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Abstract

The integration of artificial intelligence in agriculture is helping to solve the problems caused by traditional irrigation methods, which often lack precision, wasting water and increasing complexity for farmers.For this reason, we propose in this work a smart irrigation application ,which improves the use of IoT objects using AI methods. This application harnesses AI to deliver tailored irrigation recommendations based on crop type, growth stage, soil conditions, and weather forecasts. By optimizing watering schedules, the app aims to maximize crop yields while minimizing water usage and operational costs. Through real-time data analysis, our solution offers a streamlined approach to irrigation management, empowering farmers to enhance resource efficiency and agricultural productivity.

Dedications

We dedicate this work to:

Our dearest parents.

All our teachers.

All our friends.

As well as everyone who supported us.

Thanks

We thank God Almighty for his help.

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Our warm thanks to our families who have always supported us.

We also thank the members of the jury who did us honor by agreeing to examine and judge our work.

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Abreviations list

Abbreviation	Full Expression	Page
IOT	Interent of things	19
AI	Artificial Intelligence	19
ANFIS	Adaptive Neuro-FuzzyInference System	19
SIDSS	Smart Irrigation Decision Support System	19
PLSR	Partial Least Squares Regression	19
VWC1	Volumetric Water Content depth 1	20
VWC2	Volumetric Water Content depth 2	20
VWC3	Volumetric Water Content depth 3	20
SWP	SoilWterPotential	20
ST	SoilTemperature	20
RF	Rainfall	20
WS	Wind Speed	20
T	Temperature	20
RH	Relative Humidity	20
GR	Global Radiation	20
DP	Dew Point	20
VPD	Vapour pressure Deficit	20
ETc	Crop Evapotranspiration	20
ML	Machine Learning	21
KNN	k-nearestneighbors	21
SVM	Support Vector Machine	21
RMSE	Root mean square error	21

ANNs	Artificial Neural Network	24
MSE	MeanSquaredError	24
SVR	Support vectorregression	24
mT0	Moisture of layer 0 in time T	25
mT1	Moisture of layer 1 in time T	25
mT2	Moisture of layer 2 in time T	25
mT3	Moisture of layer 3 in time T	25
m3T3	Moisture of layer 3 in time T3	25
Y1	Y (value from sensor) and train source model	25
Y2	Y and train target model	25
CNN-LSTM	Convolutional Neural Network - Long Short-Term Memory	26
NB	Naive Bayes	38
C4.5	DecisionTree	38
RF	Random Forest	38
API	Application Programming Interface	40
AC	AlternatingCurrent	53
DC	Direct Current	53

Contents

General Introduction

In the domain of agriculture, the optimizing irrigation management is paramount, the intersection of artificial intelligence (AI) and irrigation systems has emerged as a promising frontier. Agriculture heavily relies on irrigation to sustain crop cultivation, particularly in regions with unpredictable rainfall patterns. However, traditional irrigation methods often fall short in efficiently delivering water according to plant needs, leading to significant water wastage and environmental concerns. The imprecise nature of these methods overlooks crucial factors such as soil moisture levels and weather forecasts, contributing to inefficiencies in water usage.

To address these challenges, previously,theexisting solutions have been limited, often requiring manual intervention and lacking real-time data analysis capabilities. While methods like surface irrigation, drip irrigation, and sprinkler irrigation have been prevalent, they come with drawbacks such as susceptibility to clogging, high operational costs, and low application efficiency in certain conditions. Despite advancements in technology, including the integration of IoT sensors, these solutions have not fully optimized irrigation management or maximized crop yields.

Precision irrigation encompasses a diverse range of techniques and methodologies aimed at precisely delivering water to crops based on their specific needs, growth stages, and environmental conditions. Unlike conventional irrigation methods that apply water uniformly across fields, precision irrigation leverages advanced sensors, data analytics, and AI-driven algorithms to tailor water distribution to the individual requirements of each plant or crop. By optimizing water usage, precision irrigation not only conserves water resources but also enhances crop health, mitigates water-related stresses, and ultimately boosts agricultural productivity.

Our proposed solution entails the development of an innovative application tailored to meet the specific needs of farmers in optimizing their irrigation practices.

The primary objective of this application isto reduce the quantity of water to irrigate a plant based on these needs in order to increase crop yields.We propose to providepersonalized irrigation recommendations based on various factors such as crop type, growth stage, soil conditions, and weather patterns.

By ensuring that plants receive the optimal amount of water at the right time, farmers can maximize crop health and ultimately achieve better quality and quantity of produce. Moreover, the application aims to reduce costs for farmers by offering features that optimize irrigation schedules, leading to minimized water usage and decreased operating expenses. By avoiding over- or under-irrigation, farmers can also reduce energy expenses associated with pumping water and improve overall resource efficiency.

Our application makes use of cutting-edge sensors and AI techniques in tandem with the goals that have been outlined. Thedevelopment patterns depend on the correct measurement of environmental conditions provided by the temperature and humidity sensor. When used in conjunction with the soil moisture sensor, which accurately measures the amount of hydration in the soil, our application makes sure that irrigation is customized to the individual requirements of the crops, maximizing water use and promoting better yields. Furthermore, wepropose an application that enables to provide smooth communication by connecting Arduino with a WiFiadapter, allowing for remote monitoring and real-time data transfer. Predictive analytics is made possible by combining this sensor data with AI algorithms to estimate the best irrigation schedules. The application is based onanAI model thatdelivers actionable insights to farmers by utilizing machine learning techniques to learn from past data, present environmental conditions, and crop traits.

Our application enhances water efficiency by utilizing data on soil moisture levels, weather forecasts, and crop water requirements to recommend precise irrigation schedules. Through these capabilities, the application empowers farmers with accurate information to optimize water usage and minimize waste, contributing to sustainable agricultural practices and environmental conservation efforts.

This report is structured into four chapters. Chapter 1 provides background information, states the problem, defines objectives, and outlines the scope of the study. Chapter 2 explores existing irrigation techniques, the role of AI in agriculture, precision irrigation technologies, and identifies gaps in current solutions. Chapter 3 describes the data collection process, software tools used, and presents the system design. Chapter 4 details the technical implementation, including the Arduino UNO microcontroller, dataset processing, analysis using Python, and discusses the results from both machine learning and deep learning approaches.

Chapter 1
Irregation methods and AI

1.1 Introduction

Irrigation systems play a vital role in sustaining agriculture, facilitating consistent water delivery to plants even in regions with unpredictable rainfall patterns. This reliability is essential for ensuring uninterrupted agricultural activities and maintaining crop health. Adequate water supply provided by irrigation is crucial for seeds to germinate and develop into healthy plants, emphasizing the pivotal role of irrigation in supporting plant growth and development. Moreover, irrigated land demonstrates significantly higher productivity compared to non-irrigated areas, contributing substantially to agricultural output and bolstering food security efforts[1].
The first chapter delves into the pivotal role of irrigation methods in agriculture, exploring both classical and modern techniques. From surface irrigation to advanced AI-driven systems, farmers have a spectrum of options to optimize water use and crop productivity. This chapter introduces the evolution of irrigation methods, highlighting their significance in ensuring sustainable agriculture and addressing challenges like water scarcity and resource management.

1.2 Methods of Irrigation

There arevarious methods of agriculturedevoloped by farmes to ensure the best produce possible, and the irrigation process is no exception. These methods can be divided into two categories, classical irrigation, representing traditional techniques, and modern irrigation, encompassing contemporary approaches.

1.2.1 Classical irrigation

Classical irrigation methods represent the historical backbone of agricultural water management, evolving over centuries to sustain crop cultivation. These techniques, deeply ingrained in farming traditions worldwide, utilize natural resources such as rivers, streams, and reservoirs to deliver water to crops, ensuring their growth and productivity. From this method, we have various examples, including surface irrigation, drip irrigation, sprinkler irrigation, subsurface irrigation, and others. Let's delve into each of these methods to understand their unique characteristics and applications in modern agriculture.

1.2.1.1 Surface Irrigation

Refers to systems that deliver water to crops using a gravity-fed, overland flow of water. In this method, water flows over the soil surface to reach crops, relying on gravity[2]. Surface irrigation is one of the oldest and most common forms of irrigation (see Figure 1).

Figure1 – Surface Irrigation

Types:

- **Basin Irrigation:** This method involves creating level, enclosed areas surrounded by dikes to allow water to fill the area uniformly and is suitable for crops that can handle temporary flooding.

- **Border Irrigation:** In this system, water flows down a sloped, rectangular strip with open drainage at the end, making it adaptable for various crops, excluding those requiring stagnant water conditions.

- **Furrow Irrigation:** This technique employs narrow channels (furrows) to direct water flow, minimizing water contact with the entire soil surface, which aids in better water management but requires more labor.

1.2.1.2 Drip Irrigation

Involves placing tubing with emitters on the ground alongside the plants, also known as trickle irrigation, it delivers water directly to the base or root zone of plants through a network of valves, pipes, tubing, and emitters[3]. It is highly efficient in terms of water use (see Figure 2).

Figure 2 – Drip Irrigation

1.2.1.3 Sprinkler Irrigation :

Involves spraying water in the form of small droplets, simulating natural rainfall[4]. It distributes water through a system of pipes, typically by pumping, and then disperses it into the air through sprinklers, allowing it to break up into small water drops that fall to the ground(see Figure 3).

Figure 3 – Sprinkler Irrigation

Types :

- **Single-point sprinklers:** These were the earliest type of sprinkler systems used, with moveable positions and water supplied through iron pipes.
- **Moveable machines with sprinkler nozzles:** Developed with sprinkler nozzles that can be transported throughout the field to irrigate entire areas with the same sprinkler setup. This type of sprinkler system has high application efficiencies and more irrigation coverage with less labor requirements.
- **Various other types of sprinkler systems:** there are many types of sprinkler systems[4]adopted as per field conditions due to specific limitations associated with each type.

1.2.1.4 Subsurface DripIrrigation

Is a type of low-pressure, high-efficiency irrigation system that utilizes buried drip tubes or drip tape to deliver water directly to the root zone of crops. This method allows for the frequent application of light irrigations and is particularly suitable for arid, semi-arid, hot, and windy areas with limited water supply, especially on sandy soils [5].

1.2.1.5 Center Pivot Irrigation

Center pivot irrigation, a method of sprinkler irrigation, employs a movable pipe structure that rotates around a central pivot point connected to a water supply[6]. It comprises several segments of pipe mounted on wheeled towers with sprinklers that rotate around the central pivot point. This system is typically utilized in flat areas and is commonly employed for field and forage crops such as alfalfa, hay, corn, soybeans, wheat, potatoes, cotton, and more (See Figure 4).

Figure 4- Center Pivot Irrigation

1.2.1.6 Micro Irrigation

Refers to low-pressure irrigation systems that spray, mist, sprinkle, or drip water onto the soil surface very near the plant or directly into the plant root zone. It is used extensively for row crops, mulched crops, orchards, gardens, greenhouses, nurseries, and urban landscapes [7].

