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Smart irrigation system for water distribution in arid areas using digital Twins

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By :
HARABI Yousra

Members of the jury :

TIGANE Samir	MCB	President
MERIZIG Abdelhak	MCB	Supervisor
ZERARKA NourElhouda	MAB	Member

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تعد ندرة المياه مشكلة كبيرة في المناطق القاحلة حيث يكون هطول الأمطار ضئيلا. وبالتالي، أصبحت الحاجة لتقليل خسائر المياه ووضع استراتيجية ري فعالة ملحة. لذلك، فإن تحديث أنظمة الري أمر ضروري، أثبت التوأم الرقمي في هذا العصر كفاءته كأداة فعالة لتمثيل سلوك الأنظمة وحالاتها في فضاء افتراضي. بفضل إنترنت الأشياء يمكن للتوأم الرقمي تمكين الفلاحين ومهندسي الري من إدارة عمليات الري عن بُعد استنادًا إلى معلومات رقمية في الوقت الحقيقي بدلاً من الاعتماد على المراقبة المباشرة والمهام اليدوية. يتم نقل البيانات المجمعة إلى النظام، الذي يقوم بمعالجتها لتحديد الاحتياجات الدقيقة لري المحاصيل. في هذا العمل، نستخدم إنترنت الأشياء بالاشتراك مع التوأم الرقمي والتعلم العميق لبناء نظام قوي وموثوق يستخدم التحليل البياني للتنبؤ بأوقات الري استنادًا إلى المتغيرات المناخية.

الكلمات المفتاحية : نظام الري ، التوأم الرقمي ، الزراعة ، خطط الرية ،التعلم العميق، إنترنت الأشياء ، المناطق الجافة ، تحليل البيانات.

Abstract

Water scarcity is a major problem in arid areas where there is minimal rainfall. Hence, the urgent need to reduce losses of water and establish an effective irrigation strategy and management. Therefore, irrigation systems upgrading is essential, in this day and age Digital Twin (DT) proved to be an efficient tool for mirroring systems behaviour and states in a virtual space. Empowered by the Internet of Things (IoT), DT is capable of helping agronomists, and irrigation engineers in managing operations remotely based on real-time digital information instead of having to rely on direct observation and manual tasks on-set for irrigation activities. The collected data is transmitted to the system, which processes it to determine the precise irrigation needs of the crops and calculate the crop irrigation requirements. In this work, we make use of IoT combined with DT and deep learning (DL) to build a system that is both robust and reliable for applying data analytic and predicting irrigation schedule based on climatic variables.

Keywords : *Irrigation systems, Digital twins, Agriculture, Irrigation plans , deep learning , Internet of things , Arid areas ,data analytic.*

Résumé

La pénurie d'eau est un problème majeur dans les régions arides où les précipitations sont minimes. Par conséquent, il est urgent de réduire les pertes d'eau et d'établir une stratégie et une gestion d'irrigation efficaces. Ainsi, la modernisation des systèmes d'irrigation est essentielle. De nos jours, le jumeau numérique (DT) s'est révélé être un outil efficace pour reproduire le comportement et l'état des systèmes dans un espace virtuel. Grâce à l'Internet des objets (IoT), le DT peut aider les agronomes et les ingénieurs en irrigation à gérer les opérations à distance en se basant sur des informations numériques en temps réel, plutôt que de devoir compter sur l'observation directe et les tâches manuelles sur place pour les activités d'irrigation.Les données collectées sont transmises au système, qui les traite pour déterminer les besoins précis en irrigation des cultures et calculer les exigences d'irrigation des cultures. Dans ce travail, nous utilisons (IoT) combiné au (DT) et à l'apprentissage approfondi (DL) pour construire un système à la fois robuste et fiable, capable d'analyser les données et de prédire les plans d'irrigation en fonction des variables climatiques. .

Mots clés : *Système d'irrigation, Jumeau numérique, Agriculture, Plans d'irrigation , L'apprentissage approfond, Internet des objets, Zones arides, Analyse de donnéesi.*

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Chapter 1

General Introduction

1.1 General context

For centuries, traditional agriculture has served as a foundation for global development. However, with expanding population , freshwater resources are becoming scarce restricting the amount of water available for both human consumption and agriculture. The availability of water is further impacted by climate change, which alters precipitation patterns . This has significant implications for irrigation, as crops require specific amounts of water at specific times to grow properly. In Algeria groundwater is a crucial source of irrigation. However, over-extraction of groundwater can result in a decline in water levels, increased pumping costs, and depletion of aquifers, which can take decades or centuries to replenish Hameed et al. [2019]. Addressing these challenges requires adaptive management strategies that respond to weather changes and ensure sustainable irrigation systems.

To provide farmers with a solution to transform their irrigation practices, new technologies such as IoT can be employed to collect and process weather data. By connecting objects to the internet and then feeding live, continuous data to DTs, farmers can receive real-time feedback and optimize irrigation based on metrics such as potential evapotranspiration and crop water requirements. This intelligent and flexible approach that use the dynamic simulation capabilities of DT is cost-effective and can be deployed in various contexts, providing agronomists with the ability to predict crop water needs and irrigation schedules accurately.

1.2 Problematic and Objectives

Agriculture faces numerous challenges. including the unpredictability of weather patterns, irregular rainfall, and extreme temperatures caused by climate change. with dwindling water resources, farmers face the challenge of providing sufficient irrigation to their crops while conserving water. This makes it difficult for farmers to plan their agricultural activities.

Furthermore, farmers have to deal with the struggle of inefficient decision-making due to a lack of real-time data and insights. Without access to accurate and timely information about weather conditions, farmers may struggle to make informed decisions regarding irrigation and resource allocation.This lack of data can lead to over-irrigation or under-irrigation, which can negatively impact crops, and water usage efficiency. Moreover, traditional farming practices often exhibit a heavy dependence on human labor. This reliance on manual labor is time-consuming and require significant physical exertion from farmers.

All of this necessitates the adoption of smart irrigation systems that utilize water efficiently and incorporate innovative technologies.

In our work, We have addressed those challenges by implementing smart irrigation techniques. We aimed to minimize water wastage, and enable precise control of water application by ensuring that plants receive the right amount of water at the right time. We also aimed to make an effective and dynamic irrigation schedules. This schedule would consider crop requirements, environmental conditions to enable farmers to make informed decisions regarding irrigation practices. Achieving these objectives, reduces the reliance on manual labor for farmer and contribute to the advancement of smart agriculture practices. In addition to promoting a more sustainable future for the agricultural sector.

1.3 Outlines

Our work is organized as following:

In the second chapter, an exploration was conducted of the current state of traditional and smart agriculture. We began by providing definitions of traditional and smart agriculture, as well as explaining concepts such as IoT and DT. Furthermore, the chapter covered the architecture of IoT and various devices and sensors that are utilized in agriculture.

Moving on to the third chapter, an overview of related research in smart irrigation was presented. Researchers have been actively working on innovative approaches and strategies to address diverse challenges. In this context, the specific approach employed in the project was introduced. Moreover, A particular attention was given to the methods of estimating evapotranspiration and how it effects irrigation process.

The fourth chapter primarily focuses on the Design and Contribution aspect. The proposed architecture, which tackles the problem of irrigation scheduling based on weather conditions and evapotranspiration, is introduced and elucidated using a UML diagram. Additionally, the algorithms employed in the project are discussed in detail.

In the fifth chapter, the implementation and results of the project are discussed. This includes an overview of the development tools and frameworks utilized, along with relevant screenshots showcasing the system. A thorough analysis of the obtained results is provided .

Finally, the sixth chapter concludes the work by summarizing the findings and contributions made throughout the project.

Chapter 2

Smart agriculture state of the art

2.1 Introduction

Agriculture replaced the early human lifestyle from nomadic hunter-gatherers dependent on foraging and hunting for survival to selective hunting, herding, and settled agriculture Gupta [2004]. Approximately 10,000 to 15,000 years ago, humanity embarked on a transformative journey, shaping the natural environment to better serve it's needs. This marked the emergence of agriculture, which gradually took root and spread across different regions of the world. Gorlinski [2013]. During this period of time humans made substantial efforts and sought to establish new techniques and methods to farther enhance agriculture through techniques like no-till farming, agroforestry, biotechnology, smart farming and smart irrigation .

2.2 Traditional agriculture

As stated by Harris and Fuller [2014]: "*Agriculture is the most comprehensive word used to denote the many ways in which crop plants and domestic animals sustain the global human population by providing food and other products*". It encompasses a range of activities such as soil preparation, planting, nurturing, and harvesting of crops. Additionally, agriculture involves the rearing and management of livestock.

The plants and animals involved in agriculture are typically domesticated, which means they have been intentionally bred by humans for their specific utility and suitability for consumption. In summary, agriculture can be described as the purposeful cultivation of crops and livestock to meet the essential requirements of human life.

2.2.1 Types of agriculture

Two primary types of agriculture are recognized: crop-based agriculture and livestock agriculture.

- **Crop-based agriculture**: This type of agriculture focuses on the cultivation and the production of various plants. It plays a crucial role in meeting the food demands of the growing population, providing raw materials for industries, and supporting rural livelihoods. It involves a wide range of crops, including grains (such as rice, wheat, and corn), fruits, vegetables, oil seeds, fiber crops, and more. It involves practices such as selecting suitable crop varieties, preparing the soil, sowing seeds, managing irrigation and fertilization, controlling pests and diseases, and ultimately harvesting the crops.

Figure 2.1: Crop-based agriculture agriculture

- **Livestock agriculture**: *"Livestock agriculture is concerned with raising and maintaining livestock, primarily for the purposes of producing meat, milk, and eggs."* Council [2003]. It revolves around the maintenance of animals. Such animals include sheeps, goats, cows, horses and silkworms. Livestock agriculture relies on food such as grass or hay and water. It results in products such as milk, meat, wool and leather Sala et al. [2017].

Figure 2.2: livestock agriculture

2.2.2 Traditional agriculture practices

Traditional agriculture practice heavily rely on human labor, farmers personally handle all tasks at first hand.

- **Soil preparation**: Soil is a very essential natural resource, it is the thin surface layer of the earth. Farmers use tools like hoes, ploughs, cultivators, and employ methods such as ploughing, leveling, and manuring to prepare the soil. These steps aim to enhance soil fertility and create favorable conditions for higher crop yields and quality.

- **Sowing**: Once the soil is prepared, seeds are scattered manually or with the help of seed drilling machines. The selection of high-quality crop strains is crucial at this stage to ensure successful germination and growth.

- **Manuring:** Crops require nutrients to thrive, so regular nutrient supply is essential. Manuring involves providing natural sources like decomposed plant and animal wastes (manure) or commercially produced chemical compounds (fertilizers). In addition to nourishing crops, manure also helps replenish soil fertility.

- **Irrigation:** Sources of water can be wells, ponds, lakes, canals, dams etc. Over irrigation may damage the crop. The frequency and interval between successive irrigation need to be controlled.

- **Harvesting:** Once the crop is matured, it is cut and gathered, this process is called harvesting. Followed by harvesting, grains are separated from the chaff either by threshing, or manually in small scale.

2.2.3 Limits and drawbacks of traditional agriculture

Despite its long-standing practice, traditional agriculture has limitations and drawbacks that hinder production. Such as dependence on weather condition that can be unpredictable. In addition to weather condition, traditional agriculture requiring significant amounts of manual labor for planting, harvesting, and processing crops. This can be daunting in areas where labor is scarce or expensive Kehinde David [2012]. Leading to time consuming processes and low yields, hence the need to find quick, efficient and easy ways for higher production in less time. Additionally, the challenges posed by water management and the lack of continuous monitoring present significant obstacles to traditional agriculture. However, thanks to technological advancements, the emergence of smart agriculture has revolutionized farming practices by integrating IoT, robots, drones, and DL techniques.

Smart agriculture enables farmers to make more informed and refined decisions. This innovative approach provides high precision and control, resulting in significant savings in water, energy, fertilizers, and time for farmers working in the field. It also offers a sustainable and efficient solutions.

Smart agriculture represents the future of farming, offering the potential to increase production, enhance resource management, and reduce costs with its transformative capabilities.

2.3 Smart agriculture

The technological advances in agriculture have revolutionized the way we interact with our environment. This filed experienced incredible transformations through advanced agriculture technologies and innovations such as IoT, robots and drones Merizig et al. [2019]. With sensors strategically placed in fields and other critical areas of the farm, valuable data is collected and analyzed. This data allows for informed decision-making on soil health, air quality, and weather patterns. Conclusions are formed regarding the status of the object or process monitored. The software and/or a human managing the platform decides on actions that need to be taken Singh et al. [2022]. Those actions are performed and the whole cycle starts again. By leveraging smart agriculture technologies, farmers can achieve high precision and control, eventually leading to considerable savings in all key resources.

2.3.1 Definition and enabling technologies of smart agriculture

The term smart agriculture refers to the use of technologies such as Internet of Things, sensors, robots and artificial intelligence to increase the quality and quantity of the crops Yassine et al. [2022].Areas of advanced technologies application in smart agriculture include :

- **Land management practices**: soil and land is considered a basic natural resource in agriculture to ensure production Chen et al. [2022]. Land management practices include soil tillage, terrace farming, irrigation techniques...etc.

