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Edge-Based Intelligent Irrigation System Using Iot and AI

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Dedication

I dedicate the fruits of my humble efforts to those who gave me life and hope, and raised me with a passion for learning and knowledge, and to those who taught me to climb the ladder of life with wisdom, patience, kindness, and loyalty: my dear father and mother.
To those whom God has blessed me with in my life, to the strong bond of support in my research journey, my brothers and sisters.
To those who supported me as we paved the way together toward success in our academic journey, to my companion, ***Hanane***.
Finally, to everyone who helped me and played a role, directly or indirectly, in completing this study. I ask God to reward everyone with the best reward in this world and the hereafter. Then, to every student of knowledge who has strived with their knowledge to benefit Islam and Muslims with all the knowledge and wisdom God has given them.

Thanks

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Abstract

This thesis presents an intelligent soil moisture monitoring and irrigation management system that integrates the Internet of Things (IoT), Artificial Intelligence (AI), and Edge Computing. The proposed architecture uses a dual-layer AI approach: the first model predicts future soil moisture levels based on historical environmental and sensor data, while the second model makes irrigation decisions by triggering the water pump when predictions fall below a critical threshold. The required water volume is calculated using a tailored formula to meet crop-specific needs.

Both AI models are deployed locally on an Edge device (field-based PC), enabling real-time decision-making without reliance on cloud connectivity. This ensures low latency, improves system resilience, and supports autonomous irrigation control. Experimental results demonstrate accurate moisture forecasting and optimized water usage, making the system highly relevant for sustainable precision agriculture, especially in water-scarce regions.

Keywords: Wireless Sensor Networks, Internet of Things, Artificial Intelligence

ملخص

تقدم هذه الأطروحة نظاماً ذكياً لمراقبة رطوبة التربة وإدارة الري يدمج إنترنت الأشياء والذكاء الاصطناعي والحوسبة الطرفية. تستخدم البنية المقترحة نهج الذكاء الاصطناعي ذو الطبقتين: النموذج الأول يتنبأ بمستويات رطوبة التربة المستقبلية بناءً على البيانات البيئية والتاريخية وأجهزة الاستشعار، بينما يتخذ النموذج الثاني قرارات الري عن طريق تشغيل مضخة المياه عندما تنخفض التنبؤات عن عتبة حرجة. يتم حساب حجم المياه المطلوب باستخدام صيغة مخصصة لتلبية احتياجات المحاصيل المحددة.

يتم نشر كلا النموذجين الذكاء الاصطناعي محلياً على جهازطرفي (جهاز كمبيوتر ميداني)، مما يتيح اتخاذ القرارات في الوقت الفعلي دون الاعتماد على الاتصال السحابي. هذا يضمن انخفاض زمن الاستجابة، ويحسن مرونة النظام، ويدعم التحكم المستقل في الري. تُظهر النتائج التجريبية توقعات دقيقة للرطوبة واستخداماً مثالياً للمياه، مما يجعل النظام ذا صلة كبيرة بالزراعة الدقيقة المستدامة، خاصة في المناطق التي تعاني من نقص المياه.

الكلمات المفتاحية: شبكات الاستشعار اللاسلكية، إنترنت الأشياء، الذكاء الاصطناعي

Résumé

Cette thèse présente un système intelligent de surveillance de l'humidité du sol et de gestion de l'irrigation qui intègre l'Internet des objets , l'intelligence artificielle (IA) et l'informatique en périphérie. L'architecture proposée utilise une approche d'IA à deux niveaux : le premier modèle prédit les niveaux futurs d'humidité du sol en se basant sur des données environnementales et de capteurs , tandis que le second modèle prend des décisions d'irrigation en déclenchant la pompe à eau lorsque les prévisions tombent en dessous d'un seuil critique. Le volume d'eau requis est calculé à l'aide d'une formule sur mesure pour répondre aux besoins spécifiques des cultures.

Les deux modèles d'IA sont déployés localement sur un appareil Edge (PC de terrain), permettant une prise de décision en temps réel sans dépendance à la connectivité cloud. Cela garantit une faible latence, améliore la résilience du système et prend en charge le contrôle autonome de l'irrigation. Les résultats expérimentaux démontrent une prévision précise de l'humidité et une utilisation optimisée de l'eau, rendant le système hautement pertinent pour l'agriculture de précision durable, en particulier dans les régions où l'eau est rare.

Mots Clée :Réseaux de capteurs sans fil, Internet des objets, Intelligence artificielle

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General Introduction

Agriculture and pastoralism are the primary sources of livelihood for most of the population, and they depend largely on natural resources [1]. Approximately 70% of the world's drylands are located in underdeveloped nations, where people suffer the harsh realities of poverty, food insecurity, hunger, poor economic conditions, and marginalization [2]. Water availability and agricultural production are two of the most significant challenges related with drylands [3]. To fulfill future food demand with higher yields and reduced water consumption, existing water must be carefully managed . Efficient irrigation management in drylands is difficult because there are so many variables to consider, including crop type, climate, soil type, and irrigation techniques [4].

Efficient water-saving irrigation solutions, particularly the use of smart irrigation systems, have the ability to address this significant obstacle in dryland production by providing water to the field in the appropriate amount, time, and location . As a result, smart irrigation methods are a practical option for improving the use of available water resources and water productivity in drylands because they allow for better irrigation decisions to be made by taking into account a variety of factors such as soil and climate variability, plant responses to water shortages, and changes in weather factors, all of which contribute to water conservation and yield increase [5].

Things have gotten considerably simpler with irrigation system automation and the development of artificial intelligence (AI) and Internet of Things (IoT) technology [6]. Due to technological advancements, the Internet and mobile devices have grown in importance. Smart irrigation systems have so seen considerable technology advances in agricultural water management. These systems offer accurate water application by combining IoT-based sensors, embedded systems, and cloud computing, hence boosting efficiency and sustainability [7]. The Internet of Things is a vital innovation that is altering agriculture because it allows devices to interact with and exchange data smoothly without requiring direct connectivity. New enhancements have been made to improve water conservation and agricultural yields utilizing technologies such as Arduino microcontrollers and GSM technology [8]. The combination of AI with wireless communication improvements enables intelligent decision-making help for irrigation systems, enabling remote monitoring and control [9].

In this context, this thesis proposes an innovative edge-based IoT system designed to op-

timize agricultural irrigation management. The main contribution lies in the integration of a two-level artificial intelligence architecture. The first level is based on an embedded K-Nearest Neighbors (KNN) model, responsible for real-time control of the actuator (the pump), using data from soil moisture sensors. The second level implements a predictive model deployed on the server side, which forecasts soil moisture levels and generates alerts in case of a likely deviation from normal thresholds in the coming hours. This hybrid approach combines local responsiveness with centralized analytical power, thereby enhancing the system's accuracy, autonomy, and reliability in the context of smart agriculture.
The main contributions are the following

- Design and implementation of a two-level AI architecture within an IoT-based smart irrigation system operating at the edge.
- Development model for real-time control of the irrigation pump based on soil moisture readings, enabling autonomous actuation .
- Integration of a second predictive model to forecast future soil moisture levels and issue alerts when abnormal values are expected, supporting proactive decision-making.

The related work are presented in Section 2 of the rest of this thesis, which highlights important researchers who have used technology to improve agriculture. The Methodology is described in Section 3, and Integrated System Implementation and Performance Overview are covered in Section 4.

Chapter 1

Basic concepts of smart agriculture and irrigation management

1.1 Introduction

With the increasing challenges associated with water scarcity, climate change, and population growth, it has become imperative to develop more efficient and sustainable agricultural systems. Among the most important pillars of these systems are smart agriculture and smart irrigation management, where the integration of modern technology contributes to improving the use of resources, especially water, and achieving higher productivity at lower costs.

1.2 Smart Farming

Smart agriculture, also known as smart farming or digital agriculture,is the incorporation of advanced technologies such as artificial intelligence (AI),the Internet of Things (IoT),sensors, data analytics,and automation into agricultural practices to optimize production processes, improve resource efficiency, and increase the quality and quantity of agricultural products.It entails integrating production variables via a sensing and acting network, as well as collecting and analysing real-time data to guide farming decision-making and management [10].