1.2.1.7 Bubbler irrigation

Is a method used for watering plants, particularly trees and shrubs, in a landscape irrigation system. It involves the use of bubblers, which are devices that emit water in the form of small fountains, allowing for targeted watering of specific plants. Bubblers are designed to deliver water directly to the root zone of individual plants, providing a more efficient and controlled method of irrigation[8].

1.2.1.8 Piped distribution system

The piped distribution system is a method of delivering water to customers through a network of pipes, valves, fire hydrants, and service connections. It can vary from simple to extremely complicated and typically consists of components such as pipes, valves, fire hydrants, service connections, and storage reservoirs. This system can be either a conventional system or a completely looped circulating system[9].

1.2.1.9 Manual Irrigation :

Watering by hand using hoses or watering cans(see Figure 5).

Figure 5- Manual Irrigation

1.2.1.10 Advantages and disadvantages of classical irrigation:

We propose in thetablebellowa comprehensive overview of the advantages and disadvantages of various classical irrigation methods. Each method is outlined along with its benefits and drawbacks, providing valuable insights for decision-making in agricultural practices.

Table 1-Advantages and Disadvantages of Classical Irrigation Methods

Irrigation Method	Advantages	Disadvantages
Drip Irrigation	• Reduces water loss evaporation. • Decreases nutrient loss through leaching. • Compatible with fields of irregular shapes.	• Not suitable for water with high iron content as it clogs the emitters. • Tubing is susceptible to damage from insects and rodents chewing through it. • Tubing can be damaged by mowers and trimmers.
Sprinkler Irrigation	• Ability to apply water to crops. • Regulate canopy temperature to enhance photosynthesis	• Associated with higher capital and operational costs. • Potential damage to delicate

	efficiency. • Protect plants from frost in cold temperatures.	fruit plants. • Low application efficiency in windy areas.
Subsurface Drip Irrigation	• Elimination of surface water evaporation. • Reducedweedgrowth. • Improveddisease control.	• Require a higher initial investment. • Repairing tubes in subsurface systems is tough. • Spotting issues like clogged emitters or rodent damage can be challenging.
Center Pivot Irrigation	• Highly cost-effective irrigation method. • Requires minimal labor to operate. • Can last for decades with proper maintenance.	• Water application rate often exceeds soil absorption rate. • Prone to runoff and related issues. • Limited effectiveness on clay soils and steep slopes.
Micro Irrigation	• Water savings from minimal conveyance loss. • Reduced energy usage compared to sprinkler systems. • Improved production on marginal land.	• Greater maintenance requirements are a potential issue. • Damage by animals, rodents, and insects is a concern. • High initial investmentcosts.
Bubbler Irrigation	• Delivers water directly to roots, reducing waste. • Adjustable flow rates meet plant needs. • Effective for trees and shrubs.	• Risk of overwatering without proper adjustment. • Regular maintenance and adjustment required. • System complexity demands careful planning.
Piped Distribution System	• Provides continuous water supply. • Efficient water transportation. • Reduces manual effort for customers.	• Costly infrastructure maintenance. • Vulnerability to contamination. • Substantial initial setup costs.

1.2.2 Modern irrigation methods

With advancements in technology, particularly in artificial intelligence (AI), modern irrigation solutions have emerged to overcome traditional method limitations. These advancements are significantly characterized by the integration of machine learning and deep learning methodologies in developing intelligent irrigation management systems.With the integration of Internet of Things (IoT) technologies, modern irrigation solutions have reached new heights of efficiency and precision.

1.2.2.1 Machine learning

Machine learning plays a crucial role in modern irrigation practices, offering innovative solutions to enhance water management efficiency in agriculture[10].With the advent of machine learning techniques, there has been a proliferation of methods tailored to optimizing irrigation strategies based on real-time data and predictive analytics. These methods encompass a diverse range of approaches, including decision support systems, predictive modeling, and optimization algorithms, all aimed at maximizing crop yield while minimizing water consumption.

The importance of machine learning in irrigation lies in its ability to optimize water usage, mitigate water scarcity issues, and promote efficient water management practices in agriculture. Machine learning algorithms can analyze data from various sources such as sensors and weather forecasts to make accurate predictions about soil moisture levels, water requirements, and irrigation scheduling. By integrating machine learning techniques into smart irrigation systems, farmers can make data-driven decisions that lead to improved crop yields, reduced water usage, and overall sustainability in agricultural practices.

- **The decision support system for managing irrigation in agriculture**

It discusses the integration of AI solutions in the context of managing irrigation in agriculture[11]. The proposed system, called Smart Irrigation Decision Support System (SIDSS), utilizes machine learning techniques as the reasoning engine. Specifically, Partial Least Squares Regression (PLSR) and Adaptive Neuro-Fuzzy Inference System (ANFIS) are proposed as the basis for the reasoning engine of the SIDSS. These machine learning techniques are used to estimate the weekly irrigation needs of a plantation based on soil measurements and climatic variables gathered by autonomous nodes deployed in the field.

The integration of AI solutions in this context aims to create a closed-loop control scheme that can adapt the decision support system to local perturbations and estimation errors. By combining soil and climate sensors in an open-loop system, the SIDSS aims to compensate

for possible deviations in future predictions. The use of machine learning techniques in the SIDSS allows for the creation of an automatic Irrigation Decision Support System, which can assist in managing irrigation requirements for crops.
The performance of the system is evaluated by comparing its decisions against those taken by a human expert. The integration of AI solutions in this decision support system represents a shift towards automated, data-driven decision-making in agriculture, with the potential to improve water optimization and sustainability in crop management.

Principe:

In the realm of agriculture, decision support systems play a pivotal role in irrigation management, with machine learning offering novel solutions for enhancing water efficiency. Two prominent methods, Partial Least Squares Regression (PLSR) and Adaptive Neuro Fuzzy Inference Systems (ANFIS), have been employed to predict irrigation needs in various agricultural contexts. PLSR is utilized for estimating weekly irrigation requirements based on historical data, while ANFIS predicts the needs of new plantations using data from other fields,even in the absence of specific historical irrigation reports.
For Partial Least Squares Regression (PLSR), the input variables are the predictor matrix X, which includes sensor and weather variables such as VWC1, VWC2, VWC3, MP, ST, ETc, RF, WS, T, RH, GR, DP, and VPD. The output variable Y is the recommended number of minutes of irrigation for a given week.

As for Adaptive Neuro Fuzzy Inference Systems (ANFIS), the input is the sensor and weather data, similar to PLSR, and the output is the estimated minutes of irrigation for a given week.

Our observation indicates several positive and negative aspects of these methods:

Table 2-AI-Based Irrigation Decision Support: Pros and Cons

Positive	**Negative**
- Enhances prediction accuracy by analyzing complex data and identifying meaningful patterns. - Excels in capturing non-linear relationships, suitable for modeling complex agricultural systems. - Can adapt to various agricultural	- Relies on large datasets, which may be challenging to obtain in agricultural settings with limited data availability. - Training and running the models demand significant computing resources, which may be limited in some agricultural contexts.

scenarios, accommodating different data types and contexts.	- Requires specialized expertise for implementation, posing challenges for users without adequate training.

- **Smart irrigation system based on IoT and machine learning**

It mentions that artificial intelligence (AI) and machine learning (ML) are being rapidly adopted in agriculture for both products and techniques[12]. The use of cognitive computing, which can understand, learn, and respond to different situations, is highlighted as a disruptive technology in agricultural services. The authors of [12] mentions a specific example where Microsoft is working with farmers in India to provide advisory services using AI, resulting in a 30% higher yield per hectare compared to the previous year.
Additionally,the use of machine learning algorithms, such as K-Nearest Neighbors (KNN), Logistic Regression, Neural Networks, Support Vector Machine (SVM), and Nave Bayes, for smart agriculture. The authors of [12] specifically mentions that K-Nearest Neighbors (KNN) showed better performance with a recognition rate of 98.3% and a root mean square error (RMSE) of 0.12 compared to other models.

Principe:

It leverages various machine learning algorithms, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression, and Naïve Bayes, to optimize irrigation processes. Specifically designed for the agricultural domain, this intelligent irrigation system integrates IoT sensors and machine learning techniques to enhance water management practices in agriculture.

The input and output for each AI method mentioned in the system are as follows:

Table 3- Input and Output for AI Methods

AI Method	Input	Output
K-Nearest Neighbors (KNN)	Data from soil moisture, temperature, and air humidity sensors.	Categorical data representing whether pumping should be stopped (value "0") or activated (value "1").

Support Vector Machine (SVM)	Data from soil moisture, temperature, and air humidity sensors.	Classification of the input data into different categories based on the training dataset.
LogisticRegression	Data from sensors measuring soil moisture, temperature, and air humidity.	Probability of a particular category of output, often used for binary classification problems.
Naïve Bayes	Data from soil moisture, temperature, and air humidity sensors.	Classification of the input data into different categories based on the probability model derived from the training data.

Our observation indicates several positive and negative aspects of these methods:

Table 4- IoT and ML-Based Smart Irrigation: Advantages and Drawbacks

Positive	Negative
- Offers advanced, intelligent solution for water management in agriculture. - Facilitates precise decision-making and oversight in agricultural operations. - High recognition rates (98.3%) and low root mean square error (RMSE).	- Requires technical proficiency for sensor installation and model development. - Relies heavily on data availability and quality. - Demandssignificantcomputationalresources for training large datasets.

1.2.2.2 Deep Learning

Deep learning revolutionizes irrigation management in agriculture by leveraging advanced machine learning techniques. Through real-time data analysis from various sources such as soil moisture sensors and weather forecasts, deep learning optimizes water usage, minimizes wastage, and enhances crop yields. Its predictive capabilities enable precise irrigation scheduling, while insights into climate variability empower farmers to adapt to changing environmental conditions. Overall, deep learning promises a more sustainable and productive agricultural future by maximizing resource efficiency and minimizing environmental impacts.

- **Smart Irrigation IoT Solution using Transfer Learning for Neural Networks:**

Involves the use of artificial neural networks (ANNs) for smart irrigation using an IoT-based system[13]. The goal is to achieve automatic, reliable, and flexible irrigation for greenhouses. The system relies on moisture sensors in all soil levels to achieve high accuracy in prediction, with a mean squared error (MSE) of less than 0.05. The integration of the AI solution can be detailed as follows:

Data Collection and Training:

Data is collected from two different soil types to demonstrate their different characteristics.
ANNs are trained for each soil separately to achieve the target MSE of 0.05. A comparison with support vector regression (SVR) is also provided, showing that SVR requires higher training data to achieve the same MSE.

Transfer Learning:

Transfer learning is employed to use the neural network trained for one soil type to train a neural network for another soil type using a few samples. This approach allows for fast adaptation to new environments and flexibility in adding new environmental sensors using transfer learning.

Model Integration and Adaptation:

The authors of[13] discusses the integration of the AI model with IoT sensors and the flexibility to adapt to new environments and add new sensors without disruption in performance.
The use of transfer learning allows for domain adaptation and extension, enabling the existing model to be adapted for different environments and new sensors to be added to the system.