- **Machinery and infrastructure:** comprised of farming equipment used in the field as well as in crop processing and storage. These technologies reduce the requirement for manual labor with equipment like harvesting combines and tractors. One machine can do the work of many laborers, making physically demanding and time consuming tasks much easier.

- **Agricultural infrastructure:** refers to the physical facilities, systems, and structures that support and facilitate agricultural activities including water pumps and storage systems like silos.

- **Agrochemical**: technologies developed to increase soil fertility and to improve crop health and yields. They typically include fertilizers, pesticides, and herbicides Mandal et al. [2020].

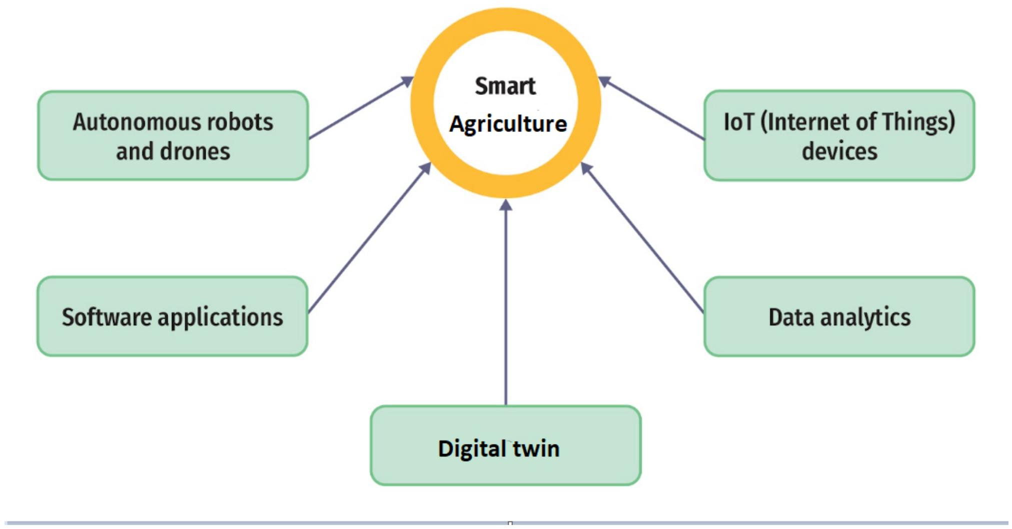

Figure 2.3: Smart agriculture enabling technologies

In all those areas IoT contributes in creating a smart environments those in which sensors and actuators are used to react to events and perform actions Vermesan et al. [2009], Zouai et al. [2019], resulting in a complex system that manages the farm based on data received from physical objects such as machinery and infrastructure to permit monitoring their environment, report their status, and even take action based on the information they receive Manyika et al. [2013]. In this hyper connected world, DT have assumed greater importance by serving as a mean to monitor and control interactions between connected things Pylianidis et al. [2021]. The increasing prevalence of IoT has made DT more significant Pylianidis et al. [2021]. The physical world meets the digital world and they cooperate. Thanks to this system, farmers can monitor the processes on their farms and take strategic decisions remotely without being on the open fields.

2.3.2 IoT definition and architectures

During the past few years IoT had a significant impact on human life, it has become one of the most important technologies of the 21st century. allowing humans to do less heavy manual labor, avoid tedious tasks and make life more healthy, productive, and comfortable.

Definition

According to James Manyika IoT can be defined as: " *the use of sensors, actuators, and* *data communications technology built into physical objects from roadways to pacemakers that enable those objects to be tracked, coordinated, or controlled across a data network or the Internet.*" Manyika et al. [2013]. While the concept of IoT has been around for a while, recent advancements in various technologies have made its practical implementation more feasible and convenient such as affordable and reliable sensors, efficient data transfer using the internet to connect sensors to the cloud and to other objects, technologies such as edge computing and cloud computing for remote data storage, machine learning and analytic to process data and make real-time decisions Rayes and Samer [2016].

Sensor Networks

Sensor networks are comprised of numerous sensor nodes that work together to collect and transmit data from the surrounding environment.

Type of sensors used in agriculture

In agriculture, a variety of sensors are used to monitor and gather data related to soil conditions, weather parameters, plant health, and environmental factors. Here are some commonly used types of sensors in agriculture:

• **Temperature sensors:** Temperature sensors can offer significant insights that help to in agriculture. These sensors are frequently employed to monitor the temperature of air, water, and soil. The substantial data collected from these sensors can be utilized to enhance the growing conditions for various crops.

• **Humidity sensors:** A humidity sensor is a device that measures the amount of moisture or water vapor present in the air. It is useful for monitoring the moisture levels in the air and soil, it allows farmers to adjust irrigation and ventilation systems in greenhouses to maintain optimal growing conditions for crops. Humidity sensors are also used to prevent plant diseases caused by excess moisture. Additionally, these sensors can be used to detect moisture levels in storage facilities, preventing spoilage and preserving the quality of harvested crops.

Figure 2.4: Temperature and humidity sensor

• **Soil moister sensors:** they are devices used to measure the amount of water present in the soil. commonly employed in agriculture to monitor the moisture level in the soil and determine when irrigation is required. These sensors play a crucial role in efficient water management and promoting healthy plant growth. Soil moisture sensors operate by utilizing various principles such as electrical conductivity or dielectric constant to assess the soil's moisture content. The electrical properties of the soil change with varying moisture levels, allowing the sensors to provide accurate readings. By measuring these properties, farmers and gardeners can gather real-time data on soil moisture and make informed decisions regarding irrigation.

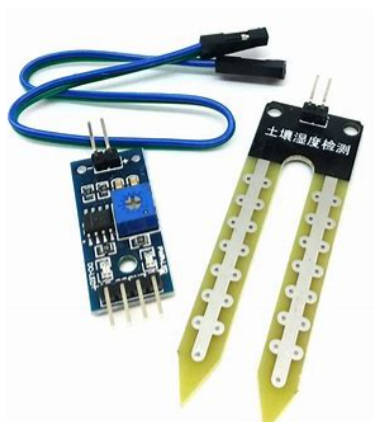

Figure 2.5: Soil moister sensors

• **Leaf and plant health sensors:** These sensors assess plant health by measuring parameters such as chlorophyll content, leaf temperature, and photosynthetic activity. They can detect early signs of stress, nutrient deficiencies, or pest infestations, allowing for timely interventions.

Figure 2.6: leaf wetness sensors

Communication technologies

Internet connectivity is crucial for communication, and every physical object on the internet is identified by an IP address. However, with the limited number of addresses available in the IPv4 addressing space, it is no longer feasible to allocate unique addresses to the growing number of devices. To address this problem, the IPv6 protocol was developed, which provides a larger addressing space and ensures scalability. the IPv6 protocol was initially designed for wired networks and it cannot fully accommodate the requirements of wireless sensor networks (WSN). As a result, the 6LoWPAN protocol was developed specifically for WSNs Lombardi et al. [2021].

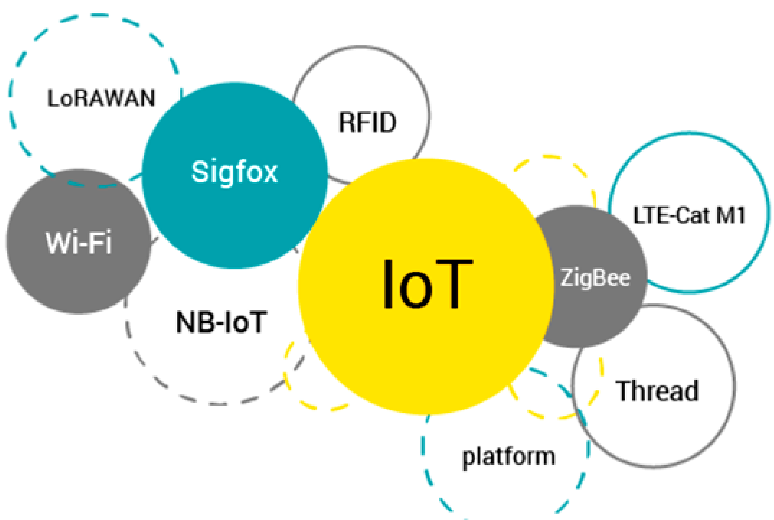

Figure 2.7: Iot communication technologies

Communication technologies in agriculture can be chosen based on the specific environment or context in which they are deployed. One of the most commonly used communication technologies in agriculture is WiFi, primarily due to its accessibility and widespread use García et al. [2020]. WiFi offers several advantages in terms of connectivity and ease of implementation. It utilizes wireless local area networks (WLANs) to establish connections between devices within a specific range allowing for seamless data transfer and communication. Low-cost IoT devices currently available in the market typically support WiFi.

In addition to WiFi, there are other wireless technologies commonly used in IoT applications, including GSM (Global System for Mobile Communications) that offers extensive coverage, it is suitable for applications that require communication over large distances, and relies on cellular networks provided by service providers operating in the area. There is also ZigBee that enables devices to communicate with each other using low-power radio signals, forming a mesh network. García et al. [2020].

Architecture

The implementation of IoT in our daily lives is hindered necessitate the establishment of a standard architecture for successful deployment. For this purpose, a universally agreed upon three-layer architecture, comprising the Perception Layer, Network Layer, and Application Layer has been proposed Krishna et al. [2021]. Overall, understanding the IoT architecture is essential to developing effective IoT applications. therefore, in the following section we will delve into the functionality of each layer in detail.

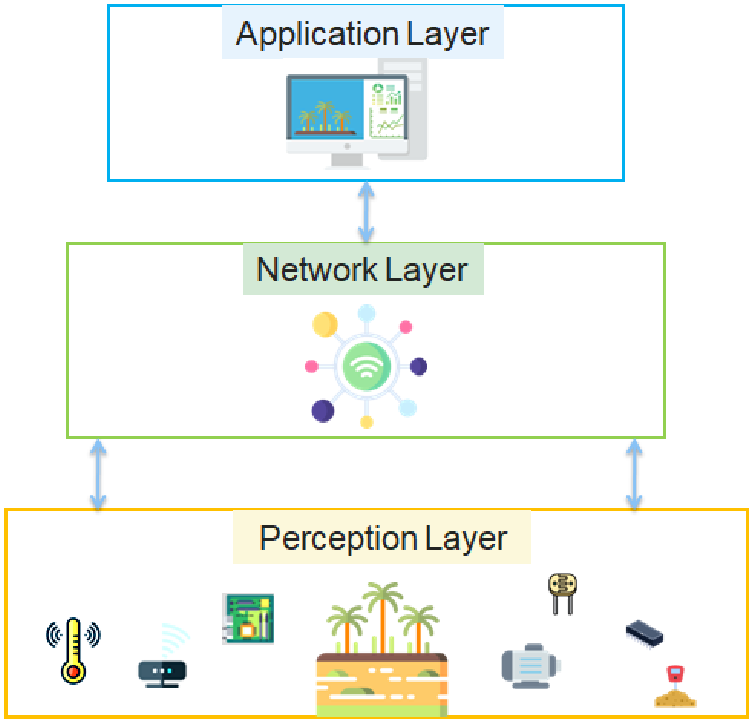

Figure 2.8: IoT architecture

Perception layer: This is the physical layer of the architecture with the task of perceiving physical properties of things around us that are part of the IoT Mahmoud et al. [2015]. Its main task is to gather data in the agricultural domain, including temperature and humidity. The collected data is then converted into digital signals, which are more suitable for transmission over the network. In summary, the physical layer consists of IoT devices that play a crucial role in collecting and digitizing data from the surrounding environment for further processing and analysis.

Network layer: The network layer plays a crucial role in IoT architecture by handling the processing and transmission of data received from the perception layer. It utilizes a range of network technologies, including wireless and wired networks, such as Ethernet , Wi-Fi, ZigBee and Bluetooth, to transmit the data to the application layer.Singh et al. [2022]. Due to the vast amount of data being transmitted through the network layer, it becomes essential to have a middleware that can effectively store and process this data. Cloud computing serves as the primary technology in this layer to address this requirement. By leveraging cloud computing, it is possible to store and process data generated by IoT devices.

Application layer: utilizes the processed data to derive meaningful insights and enable specific IoT applications. It involves data analysis, decision-making, and the execution of various applications based on the collected data. this layer is the front end that enables the exploration of the full potential of IoT Mahmoud et al. [2015].

2.3.3 Digital twins

In this subsection, we explore the concept of DT and it's significant impact across various fields. DT have demonstrated remarkable performance and proven it's value in numerous industries. In the agricultural sector, it offers immense potential to revolutionize farming practices and optimize resource management.

Definition

Michael Grieves in his work Grieves [2016] defines DT as" *a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin* ." . For a simpler definition a DT is a virtual representation or model of a physical object, process, or system. It is created by collecting real-world data from sensors, devices, or other sources and feeding that data into a computer program or software. The DT then uses this data to simulate and predict the behavior, performance, and responses of the physical object or system.