The main objectives of smart agriculture are [10]:

- To improve production efficiency and profitability .
- To improve product quality and quantity.
- To reduce costs and resource inputs (e.g. water, fertilizers, pesticides).

- To minimize environmental impact.
- To ensure food security and sustainability, particularly in light of population growth and climate change.

1.3 Technologies used in smart farming

1.3.1 Internet of Things

The internet of things (IoT)is a novel application domain that integrates different technologies software and hardware, including wireless telecommunications technology, sensors, RFID tags, actuators, and mobile phones, etc. Kevin Ashton coined the term 'Internet of Things' in 1999. The unique feature of IOT stems from its name. It consists of linked physical things, often known as "Things". Physical items include animals, humans, automobiles, habitats, and appliances. Furthermore, the term "Internet" alludes to "Things" connect to the internet. In addition, each "Thing" has an identification that allows it to be identified [11].
The Internet of Things connects many devices via the internet to gather and analyze real-time data. Sensors in smart agriculture are used to measure moisture, temperature, and light in the soil and air, allowing farmers to monitor soil, crops, water levels, climate, and livestock in real-time. These gadgets give precise, continuous data, allowing you to make quick decisions to enhance crop development [12].

1.3.1.1 General architecture of the Internet of Things

The most prominent model known for IoT is the 3 layer architecture as shown in Fig.1.1, consisting of the Perception Layer, the Network Layer and the Application Layer [13].

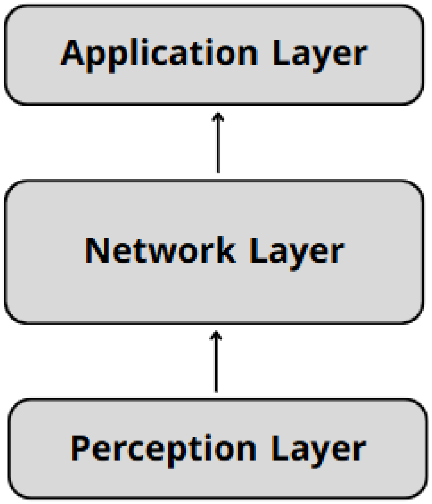

Figure 1.1: Basic IoT Architecture

- **Perception Layer:**
  The Perception Layer, also known as the Device Layer, comprises of objects and sensors. It functions like a biological organism's skin, utilizing five senses to recognize things and collect data and information. , GPS, sensor networks, and terminals are some of the technologies included.

- **Network Layer:**
  (Transmission Layer) transmits and processes data from the Perception Layer. It mimics the neural network and brain of the human body. This layer supports several technologies such as 3G, WiFi, Bluetooth, Infrared, and Zigbee. It aids in managing networks, information services, and network centers.

- **Application Layer:**
  The Application Layer focuses on the industrial requirement and social division of IoT. The primary goal is to enhance the intellectualization of industry. It covers many virtual markets.

1.3.2 Artificial Intelligence

AI is a machine's ability to learn and implement tasks similar to those of a human brain, and it is powered by computers . When applied to a certain problem domain,AI algorithms can mimic human decision-making. Irrigation systems have been integrated with AI for adaptive decision-making [14] .

Artificial intelligence is being utilized to continually analyze data obtained from agricultural areas.This data may be analyzed to calculate crops' water and nutrient requirements, allowing for more informed irrigation and fertilization decisions.For example, AI may be used to forecast weather and environmental changes, allowing farmers to take preemptive steps to safeguard crops [12].

1.3.3 Drones and robots

Drones are used to monitor agricultural land from above. They may capture comprehensive images using multispectral cameras, providing reliable data on crop health and assisting farmers in identifying areas that require special care (such as irrigation or insect treatment) [12].

1.3.4 Big Data

In smart agriculture, enormous volumes of data are collected from numerous sources, such as sensors and drones, and then evaluated using big data technology. This comprehensive analysis enables precise projections of outcomes, such as crop yields for the following season, as well as the best way to manage agricultural difficulties [12].

1.3.5 Communication Networks

To facilitate data transfer and communication between devices using techniques such as: Wifi,LoRA,GSM and ZigBee [12].

1.4 Importance of Irrigation Management

Irrigation management is managing the amount and time of water provided to plants depending on their actual requirements, therefore conserving resources and increasing output.Effective irrigation management is critical for resolving water shortages, boosting water productivity, and guaranteeing food security, particularly in areas with climate change and restricted water resources. Proper management optimizes water consumption, reduces waste, and supports sustainable agricultural practices, which are vital for both economic and environmental sustainability in agriculture [15].

1.4.1 Problems of Traditional Irrigation Systems

1.4.1.1 Inefficiency and Water Waste

Traditional surface irrigation technology can cause significant water loss due to several variables, including [15]:

- Water evaporates before reaching plant roots, particularly in hot and dry climates.
- Runoff occurs when water exceeds the soil's absorption capacity and seeps out from the root zone.
- Improper timing, resulting in over- or under-irrigation, has a detrimental influence on plant health and output.

1.4.1.2 Low Water Productivity

These systems lack the accuracy required to match water delivery to crop demands, resulting in low water usage efficiency and lower agricultural yields [15].

1.4.1.3 Maintenance and Institutional Issues

Traditional systems suffer a number of organizational and structural issues that impact their sustainability and efficiency [16]:

- Poor periodic maintenance owing to limited finances or a lack of technical experience, resulting in blocked channels or faulty pumps.
- The lack of appropriate cost recovery measures, such as equitable water consumption prices, makes systems unsustainable.
- Weak community engagement in resource management widens the gap between users and accountable authorities.

1.4.1.4 Environmental Impact

Outdated techniques can lead to groundwater depletion and increased soil salinity, as observed in Egypt's Nile Delta [16].

1.4.1.5 Social Challenges

The change from traditional to modern irrigation has an influence not only on technical issues, but also on social factors [16].

- Disputes over water rights arise when seeking to disperse resources more evenly, particularly in places that adhere to traditional water-sharing traditions.
- Farmers who are accustomed to a specific method of working and lack the skills or means to adopt contemporary technology are resistant to change.
- A shift in the administrative structure, as smart systems necessitate new management that includes technology, demanding training and rearrangement.

1.5 Importance of monitoring and predicting soil moisture levels

Monitoring and predicting soil moisture levels is critical for plant health and agricultural productivity since it directly impacts water availability for plant uptake, altering growth, yield, and stress tolerance. Accurate soil moisture data allows for more efficient irrigation management, preventing both under- and over-watering, which can lead to lower plant development, nutrient leaching, and water waste. Predictive models and real-time monitoring, which frequently include IoT and machine learning, enable timely irrigation choices, preserve water, and assist sustainable agriculture, particularly when climate change and population expansion put strain on water supplies. Soil moisture is also an important indication for drought monitoring and yield prediction, typically exceeding other environmental factors in predicting crop performance and drought effects .
Overall, monitoring and forecasting soil moisture is critical for maintaining plant health, increasing yields, saving water, and adapting to environmental unpredictability [17].

1.5.1 Advantages of soil moisture monitoring

- **Intelligent and accurate watering control:** When the soil moisture level is correctly determined, plants may be watered only as needed. This eliminates "random watering" and lowers water use, particularly during dry months.

- **Enhancing Plant Health and Productivity:** When the soil is sufficiently wet, plant roots may readily absorb water. This allows the plant to grow freely without stress, increasing the likelihood of producing high-quality fruits or leaves.

- **Increasing fertilizer efficiency :** Moisture helps to breakdown the fertilizer, making it more absorbable. Dry soil renders fertilizer useless, but excess moisture dissolves the fertilizer and washes it away with leachate.

- **Managing fungal and bacterial infections:** Some diseases, such as root rot and fungus, flourish in extremely humid conditions. Monitoring can help to avoid overwatering, lowering the risk of illness.

- **Enhancing agricultural models and projections:** When humidity data is collected continually, AI algorithms may be utilized to anticipate the ideal watering periods. This information enables farmers to precisely plan their planting seasons.