Model Replacement and Prediction:

[13]addresses the issue of model replacement when changes in the structure of the neural network are required. It provides a method for training a new model and replacing it at the right time to ensure accurate predictions.

Overall, the integration of the AI solution involves the use of ANNs for accurate prediction, transfer learning for adaptation to new environments, and the flexibility to add new sensors without disrupting the system's performance.

Principe:

In the realm of greenhouse agriculture, the Smart Irrigation System harnesses machine learning, particularly Artificial Neural Networks (ANNs), to accurately predict soil moisture levels. This is achieved by collecting data from soil moisture sensors installed at various depths in the soil, which is then used to train the ANNs.
The Artificial Neural Network (ANN) method outlined in [13] utilizes sensory data, including moisture levels, temperature, and environmental sensor data, as its input. These inputs are represented by variables such as mT0, mT1, mT2, and mT3, with mT0 denoting the initial input node. For transfer learning, an additional neuron is introduced into the input layer to incorporate new labeled data for training a secondary model targeting a different domain. The output of the ANN method is the prediction concerning irrigation management and monitoring, with prediction values like m3T3 indicating the forecasted output derived from the input variables and the trained neural network model. In transfer learning scenarios, the ultimate prediction merges predictions from both the source model (Y1) and the target model (Y2) through linear regression, yielding the combined prediction Yans.

Our observation indicates several positive and negative aspects of these methods:

Table 5- Pros and Cons of IoT Solution using Transfer Learning

Positive	**Negative**
- Utilizing IoT and AI, the system	- Advanced technologies like artificial

optimizes irrigation schedules with real-time soil moisture data, enhancing water efficiency. - The system automates the irrigation process, reducing the reliance on costly and error-prone human labor. - Transfer learning enables easy adaptation to new environments and integration of additional environmental sensors, boosting flexibility and scalability.	neural networks and transfer learning may require specialized expertise, posing adoption challenges for some farmers. - Initial investment in IoT devices, sensors, and infrastructure may pose a barrier for some farmers, particularly small-scale ones. - System accuracy relies on data quality, including soil moisture and climate variables. Limited or inaccurate data may affect performance.

- **AIDSII: An AI-based digital system for intelligent irrigation:**

It involves the development of a smart irrigation system based on the CNN-LSTM model. This system aims to address the key requirements of agricultural irrigation, such as water supply and irrigation timing, by controlling the irrigation scheduling function. The AI-based digital system for intelligent irrigation, developed using the CNN-LSTM model, is well-suited for classifying, processing, and making predictions from data obtained from IoT sensors. The system's architecture includes components and layers such as the Application layer, Intelligence layer, and Hardware layer. It empowers farmers with intelligent tools, facilitates sustainable agriculture practices, maximizes crop yields, and minimizes the environmental impact of irrigation. The system's versatility allows for the implementation of additional features, such as soil moisture monitoring and crop yield prediction, and supports farmers in making informed decisions and maximizing crop productivity.

The AI-powered irrigation system revolutionizes farming practices by providing farmers with real-time data analysis and predictive insights to optimize crop production and conserve water resources. Through advanced algorithms, the system enables precise water management by considering factors such as soil moisture levels, weather conditions, and crop requirements, resulting in optimal irrigation schedules and minimized water wastage. Additionally, the system offers smart water allocation, proactive monitoring with alerts, and historical analysis for informed decision-making.[14]

Principe:

In the realm of precision agriculture, specifically focusing on optimizing irrigation management, the "AIDSII" (AI-based digital system for intelligent irrigation) integrates machine learning techniques. Utilizing a CNN-LSTM (Convolutional Neural Network - Long Short-Term Memory) model, it processes and analyzes data obtained from IoT sensors.

The input for the CNN-LSTM model comprises data collected from IoT sensors, encompassing environmental factors such as temperature and humidity. This data is utilized for classification, processing, and prediction purposes.

The output of the CNN-LSTM model is aimed at addressing the essential requirements of agricultural irrigation, particularly concerning water supply and irrigation timing. The model controls the irrigation scheduling function, providing predictions and recommendations based on the input data. Additionally, the system is tailored for designing predictive irrigation schedules capable of forecasting rainfall depth and soil moisture levels, ultimately enhancing water storage efficiency.

Our observation indicates several positive and negative aspects of these methods:

Table 6 - AIDSII: AI-based Irrigation System - Pros and Cons

Positive	**Negative**
- Enhanced Efficiency through AI and IoT integration.	- Dependency on Data Quality for effective operation.
- Resource Conservation by minimizing water wastage.	- Complexity for Users less familiar with AI technology.
- Promotion of Sustainable Agriculture practices.	- Potential Technical Challenges in implementing and refining AI algorithms.

1.2.2.3 AI's role in the irrigation Management

In the proposed AI solutions for smart irrigation management outlined in Table 7, a range of methods is suggested to address the complexities of irrigation in agriculture. Partial Least Squares Regression (PLSR) and Adaptive Neuro Fuzzy Inference Systems (ANFIS) form a decision support system aimed at estimating weekly irrigation needs based on soil and climatic data, allowing for adaptive control to manage local variations and estimation errors effectively. K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression, and Naïve Bayes are integrated into a smart irrigation system utilizing IoT and machine learning, enabling real-time data processing and decision-making for enhanced irrigation precision. Artificial Neural Network (ANN) solutions focus on the challenges specific to greenhouse environments, ensuring reliable and flexible irrigation processes crucial for optimal plant growth. Finally, CNN-LSTM models, as seen in the AIDSII system, leverage IoT and advanced neural network architectures to offer comprehensive feedback mechanisms for intelligent irrigation management, empowering farmers to automate and optimize their irrigation practices through mobile and web technologies. These diverse AI solutions showcase the potential to revolutionize irrigation management, addressing the increasing demands for food production while managing water resources sustainably.

Table 7 - AI Solutions for Smart Irrigation Management

AI Solution	Method
Partial Least Squares Regression (PLSR) Adaptive Neuro Fuzzy Inference Systems (ANFIS)	Estimate the weekly irrigation needs of a plantation based on soil measurements and climatic variables gathered by autonomous nodes deployed in the field. Controllocal perturbations and estimation errors.
K-Nearest Neighbors (KNN) Support Vector Machine (SVM) LogisticRegression Naïve Bayes	Real-time data transmission. Processingusing the Node-RED platform and fed into decision support models employing machine learning algorithms. A web application for data visualization and supervision. Enhance irrigation efficiency and precision, crucial for meeting global food demands while managing water resources effectively.

Artificial Neural Network (ANN)	Enable automatic, reliable, and flexible irrigation for greenhouses. Addresses the practical challenges of the greenhouse industry, particularly focusing on the reliability of the irrigation process.
CNN-LSTM (Convolutional Neural Network - Long Short-Term Memory)	Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model. Offers a comprehensive feedback mechanism through mobile and web technologies, enabling farmers to automate, optimize, and streamline their irrigation processes.

1.3 Conclusion :

In conclusion, the first chapter underscores the evolution of irrigation practices, from traditional methods reliant on gravity to sophisticated AI-driven systems. By embracing innovative techniques such as drip irrigation and smart irrigation systems, farmers can enhance water efficiency, minimize environmental impact, and boost crop yields. As agriculture continues to evolve, the adoption of efficient irrigation methods remains pivotal for ensuring food security and sustainable farming practices.

Chapitre 2
IoT in the irregation

2.1 Introduction

Sensors are instrumental devices in irrigation systems, facilitating the measurement of various environmental parameters critical for effective water management. They provide real-time data on factors such as soil moisture, temperature, and humidity, empowering farmers to make informed decisions and optimize irrigation practices.

This chapter explores the diverse world of sensors, categorizing them based on the physical quantities they measure. From temperature and pressure sensors to those detecting motion and light, these devices are indispensable in modern irrigation management, enabling precise and efficient water utilization.

2.2 Sensors

The categorization of sensors is primarily based on the physical quantities they measure. Sensors play a crucial role in modern agriculture, enabling precision farming and efficient resource management. Smart sensors, integrated with IoT technology, automatically record environmental data with high accuracy and transmit it for analysis. These sensors can monitor a wide range of factors, including temperature, moisture, soil quality, pest manifestation, crop growth, and productivity. Acoustic-based sensors detect sounds emitted by insects, while LiDAR-based sensing technology provides real-time information on soil quality, moisture content, and crop growth. Additionally, mechanical sensors measure soil compactness and resistance, while mass flow sensors automate the monitoring of crop yield. Other types of sensors include those for measuring nutrient status, PH of the soil, and changes in gas levels such as CO_2 and methane. These sensors enable farmers to make data-driven decisions on irrigation, pest control, and harvest, ultimately optimizing agricultural production[15].

Here are examples of sensors commonly utilized in agriculture:

- **Temperature Sensors**: Measure temperature changes, often using resistance, voltage, or thermocouple principles.

- **Pressure Sensors:** Detect changes in pressure, typically using piezoelectric, capacitive, or strain gauge technologies.
- **Humidity Sensors:** Measure humidity levels in the air, usually using capacitive, resistive, or thermal conductivity methods.
- **Light Sensors:** Measure light intensity or illumination levels, such as photodiodes, phototransistors, or photovoltaic cells.
- **Motion Sensors:** Detect motion or movement, including accelerometers, gyroscopes, and proximity sensors.
- **Position Sensors:** Determine the position or displacement of an object, including linear or rotary encoders and proximity sensors.
- **Gas Sensors:** Detect the presence or concentration of specific gases in the environment, like oxygen, carbon dioxide, or volatile organic compounds (VOCs).
- **Sound Sensors:** Capture sound waves or vibrations in the air, such as microphones or piezoelectric sensors.
- **Chemical Sensors:** Detect specific chemical substances or compounds, such as pH sensors, gas chromatographs, or biosensors.
- **Flow Sensors:** Measure the rate of flow of liquids or gases, utilizing principles like thermal dispersion, ultrasonic, or electromagnetic flow measurement.
- **Level Sensors:** Determine the level of liquids or solids in a container or reservoir, including capacitive, ultrasonic, or float-based sensors.

Each type of sensor serves a specific function in agricultural monitoring, enabling farmers to make informed, data-driven decisions crucial for optimizing crop production and resource management.

2.3 Sensors in Irrigation

Among the most commonly used sensors in smart irrigation are:

- SoilMoistureSensors.
- WeatherSensors.

- RainfallSensors.
- Evapotranspiration (ET) Sensors.
- TemperatureSensors.
- Flow Meters.

These sensors play a crucial role in optimizing irrigation schedules, preventing over- or under-watering of crops, and enabling precise water management tailored to the specific needs of crops.

2.3.1 SelectedSensorsused

2.3.1.1 SoilMoistureSensor

Measures the moisture content in the soil, which is crucial for determining the water needs of the plants.

2.3.1.2 TemperatureSensor:

Monitors the temperature of the environment, which impacts plant growth and water requirements.

2.3.1.3 Air TemperatureSensor

Measures the temperature of the air, providing additional data for understanding environmental conditions.

