IoT-Enhanced Smart Greenhouse

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Abstract

This project focuses on revolutionizing greenhouse agriculture through IoT technology. By integrating wireless sensors and smart devices, we aim to automate data collection and optimize environmental conditions for tomato cultivation. This approach promises to boost productivity while conserving resources like water and energy, meeting the demands of a rapidly growing global population.

I. INTRODUCTION

According to the United Nations (UN), the ”main factor behind the increase in food needs” is population growth. The United Nations Food and Agriculture Organization (FAO) projects that the global population will reach 9.6 billion by 2050. Consequently, it will be challenging for the agricultural sector to meet the food needs of this growing population.

Today, another difficulty facing the agricultural sector is unstable weather conditions and global warming, which negatively impact crops. Scientists are searching for techniques and methods to meet sufficient food needs while overcoming the threats of climate change. Smart agriculture uses advanced technologies such as Big Data and the Internet of Things (IoT). It facilitates the automation of agriculture, field data collection, and analysis, enabling farmers to make precise decisions to produce high-quality crops.

In this chapter, we discuss smart agriculture in general and smart greenhouses in particular.

Smart agriculture is a revolution of traditional agriculture, involving the reorientation of agricultural systems to effectively support food development. The main objective of smart agriculture is to increase agricultural productivity and income.

Smart agriculture involves the use of information and communication technologies (ICT), particularly the Internet of Things (IoT) and Big Data analytics, to address these challenges through electronic crop monitoring, as well as for monitoring the environment, soil, fertilization, and irrigation conditions. These monitoring data can then be analyzed to identify the crops that best meet productivity goals for any agricultural operation worldwide.

Improving agricultural productivity is crucial for enhancing profitability and meeting the increasing demand for food, driven by rapid global population growth. Agricultural productivity can be boosted by understanding and predicting crop performance under various environmental conditions. Currently, crop recommendations rely on data collected from field studies, which measure crop performance under diverse conditions such as soil quality and environmental factors. However, data collection on crop performance is slow, often manual, and prone to errors due to studies being conducted in remote locations. Additionally, manually collected data may lack quality, failing to account for past conditions unnoticed by human operators, potentially leading to invalid conclusions.

Emerging Internet of Things (IoT) technologies, including wireless sensor networks, network-connected weather stations, cameras, and smartphones, offer the potential to gather extensive data on environmental and crop performance. These data, ranging from time series to sensor and camera spatial data, as well

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as human observations recorded via mobile applications, can be analyzed to filter out invalid data and generate personalized crop recommendations for specific farms.

In this project, we capitalize on technological advancements in electronics, automation, and structural mechanics to design and implement a smart agricultural greenhouse. We aim to automate data acquisition processes, such as monitoring temperature, humidity, and sunlight, using a sensor network, and action processes, such as irrigation and ventilation, using an actuator network. Sensors and actuators are connected to an Arduino board for data storage and management. Our objective is to make the greenhouse autonomous and equipped with an intelligent decision-making system. Once connected to the internet, the greenhouse can gather meteorological data and decide, based on this data, whether to irrigate or ventilate. This anticipatory approach will enable real-time response to tomato needs, conserving water and electrical energy.

II. Related Works

Several previous works have explored the use of IoT systems for smart irrigation applications and the utilization of LPWAN technologies like LoRa and LoRaWAN for enabling long-range connectivity in such systems.

A. IoT Smart Irrigation Systems

Khan et al. [1] described a decision support system for smart irrigation in an orange orchard that uses Xbee devices to cover a small area. Togneri et al. [2] designed a flexible IoT framework that enables machine learning-based solutions for smart irrigation, utilizing technologies like LoRaWAN and moisture sensor probes. Gloria et al. [3] presented a wireless sensor network for water saving in a small garden that employs LoRa peer-to-peer connections. Usmonov et al. [4] detailed a LoRaWAN-based wireless control system specifically for drip irrigation. Zhao et al. [5] implemented a LoRaWAN-based proof-of-concept smart irrigation system for urban environments.