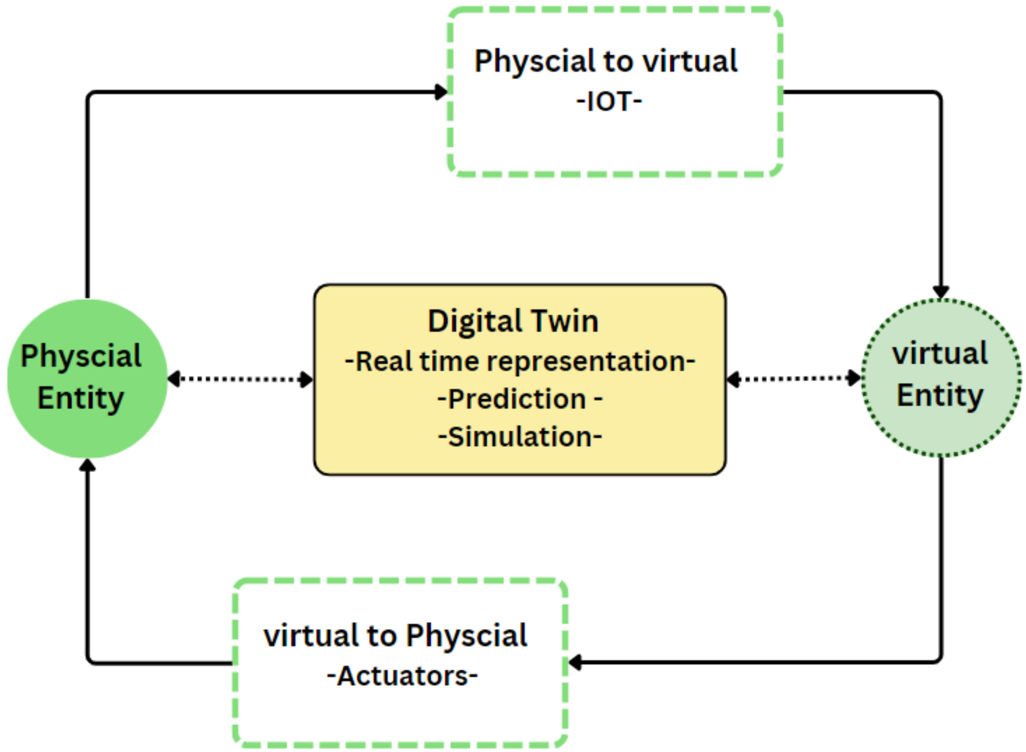

Figure 2.9: digital twins

DT systems recreate the real-time condition of a physical object or a system within a virtual environment by utilizing data. These models are designed to dynamically adapt and reflect any new information or changes that take place in the physical system.Barricelli et al. [2019]. Thus, there is a high demand for connectivity this requires data acquisition from various sources, including the use of sensors and IoT technology to merge the physical and virtual worlds. The data obtained from sensors in the physical world are transmitted to the virtual world to create a real time representation of the physical system da Silva Mendonça et al. [2022].

DT technology has the potential to support decision making, planning, and condition monitoring, making it useful for real time management in agriculture.

Digital twins in agriculture

The primary objective of implementing DT in agriculture is to solve problems such as conducting continuous monitoring and control over the farm, enabling timely corrective measures for irrigation management, animal monitoring, and greenhouse operations. By integrating data, modeling, and simulation, the agricultural industry can address existing challenges and enhance decision-making and automation in various sectors Barricelli et al. [2019].

Digital Twins is a powerful concept that holds significant promise for the future of agriculture

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2.3.4 Areas of application in agriculture

The application of IoT and DT in agriculture offers various opportunities to optimize resource utilization and improve decision-making. Some of the key areas of application include:

Livestock management and monitoring

IoT can enhance livestock management and monitoring, allowing farmers to track the behavior, feeding patterns, prolonged inactivity, unusually shorter feeding sessions, and overall health and well-being of their animals in real-time Suresh and Sarath [2019]. With the aid of cameras, sensors, GPS, and other advanced tools, farmers can identify signs of disease quickly. It provides farmers with the ability to monitor the health status of their livestock, even down to individual animals, from chickens to cows.

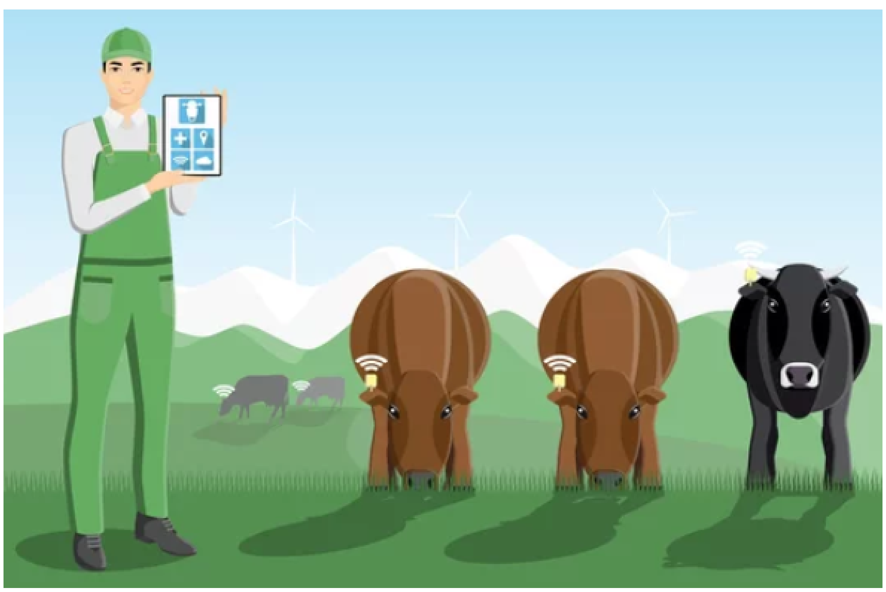

Figure 2.10: Smart livestock management and monitoring

Smart irrigation

Smart irrigation allows farmers to use on field sensors to measure and monitor variables like weather condition, evaporation, soil moisture, and humidity. IoT could contribute in all aspects of irrigation such as scheduling water cycles based on soil moisture content and requirement rather than a periodic oversupply of water.

Figure 2.11: Smart irrigation

Smart crop canagement

Traditional crop management methods are tedious and impractical for modern-day farmers. they have to be in the open fields to inspect the health of their crops for hours every day. This method is simply impractical. However, with the help of IoT sensors and drones, farmers now have access to valuable information that can enhance their crop management techniques. By continuously monitoring environmental conditions, farmers can identify potential diseases and pest damage early on and take preventive measures towards mitigating their impact. This technologically advanced method of crop management is not only more efficient, but also enhances the precision and accuracy of farming operations, leading to increased yields and better returns Ayaz et al. [2019].

Figure 2.12: Smart crop management

Greenhouse monitoring system

A smart greenhouse, is an automated greenhouse that utilizes sensors to control environmental conditions such as temperature and humidity to maintain an optimal climate for plant growth Li et al. [2021]. This innovative farming technology eliminates the need for manual control by farmers, resulting in increased efficiency and productivity.

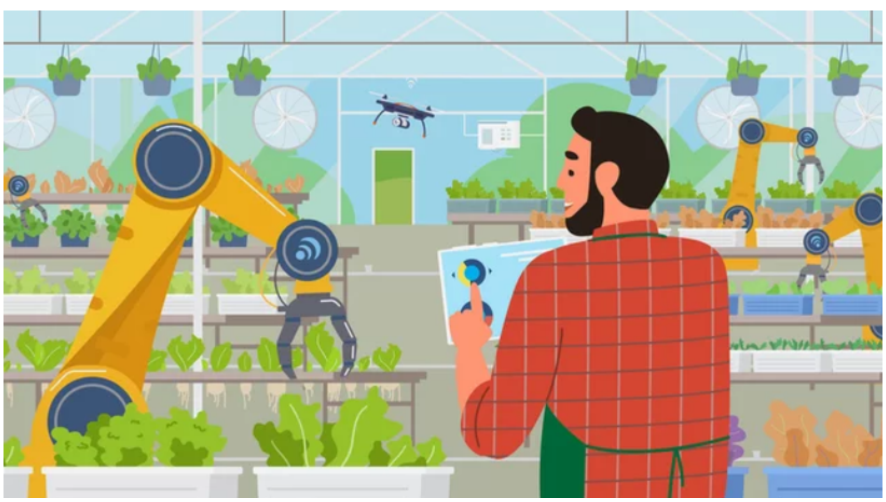

Figure 2.13: Smart greenhouse

2.4 Conclusion

The agricultural sector has encountered numerous challenges in its quest to sustainably feed the growing human population. One of the pressing issues is the need to meet food demands while mitigating costs and minimizing environmental consequences. Agriculture heavily relies on irrigation, which often leads to the depletion of limited freshwater resources. To overcome these challenges, it is crucial to embrace the next wave of agricultural technologies and sustainable practices, such as smart irrigation.

Smart irrigation represents a revolution in agricultural practices by integrating advanced technologies like IoT, DL, and DT into irrigation systems. Allowing for precise irrigation scheduling and efficient water management. This shift toward smarter and more efficient agricultural technologies is crucial for achieving food security, preserving natural resources, and building a more sustainable future.

Chapter 3

Smart irrigation

3.1 Introduction

Date farming is a common and popular farming business in arid areas, Palm trees are widely cultivated across North African nations where traditional irrigation systems have been employed over several decades with a lot of possible improvements that can be performed in terms of efficient water use and groundwater exploitation. The current methods of water management in agriculture are outdated and are struggling to cope with the challenges posed by climate change and increasing water scarcity. These traditional methods often rely on manual observation and intuition, which are not sufficient. Hence the need to find better ways to use water efficiently and manage our resources wisely.

By implementing smart irrigation techniques to ensure that water is supplied in the precise quantity and at the appropriate moment, we can increase agricultural productivity while reducing water wastage and the need for constant human supervision. investment in these transformative solutions are essential to mitigate the impending water scarcity challenges.

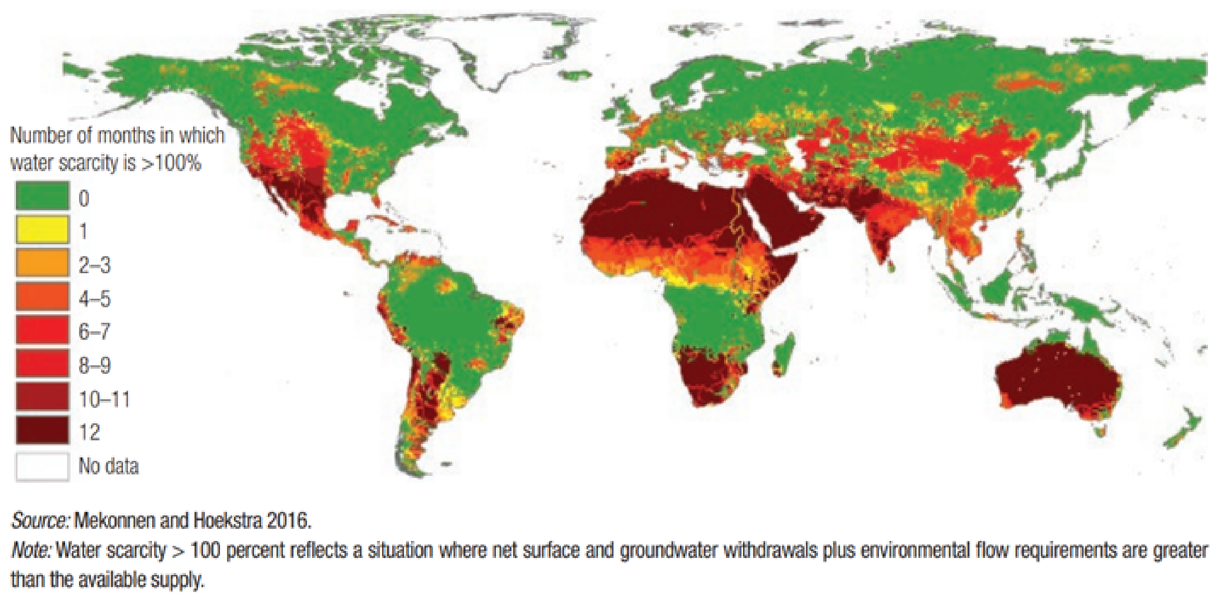

Figure 3.1: Regions that experience severe water scarcity throughout the year, 1996–2005 Mekonnen and Hoekstra [2016]

The fact that 70 percent of the available freshwater resources are utilized for irrigation purposes, highlights the need for implementing sustainable water management practices Pincheira et al. [2021]. water demand is growing exponentially while climate change is making rainfall more erratic and less predictable. Damania [2017] we are required to improve our irrigation systems using modern technologies.

Automation of irrigation activities can transform the palm tree cultivation domain from being manual and static to intelligent and dynamic.

3.2 Smart irrigation definition

The need for improved water management can be fulfilled with smart irrigation, which is the proper use of water supplies through the application of mechanism that lead to effective and efficient use of water at required time intervals.