2.3.1.4 HumiditySensor

Monitors the humidity levels in the air, which can impact plant transpiration and water loss.

2.3.1.5 DTH11 Sensor

The DTH11 sensor is selected to measure temperature and humidity in the environment, providing additional data for irrigation control.

2.3.1.6 Submersible Pump

The submersible pump is utilized to deliver water to the plants based on the moisture data obtained from the soil moisture sensor.

2.3.1.7 RainfallSensor

Detects the presence of rainfall, helping to prevent unnecessary irrigation during wet weather. This sensor assists in conserving water and avoiding over-saturation of soil.

2.3.1.8 Positive and Negative Aspects of Selected Sensors

This table encapsulates the key advantages and limitations of each sensor, providing a clear overview of their respective roles and potential challenges in an AI-driven irrigation system.

Table 8 – Positive and Negative Aspects of Selected Sensors

Sensor	Positive	Negative
SoilMoistureSensor	Provides real-time data on soil moisture levels. Enables precise irrigation scheduling. Helps in preventing overwatering or underwatering of plants.	May require calibration for different soil types. Accuracy can be affected by soil salinity and temperature.
TemperatureSensor	Understands thermal conditions for plant health and watering. Adjusts irrigation based on temperature changes.	Accuracy influenced by sunlight exposure or heat proximity. External factors affect precision, such as sunlight exposure.
Air TemperatureSensor	Enhances comprehension of plant growth's thermal impact. Improves understanding of thermal impact on plant growth.	Accuracy affected by external factors like sunlight exposure.
HumiditySensor	Assists in assessing air moisture content for understanding plant water needs.	Accuracy affected by condensation or moisture exposure.
DHT11 Sensor	Provides key environmental data for plant growth and irrigation management.	Accuracy and reliability can be affected by external factors like sunlight or moisture exposure.
Submersible Pump	Efficiently delivers water to plants, ensuring proper irrigation.	Maintenance and potential mechanical failure of the

		pump are important considerations.
RainfallSensor	Detects rainfall, preventing unnecessary irrigation during rainy periods. Helps conserve water and prevent waterlogging.	May require maintenance for accurate readings. Limited to detecting rainfall and does not provide information about soil moisture levels.

2.3.2 IoT'seffect on AI methods

2.3.2.1 Smart Irrigation System using Machine Learning and IoT:

It discusses the integration of AI solutions in the context of smart farming and automated irrigation [17]. It mentions the use of machine learning algorithms for soil categorization, as well as the benchmarking of rainfall prediction using supervised learning methods such as NB, C4.5, SVM, ANN, and RF. Additionally, an ensemble of these models is used to train a Voting Classifier for predicting rainfall. This approach involves training a single model on multiple models and predicting the output based on the cumulative majority of votes for each output class.
Furthermore, theauthor of [17] highlights the use of deep learning for plant recognition and determining the optimal watering volume based on plant type. It also mentions the exploration of deep learning and an altitude-based economical irrigation technique. These AI solutions aim to enhance the efficiency and effectiveness of agricultural irrigation and smart farming practices.

Principe:

In the domain of agricultural irrigation, machine learning techniques are harnessed through an Automated Irrigation System (AIS) to modernize practices and combat water scarcity challenges. Data collection involves gathering soil moisture content and ambient temperature data through sensors.
Our observation indicates several positive and negative aspects of these methods:

Table 9 - Pros and Cons of Smart Irrigation System

Positive	Negative
- Optimizes water usage, reducing wastage.	- Dependency on sensors and connectivity may lead to reliability issues.
- Enhances crop yield and agricultural output.	- System performance may vary based on environmental factors.
- Uses low-cost hardware and open-source technologies.	- Technical failures could disrupt irrigation processes.

The figure below illustrates the model used in the smart irrigation system discussed in the article (Figure 6).

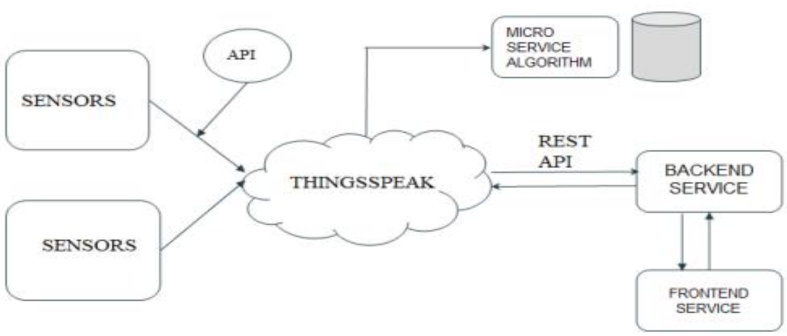

Figure 6 - Model of Smart Irrigation System[17]

This model demonstrates the flow of data from sensors to the cloud platform, ThingSpeak, where it is processed by microservices and algorithms. The processed data is then made available via REST APIs to backend services, which in turn communicate with frontend services to provide actionable insights and control to the users.

This integration of AI and IoT exemplifies how modern technology can revolutionize traditional agricultural practices, making them more efficient, sustainable, and responsive to environmental conditions.

2.3.2.2 The IoT-enabled Deep Learning-based Smart Irrigation System (IoTDL-SIS):

It discusses the integration of AI solutions, specifically deep learning, in the context of a smart irrigation system[16]. The proposed IoTDL-SIS technique involves the use of distinct sensors for data acquisition, which are then transmitted to the cloud server for further processing. The cloud server performs data analysis using regression, clustering, and binary classification processes. Deep support vector machine (DSVM) based regression is employed for predicting soil and environmental parameters in advance, such as atmospheric pressure, precipitation, solar radiation, and wind speed. This integration of AI solutions allows for efficient water utilization with less human intervention in the smart irrigation system.

Principe:

In the domain of precision agriculture, particularly focusing on optimizing irrigation management, the IoT-enabled Deep Learning-based Smart Irrigation System (IoTDL-SIS) integrates machine learning techniques for efficient irrigation management. Deep Support Vector Machine (DVSM) based regression analyzes environmental and soil variables, while the Artificial Immune Optimization Algorithm (AIOA) with Deep Belief Network (DBN) based classification categorizes instances into irrigation required or not required.
Our observation indicates several positive and negative aspects of these methods:

Table 10 - IoTDL-SIS: Positives and Negatives

Positive	**Negative**
- The system optimizes irrigation scheduling using sensor data and AI, reducing water wastage and improving crop yield.	- Implementing and maintaining an IoT-enabled system with deep learning algorithms can be complex and may require technical expertise.
- The system automates the process of irrigation scheduling, reducing the need for manual intervention and saving farmers time and effort.	- Reliable connectivity is essential for data transmission between sensors, Arduino, cloud servers, and client devices. Poor connectivity can affect the system's performance.

- Deep learning techniques enable accurate prediction of environmental and soil variables, ensuring precise irrigation recommendations tailored to specific crop needs.	- The reliance on advanced technologies like deep learning may pose barriers to adoption in regions with limited technical resources or expertise.

The figure below illustrates the working process of the IoT-enabled Deep Learning-based Smart Irrigation System (IoTDL-SIS) discussed in the article.

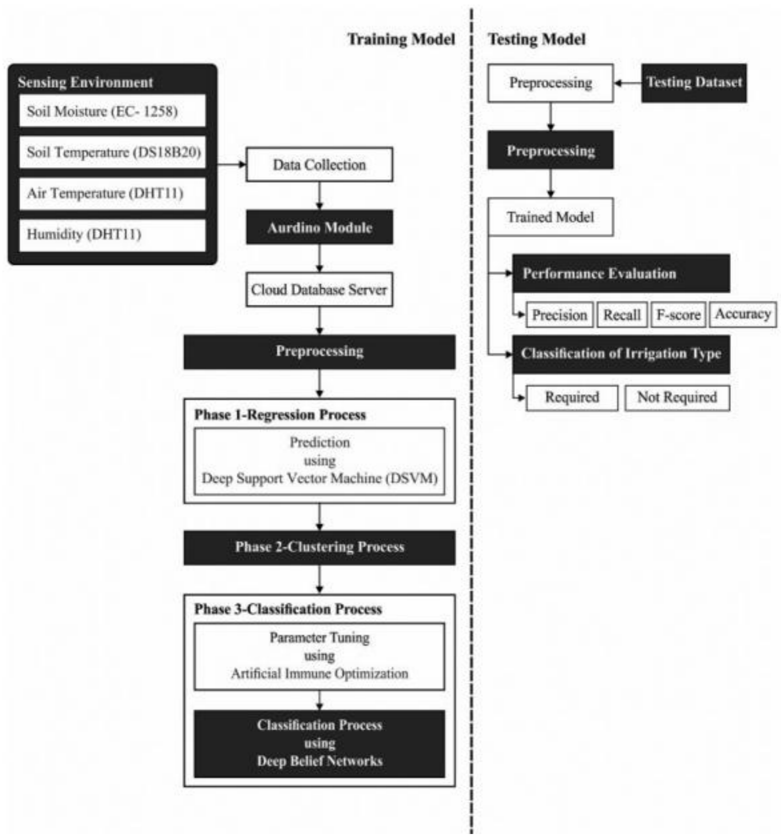

Figure 7-Working process of IoTDL-SIS method [16]

This model demonstrates the comprehensive workflow, starting from the data collection using various sensors and the Arduino module, to the cloud server for data preprocessing and analysis. The process involves three phases: regression, clustering, and classification, employing deep learning techniques to predict environmental parameters and determine irrigation needs.

This integration of IoT and deep learning techniques showcases how modern technology can revolutionize traditional agricultural practices, making them more efficient, sustainable, and responsive to environmental conditions.

2.4 Conclusion

In conclusion, sensors are vital tools in irrigation, providing real-time data for informed decision-making. While they offer immense benefits, challenges like calibration complexity and spatial variability must be addressed. Nonetheless, harnessing sensor technology holds great promise for optimizing agricultural practices and ensuring sustainability in irrigation management.

Chapitre 3
Conception of AI based irrigation model

3.1 Introduction

We propose an AI-based irrigation model designed to optimize water usage in agriculture by leveraging machine learning (ML) and deep learning (DL) techniques. The model integrates real-time data from various sensors to predict and manage irrigation needs, ensuring efficient and sustainable water use. We will discuss the components of the model, the data collection process, preprocessing steps, analysis methods, and results obtained from both ML and DL models.