B. LoRa/LoRaWAN for Underground Scenarios

Several works have studied the performance of LoRa and LoRaWAN in underground and soil environments, which is relevant for buried irrigation system components. Wan et al. [6] designed and evaluated a LoRa propagation test node, providing recommendations on aspects like transmission power and burial depth. Xue-fen et al. [7] proposed a smartphone-based system for measuring LoRa underground propagation, analyzing the impact of soil characteristics and moisture. Lin et al. [8] experimentally analyzed how different LoRa physical layer parameters influence its underground propagation performance.

The current work builds upon these prior efforts by designing, implementing a LoRa/LoRaWAN-based smart irrigation system with a fog computing architecture. It utilizes a well established machine learning algorithm (i.e. Logistic regression) to automate decisions.

III. Various Techniques

Some of the various techniques being practiced worldwide are discussed below.

A. Monitoring Nutrient Levels

Potassium, nitrogen, and phosphorus sensors to measure the levels of these nutrients in the soil. These data enable adjustment of fertilizer inputs to maintain optimal soil fertility.

B. Temperature Monitoring

Temperature sensors to monitor temperature variations in the greenhouse. This helps adjust environmental conditions to ensure optimal growth conditions for plants.

C. Soil Moisture Monitoring

Soil moisture sensors to measure the moisture level in the soil at different depths. These data help determine the optimal time for irrigation and optimize water usage.

D. Water Level Monitoring

Water level sensors to monitor the water level in the irrigation reservoir or greenhouse water supply system. This ensures that plants receive adequate irrigation while avoiding water excess.

IV. Newtork Architecture

We have used an IoT LoRa/LoRaWAN smart irrigation system with a fog computing-based architecture. LoRa/LoRaWAN communication technology is chosed due to its characteristics. See Table I [9].

TABLE I

LoRa/LoRaWAN main specifications.

Parameter	Value
Frequency band	EU433 (433.05-434.79 MHz), EU864-870 (863-870 MHz)
Channels	10
Channel bandwidth	125 KHz or 250 KHz
Transmission power	14 dBm
Max output power	20 dBm
Spreading factor	7-12
Data rate	250 bps-5.5 kbps
Link budget	155 dB
Range	5 km (urban), 15 km (suburban), 45 km (rural)
Topology	star
Battery lifetime	years
Power efficiency	very high
Interference immunity	very high
Scalability	yes

As you can in Figure 1 the proposed architecture is composed of three layers :

1) IoT Node Layer. This layer contains IoT nodes that include LoRaWan transceivers and nutrients sensors, temperature sensors, soil moisture sensors and the water level sensors. The IoT nodes sent LoRaWAN packets that can be collected by one or more nearby LoRaWAN gateways.
2) Fog Computing Layer. In this layer, the LoRaWAN gateways collect packets from the IoT nodes and send them to a central LoRaWAN server so they can be processed and decoded.
3) Remote Service Layer. This layer is located in the cloud. Here we collect, store and process the data from the IoT nodes and then we can display them to remote user in a user-friendly interface.

V. Circuit

The circuit shown in the image 3 is an automated irrigation monitoring and control system based on an Arduino microcontroller. Here is a brief description:

Components

- **Arduino Uno**: Main microcontroller.
- **Temperature and Humidity Sensor (DHT11 or DHT22)**: Measures ambient temperature and humidity [10], [11].
- **Water Level Sensor (Ultrasonic Sensor)**: Measures the water level in a tank [12].
- **Soil Moisture Sensor**: Measures the soil moisture level.
- **LCD Display**: Shows information such as temperature, humidity, water level, and pump status.
- **Water Pump**: Controlled by the Arduino for irrigation.