This efficiency can be enhanced by using advanced methods such as Automatic irrigation, scheduling techniques, and the application of modern Technologies such as DT and IoT.

3.3 Traditional irrigation and smart irrigation

Traditional irrigation is a common practice in many parts of the world that dates back centuries. It involves the process of watering crops by using canals, pipes, sprinklers, or other man-made techniques, rather than depending on rainfall alone. Farmers in arid areas commonly use groundwater sources to supply water to their fields. Traditionally, date palm trees are irrigated using surface irrigation systems, the water application in such systems is typically determined based on the farmer's experience Elfeky and Elfaki [2019]. This often results in significant water consumption that could be effectively reduced using advanced technologies. However, the utilization of new technologies in date palm irrigation is relatively limited. Therefor, there is a pressing need to embrace it in order to support date palm growers and facilitate their progress. In this section, we will delve into the influence of technology on the field of irrigation.

3.4 Weather factor in irrigation

Farmers rely heavily on daily weather conditions to make important decisions related to agriculture. Crops water needs are strongly influenced by weather parameters such as temperature and humidity. One of the most important factors that farmers monitor is evapotranspiration (ET), the amount of water given up to the atmosphere by a crop due to evaporation from the soil surface and transpiration through the plant leaves Pereira et al. [1996]. This parameter is difficult to measure directly and is often estimated using weather data. Several factors can impact ET, including the growth stage of the crop, climatic conditions, and soil type.

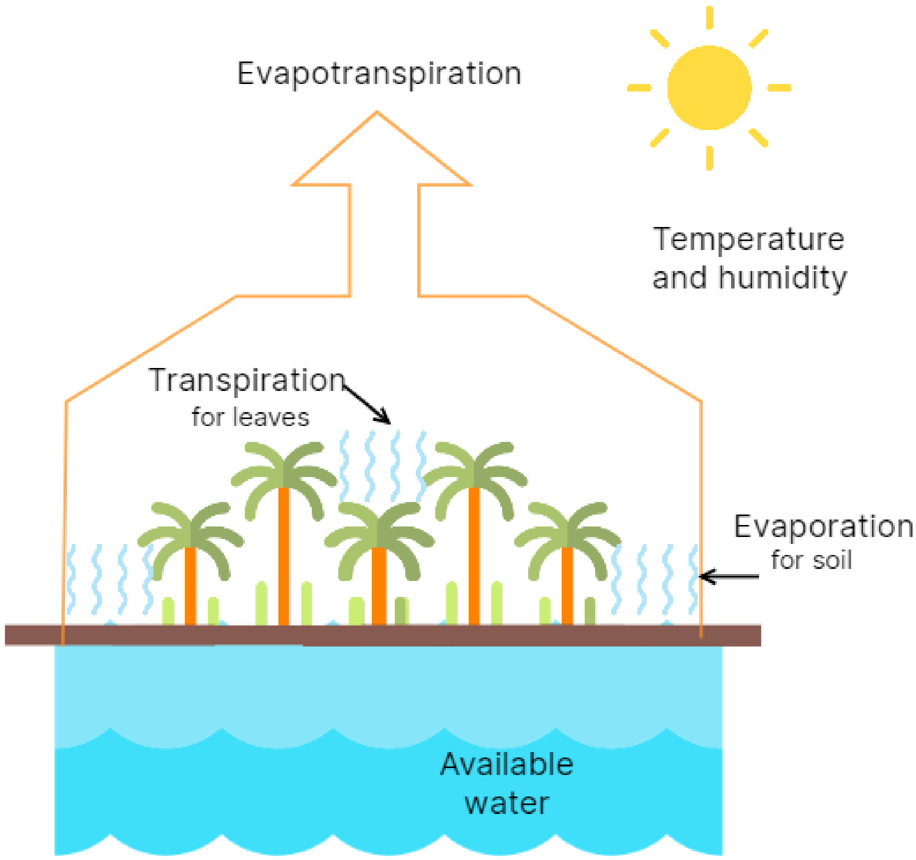

Figure 3.2: Evapotranspiration includes evaporation from soil and transpiration from leaves.

Temperature and humidity are key weather parameters that affect ET and can help farmers determine the need for irrigation. In cases where temperature is high the soil will experience increased water loss, and irrigation may be necessary.

Therefore, farmers must carefully monitor these parameters to determine the optimal water quantity required for irrigation if deemed necessary. ET measuring is done using the following FAO penman-montithe mathimaticl calculation :

$$ETo = \frac{0.408\Delta(Rn - G) + \gamma \frac{900}{T+273} u2(es - ea)}{\Delta + \gamma(1 + 0.34)u2}$$

where :

ETo reference evapotranspiration $[mmday-1]$,

Rn net radiation at the crop surface $[MJm-2day-1]$,

G soil heat flux density $[MJm-2day-1]$,

T mean daily air temperature at 2 m height $[$řC$]$,

$u2$ wind speed at 2 m height$[ms-1]$,

es saturation vapour pressure $[kPa]$,

ea actual vapour pressure $[kPa]$,

$es - ea$ saturation vapour pressure deficit $[kPa]$,

Δ slope vapour pressure curve $[kPa$řC$-1]$,

γ psychrometric constant $[kPa$řC$-1]$.

FAO Penman-Monteith equation allows for the calculation of evapotranspiration on a daily, weekly, ten-day, or monthly basis. This equation takes into account several meteorological parameters(solar radiation, air temperature, air humidity, wind speed, atmospheric pressure, latent heat of vaporization, psychrometric constantdew point temperature , extraterrestrial radiation..etc) . To ensure accurate computations, weather measurements should be taken at a height of 2 meters above a well-vegetated surface of green grass, with shading and sufficient water supply Allen et al. [1998].

In cases where data for certain weather variables are missing, it is generally not recommended to rely on alternative calculation procedures that require limited meteorological parameters. Instead, it is advised to address the issue of missing data and then calculate evapotranspiration using the standard Penman-Monteith method Allen et al. [1998]. using a programmed function based on Penman-Monteith alternative calculation procedures may not yield satisfactory solutions without the appropriate data. However, Machine Learning techniques can offer a viable solution by using the available weather parameters inputs to predict evapotranspiration using historical data , which can be treated as a regression task using models like Linear Regression, Polynomial Regression, Support Vector Machines (SVM), Random Forest Regression, or artificial neural networks .

3.5 Related work

DT have attracted significant attention in recent years, thanks to it's potentials in diverse industries.

Skobelev et al. [2020] introduces a solution for creating a DT of wheat, utilizing a smart system that combines a knowledge base of the macrostages of plant development and multi-agent technology for modeling wheat cultivation. The goal of this approach is oversee and manage the growth and development of plants.

The suggested architecture addresses the shortcomings of data-driven modeling techniques which may struggle to accurately predict and classify the states of crops when the modeled system diverges from the real-world system, especially in the face of climate change.By employing a multi-agent approach, the system can simulate the dynamics and identify abnormal states. It utilizes the knowledge base to suggest suitable corrective actions. This research is a significant advancement in the development of climate-resilient decision-support technologies, which are crucial for the long-term prosperity of the agriculture sector.

Kampker et al. [2019] explore the development of a DT of a potato for harvesters. During the harvesting process, which is typically mechanized using self-propelled machines, the utilization of a Digital Potato can greatly assist operators. These digital representations of real potatoes are equipped with sensors capable of detecting impacts and rotations. Real-time analysis of the collected data takes place on the agricultural machine, with the resulting insights displayed to the farmer or driver.

To evaluate the data, machine learning techniques are employed, including the classification of harvests and continuous calculation of crop damage distribution based on the type of potato and its specific characteristics. This approach allows manufacturers and farmers to minimize potential damage to the potatoes and ensure optimal machine calibration. By employing a sensor-equipped artifact that resembles a real potato in size and weight, data can be gathered. When combined with variety information and machine learning algorithms, the system can monitor the artifact and determine the ideal harvester configuration for proper operation.

Jans-Singh et al. [2020] proposed a DT of a hydroponic underground farm in London to enhance the efficiency and productivity of indoor farming. This innovative approach utilizes advanced technologies such as artificial lighting and smart heating, ventilation, and air conditioning systems to create an optimized environment for crop growth.

The primary objective of the DT is to enable remote monitoring, forecasting, decision-making support, and optimization of the hydroponic farm. By leveraging automated and manual data collection methods, the DT aims to minimize energy consumption while maximizing crop yield by maintaining optimal growing conditions.

To achieve the desired outcomes, the authors employed various data analysis techniques, including data fusion and a dynamic linear model with time-varying parameters. These methods help in analyzing and interpreting the collected data to identify patterns, make predictions, and optimize operations.

3.6 Synthesis

To resume the presented works mentioned in the previous section the following table explains the differences

	Skobelev et al. [2020]	**Kampker et al. [2019]**	**Jans-Singh et al. [2020]**	Our work
Domain	Agriculture	Agriculture	Agriculture	Agriculture
Objective	Planning and modeling plant development	Minimizing potato damage, optimizing harvest machine calibration, and classifying harvests	Minimize the energy use while maximizing crop growth by maintaining optimal growing conditions	Efficient use of water resources and making effective and dynamic irrigation schedules
Physical twin	Wheat	Potato	Hydroponic underground farm	Date palm tree farm
approach	Digital twins and ontological models and multi-agent systems.	Digital twins and machine learning methods.	Digital Twin ,data analysis, data fusion, random forest and multivariate regression algorithms	Digital twins, deep neural network (DNN)

Table 3.1: Related work comparison

3.7 Conclusion

In conclusion, the utilization of technology in the field of irrigation has the potential to revolutionize the agricultural sector. Smart irrigation systems, enabled by IoT, DT, and DL offer benefits such as remote monitoring, and decision-making support. These systems can help minimize water wastage .

Weather factors, especially evapotranspiration, are crucial for effective irrigation management. By monitoring temperature, humidity, and other meteorological parameters, farmers can make informed decisions about when and how much to irrigate. The FAO Penman-Monteith equation is a widely used method for estimating evapotranspiration, but it requires accurate and complete weather data for accurate results. In cases where data is missing, machine learning and deep neural networks (DNN) can be employed to estimate evapotranspiration using the available weather parameters.

The discussed related works highlight the application of DT and machine learning in different agricultural contexts including the development of a DT for wheat cultivation, a digital potato for potato harvesting, and a DT for hydroponic farming. This demonstrates the potential of the advanced technologies .

Overall, the integration of DT and DNN algorithms in irrigation systems can lead to more efficient and sustainable agricultural practices. By embracing these advancements, we can address the challenges of water scarcity, optimize resource utilization, and ensure the long-term prosperity of the agriculture sector.

Chapter 4

Design and Contribution

4.1 Introduction

This chapter presents the modeling and design of our proposed irrigation system, which involves creating a digital twin of a physical date palm trees farm. The digital model utilizes data from IoT devices, and other sources to make precise decisions for irrigation scheduling.

A significant aspect of our system is the incorporation of DNNs to estimate evapotranspiration using real-world weather data. By leveraging the power of DNNs, our system can optimize irrigation strategies.

In the following sections, we will provide a detailed overview of the system architecture, highlighting the roles of each layer. We will also describe the step-by-step process of smart irrigation and the algorithm we used to ensure accurate and efficient irrigation decisions regarding the timing and quantity of water to be used .

4.2 Proposed architecture

The system goal is to optimize the water usage in agriculture by applying advanced technologies and intelligent decision-making. The system aims to efficiently deliver the right amount of water to plants based on their specific needs, environmental conditions, and other relevant factors.

The proposed architecture is structured into three layers that work together and facilitate real-time data exchange. The first layer is the starting point, it represent the physical twin (the farm) it is responsible for collecting weather data. This data is sent to the second layer, the cloud, where it is stored. The third layer, also known as the digital twin, processes the data, estimates evapotranspiration, and provides insights on the crop's water requirement. The system architecture is depicted in the figure below.