3.2 AI basedof irrigation model

The data processing and decision-making pipeline involves several critical stages, beginning with the collection of raw data from various sensors that measure parameters like temperature, pressure, and humidity. This data is then transferred to a storage system, which could be a database or data warehouse capable of holding large volumes of information. Following storage, the data undergoes preprocessing, which includes cleaning, normalizing, and transforming the data to improve its quality and accuracy for subsequent analysis. The analysis stage leverages advanced techniques, applying both machine learning and deep learning models to extract meaningful insights and uncover deeper patterns within the data. The insights derived from these models are then used to make decisions, which can be communicated to an actor (an automated system) who takes the appropriate actions based on these insights. Like the figure illustrates, this comprehensive pipeline transforms raw data into actionable insights through a structured and methodical process. See Figure 8

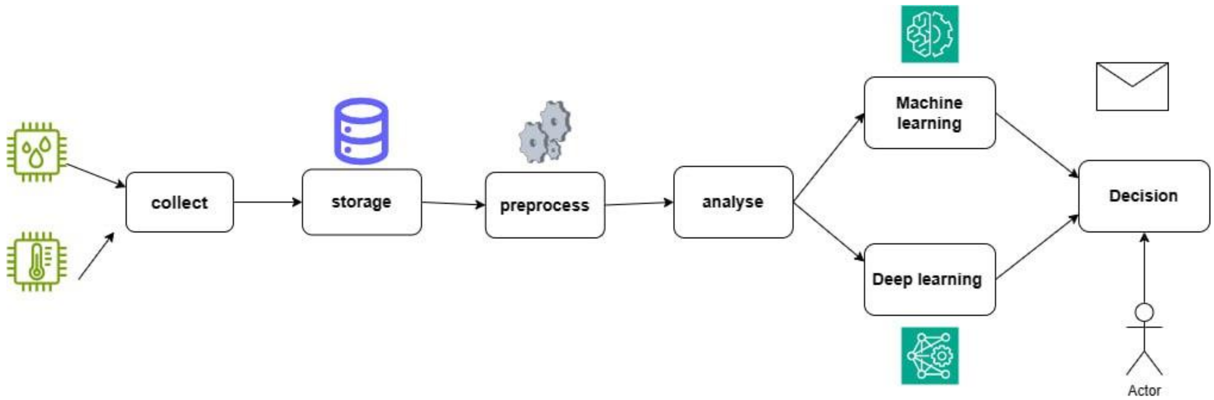

Figure 8- Data Processing and Decision-Making

3.2.1 Collect : Database and Sensors

3.2.1.1 Database

The database used in this AI-based irrigation model consists of a dataset containing six elementarydata:CropType, CropDays, SoilMoisture, Temperature, Humidity, and Irrigation.

This dataset containsvarious crops such as Wheat, Groundnuts, Garden Flowers, Maize, Paddy, Potato, Pulse, Sugarcane, Coffee and cotton. It serves as the foundation for training and testing the machine learning models.

Example from the dataset:

- CropType: Wheat
- CropDays: 10
- SoilMoisture: 400%
- Temperature: 30 °C
- Humidity: 15%
- Irrigation: 0

3.2.1.2 Sensors

The model relies on three primary types of sensors:

- Soil Moisture Sensors: These sensors measure the moisture content in the soil, which is critical for determining irrigation needs.

- Temperature Sensors: These sensors monitor the ambient temperature, as temperature influences plant growth and water requirements.

- Humidity Sensors: These sensors track the air moisture levels, which affect both soil moisture and plant transpiration rates.

These sensors continuously collect data and update the database, ensuring that the model has access to real-time environmental conditions.

3.2.2 Preprocessing:

3.2.2.1 Algorithm

The preprocessing is crucial for preparing the data before it is fed into the AI model.We propose in this section our preprocessing algorithm.

Algorithm:Preprocessing_data

input: data

output:train_data, test_data

Begin

```
    data = load_data('data')

     Handle Missing Values:

    For (line in data):

    For(attribute in data):

        processing(attribut)

    EndFor

    Remove Duplicates(line)

    Outlier Detection(line)
```

```
    For(attribute in data):
        Normalize(attribut)
        scale(attribut)
    EndFor
    EndFor
    Train-Test Split(data)
    Return (train_data, test_data)
End
```

3.2.2.2 Sequence Diagram

Our data processing system isdesigned to prepare data for machine learning or data analysis. It begins with a user class that has a method to load data. This data is then passed to the~~a~~ Data Processing System, which reads the data from the source and performs initial cleaning. The system identifies and handles missing values by either deleting them or replacing them with appropriate values.

After cleaning, the data is normalized and scaled to ensure consistency and improve the algorithm's performance. The final step in the process is splitting the data into training and test datasets. The training data is used to build the machine learning model, while the test data is used to evaluate its performance.

We propose in Figure 9 the sequence diagramof the data preprocessing.This diagram is crucial as it visually outlines the workflow and interaction between the user and the system, emphasizing the importance of data preparation in the machine learning pipeline. Proper data handling, such as cleaning and normalization, is essential for developing robust and accurate models.

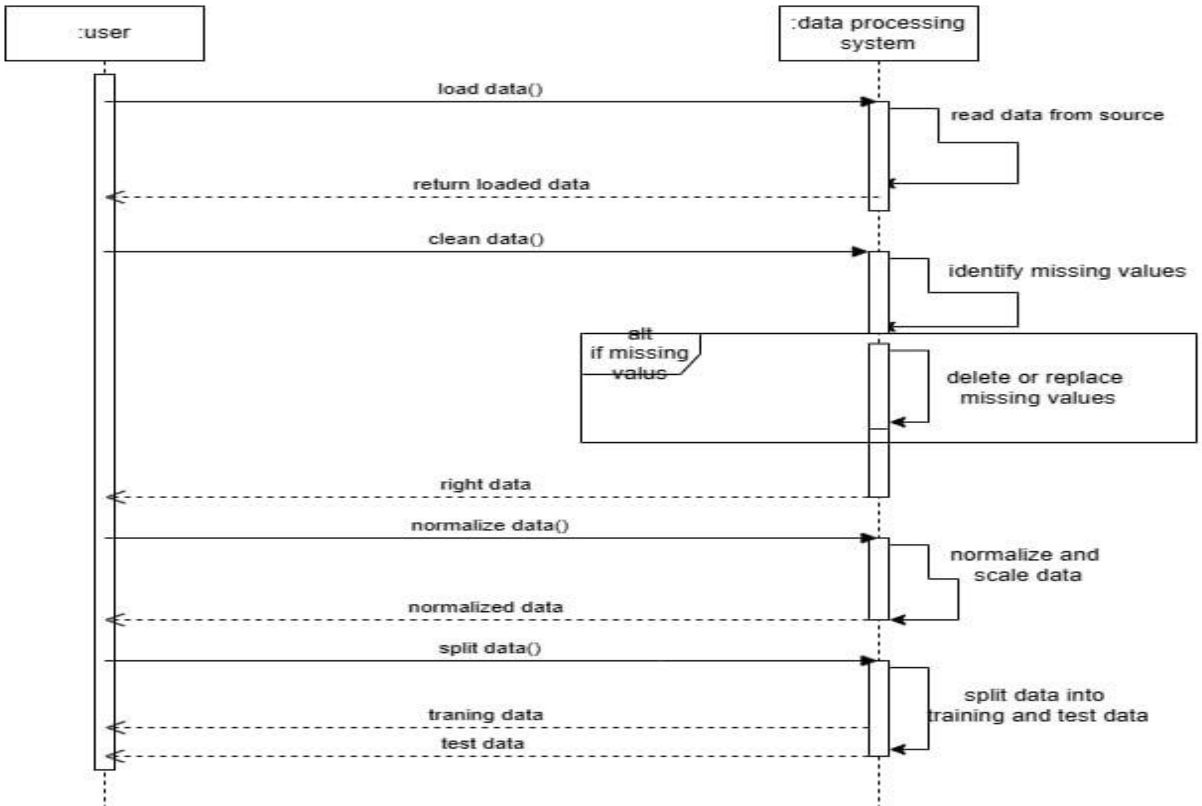

Figure 9-Data Preprocessing Workflow Sequence Diagram

3.2.3 Analyse

3.2.3.1 Machine Learning analysis

This class diagram represents a machine learning model workflow tailored for agricultural predictions, likely to optimize crop yield or manage farming resources. The createModel class defines the structure of the model with attributes like croptype, cropdays, soilmoisture, humidity, temperature, and irrigation, and includes a method insert() to initialize or populate these attributes. The Configuration class, associated one-to-one with createModel, specifies the model’s hyperparameters such as optimizer name, loss, and metrics, and provides the compile() method to set these parameters for the model. The Training class takes the training data (X_Train and Y_Train) and has a fit() method to train the model.

The Evaluation class, which uses test data (X_test and Y_test), includes the evaluate() method to assess the model's performance. Finally, the Prediction class uses the trained model to make predictions based on the input attributes and has a predict() method. This diagram encapsulates the typical stages of a machine learning model lifecycle from creation and configuration through training, evaluation, and prediction. See Figure 10.

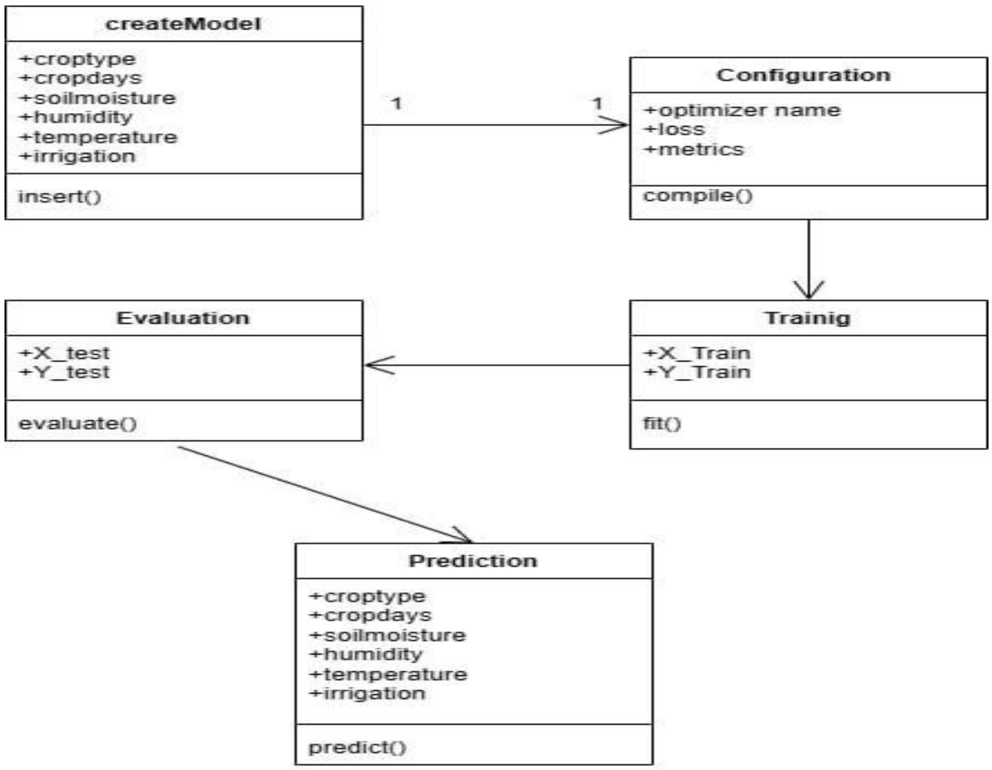

Figure 10 - Class Diagram for Machine Learning Model

3.2.3.2 Deep Learning analysis

This class diagram outlines the workflow for a machine learning model focused on agricultural applications, possibly for predicting crop yields or optimizing farming practices. The createModel class is responsible for defining the model's structure with an attribute croptype, and it includes methods for data preprocessing such as oneHotEncoder() and transform(). The Splitting class, which is linked to createModel, specifies the model's hyperparameters including optimizer name, loss, and metrics, and provides a compile() method to configure the model. The Training class handles the training process using training data (X_Train and Y_Train) and includes a train() method to fit the model. The Test class is designed to evaluate the model's performance using test data (X_test and Y_test) and has a test() method for this purpose. Finally, the evaluate class is responsible for comparing the model's predictions (predict) against the actual test outcomes (Y_test) using the comparison() method. This diagram illustrates the sequential steps in a machine learning pipeline, from model creation and configuration to training, testing, and evaluation. See Figure 11