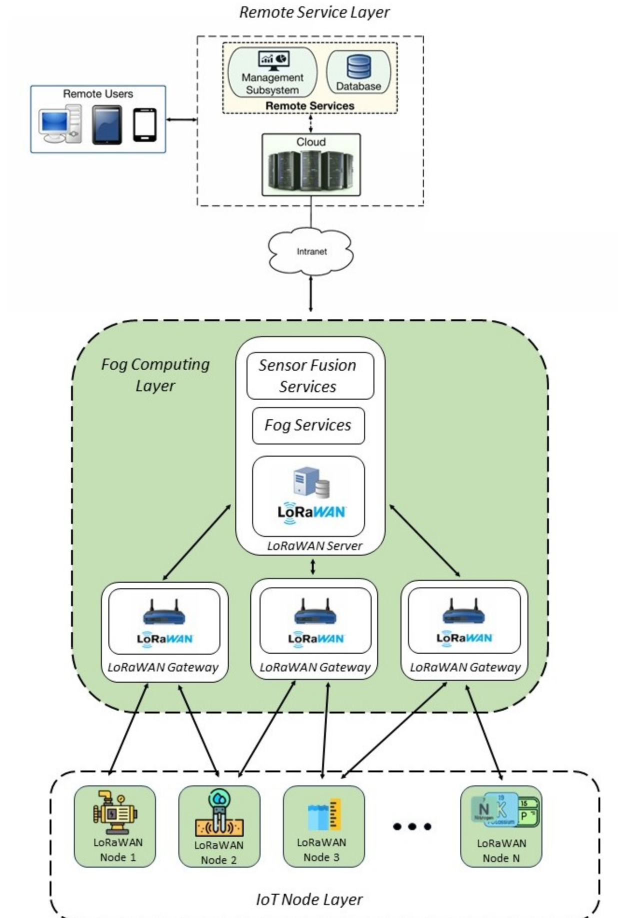

Fig. 1. The proposed network architecture

- **Relay**: Controls the water pump based on signals from the Arduino.
- **Virtual Terminal**: Displays real-time data on a computer via the Arduino's serial connection.

OPERATION

- **Measurement**: Sensors measure environmental conditions (temperature, humidity, water level, and soil moisture) and send data to the Arduino.
- **Display**: The data is shown on the LCD and virtual terminal.
- **Control**: Based on soil moisture readings, the Arduino activates the relay to turn the water pump on or off, maintaining optimal soil moisture levels.

