



(b)

Fig. 22 **a** Plot of Model Loss on Training and Validation of Air-Humidity using LSTM-based models. **b** Plot of Model Loss on Training and Validation of Air-Humidity using GRU-based models

Table 4 Results of the prediction model of the air-temperature (Day)

Models	LSTM			GRU		
Step forward/error	MSE	RMS	MAE	MSE	RMS	MAE
1	1.012	1.006	0.656	1.19	1.09	0.778
2	1.874	1.368	0.867	3.42	1.849	1.327
3	5.12	2.26	1.48	6.75	2.598	1.889
4	7.78	2.79	7.86	10.87	3.298	2.442
5	10.35	3.21	2.18	15.34	3.91	2.95
6	12.54	3.54	2.451	19.82	4.45	3.36

Table 5 Results of the prediction model of the soil-moisture (Day)

Models	LSTM			GRU		
Step forward/error	MSE	RMS	MAE	MSE	RMS	MAE
1	9.899×10^{-5}	0.00994	0.00890	3.9833×10^{-5}	0.00631	0.00304
2	0.00064	0.0253	0.0247	0.00011	0.01054	0.00634
3	0.001475	0.0384	0.03723	0.000199	0.01413	0.01017
4	0.0025	0.0502	0.0477	0.000295	0.01718	0.013828
5	0.00426	0.0652	0.0625	0.00041	0.02029	0.017698
6	0.00698	0.0835	0.08127	0.00054	0.02336	0.02128

Table 6 Results of the prediction model of the Air-Humidity

Models	LSTM			GRU		
Step forward/error	MSE	RMS	MAE	MSE	RMS	MAE
1	153.09	12.372	9.5758	148.556	12.188	9.2503
2	271.742	16.484	13.300	278.59	16.691	12.781
3	323.030	17.973	14.16302	341.022	18.466	14.474
4	372.869	19.309	14.7577	388.268	19.704	15.432
5	408.22	20.204	15.092	424.656	20.607	15.562
6	423.875	20.588	15.3606	445.951	21.117	16.165

Table 7 RMSE, MSE, MAE of the LSTM and GRU based models for environmental factors Training and Validation

Parameters	LSTM			GRU		
	RMSE	MSE	MAE	RMSE	MSE	MAE
Air-temperature	1.4090	1.9855	1.0777	1.3331	1.7771	1.0167
Soil-moisture	0.0268	0.00072	0.0114	0.0220	0.00048	0.0101
Air-humidity	11.7550	138.18	8.1946	12.9778	168.4255	8.4585

Table 8 Comparison of RMSE and MAE between SVM, ANN, LSTM and GRU for the soil-moisture prediction

Ref	Parameter	RMSE	MAE
Gill et al. [50]	SVM	8.55	8.66
	ANN	9.14	6.99
Our prediction model	LSTM	0.0268	0.0114
	GRU	0.0220	0.0101

Table 9 Comparison of MSE between SVR, (SVR + KMEANS), LSTM and GRU for the soil-moisture prediction

Ref	Parameter	MSE
Goap et al. [10]	SVR	0.15
	SVR + Kmeans	0.10
Our prediction model	LSTM	0.00072
	GRU	0.00048

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Data Availability Data transparency.

Code Availability Software application or custom code.

Declarations

Conflicts of interest The authors declare no conflict of interest.

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