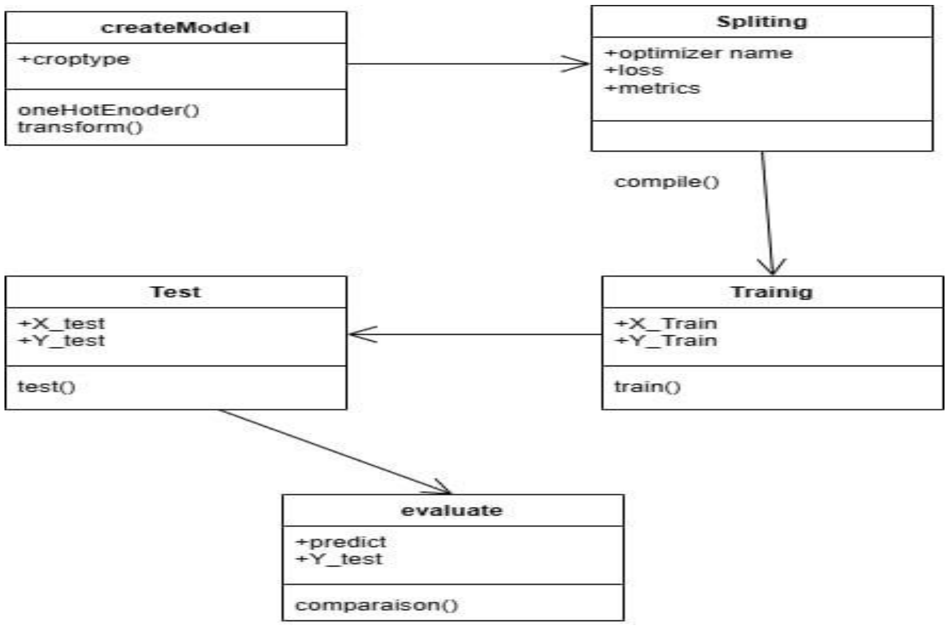

Figure 11 - Class Diagram for Deep Learning Model

3.2.4 Reslut

Our models based onmachine learning (ML) and deep learning (DL) are both designed to predict the amount of water needed for plants based on various factors like crop type, soil moisture, temperature, and humidity. Each model has its own approach to predicting irrigation needs.

The Random Forest Regressor model utilizes an ensemble of decision trees to make predictions. It learns from the data and builds multiple trees, where each tree contributes to the final prediction. This model aims to provide estimates of water requirements for different plants based on the input features.

On the other hand, the Deep Neural Network (DNN) model is designed with layers of interconnected nodes that learn complex patterns in the data. It starts with an input layer, followed by hidden layers that extract features, and finally an output layer that provides the prediction. In this case, the DNN model is trained to predict the irrigation needs of plants using a sequential architecture.

Both models are expected to provide estimates of water requirements for different plants, given the input features such as crop type, soil moisture, temperature, and humidity. These estimates are valuable for optimizing water usage in agriculture, ensuring that plants receive adequate irrigation while minimizing water wastage.

Ultimately, the expected result from these models is accurate predictions of water needs for various plants, which can inform decision-making processes for farmers and agricultural practitioners. These predictions can help optimize irrigation schedules, conserve water resources, and enhance crop yield and quality.

3.3 Conclusion

In conclusion, we proposed an AI-based irrigation model to optimize water usage in agriculture using ML and DL techniques. This chapter covered data collection from sensors, preprocessing algorithms, and analysis methods, demonstrating the model's effectiveness in managing water efficiently.

In the next chapter, we will focus on implementing the model. We'll discuss the tools needed, including Arduino and Python, detail the dataset, and explain the preprocessing, analysis steps, and results from ML and DL models.

Chapitre 4

Implementation of AI based irrigation model

4.1 Introduction

Embarking on our exploration, we delve into pivotal components that form the backbone of our study, setting the stage for insightful analysis and discoveries.We first explore the Arduino UNO microcontroller board, followed by an in-depth examination of a diverse dataset sourced from Kaggle. This dataset, rich in parameters related to crop cultivation, serves as the backbone of our analysis. Through meticulous preprocessing, we refine the data for comprehensive exploration. Our investigation culminates in insightful results from both machine learning (ML) and deep learning (DL) approaches, offering precise predictions of irrigation needs for various plants, thus contributing to optimized water management practices in agriculture.

4.2 Arduino UNO

4.2.1 Definition

Arduino UNO is a microcontroller board based on the **ATmega328P**. It has 14 digital input/output pins (of which 6 can be used as PWM outputs), 6 analog inputs, a 16 MHz ceramic resonator, a USB connection, a power jack, an ICSP header and a reset button. It contains everything needed to support the microcontroller; simply connect it to a computer with a USB cable or power it with a AC-to-DC adapter or battery to get started [18].

4.2.2 Lecture of our data

In this section, we dive into the process of loading and understanding the dataset crucial for our AI-based irrigation model. This step is vital to comprehend the characteristics of the data we'll be working with, ensuring its suitability for our analysis.

4.2.2.1 Reading and Inspection of Dataset

To start our data exploration, we load the dataset from a CSV file using the pandas library, a fundamental tool for data manipulation and analysis in Python. The following code snippet showcases how we read the dataset into a DataFrame and inspect its structure: See figure 12

```
import pandas as pd
# Load the CSV file into a DataFrame
data = pd.read_csv('datasets.csv')
# Display the first few rows of the DataFrame
print(data.head())

# Check the structure of the dataset
shape = data.shape
print("Dataset Shape:", shape)

# Check summary statistics
summary_statistics = data.describe()
print("Summary Statistics:\n", summary_statistics)
```

Figure 12-Dataset Loading and Inspection

By examining the initial rows and summarizing statistics of the dataset, we gain insights into its structure, attributes, and numerical distribution. This initial exploration sets the stage for further preprocessing and analysis steps.

4.3 Dataset

4.3.1 Source of Dataset :

The dataset used in this study was obtained from Kaggle, a platform for data science and machine learning enthusiasts. Kaggle provides a wide range of datasets for various purposes, and it serves as a valuable resource for researchers, practitioners[19].

4.3.2 Content of Dataset :

The dataset contains information on various crops and several parameters associated with their growth conditions. Theseparametersinclude :

- **CropType**: The type of crop being considered. Examples include Wheat, Groundnuts, Garden Flowers, Maize, Paddy, Potato, Pulse, Sugarcane, and Coffee.

- **CropDays**: The number of days the crop has been growing or the duration of its growth cycle.

- **SoilMoisture**: The level of moisture in the soil, which is essential for plant growth and health.

- **Temperature**: The temperature conditions under which the crops are growing. Temperaturesignificantly influences cropgrowth rates and patterns.

- **Humidity**: The amount of moisture present in the air, which affects plant growth and can influence crop diseases and pests.

- **Irrigation:** Indicates whether the crops have been irrigated or not. Irrigation is crucial, especially in regions with insufficient rainfall, to ensure proper crop growth.

The screenshot below provides a preview of the dataset, including 702 rows and 6 columns.

1	CropType	CropDays	SoilMoisture	temperature	Humidity	Irrigation
2	Wheat	10	400	30	15	0
3	Wheat	7	200	30	32	0
4	Wheat	9	300	21	28	0
5	Wheat	3	500	40	22	0
6	Wheat	2	700	23	34	0
7	Wheat	6	800	21	29	0
8	Wheat	5	500	33	26	0
9	Wheat	8	350	21	28	0
10	Wheat	11	123	17	45	0
11	Wheat	12	543	25	53	0

Figure13- Dataset Preview

4.4 Preprocessing and Analysis

4.4.1 Python

4.4.1.1 Definition :

Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together[20].

4.4.1.2 Package used

In our AI-based irrigation model, we chose specific Python packages based on their functionalities and how well they meet the needs of our project. Each package was selected to ensure efficient data manipulation,robust model building, and effective data visualization. Below is a summary of the packages used and the rationale for their selection:

- numpy: For numerical operations.
- pandas: For data manipulation and analysis.
- sklearn: For machine learning tasks such as preprocessing and model selection.
- tensorflow.keras: For building and training neural network models.
- seaborn: For statistical data visualization.
- matplotlib.pyplot: For creating plots and visualizations.

4.4.1.3 FunctionsUsed

LoadDataset

This function loads the dataset from a CSV file into a DataFrame using pandas. It takes as input the path to the CSV file containing the dataset and outputs a DataFrame containing the loaded dataset.

Calculate Summary Statistics

This function calculates summary statistics (e.g., mean, standard deviation) of numerical attributes in the dataset using the describe() method of pandas DataFrame. It takes as input a DataFrame containing the dataset and outputs summary statistics of the dataset. See Figure 14

```
# Check summary statistics
print(data.describe())
```

```
         CropDays  SoilMoisture  temperature    Humidity  Irrigation
count  501.000000    501.000000   501.000000  501.000000  501.000000
mean    64.053892    411.391218    24.682635   39.381238    0.393214
std     45.935554    199.099590    12.111527   22.618231    0.488952
min      1.000000    120.000000    14.000000   11.000000    0.000000
25%     27.000000    230.000000    20.000000   19.000000    0.000000
50%     57.000000    369.000000    24.000000   32.000000    0.000000
75%     90.000000    554.000000    28.000000   65.000000    1.000000
max    210.000000    990.000000   263.000000   85.000000    1.000000
```

Figure 14- Summary Statistics of the Dataset

Calculate Average Soil Moisture

This function groups the dataset by CropType and calculates the average SoilMoisture for each group using the groupby() and mean() methods of pandas DataFrame. It takes as input a DataFrame containing the dataset and outputs a DataFrame containing the average soil moisture for each crop type. See Figure 15