1.6 AI models used with the Internet of Things in agriculture

Artificial intelligence (AI) models are critical components of smart agriculture systems driven by the Internet of Things (IoT). They are used to analyse huge volumes of agricultural data acquired in real time from fields using sensors like humidity, temperature, and soil quality gauges, as well as drones. These models convert raw data into precise indications that assist to increase manufacturing efficiency, decrease waste, and promote environmental sustainability. These models differ in structure and computational approaches, as well as in how they analyze data—whether for prediction, categorization, aggregation, or decision-making. They also differ in computing complexity and the ability to learn from fresh data or adapt to changing agricultural circumstances. This diverse set of models enables the development of integrated smart systems capable of addressing a wide range of modern agricultural concerns, including crop growth monitoring, resource management, and overall agricultural value chain optimization,These models used with the Internet of Things in agriculture are classified according to several factors, including the type of task they perform.

1.6.1 Classification and Pattern Recognition Models

- **Convolutional Neural Networks (CNNs):** Used in image analysis (such as detecting diseases in plant leaves or classifying plant species).
- **Support Vector Machines (SVMs):**To classify agricultural conditions (such as determining soil quality or pest infestation).
- **Decision Trees and Random Forests:**To make decisions about the optimal time for irrigation or fertilization, based on sensor data.
- **KNN (K-Nearest Neighbors):**It is used to determine the class to which a new sample belongs based on its nearest neighbors in the database.

1.6.2 Regression Models

- **Linear and nonlinear regression :**to predict crop yields or temperature and humidity changes.
- **LSTM (Long Short-Term Memory) Networks:**To analyze weather data or plant growth over time, due to their ability to handle sequential data.

1.6.3 Optimization and Decision-Making Models

- **Reinforcement Learning:**To develop smart irrigation or fertilization systems that learn from their experiences and improve performance over time.
- **Genetic Algorithms:**To select the best agricultural strategy based on a set of environmental and production conditions.

1.6.4 Clustering Models

- **K-means and DBSCAN:**To group soil or plants based on common characteristics and identify field areas that require special intervention.

Other classifications are shown in Tables 1.1,1.2and 1.3.

Table 1.1: Classification according to the type of input data

Data Type	Suitable Models	Examples
Images	Convolutional Neural Networks (CNN)	Disease diagnosis, crop growth analysis
Time-series data	Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM)	Weather forecasting, soil moisture estimation, water consumption prediction
Sensor Data	Regression,Random Forests, Support Vector Machines (SVM)	real-time monitoring
Multimodal Data	Hybrid Models	Integrating drone imagery with IoT sensor data

Table 1.2: Classification by intelligence level (complexity level)

Level	Suitable Models	Usage
Basic AI	Regression, Decision Trees	Output prediction, simple classification.
Intermediate AI	SVM, Random Forest, KNN	Deeper analysis and multiple conclusions.
Advanced AI	CNN, RNN, Reinforcement Learning	Self-learning systems, visual disease detection, autonomous resource control.

Table 1.3: Classification by learning type (Learning Paradigm)

Type of learning	**Suitable Models**	**Usage**
Supervised Learning	SVM, Decision Trees, KNN, Regression	Production forecasting, disease classification, irrigation recommendation
Unsupervised Learning	K-means, DBSCAN, PCA	Group fields, uncover hidden patterns, identify anomalies
Reinforcement Learning	Q-Learning, DQN	Smart irrigation systems, agricultural drones.
Deep Learning	CNN, RNN, LSTM, DNN	Image analysis, temporal prediction, multi-source processing.

1.7 Definition of Edge Computing

Edge computing is a decentralized computing paradigm that analyzes data close to the source of data creation (such as sensors or IoT devices), usually at or near the network's edge, rather than depending on centralized cloud servers. This strategy takes advantage of current devices' increased computational capability to do sophisticated computations on-site, enabling a new set of services and applications, particularly for the Internet of Things. Edge computing enables the processing of latency-sensitive applications.It minimizes the quantity of data sent to the cloud, making it appropriate for real-time applications like smart irrigation systems [18].

1.7.1 Definition of Edge IoT

Edge IoT refers to the integration of edge computing with IoT systems, in which data generated by IoT devices and sensors is processed locally at the network's edge. This combination overcomes the limits of traditional cloud-based IoT, such as high latency, bandwidth constraints, and restricted device resources, by providing real-time analytics, increased scalability, and more effective resource management. Edge IoT is essential for applications in smart cities, healthcare, agriculture, transportation, and other fields where quick data processing and reaction are required [18].

1.7.2 Features of Edge IoT

- **Low Latency:** Edge computing decreases the time necessary for data transmission and reaction dramatically, making it perfect for real-time and delay-sensitive applications [19].

- **Scalability:**Edge computing systems are made up of many distributed edge devices (Edge Nodes), each of which handles a piece of data locally. This enables more devices to be added without placing strain on a single hub (such as the cloud) [20].
- **Energy Efficiency:** Shifting computing from resource-constrained devices to more competent edge nodes can increase device lifespan [21].
- **Context-Aware Services:**Edge computing allows devices to make decisions depending on local context, such as temperature, time, location, soil type, plant kind, and so on. This contextual information is readily available on the device, allowing for intelligent and rapid judgments [22] .
- **Enhanced Privacy and Security:** Keeping sensitive data near to its source can increase privacy while also reducing the risk of data breaches [22].
- **Support for Mobility:** Edge computing provides localized services to mobile and dynamic contexts like as automobiles, wearable devices, and drones. Because processing takes place locally, there is no need for a continuous, persistent connection to the cloud [22].

1.7.3 Edge IoT Architecture

The Edge IoT architecture in smart agriculture is based on the notion of decreasing the burden on cloud data centers by moving processing and decision-making processes to edge gateways near data sources.This methodology enables faster reaction times, lower energy use, and better use of agricultural resources like water. This design is commonly utilized in smart irrigation systems, which integrate sensors, communication devices, and irrigation control units into a single system.
Zhang et al (2025) [20].presented the architecture of the edge IOT as follows:

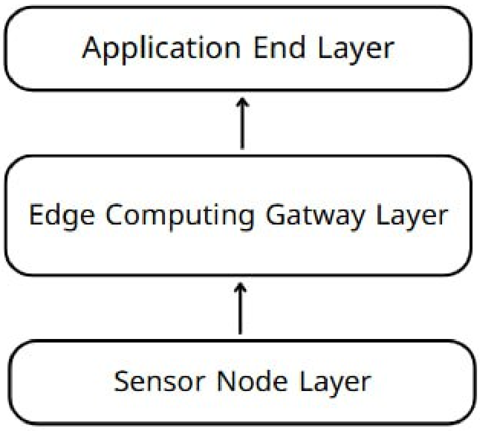

Figure 1.2: Edge IoT Architecture 1

- **Sensor Nodes Layer:** This layer contains a collection of sensors installed in agricultural areas, including soil moisture, temperature, and air humidity sensors. The node part primarily stores and communicates regularly acquired sensor information to the gateway.
- **Edge Computing Gateway Layer:** It is made up of terminal gateways outfitted with processing units that process data received from sensors locally. Data analysis techniques are utilized to calculate irrigation requirements based on environmental data, decreasing dependency on cloud computing and response time.
- **Application End Layer:** The program gives users an interface to see field data and allows them to save and manipulate it remotely.

Munir et al(2021) [23].presented the architecture of the edge IOT as follows:

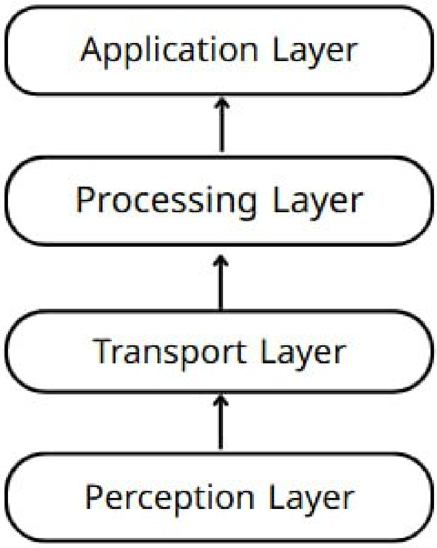

Figure 1.3: Edge IoT Architecture 2

- **Perception Layer:** The perception layer, also known as the physical layer, includes sensors for data collecting. This layer monitors temperature, soil moisture, and ambient humidity.
- **Transport Layer:** The transport layer is responsible for transmitting previously acquired sensor data to the processing layer across networks such as wireless networks, 2G and 3G networks, and local area networks.
- **Processing Layer:**The processing layer stores, analyzes, and processes vast volumes of data received from the transport layer. It employs technologies including databases, cloud computing, and edge computing.
- **Application Layer:** This layer provides an interface to the end user, allowing farmers to monitor field conditions, obtain irrigation advice, and remotely manage water valves depending on decisions made in earlier levels.