CIRCUIT DIAGRAM

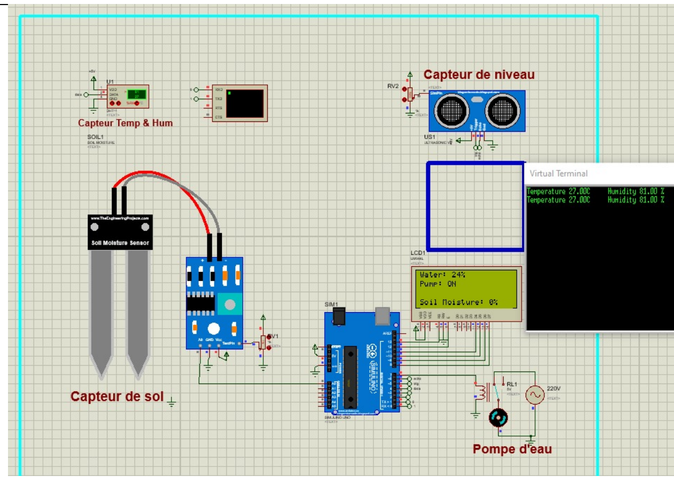

Fig. 2. Automated irrigation system circuit diagram

VI. Code Source

```
// include the library code:
#include <LiquidCrystal.h> //library for LCD
#include <DHT.h>
DHT dht(4, DHT11);
int dataPin=4;
// initialize the library with the numbers of the interface pins
LiquidCrystal lcd(13, 12, 11, 10, 9, 8);
const int trigPin = 5;
const int echoPin = 6;
const int Motor_Pin = 7;
const int SensorPin = A0;
long duration;
int distance;
bool Motor; //Make a bool Function for Motor ON/OFF
void setup()
{
  Serial.begin(9600);
  dht.begin();
  pinMode(trigPin, OUTPUT); // Sets the trigPin as an Output
  pinMode(echoPin, INPUT); // Sets the echoPin as an Input
  pinMode(Motor_Pin, OUTPUT); // Sets the Motor Pin as an Output
  lcd.begin(20, 4); // set up the LCD's number of columns and rows:
}
void loop()
{
  // Clears the trigPin
  digitalWrite(trigPin, LOW);
  delayMicroseconds(2);
  // Sets the trigPin on HIGH state for 10 microseconds
  digitalWrite(trigPin, HIGH);
  delayMicroseconds(10);
  digitalWrite(trigPin, LOW);
  // Reads the echoPin, returns the sound wave travel time in microseconds
  duration = pulseIn(echoPin, HIGH);
  // Calculating the distance in cm
  distance = duration*0.034/2;
  int Level = map(distance, 0,1106, 0,100);
  // Prints the distance on the LCD
  lcd.setCursor(0,0);
  lcd.print("Water: ");
  lcd.print(Level);
```

```
  lcd.print("%     ");
  if(Level < 30)  //if Water Level is Less than 30%
  { Motor = true; } //Make The Bool True}
  if(Level >= 100)  //if Water Level is Greater than or Equal to 100%
  {Motor = false;}  //Make The Bool False
  if(Motor) //if Bool is True
  { digitalWrite(Motor_Pin, HIGH);
    lcd.setCursor(0,1);
    lcd.print("Pump: ON      ");}
  else //if Bool is False
  { digitalWrite(Motor_Pin, LOW);
    lcd.setCursor(0,1);
    lcd.print("Pump: OFF      ");}
  //####################
  float temp=dht.readTemperature();
  float hum=dht.readHumidity();
  Serial.print("Temperature ");
  Serial.print(temp);
  Serial.print("C");
  Serial.print("     Humidity ");
  Serial.print(hum);
  Serial.print(" %");
  Serial.println();
  //####################
  int Val = analogRead(SensorPin);
  int Moisture = map(Val,0,1023,0,100);
  lcd.setCursor(0,3);
  lcd.print("SOIL MOISTURE SENSOR");
  lcd.setCursor(0,4);
  lcd.print("Soil Moisture: ");
  lcd.print(Moisture);
  lcd.print("%   ");
}
```

VII. Dataset

In this project based on the Internet of Things (IoT), we used a specific dataset rich in environmental and soil nutrient information to effectively manage ventilation and irrigation. This dataset originates from Iraq and contains crucial measurements for precision agriculture [13]. Here is a detailed description of the parameters included in this dataset:

- *Temperature:* Temperature data is essential for regulating the microclimate of the greenhouse. Temperature directly affects plant growth, photosynthesis, and transpiration. By monitoring and adjusting the temperature, we can create an optimal environment for plant growth.
- *Humidity:* The relative humidity of the air plays a key role in plant health. An appropriate level of humidity can prevent fungal diseases and promote effective transpiration. The dataset includes humidity measurements to allow us to control the ventilation system and maintain an ideal atmosphere.
- *Potassium (K):* This nutrient is vital for photosynthesis, protein synthesis, and the regulation of stomatal opening. The levels of potassium in the soil are monitored to ensure that plants receive an adequate amount for optimal development.
- *Nitrogen (N):* Nitrogen is a crucial element for plant growth, involved in the production of chlorophyll and amino acids. The data on nitrogen in the soil helps us adjust fertilization practices to avoid deficiencies or excesses that could harm plant health.
- *Phosphate (P):* Phosphate is indispensable for root development and flowering. By monitoring phosphate levels, we can ensure healthy growth and optimized fruit or flower production.
- *Datetime:* By including the datetime data, we can analyze the trends over time and make informed decisions about irrigation scheduling and ventilation control based on the time of day, season, or

other relevant temporal factors.
- *Reservoir Water Level:* Monitoring the water level in the reservoir is essential for efficient irrigation management and prevent water shortages, ensures consistent water supply for the plants, and facilitates more precise irrigation scheduling based on the available water resources [14]..