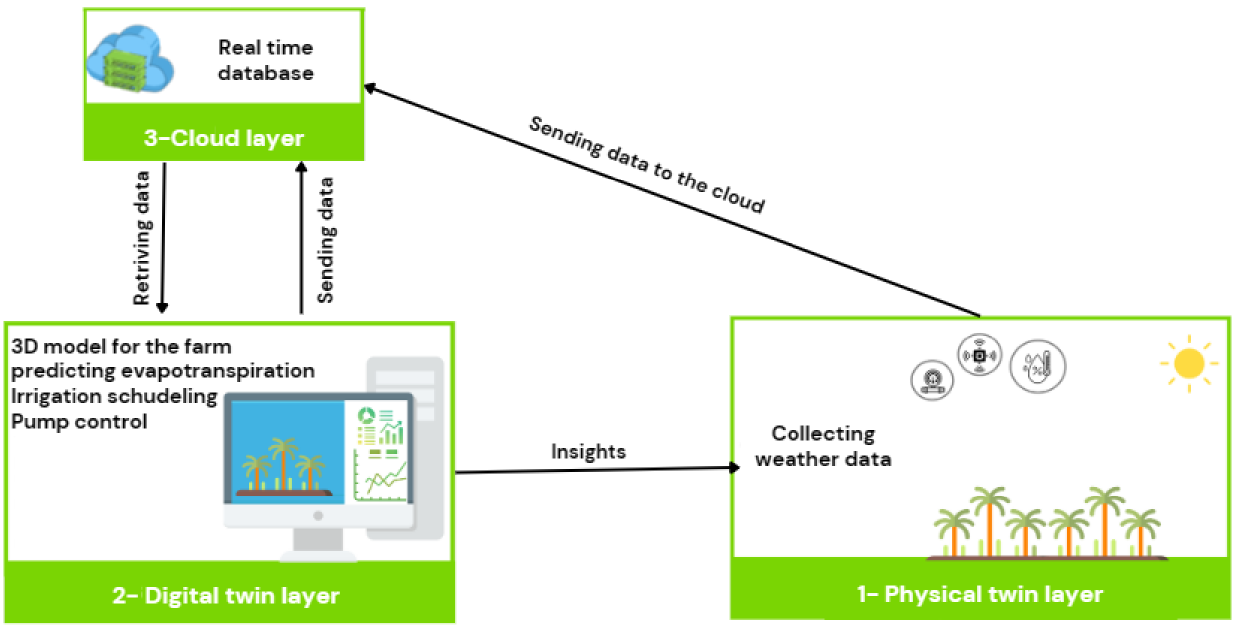

Figure 4.1: The proposed architecture

4.2.1 Architecture description

1.The physical twin : It is responsible for gathering weather data from a real-world entity, specifically a date palm tree farm. It collects various parameters such as temperature, humidity, rain, cloud coverage, and wind speed. The main objective of this layer is to acquire the essential data required for making predictions, generating insights, and developing future irrigation schedules. Once the data is collected, it is forwarded to the subsequent layers for further processing and analysis.

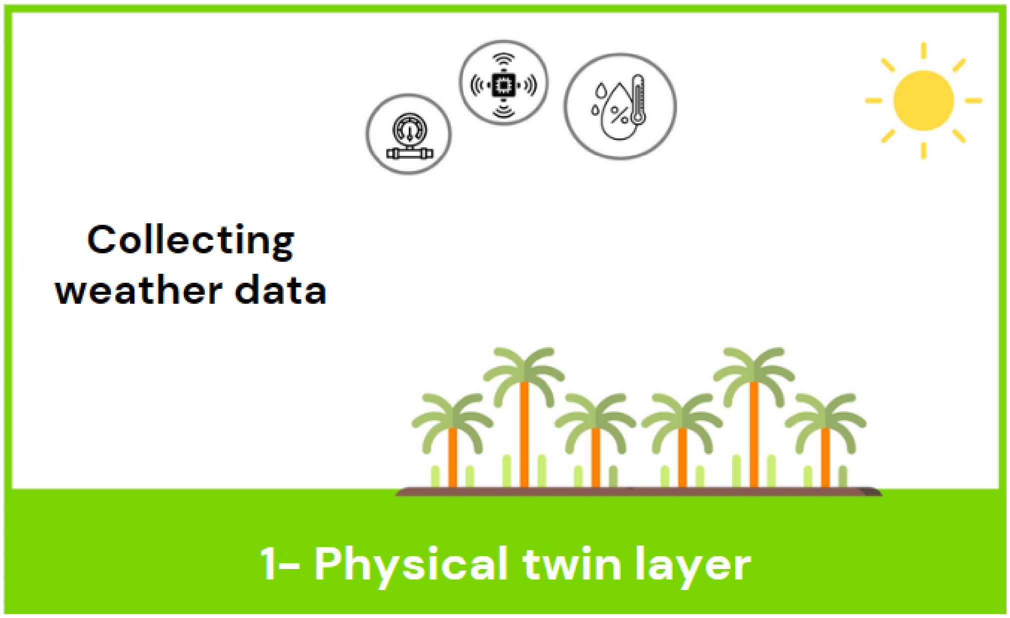

Figure 4.2: The physical twin layer

2. The digital twin: It is represented through a 3D model within a desktop application. After the collection and retrieval of relevant information the later is streamed to the DT, which tasked with the responsibility of displaying the collected data and insights . The primary task of the digital twin is to provide irrigation schedule for better water management.

At this layer, the farmer can monitor the farming field through the desktop application and control the pump manually or automatically.

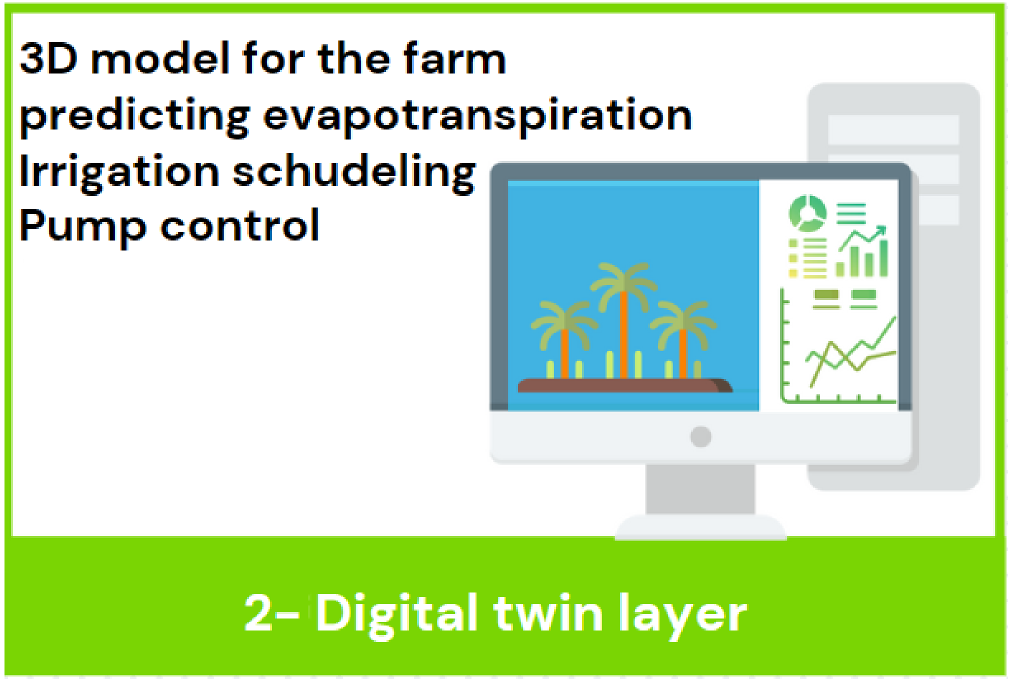

Figure 4.3: The digital twin layer

3. Cloud layer : In the proposed architecture, the cloud layer represent the connection between the physical and digital twins. It rovides functionalities and features accessible over the internet. including cloud storage and real-time database

leveraging a cloud server like Firebase, enables the application to handle the large volumes of data generated by the first layer. This ensures that there is ample storage capacity available. By storing the data on the cloud, the application can access it via the internet. The data is transmitted in a structured format, such as JSON, for convenient and efficient utilization at a later stage.

Figure 4.4: The cloud layer

4.2.2 The process of smart irrigation

The smart irrigation process encompasses several steps that utilize deep learning techniques and digital twins to optimize water usage and enhance irrigation efficiency. The process includes the following steps :

Figure 4.5: The process of smart irrigation

1. **Data collection** :The process of gathering the necessary data involves capturing real-time environmental conditions such as temperature, wind speed and humidity levels. The data collection can also be facilitated by leveraging a weather API, which provides access to weather information from reliable sources. This enables in-depth analysis and insights into the environmental factors impacting the studied area.

2. **Data analysis**: The collected data is analyzed using advanced algorithms and machine learning techniques. This enables the irrigation system to extract valuable insights on the water needs of plants.

3. **Decision making:** Using the insights gained from data analysis, the smart irrigation system makes informed decisions to schedule irrigation.

4. **Automated irrigation control:** The smart irrigation system automatically controls the irrigation process based on the decisions made. It can activate or deactivate the pump in response to plant needs.

5. **Monitoring:** The DT provides a 3D visualization of the field, providing users with real-time monitoring capabilities. Users can track various aspects, including the status of the

pump, areas currently undergoing irrigation, as well as areas that require irrigation in the near future. Moreover, the farmer can retains manual control over the irrigation system, allowing them to make adjustments.

Overall, the smart irrigation process leverages deep learning, decision-making, digital twins to optimize water usage and conserve resources in an efficient and sustainable manner.

4.3 Specifications and use cases diagram of the the system

specifications and use case diagram demonstrate the key features and functionalities of the smart irrigation system for enabling precise irrigation scheduling.

4.3.1 Specifications

id	specification	state	Criticism
1	The system should verify the user identity .	Incorporated	Critical
2	The system should show the user real time weather data.	Incorporated	Important
3	the system should show evapotranspiration values .	incorporated	critical
4	the system should calculate the amount of time needed for irrigation .	proposed	useful
5	the system should calculate the amount of water to be used for irrigation for each palm tree .	incorporated	critical
6	the system should provide irrigation schedule .	incorporated	critical
7	the system should show the state of the pump on/off .	incorporated	critical
8	The system should show the time left before irrigation is done.	Incorporated	Important

Table 4.1: Functional specifications

id	specification	state	Criticism
1	the system should have both the virtual twin and physical twin .	proposed	useful
2	the system should predict evapotranspiration using DNN .	incorporated	critical

Table 4.2: Technical specifications

4.3.2 UML Diagram

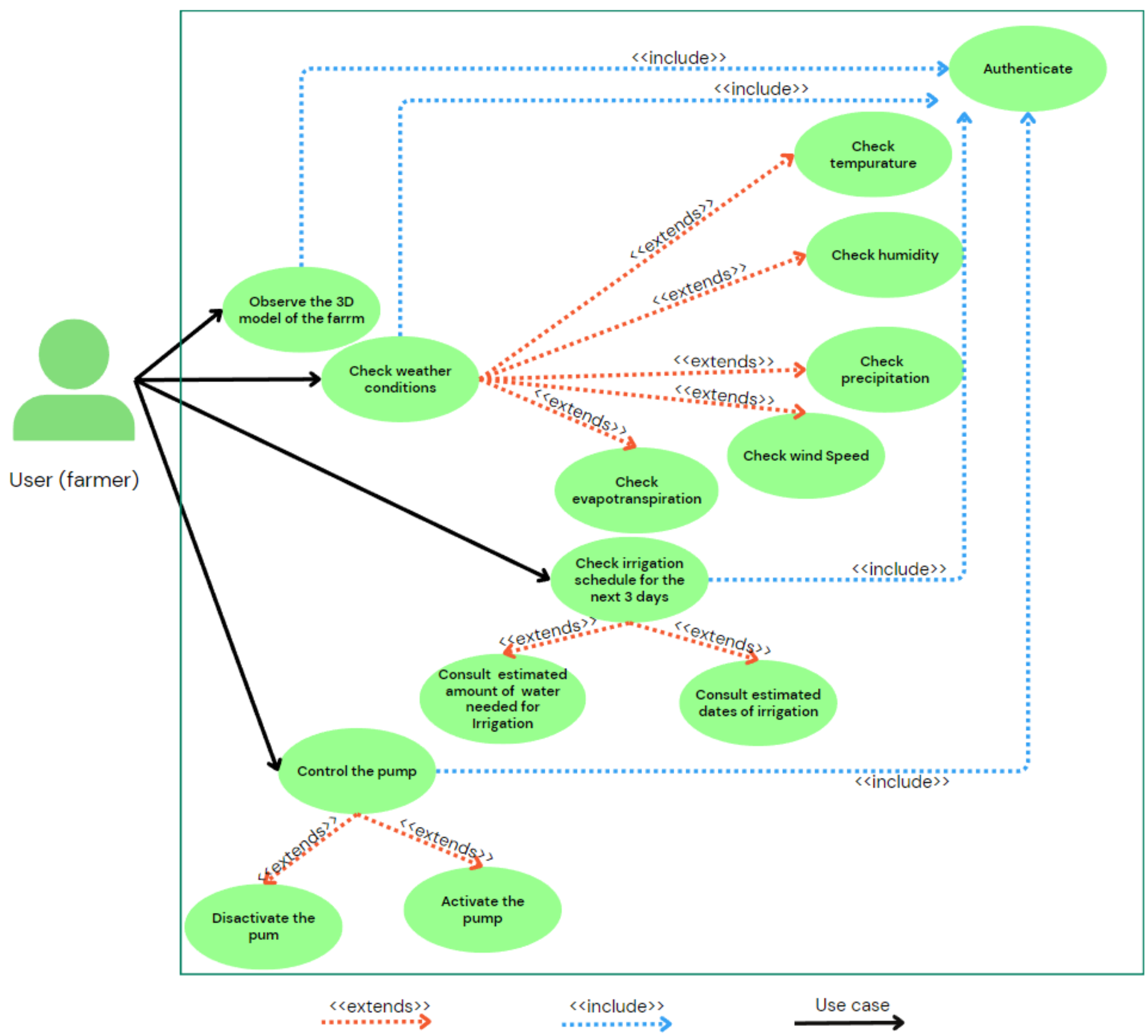

Figure 4.6: Use case diagram

4.4 Used algorithm

In this section, we present the used algorithm that helped to create our models.