1.8 Advantages of using iot

The advancement of contemporary agricultural technologies, especially in the area of intelligent irrigation systems, has made the Internet of Things (IoT) a crucial component. These systems are based on a network of interconnected sensors that gather environmental data in real time, which is essential for accurate irrigation control. Measurements including temperature, humidity, light intensity, rainfall totals, and soil moisture levels are all included in this data. Additional data from weather stations includes temperature variations, wind speed, and precipitation rates [].

- One of the most notable benefits of the Internet of Things (IoT), a cutting-edge technology with many applications in the irrigation industry, is the ability to reduce water consumption. Conventional irrigation techniques frequently resulted in large water waste because they mostly depended on human interaction. The use of IoT-based smart irrigation systems, on the other hand, lessens the need for human involvement and enables more accurate and effective water management that is based only on the requirements of the soil and plants.

- Another benefit of integrating the Internet of Things into irrigation systems is its great cost effectiveness. In addition to helping to preserve this essential resource, wise and accurate water use also drastically lowers operating expenses. Reducing the amount of water that plants use for irrigation reduces waste of resources like power or fuel for pump operation, which in turn results in lower energy consumption and increased agricultural system performance efficiency.

- Real-time monitoring and control are critical components of implementing the Internet of Things in irrigation systems. IoT-enabled sensors gather data on temperature, weather, and soil moisture, allowing farmers to make informed decisions and instantly change irrigation schedules. This optimizes resource utilization and boosts agricultural output. This ability to respond instantly to environmental changes addresses immediate needs; however, long-term efficiency also requires systems that can grow and adapt over time.

- Beyond real-time control, the long-term success of smart irrigation systems depends on their ability to expand and adapt to evolving agricultural demands The modular nature of the Internet of Things (IoT) is another important advantage of using technology in to irrigation systems. Adding new sensors or changing the data being gathered are just two examples of how the system may be readily expanded or changed at any time. This adaptability guarantees the system's long-term scalability by enabling it to adjust to the unique requirements of every agricultural setting.

1.9 Advantages of using IoT and AI

The fundamental infrastructure for data gathering and transmission is provided by the Internet of Things (IOT), but artificial intelligence (AI) enables a wide range of advanced capabilities for better outcomes that are challenging to do with the Internet of Things

(IOT) alone. The best use of resources, higher agricultural yields, lower energy use, and improved system performance are some of the most noteworthy enhancements. Additionally, there are a number of other benefits to integrating artificial intelligence (AI) with the Internet of Things (IOT), such as...

- A key advantage of this integration in smart irrigation systems is the ability to predict the water requirements of the soil. Real-time data on temperature, climate, and soil moisture is gathered using Internet of Things (IOT)-connected sensors. In order to precisely ascertain the proper timing and water requirements of the soil, artificial intelligence (AI) evaluates this data in conjunction with data from earlier times. Artificial intelligence (AI) and the Internet of Thingss (IoT) work together to prevent over- or under-irrigation, which improves water use and lowers waste.

- Moreover, the capacity to make decisions in real time based on shifting environmental circumstances is one of the most notable benefits of the AI-IoT combination in smart irrigation systems. For instance, the system immediately evaluates data and adjusts the pump's status to reflect the new circumstances if abrupt rainfall or unanticipated temperature changes are observed. This instant communication lessens the need for human involvement and avoids needless watering, which can waste water or harm the land.

- Furthermore, one of the essential features offered by the AI-IoT combination in contemporary irrigation systems is remote control. Without physically being on the farm, users can monitor the system and make decisions about irrigation using user interfaces based on cloud platforms or mobile applications. This function is especially crucial in locations that are hard to regularly reach or on huge farms. Remote interaction with the system also makes it possible to make quick changes, including modifying the irrigation schedule or duration or stopping the system in the event of a problem. This improves operational efficiency and lowers the expenses related to human management.

- Another advantageous aspect of combining artificial intelligence and the Internet of Things in smart irrigation systems is the system's capacity to learn and get better over time. This is accomplished by continuously analyzing both historical and current data, allowing AI algorithms to see trends in soil behavior, environmental shifts, and the results of earlier irrigation campaigns. This enables the system to adjust to the unique properties of the soil and seasonal variations while progressively enhancing watering techniques. Without the need for constant reprogramming or frequent human intervention, irrigation decisions become more precise and suitable, improving long-term efficiency and resource management.

Chapter 2

Related Works

Given the notable advancements in a variety of industries, including agricultural, many academics are very interested in the integration of wireless sensor network technologies with the Internet of Things and artificial intelligence. This section provides a summary of recent research, which is displayed in TABLE 2.1

2.1 Internet of things in irrigation

Baingwede et al(2022) [24]. created a technique to identify the quality of the soil and give details on the kind and amount of fertilizers that may be applied. This information is kept in the cloud, where it is always accessible and may be shown graphically through the Internet of Things. To gather data, the study employed the following instruments: An LCD screen, an Arduino UNO board, a transformer, a voltage regulator, a GSM voice modem, and an NPK sensor.

Sabrine Khriji et al [25] created an Internet of Things (IoT)-based smart irrigation system that seeks to increase water efficiency through real-time soil monitoring and automated irrigation control. The system measured ambient temperature and humidity using a wireless sensor network consisting of capacitive soil moisture sensors, DS18B20 temperature sensors, and DHT11 sensors. Sensor readings were transferred to the ThingSpeak cloud platform using the MQTT protocol, allowing for visual data display, remote monitoring, and information storage. Actuators, such as electric pumps and electromagnetic valves, regulated irrigation and responded automatically to sensor inputs. Users may access the system through a web or mobile application, allowing them to monitor irrigation status and act as needed. The system's actual implementation verified its efficacy in lowering water usage while preserving irrigation efficiency, highlighting its potential for use in sustainable smart agriculture.

Ravi Kant Jain [26] did a research called "Experimental Performance of an IoT-Enabled Smart Drip Irrigation System Controlled via Web Applications." The project aims to create a smart drip irrigation system using Internet of Things (IoT) technology and web/Android applications. The technology is designed to continually monitor and operate the irrigation system, eliminating the need for constant human monitoring and decreasing water wastage. The system was built around a few simple components: a microcontroller for data processing, soil moisture, temperature, and humidity sensors, a water pump to regulate the irrigation process, and a web application that allowed users to monitor and control the system remotely. The results revealed that the technology dramatically decreased water use by precisely providing the appropriate quantity without harming plant health, hence increasing water efficiency and decreasing the need for direct human intervention. The study also found that integrating IoT and web apps is a cost-effective and efficient way to monitor irrigation systems and improve water resource management in agriculture.

2.2 Internet of things and artificial intelligence in irrigation

Faeze Behzadipour et al [27].The goal of this project was to increase agricultural water use efficiency by creating a smart irrigation system utilizing artificial intelligence (AI) and the Internet of Things (IoT). In order to track plant health, the researchers employed sensors to assess temperature, light intensity, ambient humidity, and soil moisture. They also analyzed photos of plant leaves. To develop a model for forecasting irrigation requirements, data were examined using a statistical regression model in SPSS and genetic programming in MATLAB 2018. According to the study's findings, the smart irrigation system reduced water use by 11% when compared to traditional irrigation without compromising crop output or physical attributes.
To increase agricultural water use efficiency and decrease waste,Kumar Anusha et al [28]. created a smart irrigation system based on Internet of Things (IoT) technology and a regression algorithm. In addition to cloud-based weather data and past irrigation records, the system gathers real-time environmental data from sensors measuring soil moisture, temperature, rainfall, and water flow. Farmers can obtain precise recommendations through a mobile app once the regression algorithm evaluates this data to forecast real watering requirements. The system uses a Raspberry Pi module to process data, and cloud computing is used to store and analyze the data. According to the study's findings, this approach helps increase crop yields, decrease human involvement, and improve water use efficiency—all of which encourage the use of contemporary technology in sustainable agriculture.