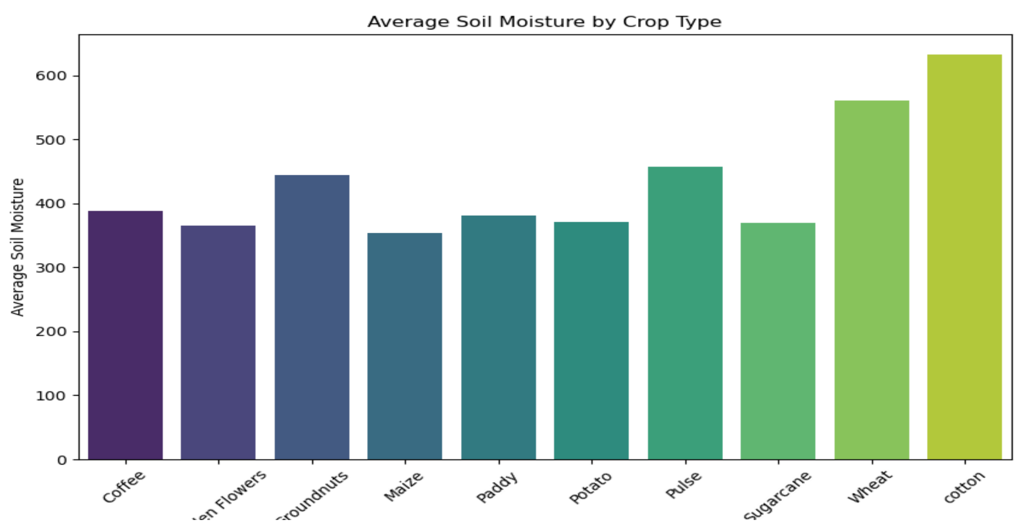

Figure 15-Average Soil Moisture by Crop Type

The bar chart titled "Average Soil Moisture by Crop Type" displays the average soil moisture levels associated with various crop types. The data reveals that Cotton exhibits the highest average soil moisture requirement, exceeding 600, indicating its substantial water needs for optimal growth. Wheat also maintains a high soil moisture requirement, closely following cotton, with an average value slightly above 500. Groundnuts and pulse crops continue to show high average soil moisture levels, reflecting their need for significant water content in the soil. In contrast, garden flowers and sugarcane remain on the lower end of the spectrum, each with average soil moisture values around 300, suggesting they thrive with less water. Coffee, maize, paddy, and potato fall in the intermediate range, indicating moderate water requirements. These insights emphasize the variability in water needs across different crops, which is crucial for efficient irrigation management and sustainable agricultural practices. By understanding these differences, farmers can better plan their water usage to ensure optimal crop yields and resource conservation.

Delete Missing Values

This function removes rows with missing values in selected columns (CropType, CropDays, SoilMoisture, temperature, Humidity, Irrigation) using the dropna() method of pandas DataFrame. It takes as input a DataFrame containing the dataset and outputs a DataFrame containing cleaned data after removing rows with missing values. See Figure 16

Figure 16- Removing Missing Values

```
# Deleting missing values from the columns 'CropType', 'CropDays', 'SoilMoisture', 'temperature', 'Humidity', 'Irrigation'
olddata = data.shape
cleanedata = data.dropna()
newdata = cleanedata.shape
print("Initial: {} Final: {}".format(olddata,newdata))
```

Visualize Soil Moisture Distribution

This function plots a boxplot to visualize the distribution of SoilMoisture across different CropTypes using seaborn and matplotlib libraries. It takes as input a DataFrame containing the cleaned dataset and outputs a visualization showing the distribution of SoilMoisture across different CropTypes. See Figure 17.

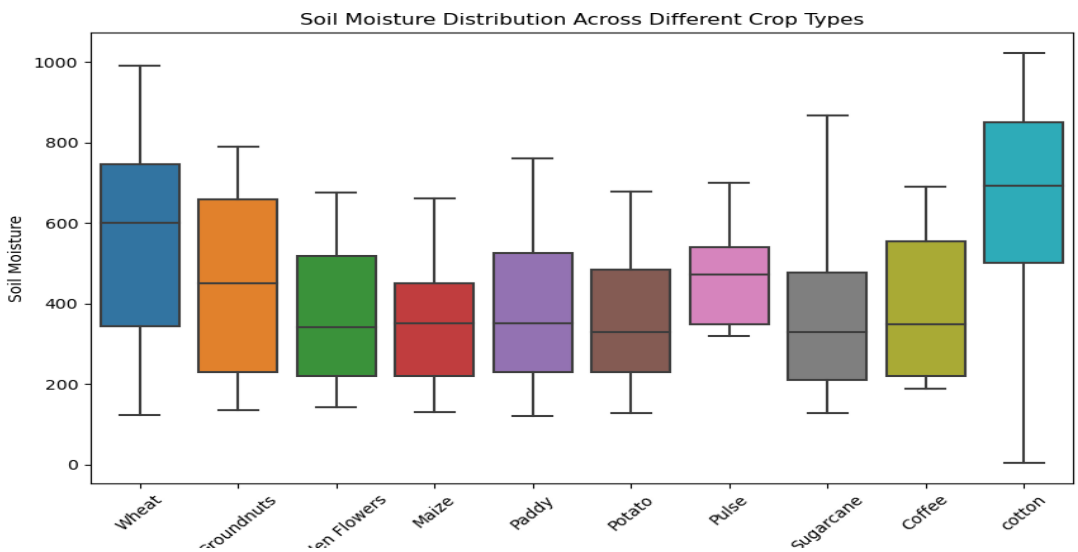

Figure 17- Soil Moisture Distribution Across Different Crop Types

The box plot titled "Soil Moisture Distribution Across Different Crop Types" . Wheat and cotton stand out with the widest distributions, indicating high variability in soil moisture requirements. Wheat has a median soil moisture around 600, with values ranging from about 200 to 1000, while cotton has a median slightly above 600 and an even broader range. Groundnuts and garden flowers show moderate variability, with medians around 500 and 400, respectively. Maize, paddy, potato, pulse, sugarcane, and coffee exhibit narrower distributions, indicating more consistent soil moisture needs. Notably, sugarcane and coffee have lower median soil moisture levels, around 400 and 350, respectively. This comprehensive view emphasizes the diverse water requirements and variability among crops, underscoring the need for tailored irrigation strategies to meet the specific demands of each crop efficiently. Understanding these distributions aids in optimizing water use and improving crop management practices.

Balance Data

This function balances the dataset by sampling up to 50 records for each CropType to address any class imbalance using pandas DataFrame operations. It takes as input a DataFrame containing the cleaned dataset and outputs a DataFrame containing balanced data with up to 50 records for each CropType. See Figure 18.

```python
#balancing data
grouped = cleaned_data.groupby("CropType")
# You can inspect the groups with grouped.groups.keys() to see different CropTypes

# Creating a list of DataFrames, each containing samples from each 'CropType' group
# Here, we ensure each CropType group has, for instance, up to 50 samples.
# Adjust the number 500 based on your dataset's size and needs.
frames_of_groups = [group.sample(min(len(group), 50)) for _, group in grouped]

# Concatenating the sampled DataFrames back into a single DataFrame
balanced_data = pd.concat(frames_of_groups)
balanced_data.reset_index(drop=True, inplace=True)

# Now, you can visualize the distribution of your data points across CropTypes to confirm balancing
sns.set(rc={'figure.figsize':(15, 5)})
sns.countplot(x="CropType", data=balanced_data)
plt.title('Balanced Distribution Across Crop Types')
plt.xlabel('Crop Type')
plt.ylabel('Number of Data Points')
plt.xticks(rotation=45)
plt.show()

print(balanced_data.info())
```

Figure 18- Balancing data

4.5 Application Pages

The following screenshots depict the main pages of our irrigation application:

4.5.1 Registration Page

Users can register by providing their full name, email, and password. See Figure 19

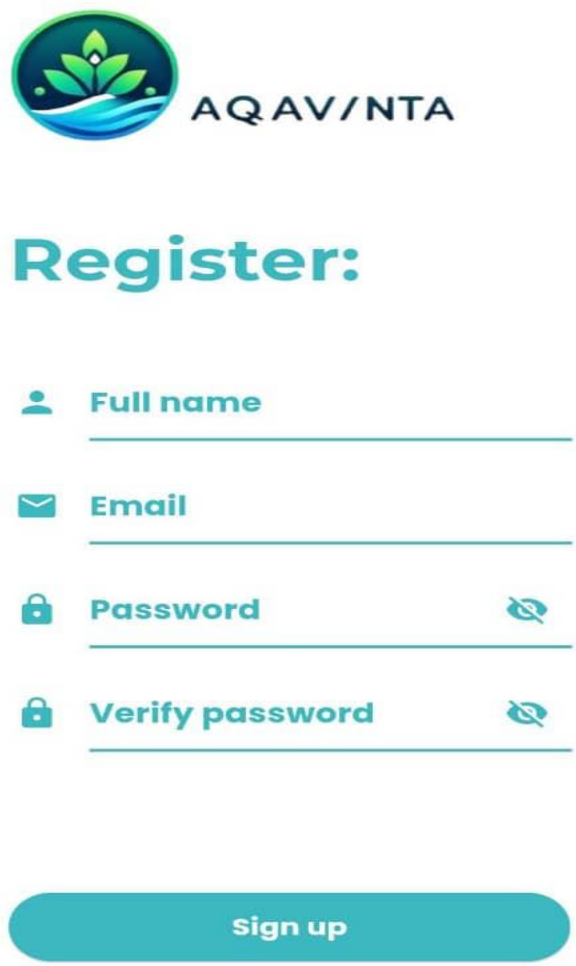

Figure19-Registration page

4.5.2 Login Page

Registered users can log in by entering their email and password. The login page also provides options to sign up and recover forgotten passwords.See Figure 20.

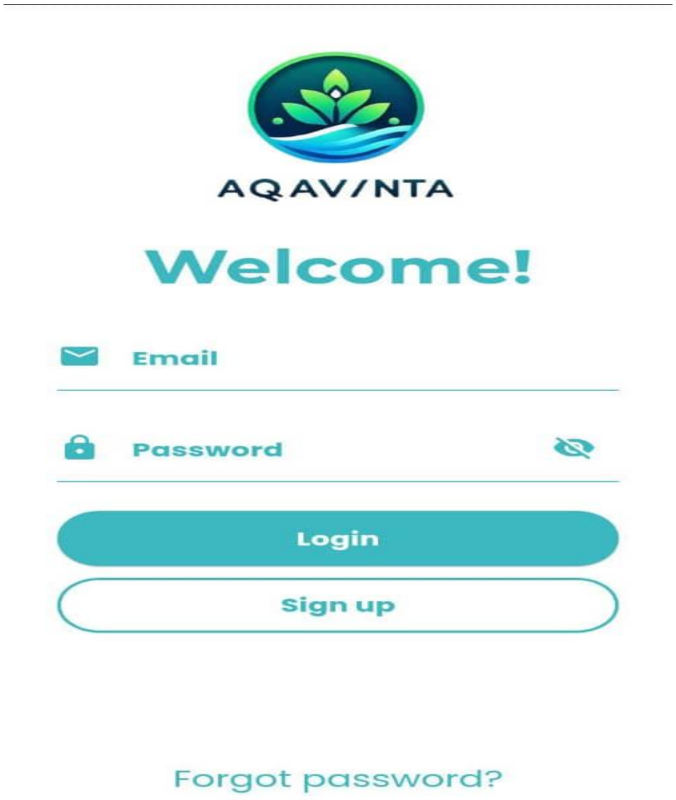

Figure 20-Login page

4.5.3 Dashboard

The dashboard provides an overview of the irrigation system's status, including humidity, temperature, soil moisture, and irrigation activity for different plant. Users can open or close irrigation systems as needed. See Figure 21.