4.4.1 Deep Neural Network (DNN)

DNN stands for Deep Neural Network. It is composed of multiple artificial neural network of interconnected nodes called neurons, each layer receives input from the previous layer and pass its output to the next layer. The first layer is the input layer, which receives the raw data, such as images, text, or numerical values. The middle layers are called hidden layers, and they perform various mathematical operations to extract features and learn patterns from the input data. The final layer is the output layer, which produces the desired output or prediction based on the learned patterns Georgevici and Terblanche [2019].

4.4.2 DNN pseudocode and architecture

The process of creating our model is as following :

1. **Getting the data**: we used a dataset containing ET values that correspond to various environmental conditions. Using the labeled data the model was able to learn the relationship between the inputs and their corresponding ET values, enabling it to make predictions when provided with new inputs. The dataset includes metrics such as minimum and maximum temperature, humidity, wind speed,rain and ET values for the city of Biskra, collected since January 1, 2019. These measurements were taken at specific geographical coordinates: latitude 34.83 degrees, longitude 5.7 degrees, and an altitude of 87 meters. By training on this data, the model acquired the ability to predict ET values.

	T_max	T_min	H	WS	P	C	ND
0	19.0	5.1	62.347826	18.1	1027.091304	0.173913	1
1	18.9	3.8	55.521739	22.3	1023.982609	0.000000	2
2	17.4	8.3	53.608696	20.1	1022.600000	3.956522	3
3	14.2	5.6	62.391304	14.6	1026.982609	37.000000	4
4	15.7	5.9	54.521739	19.4	1028.226087	3.130435	5
...	...	...	...	...	...	...	...
1590	29.6	16.4	39.391304	14.8	1014.617391	3.217391	130
1591	30.7	20.6	32.217391	25.1	1011.626087	7.173913	131
1592	30.7	18.8	33.478261	24.5	1008.282609	27.739130	132
1593	32.0	19.9	35.478261	32.7	1005.908696	25.695652	133
1594	25.7	16.7	43.956522	26.0	1009.373913	32.173913	134

Figure 4.7: The dataset

2. **Preparing data :**Prior to inputting the data into the model, it was crucial to prepare the data including splitting it into training and test sets and normalizing it. Feature-wise normalization plays a vital role when the features exhibit variations in scales or units. Its purpose is to prevent any single feature from dominating the learning algorithm due to its larger magnitude or scale. Hence, it is considered best practice to perform feature-wise normalization on each feature of the input data. In this scenario, we utilized Z-Score Normalization (Standardization), a technique that involves subtracting the mean and dividing by the standard deviation of each feature. This process results in transformed features with a mean of 0 and a standard deviation of 1. when performing feature-wise normalization, the quantities used for normalization, such as the mean and standard deviation, are computed using the training data. This means that the normalization parameters are derived from the training dataset and then applied to normalize both the training and test data.

	T_max	T_min	H	WS	P	C	ND
1204	-0.072656	-0.248028	-1.097424	1.411485	-0.562209	-0.511631	-0.600893
231	1.305091	1.461476	-0.767956	0.763935	-0.873832	-0.762761	0.555776
822	0.360668	-0.141184	-1.244161	0.621475	-0.246971	0.478780	-0.760758
735	-1.839283	-1.803202	0.151229	-0.259192	-0.095136	0.721444	-1.578890
727	-1.772618	-1.767587	0.721567	-0.557065	-0.690907	-0.139169	1.787676
...	...	...	...	...	...	...	...
1082	-1.228186	-1.625129	0.574829	-1.347075	1.774601	-0.779691	1.684234
1291	1.016208	1.283403	-0.720890	-0.000173	-0.484846	-0.847412	0.217238
115	0.605107	0.298064	-0.803949	0.479014	-0.215158	-0.771226	-0.535067
1048	-0.772640	-0.995936	1.305748	-0.220339	-0.149363	-0.655537	1.364504
1554	-0.672642	-0.877221	-0.233611	-0.777232	-0.640296	-0.000907	-0.741951

Figure 4.8: The training dataset after normalization using Z-Score normalization

3. **Creating the model**: The selection of an optimal model and architecture significantly influences the accuracy and performance of predictions. Our model utilizes offline learning, commonly known as batch learning. In this approach, the model is trained using all the available data during the training phase. Once the training is complete, the model is deployed and operates without further learning. It applies the knowledge it has gained during training to make predictions. Furthermore, our model is based on supervised learning, meaning that it requires a labeled training set.

   We started by determining the structure of the deep neural network , including the number of the layers, the number of neurons in each layer and the activation functions. The model ends with a single unit and no activation function .This is a typical setup for scalar regression . The model architecture consists of an input layer, hidden layers, and an output layer. The complexity of the problem determines the number of layers and neurons in the model. Once the structure is determined, the layers are configured by setting the activation function and other parameters. In this case, the ReLU (Rectified Linear Unit) activation function was used.

$Relu(z) = max(0, z)$

ReLU is a simple mathematical function that returns the input value if it is positive or zero, and returns zero for any negative input. In other words, ReLU "rectifies" negative values to zero, while leaving positive values unchanged.

4. **Compile the model**: In the this phase we specify the loss function and optimizer for training the model. The loss function defines how the model's output is compared to the desired output, and the optimizer determines how the model's weights are updated during training to minimize the loss. A typical performance measure for regression problems is the mean absolute error.

   $\sum_{i=1}^{D} |x_i - y_i|$

   It gives an idea of how much error the system typically makes in its predictions, Performance Measures are ways to measure the distance between two vectors: the vector of predictions and the vector of targets.

5. **Train the model**: We split the tarinig data into a training set and a validation set then Fed the training data into the model . During training, the model learns to make predictions by minimizing the defined loss function.

6. **Evaluate the model**: we assessed the performance of the trained model on the validation set using K-fold cross-validation. it consists of splitting the available data into K partitions instantiating K identical models, and training each one on K – 1 partitions while evaluating on the remaining partition. The validation score for the model used is the average of the K validation scores obtained.

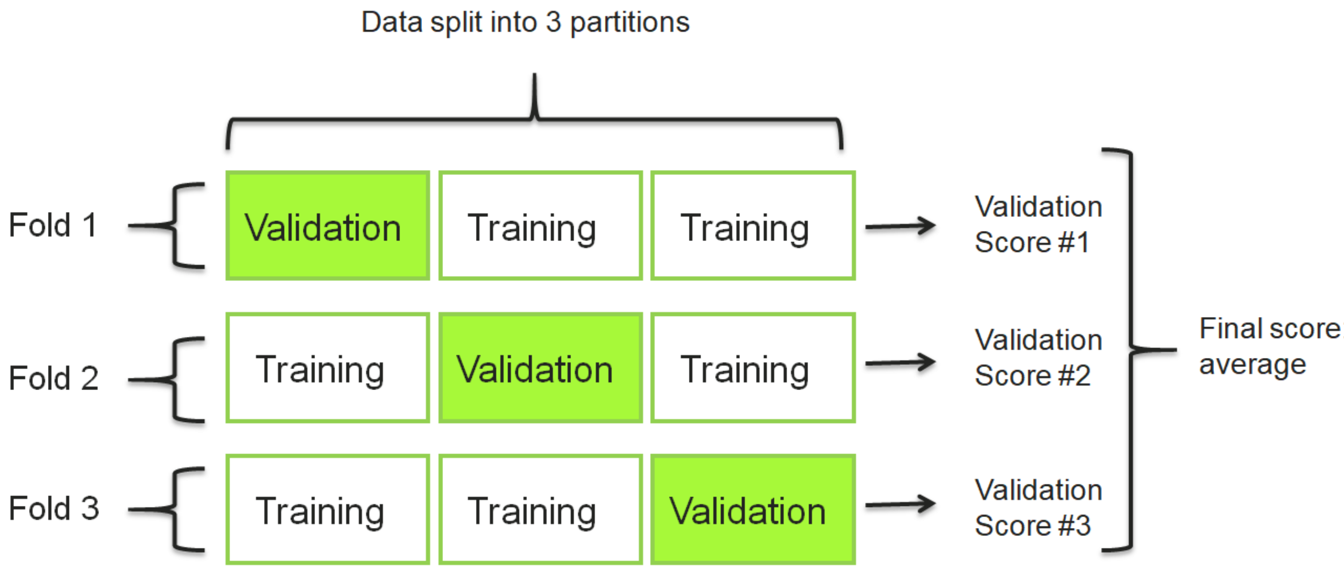

Figure 4.9: K-fold cross-validation

7. **Tuning and optimizing**: By carefully adjusting hyperparameters and experimenting with different combinations, we can fine-tune our model to achieve the best possible performance on the given task and dataset. Hyperparameter optimization is an essential step in machine learning to ensure optimal model performance, such parameter include batch size, and number of epochs.

8. **Predictions**: Once we achieved a satisfactory level of performance with our model, we utilized it to make predictions on new data that was not included in the training set. This allows us to assess the model's generalization and its ability to make accurate predictions on new and unfamiliar data. and to apply the model's learned patterns and insights to real-world scenarios and make accurate predictions.

9. **Save the model**:After the creation of the model, it needs to be saved or exported and deployed to the digital twin. This deployment allows users to access and utilize the services provided by the model.

pseudocode

Algorithm 1 DNN model algorithm

$x_{t}rain, y_{t}rain, x_{t}est, y_{t}est \circ split_{d}ata(data, 0.2)$ ▷ data is divided into training and testing subsets (20% testing)

$normalize\_data()$ ▷ with a mean of 0 and a standard deviation of 1

$model \leftarrow Sequential($

$layers.Dense(20, activation = relu)$

$layers.Dense(4, activation = relu)$

$layers.Dense(1))$

$model.compile()$

$K - foldcross - validation()$

$model.fit(train\_data, train\_targets)$

$model.evaluate(test\_data, test\_targets)$

$results \leftarrow model.predict(test\_data)$ ▷ Testing the model and making predictions

4.5 Conclusion

In this chapter, we have provided an overview of our system architecture, which consists of a hardware component based on IoT, and the software implemented as a desktop application with deep learning capabilities to analyze the data and make intelligent decisions for the irrigation process.

Moving forward, in the next chapter we will explore the implementation details of our system and present the results obtained. Furthermore, we will evaluate the performance and effectiveness of our system . The implementation and results chapter will provide insights into the practicality and usefulness of our proposed approach for irrigation management.

Chapter 5

Implementation and results

5.1 Introduction

In the previous chapters, we covered the theoretical aspects of our project, including the algorithms, approaches, and system architecture, our next step is to follow the application development process that involves a sequence of steps to create a product that satisfies the needs and preferences of its intended users and customers in our case farmers and irrigation engineers.

We will discuss the tools , platforms and softwares that were used to make our system,we will aslo showcase some of the interfaces of our system. Furthermore, we will engage in a comprehensive analysis and discussion of the results obtained from our implementation. This will provide insights into the effectiveness and performance of our system, enabling us to evaluate its overall success and impact.

5.2 Development tools and used platforms

The proposed system is a combination of both hardware and software. The hardware aspect refers to the physical elements of the system that are installed on-site, while the software aspect pertains to the desktop application that runs on a computer.

The following list provides a brief explanation and definition of the utilized tools and platforms.

5.2.1 Hardware:

The hardware part primarily consists of the following components:

ESP8266 microchip

The ESP8266 microchip is designed to be integrated into various IoT applications and projects, and it can be programmed using a variety of programming languages and development environments, including to Arduino IDE, Lua, MicroPython, and others. These programming languages provide flexibility and versatility in developing software for the hardware components. Additionally, the hardware is equipped with built-in support for Wi-Fi connectivity, allowing seamless integration with the internet and facilitating communication with other IoT devices or the software system. This capability makes it well-suited for building IoT devices that require internet connectivity and data exchange. Key features of the ESP8266 include:

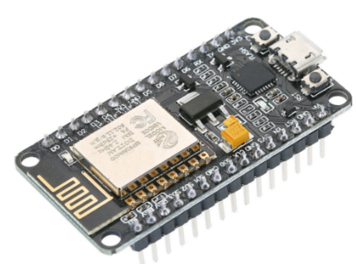

Figure 5.1: ESP8266 microchip

- The ESP8266 is a 32-bit microcontroller with a 80 MHz clock speed.
- has 64 KB of instruction RAM and 96 KB of data RAM. It also has 4 MB of flash memory for storing code and data.
- has 17 GPIO (General Purpose Input/Output) pins, which can be used for interfacing with various sensors and devices.
- SPI, I2C, and UART interfaces for communication with other devices
- Built-in TCP/IP stack for internet connectivity
- The microchip is designed to operate at low power, making it ideal for battery-powered IoT applications.