The integration of this dataset into our IoT system enables intelligent automation of greenhouse management. Thanks to connected sensors and actuators, we can:
- *Regulate Ventilation:* Based on temperature and humidity values, the system automatically adjusts fans and vents to maintain ideal conditions. This helps prevent thermal stress and maintain good air circulation.
- *Manage Irrigation:* Soil moisture data, combined with nutrient levels (potassium, nitrogen, phosphate), allows us to define precise irrigation schedules. Irrigation is adjusted to avoid over- or under-watering, ensuring efficient water use and adequate plant nutrition.

VIII. Model development

In this section, we elaborate on the model utilized for forecasting the operational state of the fan actuator, watering plant pump, and water pump actuator, determining whether they are in an ”on” or ”off” state to optimize tomato growth conditions. Our chosen method for these predictions is logistic regression, a statistical technique used for binary classification tasks.

Logistic regression works by modeling the probability of a certain outcome, in this case, whether the actuator is on or off, based on one or more predictor variables. Unlike linear regression, which predicts continuous values, logistic regression predicts the probability that a given instance belongs to a particular category [15].

Here’s how logistic regression works in detail:

1) **Probability Calculation**: Logistic regression calculates the probability that a given input belongs to a particular category using the logistic function (also known as the sigmoid function). The formula for logistic regression is:

$$P(Y=1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+...+\beta_n X_n)}}$$

   Where:
   - $P(Y=1|X)$ is the probability that the outcome Y is 1 (actuator is on) given the input X.
   - $X_1, X_2, ..., X_n$ are the predictor variables.
   - $\beta_0, \beta_1, ..., \beta_n$ are the coefficients of the model [16].
2) **Decision Boundary**: Logistic regression predicts that an instance belongs to the positive class (actuator is on) if the probability calculated is greater than a threshold (usually 0.5), and to the negative class otherwise.
3) **Model Training**: The logistic regression model is trained by finding the values of the coefficients $\beta_0, \beta_1, ..., \beta_n$ that maximize the likelihood of observing the given data.
4) **Model Evaluation**: The accuracy [17] of the logistic regression model is evaluated using metrics such as accuracy, precision, recall, and F1-score, which assess its performance in correctly classifying instances.

IX. Interface

The user interface of our IoT Smart Greenhouse project, as shown in the image bellow, is designed to provide users with a clear and precise overview of their smart greenhouse environment. By continuously monitoring internal conditions and nutrient levels, users can make informed decisions to optimize plant growth. The statuses of various devices, managed by the intelligent model, also ensure that all control systems are functioning correctly, guaranteeing a stable and optimal environment.