In order to optimize water utilization in agriculture, Tace Youness et al [29].created a smart irrigation system that combines machine learning and Internet of Things (IoT) technology. While preserving crop health, the system's primary objective is to lower water usage and operating expenses. Information from sensors that measure temperature, rainfall, and soil moisture is one of the system's inputs. This data is gathered using the Node-RED platform and kept in a MongoDB database. Models for machine learning are then trained using these inputs. These consist of naive Bayes' theorem, logistic regression, neural networks, and support vector machines. The K-Nearest Neighbors (KNN) model performs the best, with an accuracy of 98.3% .The system's outputs, which guarantee effective water usage, include automated water pump control or irrigation suggestions. Furthermore, a web-based application was created to display the gathered information and forecasts, enabling users to efficiently monitor and control agricultural surroundings. Using IoT technology,Zhiming Hu et al [30]. created a machine learning-based method to forecast reference evapotranspiration (ET_0). The system's main objective is to improve irrigation water management by offering precise ET_0 estimates, which are crucial for figuring out crops' true water requirements. The system's inputs include real-time environmental data from agricultural fields, such as temperature, humidity, wind speed, and sun radiation, that is gathered via an Internet of Things-based infrastructure. To forecast ET_0 levels, these data are put into a variety of machine learning algorithms. The K-Nearest Neighbors (KNN) algorithm outperformed conventional estimating techniques such as the FAO Penman-Monteith approach and showed the greatest accuracy among the investigated models, with a prediction rate of 92%.The system's output, the anticipated ET_0 value, is a dependable input for scheduling irrigation, either manually or automatically. An Internet of Things platform supports this system by continually collecting and transmitting environmental data, allowing for timely and data-driven irrigation choices.

In order to improve water and energy efficiency in agriculture,Nicoleta Cristina Gaitan et al [31].created an automated irrigation system that incorporates artificial intelligence. The system's primary objective is to maximize irrigation by lowering water usage, fostering plant health, and encouraging environmentally friendly agricultural production. Sensors attached to an ESP32 microcontroller gather environmental data, such as temperature, humidity, and soil moisture, which are then used as inputs into the system. WebSocket wirelessly sends this data to a central database. In order to evaluate the gathered data and produce dynamic watering suggestions, the system makes use of AI models, particularly those from OpenAI.The resultados incluyen programas de irrigación optimizados y reportes climáticos, que facilitan la adaptación a condiciones climáticas extremas. The system is based on an IoT-based platform that incorporates artificial intelligence capabilities, providing a replicable framework for agricultural areas susceptible to climatic variations.

Table 2.1: Survey Summary

Cite	Goal	Input	Output	Model	Platform
[27]	Improve water use efficiency in agriculture	Soil moisture, temperature, humidity, light, leaf images	Optimal irrigation schedule recommendations	Genetic Programming,statistical regression model	MATLAB 2018
[28]	Predicting the amount of water required	Soil moisture, temperature, rainfall	Receive accurate recommendations via a mobile app.	Regression algorithm	/
[29]	Reduce water consumption and oper- ational costs	Soil moisture, temperature, and rainfall	Irrigation recommendations or automatic control of water pumps	KNN	Node-RED platform, MongoDB database
[30]	Predict reference evapotranspiration (ET)	Temperature, humidity, wind speed, and solar radiation	Predicted ET value	KNN	/
[31]	Optimize irrigation by reducing water consumption	TTemperature, humidity, and soil moisture	Optimized irrigation schedules and climate reports	From OpenAI	/

2.3 Edge ioT in Smart Irrigation

Kasera and Acharjee (2024) [32].presented an experimental research on the design and implementation of an edge computing-based smart irrigation system that use the LoRa low-power communication protocol. The study sought to increase water consumption efficiency in tomato growing by using a network of sensors that collect environmental data such as soil moisture. These sensors communicate between nodes using a hybrid method known as Linked Least Traversal (LLT),as well as a reinforcement learning-based smart watering strategy known as the Optimal Soil Wetness Closeness Policy (OSWCP).Field trial findings demonstrated that the suggested system achieved an irrigation schedule accuracy of 97.88%,minimizing water waste and increasing system efficiency when compared to standard approaches. This study emphasizes the relevance of combining AI and edge computing technologies for constructing smart agriculture systems and attaining agricultural sustainability.

Premkumar and Sigappi (2022) [33].presented an experimental research titled "IoT-enabled Edge Computing Model for Smart Irrigation System," which focused on the creation of a smart agricultural irrigation management model using edge computing and Internet of Things (IoT) technology. The study sought to create a system capable of forecasting soil moisture in real time while also adding rainfall projections to increase water usage efficiency. To obtain high prediction accuracy, the researchers employed machine learning methods such as XGBoost and K-Means. The system was built with a Raspberry Pi device as an edge computing unit that was connected to sensors and actuators, as well

as a cloud platform (Heroku) and a database (MongoDB) with a visual control interface. The results showed that the edge computing-based model beat the cloud model in terms of reaction time and resource efficiency, emphasizing the importance of edge computing in promoting smart agriculture and attaining water sustainability.
In the framework of building realistic and low-cost smart agricultural solutions, Et-taibi et al(2024) [34]. presented a pilot research titled "Cloud and Edge-based Smart Agriculture: A Real-World Deployment." The study focused on designing and implementing a smart agricultural system using Internet of Things (IoT), edge computing, and cloud technologies. The system included three layers: a local layer with wireless sensors to gather environmental data, an edge computing layer that uses fuzzy logic algorithms to make irrigation choices, and a cloud layer for data processing, storage, and visualization.The method was tested in a real-world agricultural setting based on soilless farming using drip irrigation. Field application findings proved the system's capacity to enhance water efficiency, minimize waste, and boost crop output. This study emphasizes the importance of distributed computing technologies in promoting smart agriculture and increasing resource efficiency among farmers with limited resources.
Munir et al (2021) [23]. presented a pilot research titled "Intelligent and Smart Irrigation System Using Edge Computing and IoT," which created and implemented a smart irrigation system that incorporates IoT and edge computing technologies to increase agricultural water usage efficiency. The system used a network of sensors to monitor environmental factors such soil moisture, temperature, and light intensity. This data was evaluated locally using the K-Nearest Neighbor (KNN) algorithm and an ontology system to make precise irrigation time and quantity recommendations. An edge computing server was added between the main controller and the IoT platform to minimize latency and reaction time. A smartphone app was also created to let farmers monitor field conditions and manage the device. The study's findings revealed that the suggested solution helped to reduce water use by up to 50% when compared to standard irrigation systems, demonstrating the effectiveness of edge computing in promoting agricultural sustainability.

2.4 Conclusion

A comparison of these research demonstrates that the majority of systems rely on accurate sensors to gather multiple environmental data, which is subsequently analyzed using machine learning algorithms of variable complexity and performance. Several studies have found that the KNN algorithm is among the most accurate models. Furthermore, combining low-cost IoT platforms like the ESP32 and Raspberry Pi with cloud computing has enabled more flexible and cost-effective solutions. Thus, these investigations indicate the enormous potential for combining AI and IoT technology to create smart irrigation systems capable of rationalizing water usage, attaining sustainable agricultural productivity, and eliminating human involvement.

Chapter 3

Methodology

3.1 Introduction

This chapter explains the methodology used to create a smart irrigation system based on IoT and AI technology.It reviews the practical steps followed, beginning with a system schema that depicts the overall structure and interactions between its components, as well as a full description of the purpose of each layer. It next describes how the data flows between the various components, and lastly shows the advantages of merging the real-time sensing capabilities of IoT technologies with the predictive analytical powers afforded by AI algorithms, resulting in a successful smart system.