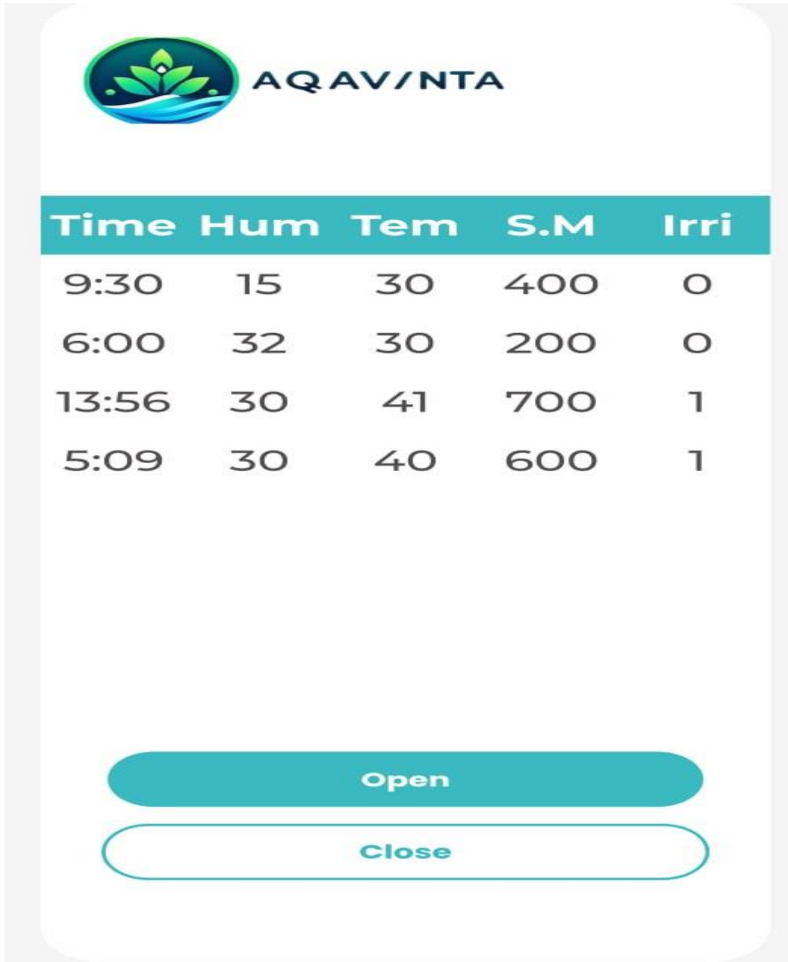

Figure 21-Dashboard

The figure displays sensor data from our system, used for agricultural monitoring. The table presents measurements of humidity (Hum), temperature (Tem), soil moisture (S.M), and irrigation status (Irri) at various times of the day. Additionally, two buttons labeled "Open" and "Close" are shown, for controlling an irrigation valve. This data highlights the importance of timely irrigation to manage soil moisture, particularly during high-temperature periods. The control of the irrigation valve through the "Open" and "Close" buttons allows for flexible responses to changing environmental conditions, ensuring that soil moisture levels remain within the desired range.

4.6 Result

4.6.1.1 Machine learningResult

- **Description of Analysis**

In this section, we present the results obtained from the machine learning model trained to predict water needs for various plants based on features such as CropType, CropDays, SoilMoisture, temperature, and Humidity. The trained model aims to estimate the water needs (Irrigation) for each plant in units (ml).

- **Model Output**

The machine learning model provided the following estimated water needs (Irrigation) for each plant, see Figure 22.

```
Plant 1: Estimated Water Needs = 1.0 ml
Plant 2: Estimated Water Needs = 1.0 ml
Plant 3: Estimated Water Needs = 0.1 ml
Plant 4: Estimated Water Needs = 0.0 ml
Plant 5: Estimated Water Needs = 0.09 ml
Plant 6: Estimated Water Needs = 0.0 ml
Plant 7: Estimated Water Needs = 1.0 ml
Plant 8: Estimated Water Needs = 1.0 ml
Plant 9: Estimated Water Needs = 0.95 ml
Plant 10: Estimated Water Needs = 0.0 ml
Plant 11: Estimated Water Needs = 0.0 ml
Plant 12: Estimated Water Needs = 1.0 ml
Plant 13: Estimated Water Needs = 1.0 ml
Plant 14: Estimated Water Needs = 0.0 ml
Plant 15: Estimated Water Needs = 0.0 ml
Plant 16: Estimated Water Needs = 0.0 ml
Plant 17: Estimated Water Needs = 0.92 ml
Plant 18: Estimated Water Needs = 1.0 ml
Plant 19: Estimated Water Needs = 0.09 ml
```

Figure 22- Estimated Water Needs for Plants

The data in the image shows the estimated water needs for 19 plants, with the values ranging from 0.0 ml to 1.0 ml. A notable pattern is that many plants have either 1.0 ml or 0.0 ml water needs, indicating a binary distribution for some of the entries. For instance, Plants 1, 2, 7, 8, 12, 13, and 18 each require 1.0 ml of water, while Plants 6, 10, 11, 15, and 16 require no water at all. Other plants have varying needs between these extremes. For example, Plant 3 needs 0.1 ml, Plant 4 needs 0.01 ml, Plant 5 needs 0.09 ml, Plant 9 needs 0.95 ml, and Plant 17 needs 0.92 ml. This variation could indicate different plant types or environmental conditions influencing their water requirements. The data suggests that a significant number of plants are either fully hydrated or dehydrated, while a smaller subset requires precise amounts of water, highlighting the diversity in water needs among the plants being analyzed.

- **Model Evaluation**

The machine learning model achieved a mean squared error of 0.0404 and a mean absolute error of 0.0686, indicating good performance in predicting water needs for the plants. The estimated water needs for each plant provide insights into the irrigation requirements, which can be useful for optimizing water usage in agricultural practices. See Figure 23.

```
Mean Squared Error: 0.04036241134751773
Mean Absolute Error: 0.06858156028368795
```

Figure 23-Model Evaluation: MSE and MAE

4.6.1.2 Deep Learning Result

Training Process and EpochAnalysis

The deep learning model was trained over 50 epochs to predict the water needs of plants. Here, we analyze the results in detail:

Initial Phase (Epochs 1-10):

Loss and MAE: The training loss started at 0.3005 and validation loss at 0.1398. Correspondingly, the training MAE was 0.4027, and the validation MAE was 0.3196.

Trend: Both loss and MAE exhibited a significant decrease, indicating effective learning from the data.

Example Values:

Epoch 1: Training Loss = 0.3005, Training MAE = 0.4027, Validation Loss = 0.1398, Validation MAE = 0.3196

Epoch 10: Training Loss = 0.0382, Training MAE = 0.1291, Validation Loss = 0.0582, Validation MAE = 0.1715

Middle Phase (Epochs 11-30):

Loss and MAE: A continued decrease in both metrics was observed, suggesting sustained learning and improved fitting to the training data.

Example Values:

Epoch 20: Training Loss = 0.0226, Training MAE = 0.0857, Validation Loss = 0.0403, Validation MAE = 0.1297

Epoch 30: Training Loss = 0.0157, Training MAE = 0.0647, Validation Loss = 0.0298, Validation MAE = 0.1087

Final Phase (Epochs 31-50):

Convergence: Loss and MAE values began stabilizing, indicating model convergence.

Example Values:

Epoch 40: Training Loss = 0.0116, Training MAE = 0.0523, Validation Loss = 0.0278, Validation MAE = 0.0954

Epoch 50: Training Loss = 0.0088, Training MAE = 0.0432, Validation Loss = 0.0244, Validation MAE = 0.0861

Prediction Analysis

The model's predictions for the water needs of 101 plants provide a range of values, demonstrating its ability to generate diverse and contextually appropriate outputs.

Interpretation:

The model successfully identifies plants that need varying amounts of water, with predictions ranging from 0.0 to 1.192 units.

The zero predictions might indicate plants that do not need additional water based on their input features.

Evaluation Metrics

- MeanSquaredError (MSE):0.0411
- MeanAbsoluteError (MAE):0.0902

The low MSE and MAE values suggest that the model performs well, making accurate and reliable predictions for the water needs of plants.

4.7 Conclusion

In conclusion, delving into microcontrollers, datasets, and data analysis tools has enriched our understanding of agricultural data science. By leveraging technology and data-driven approaches, we're poised to make informed decisions and drive innovation in agriculture. Moving ahead, let's capitalize on these insights to foster sustainable agricultural practices and advancements.

General conclusion

In conclusion, this report has delved into the integration of artificial intelligence (AI) with irrigation systems in agriculture, emphasizing the critical need to optimize irrigation management for sustainable crop cultivation. Traditional irrigation methods have often been inefficient, resulting in considerable water waste and environmental issues. However, the advent of precision irrigation techniques, which utilize advanced sensors, data analytics, and AI-driven algorithms, offers a transformative approach to agricultural practices. Our primary objective is to develop an AI-driven irrigation management system tailored to farmers' needs, aiming to optimize water usage by providing personalized irrigation recommendations based on crop-specific requirements, soil conditions, and weather patterns. By minimizing water waste and boosting crop yields, our solution seeks to foster sustainable agricultural practices and enhance economic efficiency for farmers.

To achieve this objective, we conducted an in-depth analysis using a comprehensive database sourced from Kaggle. Rather than employing sensors, we focused on processing this existing data to develop a machine learning model that accurately determines the optimal amount of water each plant needs. Our efforts culminated in the creation of an application designed to assist farmers with precise irrigation management. This application leverages data analytics to offer tailored irrigation schedules, thereby enhancing resource efficiency and crop productivity.

Despite these advancements, there are several critical steps that need to be undertaken. Our next goal is to develop an automated irrigation system that utilizes tubing to deliver water directly to plants based on the recommendations provided by our application. This involves integrating our AI model with hardware components to create a fully automated, efficient irrigation process. Ensuring the reliability and robustness of this system will be key to its successful deployment in diverse farming environments.

Looking ahead, our focus will expand beyond irrigation management to encompass broader aspects of crop health. We plan to incorporate functionalities for detecting plant diseases and providing targeted solutions to enhance crop quality and yield. By leveraging advanced AI techniques and real-time data analysis, we aim to equip farmers with comprehensive tools to manage both water usage and plant health effectively. Our commitment to innovation will drive continuous improvement in precision agriculture, contributing to global efforts in food security, resource conservation, and environmental stewardship.

In conclusion, the intersection of AI and irrigation management holds immense potential for transforming agriculture. By optimizing water usage and enhancing crop productivity, we can pave the way for a more sustainable and prosperous future. Our journey is ongoing, and with continued research, development, and collaboration, we are confident in our ability to make a significant impact in the agricultural sector.

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