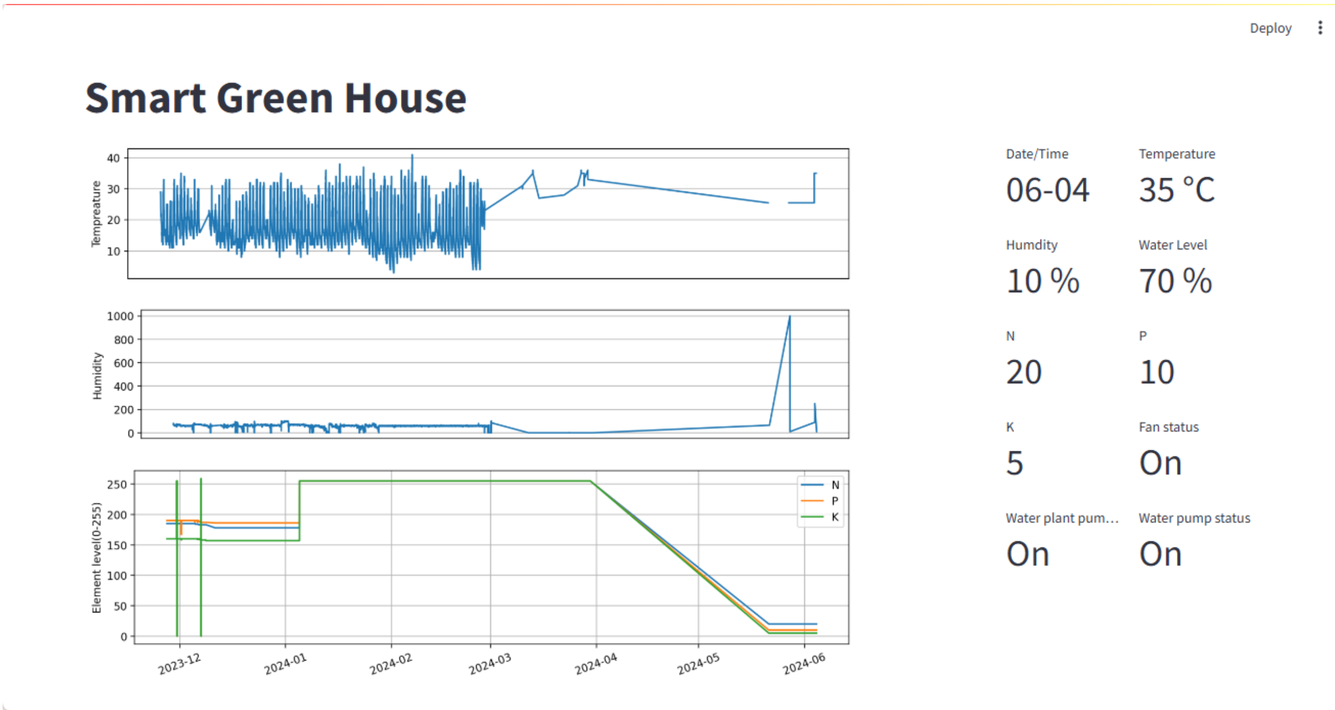

Fig. 3. Monitoring interface

A. Dashboard

- Temperature Graph: The first graph shows the temperature variations inside the greenhouse over a given period. This allows monitoring of thermal conditions to ensure they remain within an optimal range for plant growth.
- Humidity Graph: The second graph displays the humidity levels over time. This parameter is crucial for maintaining a favorable environment for plants, avoiding conditions that are too dry or too humid.
- Nutrient Levels Graph (N, P, K): The third graph represents the levels of essential nutrients - nitrogen (N), phosphorus (P), and potassium (K) - on a scale of 0 to 255. Monitoring these levels ensures adequate plant nutrition.

B. Real-Time Indicators

On the right side of the interface, real-time indicators display the current values of various parameters:

- Date/Time: Shows the current date and time, ensuring the data visualized is up-to-date.
- Temperature: Displays the instantaneous temperature inside the greenhouse.
- Humidity: Displays a humidity level indicating the current state of the ambient air.
- Water Level: Represent the amount of water available for the plants.
- Nutrient Levels (N, P, K): Current levels of each nutrient are indicated to monitor the fertilization status.

X. Results

Regarding the accuracy of the prediction models, we have achieved very high accuracy rates across all predictions, indicating the effectiveness of logistic regression in forecasting the operational states of the fan actuator, watering plant pump, and water pump actuator. This high accuracy underscores the reliability of our model in optimizing the conditions for growing tomatoes.

XI. Conclusion

The project is invested in the context of smart agriculture in general and smart greenhouses in particular. Our general objective was to develop a Web application for controlling smart greenhouses with the possibility of supervision and perception of soil environmental situations and weather conditions in a set of greenhouses. With its actuation capability, this application can intelligently provide adequate services, namely irrigation and temperature management, ventilation, and reservoir management. The problem we addressed in the project was the automatic recognition of greenhouse situations using strong, uncertain, and incomplete data provided by sensors deployed in the greenhouse. The major problem was precisely the difficulty of integrating numerous data from simple sensors in concluding prevailing situations in the greenhouse. Another problem we addressed in this work is related to automatic decision-making and utilization of sensor data for prediction.

References

[1] R. Khan, I. Ali, M. Zakarya, M. Ahmad, M. Imran, and M. Shoaib, "Technology-assisted decision support system for efficient water utilization: A real-time testbed for irrigation using wireless sensor networks," *IEEE Access*, vol. 6, pp. 25 686–25 697, 2018.