3.2 Presentation of the system Architect

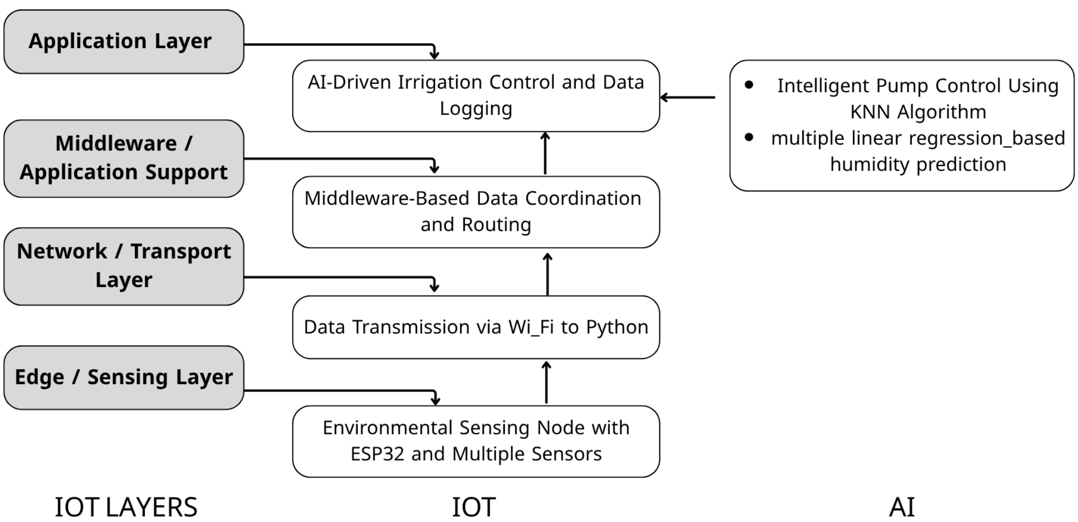

Figure 3.1: Schema of the general structure of the system

3.3 Presentation of the system layers

- **Sensing Layer:** The sensing layer in our system relies on a soil moisture sensor as the main source for collecting environmental data from the agricultural area. The sensor is connected to the ESP32 unit, which detects the moisture level as an analog electrical signal. Then, the ESP32 module converts this signal into a digital value using an analog-to-digital converter (ADC), preparing it for processing in the higher layers. This stage reflects the "perception" or "sensing" component of the system, as it gathers precise information about soil moisture levels, which is a critical input for making automated irrigation decisions later. The sensor and ESP32 form the physical foundation of the project's Internet of Things architecture

- **Network/Transport layer:**
  he network/transport layer in our system is responsible for transmitting moisture measurements to the computer from the soil sensor, which is attached to the ESP32 module. At the moment, a USB cable is used to establish this connectivity, enabling the ESP32 to send the sensor data to an environment that uses Python. In upper layers of the IoT architecture, this .layer guarantees dependable data flow from the physical layer to the processing element

- **Middleware/Application support:**
  The object abstraction layer of our smart irrigation system provides the application support layer (middleware) with raw data, including rainfall forecasts retrieved through the WeatherAPI interface and soil moisture readings gathered by sensors. Without changing the data's original structure, this layer is in charge of arranging, guiding, and getting it ready for eventual transmission to the smart model. Delivering data to the system components that require it, like the AI model or the display interface, is another duty of this layer. Thus, without carrying out any direct analysis or classification, this layer acts as a coordinated link between the data and the relevant services in the system

- **Application Layer:** Our smart irrigation system's application layer shows and controls the pump's status (on or off) according to the artificial intelligence model's judgment. Through the transmission of control commands to the pump operating unit, this layer is in charge of actually carrying out the intelligent choice. This layer ensures that intelligent analytic results are used in the actual agricultural environment by acting as the system's last interaction with the outside world. Furthermore, this layer is in charge of storing data permanently after the final decision is made. It does this by accurately recording data such as timestamps (in seconds), temperature readings, soil moisture levels, rainfall probability forecasts, and the final pump status (on or off) in a PostgreSQL database. This guarantees monitoring, traceability, and assistance for upcoming reporting or analysis.

3.4 Data flow and decision making process

The smart irrigation system works through a number of linked processes, beginning with the collecting of data from the field via specific sensors that assess temperature and soil moisture .The values are delivered to an ESP32 controller ,Where it is passed to a pre-trained artificial intelligence model on historical data, and using the KNN algorithm, it analyzes the current conditions and evaluates the need to turn the water pump on or off. After the model makes its first choice based on the humidity and temperature data, the system queries the Weather API for the chance of rain for the next hour . If the likelihood surpasses 65%, the final decision is changed to prohibit the pump from running, even if the data shows that irrigation is required. In contrast, if the model determines to turn off the pump and the likelihood of rain is less than 65%, the decision is reversed to turn on the pump. After the final choice is made, it is saved in a PostgreSQL database, where correct information is kept, such as the time in seconds, temperature readings, soil moisture, rainfall prediction%, and final pump status (on or off).This decision is sent to the controller, which executes the command directly on the pump.

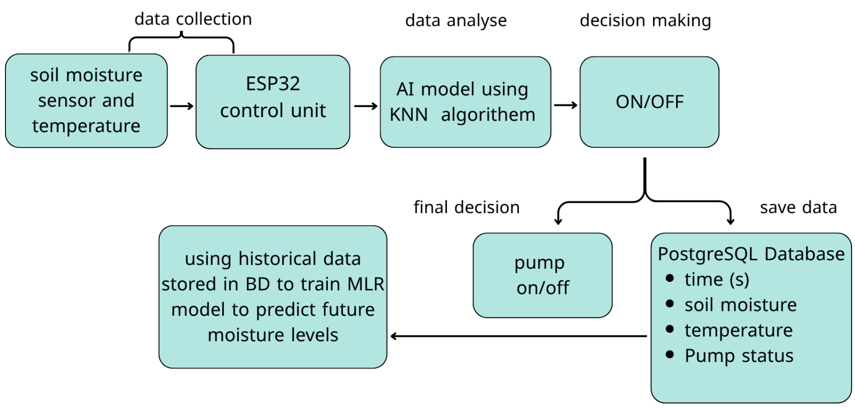

Figure 3.2: Data flow diagram

3.5 AI with the iot system

3.5.1 AI Pump Control via Actuator

The knn model is implemented to control the irrigation pump in real time, based on readings from soil moisture sensors. The K-Nearest Neighbors (KNN) model is used to classify the current soil condition and decide whether the pump should be turned ON or

OFF. The model compares the current input values with previously labeled data to find the closest matches and infer the most appropriate action.

The K-Nearest Neighbors (KNN) algorithm is used in the application layer of our smart irrigation system. Based on inputs including soil moisture content, temperature, and rainfall likelihood projections, this model first decides whether to turn the pump on or off. Unless the rainfall probability is equal to or greater than 65out exactly as it is; in that situation, even if the model chose to activate the pump, it would not operate. Even if the model decides to switch off the pump, it makes no changes if the rainfall chance is less than 65the main hub for integrating AI into the system since it is where this intelligent decision-making process is fully implemented. The KNN (K-Nearest Neighbors) is a classification technique that categorizes data points based on the values indicating their nearest neighbors in the dataset. KNN is founded on the premise that things with similar features are closer together.It is usually used for classification tasks, in which a new sample is provided and the model compares it to previous samples in the dataset before classifying it based on the most prevalent class among its nearest neighbors.

3.5.2 AI Model for moisture prediction

3.5.2.1 Data Acquisition and Preprocessing

Sampling Frequency: Sensor data are collected every 30 seconds to ensure high temporal resolution.
Variables Collected: Soil moisture(%) Soil temperature (°C), Irrigation system status (ON/OFF).

3.5.2.2 Preprocessing Steps

Sensor data collected from the field is first cleaned to ensure quality. This involves removing outliers and erroneous readings (e.g., abnormally high or negative values), which could skew the model. After cleaning, the relevant input features—such as temperature, soil moisture, and pump status—are normalized or scaled to enhance model performance and training stability.

3.5.2.3 Predictive Modeling

The objective is to forecast future soil moisture levels based on the precedent values. The modeling phase begins with a multivariate linear regression model as a baseline, due to its simplicity and interpretability. This model estimates future moisture based on temperature, current moisture, and irrigation status.

3.5.2.4 Training and Validation

Historical data split into training (80%) and testing (20%) sets.