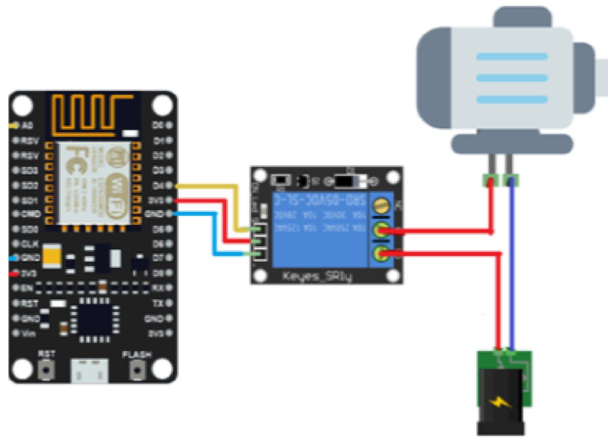

Figure 5.2: ESP8266 microchip connected to a pump via electrical wires

sensors

In order to enable real-time functionality, the system relies on sensors to gather data on climate and soil properties. While a range of sensors can be utilized for this purpose, our work primarily focuses on a humidity and temperature sensor . This choice is driven by the availability of data from the OpenWeatherMap API and the limited accessibility of other types of sensors in our country.

computer

a personal laptop is utilized as a server for hosting the deep learning model API, which is developed using the Django framework. The personal laptop is equipped with the following specifications :

- Ram: 8 GB
- System Type: Windows 10, 64-bit operating system, x64-based processor
- CPU: Intel(R) Core(TM) i5-8300H CPU @ 2.30GHz 2.30 GHz
- Storage: 1 TB
- Graphics Card :NVIDIA GeForce RTX

5.2.2 Software:

Unreal Engine

Unreal Engine is a powerful game engine and development framework created by Epic Games. It is used to develop high-quality video games, virtual reality (VR) experiences, and other interactive applications across a variety of platforms including PCs. It is known for its advanced graphics rendering capabilities, robust physics engine, and flexible scripting and programming languages, allowing developers to create immersive, visually stunning games and applications with ease. It is also widely used in industries beyond gaming, such as architecture, film, and the growing digital twins community.

Figure 5.3: Unreal Engine

Google Colab

Google Colab, or Google Colaboratory, is a cloud-based platform by Google for running and executing Python code . One of the key advantages of Google Colab is its access to GPUs (Graphics Processing Units) and TPUs (Tensor Processing Units), which are powerful hardware accelerators commonly used for deep learning tasks.

Figure 5.4: Unreal Engine

Visual Studio

Visual Studio, developed by Microsoft, is a robust and versatile integrated development environment (IDE) that offers a wide range of tools and features for efficient software development. It provides developers with a set of resources to streamline the entire development process. With Visual Studio, developers can write, debug, and test code efficiently across a wide range of programming languages and platforms. The IDE offers a user-friendly code editor with intelligent code completion, syntax highlighting, and refactoring capabilities, making it easier to write clean and error-free code

Figure 5.5: Unreal Engine

Python

Python is a widely-used programming language valued for its simplicity and readability. It provides a clean syntax that makes it easy to write and understand code. Python's extensive standard library and vast ecosystem of third-party packages make it versatile for a variety of task.

- **Django**:a popular Python web framework, provides built-in capabilities for creating APIs.

- **Tensorflow** :TensorFlow is an open-source machine learning framework developed by Google. It is designed to facilitate the creation of powerful and efficient machine learning models.

- **keras**: a deep learning framework that provides a user-friendly interface for building and training neural networks. It is built on top of other powerful frameworks like TensorFlow

- **Pandas**: an open-source library in Python that provides powerful data manipulation and analysis capabilities. It offers intuitive data structures, such as data frames, that allow for efficient handling and processing of structured data. Pandas simplifies tasks like reading and writing data from various file formats, cleaning and transforming data, and performing complex data operations

Figure 5.6: Unreal Engine

Microsoft Visio

Microsoft Visio is a diagramming and vector graphics application used for creating visual representations of data and information . It is a part of the Microsoft Office suite and is commonly used by businesses, engineers, architects, and other professionals to communicate complex information in a clear and concise manner. With its user-friendly interface and extensive range of templates and tools, Microsoft Visio is a popular choice for creating professional-quality diagrams and illustrations.

Figure 5.7: Microsoft Visio

Firebase

Firebase, developed by Google, is a platform for building mobile and web applications. It provides a comprehensive set of backend services and tools to facilitate app development and scalability. Some of its features include user authentication, real-time database, cloud storage, hosting, and messaging. The real-time database feature allows for synchronized data storage across multiple clients, ensuring seamless real-time updates.

Figure 5.8: Firebase

Arduino IDE

The Arduino IDE (Integrated Development Environment) is a software platform used to programming Arduino boards.
It offers a user-friendly interface that enables developers. The Arduino IDE supports C, C++, and a simplified version of C++ known as the Arduino Programming Language.

Figure 5.9: Pycharm

5.2.3 OpenWeatherMap api

OpenWeatherMap is a an online platform that provides weather data and related services to developers and businesses. It offers APIs (Application Programming Interfaces) that allow developers to access weather data in real-time and use it in their applications or websites.
we can acces weather forcats by making HTTP requests to the OpenWeatherMap API endpoints and parse the JSON responses. Popular programming languages like Python, Java, JavaScript, and PHP all have libraries that can make HTTP requests and handle JSON data.
By using OpenWeatherMap APIs, we can access a wealth of weather data, including current conditions, hourly forecasts, daily forecasts, and historical data for over 200,000 cities worldwide. This data can be used to integrate weather data into applications.
The API provides data for weather parameters such as temperature, humidity, pressure, wind speed and direction among other variables. This data can be used to inform irrigation decisions by providing insights into current and predicted weather patterns it could also be used to estimate evapotranspiration .

Figure 5.10: OpenWeatherMap

5.3 System interfaces

The DT offers farmers multiple interfaces to interact with different services.

5.3.1 The 3D model

A digital twin 3D model is a virtual representation or replica of a physical object, system, or process. It combines the concepts of digital twinning and three-dimensional modeling to create a highly realistic and interactive simulation.

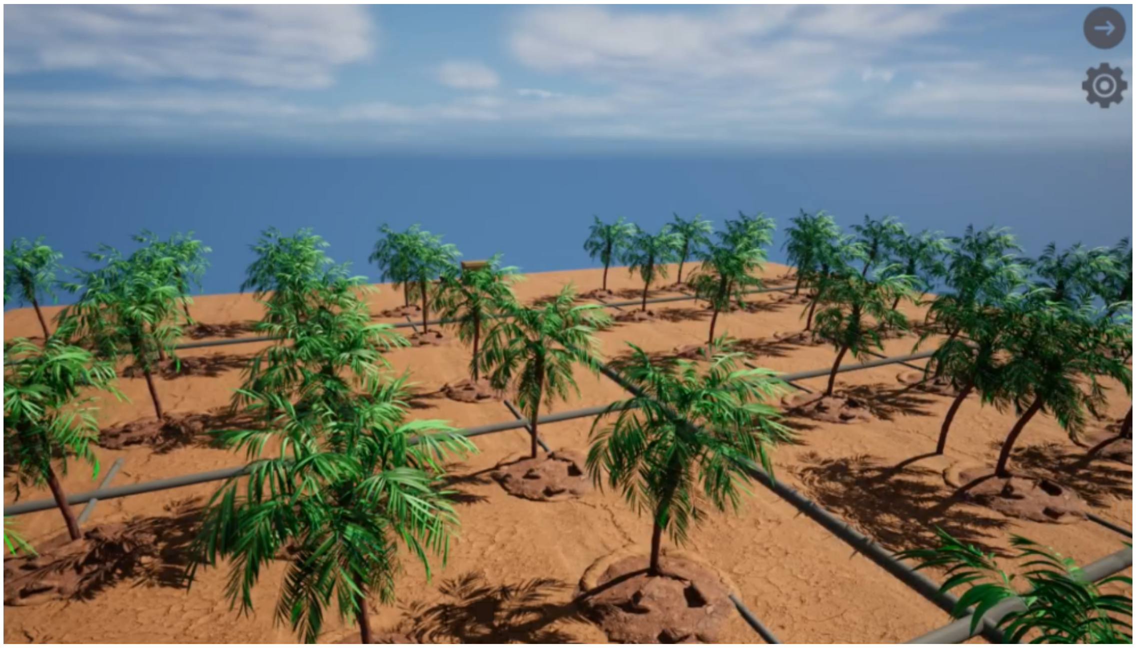

Figure 5.11: The 3D model

5.3.2 Log in/Sign up

Users can access the system's services by logging in with their account credentials. If a user does not have an account, they can sign up for one to create a new account and gain access to the system.

Log in

The login functionality enables users to access the different services offered by the DT. User information, such as email, password, and username, is stored in the cloud for authentication purposes.

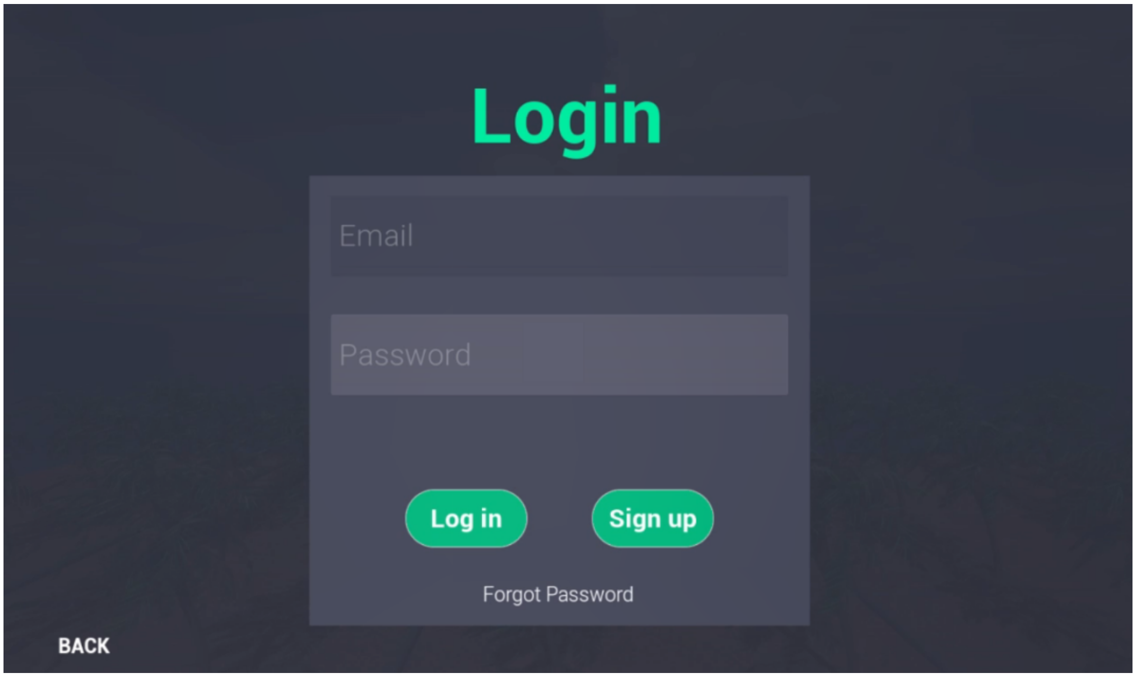

Figure 5.12: Log in interface

Sign up

The sign-up feature allows users to create a new account. During the sign-up process, users provide their email, password, and desired username

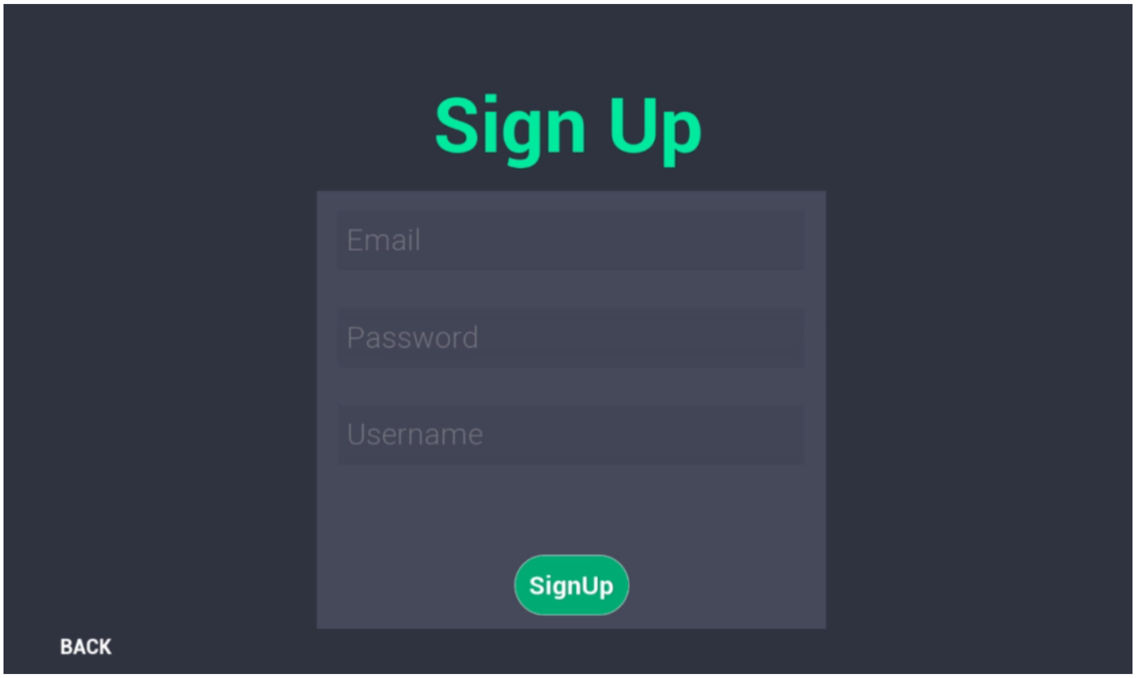

Figure 5.13: Sign up interface

5.3.3 Settings

The settings interface provides farmers with a convenient way to customize and personalize the smart irrigation system according to their specific farm requirements. This interface allows farmers to modify parameters such as location, rooting depth of the crop, soil water holding capacity...etc.