[2] R. Togneri, C. Kamienski, R. Dantas, R. Prati, A. Toscano, J.-P. Soininen, and T. S. Cinotti, "Advancing iot-based smart irrigation," *IEEE Internet of Things Magazine*, vol. 2, no. 4, pp. 20–25, 2019.

[3] A. Gloria, C. Dionisio, G. Simões, P. Sebastião, and N. Souto, "Wsn application for sustainable water management in irrigation systems," in *2019 IEEE 5th World Forum on Internet of Things (WF-IoT)*. IEEE, 2019, pp. 833–836.

[4] M. Usmonov and F. Gregoretti, "Design and implementation of a lora based wireless control for drip irrigation systems," in *2017 2nd international conference on robotics and automation engineering (ICRAE)*. IEEE, 2017, pp. 248–253.

[5] W. Zhao, S. Lin, J. Han, R. Xu, and L. Hou, "Design and implementation of smart irrigation system based on lora," in *2017 IEEE Globecom Workshops (GC Wkshps)*. IEEE, 2017, pp. 1–6.

[6] X.-f. Wan, Y. Yang, J. Cui, and M. S. Sardar, "Lora propagation testing in soil for wireless underground sensor networks," in *2017 Sixth Asia-Pacific Conference on Antennas and Propagation (APCAP)*. IEEE, 2017, pp. 1–3.

[7] W. Xue-fen, D. Xing-jing, Y. Yi, Z. Jing-wen, M. S. Sardar, and C. Jian, "Smartphone based lora in-soil propagation measurement for wireless underground sensor networks," in *2017 IEEE Conference on Antenna Measurements & Applications (CAMA)*. IEEE, 2017, pp. 114–117.

[8] K. Lin, T. Hao, Z. Yu, W. Zheng, and W. He, "A preliminary study of ug2ag link quality in lora-based wireless underground sensor networks," in *2019 IEEE 44th Conference on Local Computer Networks (LCN)*. IEEE, 2019, pp. 51–59.

[9] J. Haxhibeqiri, E. De Poorter, I. Moerman, and J. Hoebeke, "A survey of lorawan for iot: From technology to application," *Sensors*, vol. 18, no. 11, p. 3995, 2018.

[10] D. Srivastava, A. Kesarwani, and S. Dubey, "Measurement of temperature and humidity by using arduino tool and dht11," *International Research Journal of Engineering and Technology (IRJET)*, vol. 5, no. 12, pp. 876–878, 2018.

[11] M. Chakraborty, A. Malkani, and K. Biswas, "Hand-held soil moisture meter using polymer coated sensor," *IEEE Instrumentation & Measurement Magazine*, vol. 22, no. 5, pp. 24–29, 2019.

[12] S. L. Mohammed, A. Al-Naji, M. M. Farjo, and J. Chahl, "Highly accurate water level measurement system using a microcontroller and an ultrasonic sensor," in *IOP Conference Series: Materials Science and Engineering*, vol. 518, no. 4. IOP Publishing, 2019, p. 042025.

[13] W. ABDULLAH. (2024) Iot agriculture 2024. Accessed on Avril 2024. [Online]. Available: https://www.kaggle.com/datasets/wisam1985/iot-agriculture-2024

[14] X. Fang, Y. Yang, Z. Zhao, Y. Zhou, Y. Liao, Z. Guan, S. Chen, W. Fang, F. Chen, and S. Zhao, "Optimum nitrogen, phosphorous, and potassium fertilizer application increased chrysanthemum growth and quality by reinforcing the soil microbial community and nutrient cycling function," *Plants*, vol. 12, no. 23, p. 4062, 2023.

[15] O. Cokluk, "Logistic regression: Concept and application." *Educational Sciences: Theory and Practice*, vol. 10, no. 3, pp. 1397–1407, 2010.

[16] D. W. Hosmer Jr, S. Lemeshow, and R. X. Sturdivant, *Applied logistic regression*. John Wiley & Sons, 2013.

[17] B. Ashar. What is accuracy in machine learning? https://www.educative.io/answers/what-is-accuracy-in-machine-learning.