3.5.2.5 Performance evaluated using metrics

The performance of the trained model was assessed using the Mean Squared Error (MSE) metric, which quantifies the average squared difference between predicted and actual future moisture values. A lower MSE indicates better prediction accuracy. This evaluation provides insights into how well the model generalizes to unseen data, ensuring reliable real-time predictions for irrigation planning.

3.6 Dashboard and User Interface

The dashboard was developed using modern web technologies such as Flask (Python) and Node.js to ensure responsive and scalable backend functionality. Real-time visualization of sensor data and future soil moisture predictions is implemented using Chart.js and D3.js, providing an interactive and intuitive user experience. The interface displays dynamic charts for temperature, current and predicted moisture levels, and irrigation status.

Chapter 4

Implementation, Results and Performance Overview

4.1 Introduction

The chapter looks into the system's hardware and software components, as well as its overall design and data collecting and organizing techniques. It also covers how to connect hardware and smart components to achieve operational efficiency and sustainability in a smart agricultural setting.

4.2 Hardware Components

4.2.1 Soil Moisture Sensor

A soil moisture sensor is an essential tool in gardening and agriculture for detecting soil water content. It monitors soil moisture levels to ensure plants have adequate water for growth and diversity. These sensors are crucial to irrigation systems because they provide real-time data, which is especially true for smart irrigation.Configurations that aim to maximise agricultural yields while conserving water [35].

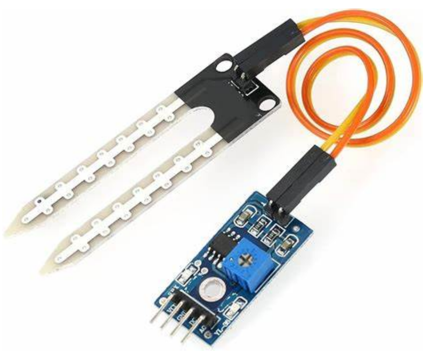

Figure 4.1: Soil Moisture Sensor

4.2.2 Temperature Sensor

A temperature sensor, such as the DHT11 or DHT22, is used to monitor the ambient temperature (and often humidity) in the agricultural environment. This data is sent to the microcontroller to help optimize irrigation schedules based on current weather and environmental conditions, ensuring efficient water use and healthy crop growth [36].

Figure 4.2: Temperature Sensor

4.2.3 ESP32

The ESP32 microcontroller is a low-cost, Wi-Fi-enabled microcontroller that is used as the main processing unit in many smart irrigation systems. It takes data from sensors (such as soil moisture and temperature sensors), analyzes it, and manages irrigation devices like pumps and valves. The ESP32 also allows for remote monitoring and control via ioT platforms and mobile applications, making it an important component for automation and data-driven decision-making in smart agriculture [36].

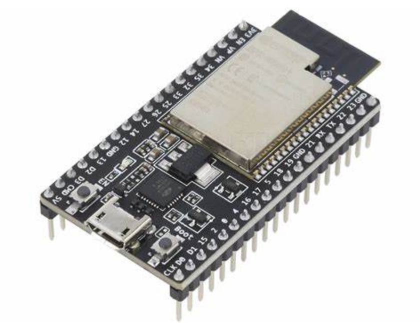

Figure 4.3: ESP32 microcontroller

4.2.4 Male Wires

They are connector lines with exposed metal pins ("male" ends) that link sensors, modules, and the microcontroller within the control hardware box. These cables enable the integration and communication of various components in the system, like as sensors and microcontrollers, for data collecting and control purposes [35].

Figure 4.4: Male Wires

4.2.5 Water pump

Is an electromechanical device used to move fluids from one location to another by increasing the fluid pressure and providing energy to move the pipes to the desired location [36].

Figure 4.5: Water pump

4.2.6 Breadboard

A breadboard is a reusable platform for prototyping electronic circuits, allowing easy connections between the ESP32, sensors, and other components without soldering.

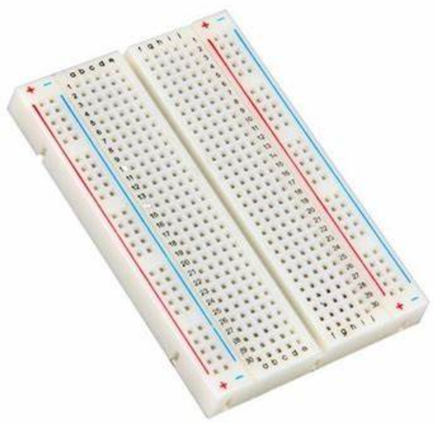

Figure 4.6: Breadboard

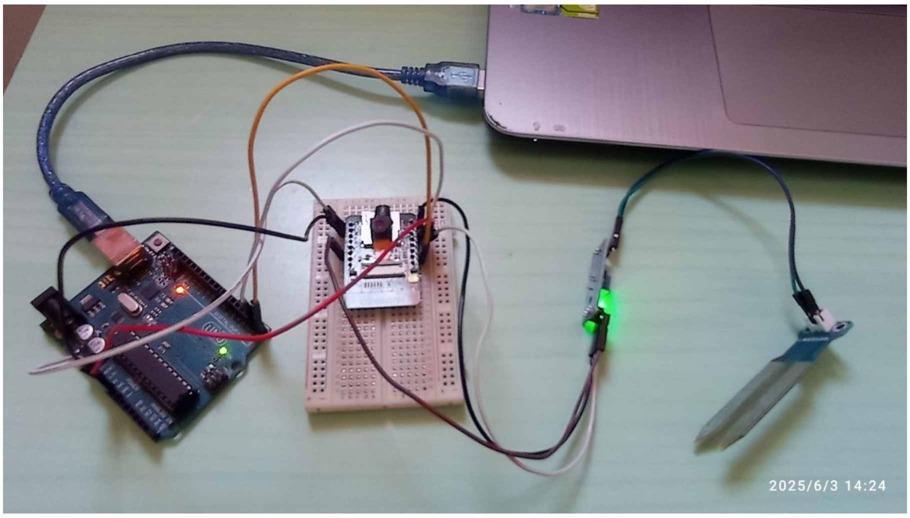

Figure 4.7: IoT System Architecture

4.3 Software Architecture

4.3.1 Arduino IDE Setup for Sensor Data Acquisition

The Arduino IDE, a development environment specifically designed for Arduino and ESP32 board programming, was downloaded and installed as the initial stage in the system development process. To read soil moisture data from the sensor, the ESP32 board was programmed using the Arduino C programming language. The Arduino Json library is used by the software to generate JSON objects that format the data that is transmitted to the computer through the wifi. The code reads the analog moisture value from the sensor and wraps it in a JSON object that includes the pump status and the current moisture value. The Python application receives this data, which is supplied via the wifi every two seconds, for analysis and intelligent irrigation system decision-making.

4.3.2 Python Environment

A crucial platform in the smart irrigation system for processing data gathered from sensors attached to the ESP32 board is the Python programming environment. The data is read using specialized libraries like PySerial and JSON after being received via the wifi communication interface, and it is subsequently converted into a format that can be analyzed.Utilizing both historical and current data, this processed data is subsequently employed in a variety of analytical and decision-making processes. Furthermore, Python incorporates third-party services, such as weather forecast APIs, which improve the system's capacity to decide precisely whether to turn on or off the water pump in response to shifting environmental conditions.

4.3.3 Data Storage Using PostgreSQL Data Base

A PostgreSQL database is used for data storage, and it is a reliable way to manage the records related to the smart irrigation system. All sensor measurement data, such as temperature and moisture readings, weather predictions, and the final pump status, are captured with exact timestamps. By offering dependable historical data that can be used to update and develop algorithms and operational decisions, this method contributes to the long-term efficacy of the system and enables structured and organized data storage, which facilitates future performance tracking and analysis.

4.4 AI-Driven Irrigation Decisions

4.4.1 Data Collection

A dataset including data on temperature, pump status, and moisture levels in a cotton field was obtained from the Kaggle platform (found at Kaggle platform). This dataset contained temperature information, pump status, and readings from a moisture sensor that recorded values between 0 and 1022. The numbers 1 and 0 stood for "on" and "off", respectively, to indicate the pump's condition. This data served as the basis for the creation of a smart irrigation system and was processed and analyzed in order to train a model that could effectively decide when to activate the pump in response to environmental factors.

4.4.2 Data Balancing

There was a significant imbalance when the data was loaded, with 150 occurrences of the pump being "on" and 50 instances of the pump being "off." The model may be biased toward a certain class (in this case, the more prevalent "on" class) as a result of this skewed distribution. To address this problem and ensure proper training of the model, the data was balanced with 50 instances of each class: "on" and "off." To achieve this, the number of "on" instances was reduced to match the "off" class. In order to properly train artificial intelligence models, this process is a component of the preparatory data preparation.

4.4.3 Data Processing and Saving

The KNN model was trained using the modified dataset, which had been balanced and saved as a new CSV file. The model can train without favoring one class over another because to the balance of data classes, which raises prediction accuracy.

4.5 Integrating Weather Forecasts into the Smart Irrigation System

Weather predictions are critical for improving the efficiency of smart irrigation systems by making educated decisions about whether to turn on or off the pump depending on forecasted weather conditions. In this system, a weather API is utilized to receive real-time weather data, including the likelihood of rain in the next hour. This data is obtained by precisely specifying the target geographic location.
When utilizing the KNN model to identify pump condition, the system takes moisture data obtained by the sensor and a predetermined constant temperature. The rain chance calculated from the weather API is then verified. If this likelihood reaches a particular level (for example, 65%), the model's decision is altered to avoid running the pump, even if moisture and temperature data show that irrigation is required. This combination of sensor data with weather forecasts improves the precision of irrigation choices and eliminates wasteful water consumption, contributing to increased water resource sustainability.

4.6 Results and Analysis

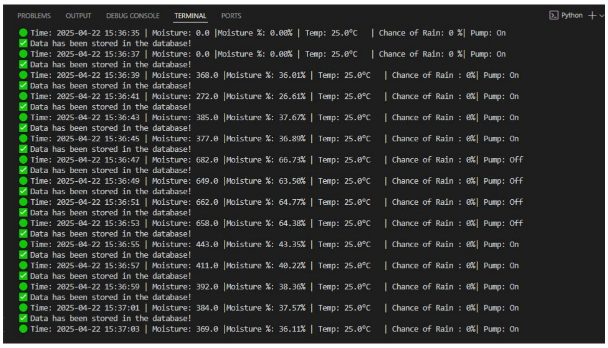

Figure 4.8: Final result.

The smart irrigation system's results display a set of essential information that reflects the real-time performance of the agricultural system.

- **Timestamp:** Indicates when the moisture and temperature values were recorded
- **Moisture Value:** represents the soil moisture level detected by the sensor.
- **Moisture Percentage:**This percentage shows how near the soil's moisture is to the maximum range, indicating the necessity for irrigation.
- **Temperature:** Measures ambient temperature and helps make irrigation decisions.
- **Chance of Rain**:Using the weather API, anticipate weather conditions and avoid wasteful watering.

4.7 Dashboard

Developed using web technologies Flask and Chart.js, ensuring interactivity.The dashboard is a critical component of the intelligent irrigation system, designed to monitor, visualize, and analyze data in real time. It enables farmers and agricultural managers to track essential environmental variables and make informed decisions based on AI-driven insights. By integrating real-time data from IoT sensors, historical analysis, and predictive modeling, the dashboard offers a comprehensive overview of soil and climate conditions, ultimately contributing to more efficient and sustainable irrigation practices.

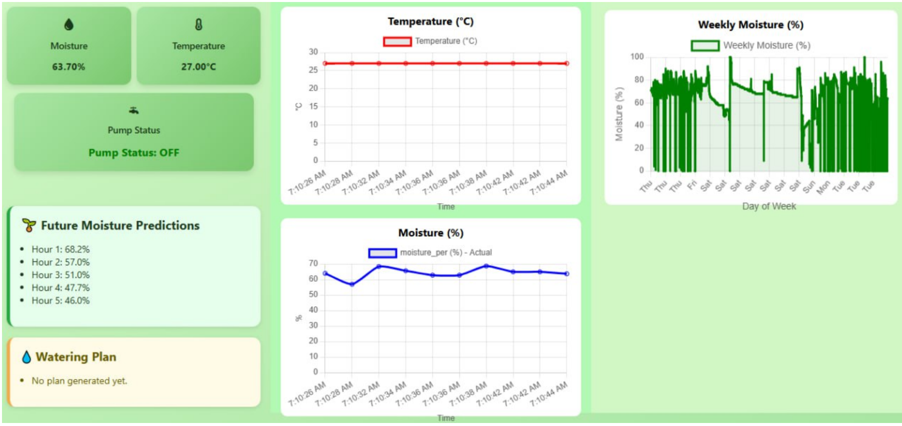

Figure 4.9: Dashboard

An example output of future predictions generated by the trained model is shown below: After 1 hour: 60.71%
After 2 hours: 57.99%
After 3 hours: 57.5%
After 4 hours: 57.41%
After 5 hours: 57.4%

These results demonstrate that the model can reasonably forecast short-term soil moisture levels.
Key functionalities of our dashboard :

- **Real-Time Monitoring:** Continuously displays the current values of soil moisture and temperature collected from sensors deployed in the field. This allows immediate assessment of the crop environment.
- **Historical Analysis:** Visualizes temperature variation over the last seven days through dynamic charts, helping users detect patterns, fluctuations, and potential climate stressors.
- **Predictive Insights:** Uses an AI-powered regression model to forecast future moisture levels for the upcoming hours, enabling proactive planning .
- Intelligent Alerts: Automatically issues warnings if predicted temperatures are expected to exceed a predefined critical threshold.

4.7.1 Model Evaluation

We evaluated the performance of the model using standard metrics. The accuracy obtained is as follows:

Table 4.1: Data training model results

Models	**Accuracy**
KNN	95%

4.8 Discussion

4.8.1 Strengths

- Real-time soil moisture forecasting.
- Efficient water usage through predictive irrigation planning.
- User-friendly interface with real-time charts and alerts.

4.8.2 Limitations

- Models does not yet incorporate all objectives of the smart farming.

General Conclusion

Smart agriculture is one of the most significant scientific and practical answers to the agricultural sector's expanding issues in the contemporary period, particularly in terms of natural resource scarcity, most notably water. This study focuses on one of the fundamental pillars of smart agriculture: the smart irrigation management system, which is a realistic and successful solution for increasing water usage efficiency and crop output.
This study contributes to a better practical and technical understanding of how to build an integrated smart irrigation management system, paving the way for the widespread adoption of innovative, low-cost solutions, particularly in developing countries or regions suffering from water scarcity.
We first presented the concept of smart agriculture and its objectives, highlighting the most important technologies used in it. Then, we discussed the problems of traditional irrigation and the importance of irrigation management to achieve environmental sustainability. This research aims to propose a smart irrigation system based on the Internet of Things, artificial intelligence, and edge computing, with the goal of precise irrigation scheduling to improve water management, reduce waste, and enhance productivity quality. This system is designed based on the integration of edge Internet of Things sensors that provide real-time data about the fields and process it locally, resulting in faster response times, increased energy efficiency,and reduced reliance on the internet, and artificial intelligence that allows for data analysis and informed irrigation decisions.
Following a thorough examination of the theoretical and technological elements of the irrigation management system in smart agriculture, as well as the stages of requirements analysis, system design, and implementation, the important conclusions are summarized as follows:

- The study found that conventional irrigation has several issues, the most obvious of which are large water waste, lower output, inadequate maintenance, and harmful environmental implications.

- Modern smart irrigation models have demonstrated that integrating sensors, control systems, the Internet of Things, and artificial intelligence enables continuous monitoring of soil and weather, resulting in more accurate and effective watering decisions.

- Even in resource-constrained agricultural areas, the construction of an intelligent irrigation system employing basic and low-cost technology like as ESP32 and humidity and temperature sensors is seen as a viable and feasible solution.

- The experimental case study demonstrated that the system works efficiently in automatic irrigation control based on soil moisture levels, helping to conserve water and improve soil and plant quality.

The move from traditional to smart agriculture is not a technical luxury, but rather a pressing need dictated by present environmental and economic realities. This study found that building a smart irrigation management system is a significant step toward more sustainable, productive, and resource-efficient agriculture. We anticipate that our study will serve as a foundation for future research and development in the area of agricultural digital transformation.

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