By adjusting these parameters, farmers can fine-tune the system's behavior to match the unique characteristics of their farm, which in turn affects the irrigation scheduling.

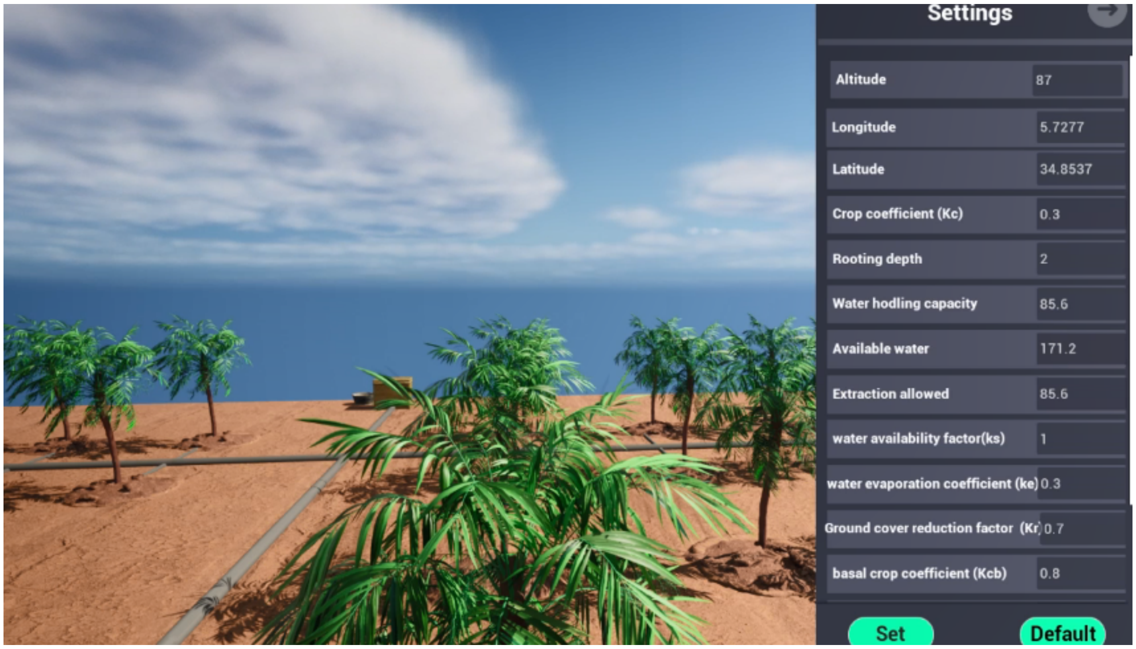

Figure 5.14: Settings interface

5.3.4 Irrigation scheduling

The irrigation scheduling interface provides users with valuable information about the weather conditions, pump state, and areas currently being irrigated. Through this interface, users can access real-time data on temperature, humidity, rainfall, and other relevant weather parameters. They can also monitor the status of the irrigation pump, whether it is turned on or off. Additionally, the interface displays the areas that are currently being irrigated, allowing users to track the progress of the irrigation process . The irrigation scheduling interface also offers farmers the flexibility to choose between manual control and automatic control modes. In the manual control mode, users have the ability to manually turn on or off the irrigation pump. This empowers users to make informed decisions about irrigation based on the system's analysis of the weather conditions. On the other hand, in the automatic control mode, the system takes charge of the pump operation and automatically turns it on when the analysis indicates the need for irrigation. This automated process ensures timely and efficient irrigation based on real-time data, relieving users from the need for constant monitoring and intervention.

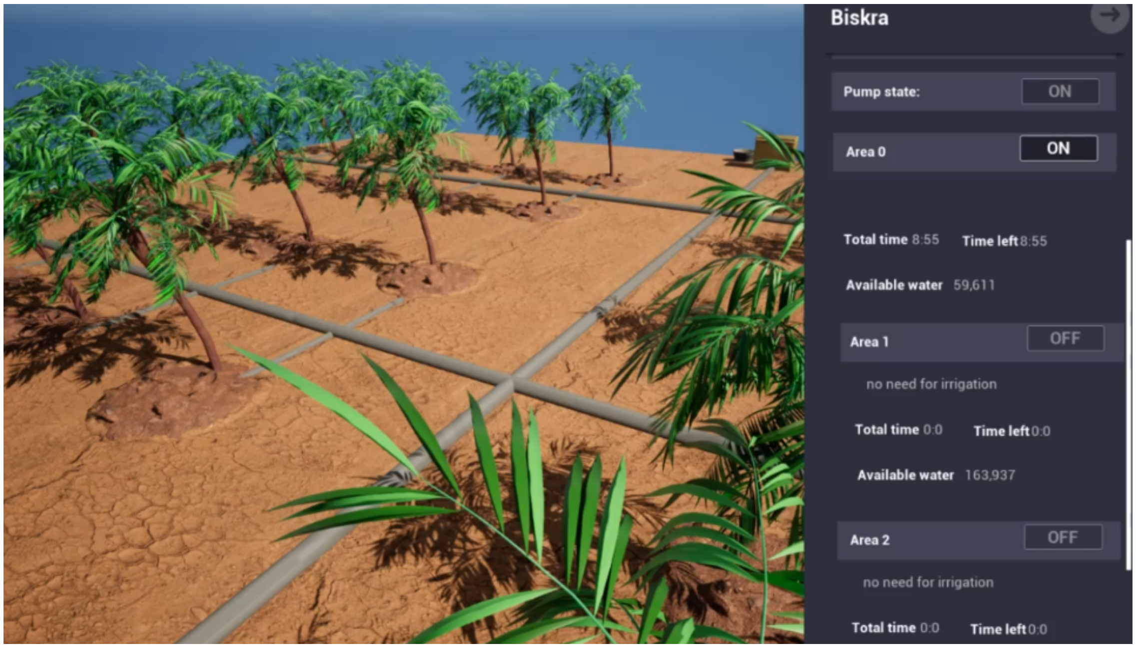

Figure 5.15: Irrigation scheduling interface

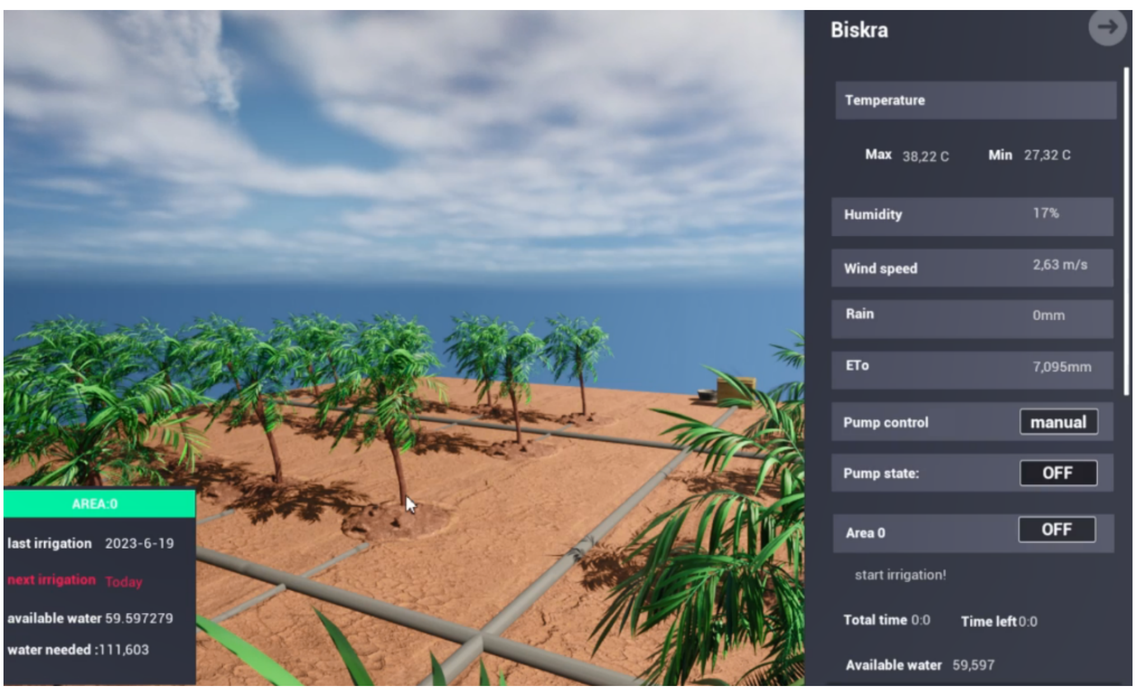

Figure 5.16: scheduling interface

5.4 Obtained results and discussion

The output of the model is a single continuous numerical value that represents the evapotranspiration in a certain day based on the input features.

Figure 5.17: Heatmap of the features

During the training process, our model captured the relationship between the input data (features) and the corresponding evapotranspiration output (targets). The ultimate goal was to accurately define and predict ET. Initially the model exhibited a high mean absolute error (MAE) and loss .

```
Epoch 1/500
80/80 [==============================] - 1s 2ms/step - loss: 3.2214 - mae: 3.2214
Epoch 2/500
80/80 [==============================] - 0s 2ms/step - loss: 0.9745 - mae: 0.9745
Epoch 3/500
80/80 [==============================] - 0s 2ms/step - loss: 0.7285 - mae: 0.7285
Epoch 4/500
```

Figure 5.18: The beginning of the training with the model

However, as the training progressed, the model gradually learned the patterns and relationships within the input data, resulting in a reduction in both the mean absolute error and the loss . This indicates that the model improved its ability to make more accurate predictions .

```
80/80 [==============================] - 0s 2ms/step - loss: 0.2025 - mae: 0.2025
Epoch 497/500
80/80 [==============================] - 0s 2ms/step - loss: 0.2002 - mae: 0.2002
Epoch 498/500
80/80 [==============================] - 0s 2ms/step - loss: 0.2052 - mae: 0.2052
Epoch 499/500
80/80 [==============================] - 0s 2ms/step - loss: 0.2019 - mae: 0.2019
```

Figure 5.19: The ending of the training with the model

We conducted a thorough evaluation of our model by comparing its performance with other regression models and an alternative calculation procedure, considering the limited meteorological parameters available to us. The results were quite promising, as our model outperformed the other methods we tested. In terms of mean absolute error (MAE), our model achieved a score of 0.3, which was the lowest among all the models. The K-neighbors regressor model secured the second position with a MAE of 0.41, followed by the linear regression model with a MAE of 0.42. The decision tree regressor ranked fourth with a MAE of 0.55, and finally, the alternative calculation procedure of the FAO mathematical model had the highest MAE of 1.17. The figure below illustrates the predictions obtained for the same first ten inputs in the testing dataset through the different approaches .

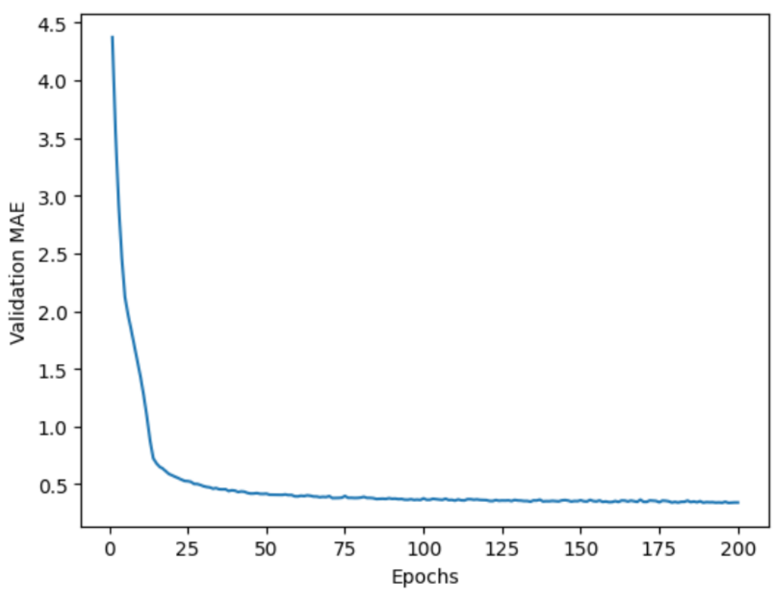

Figure 5.20: The model mean absolute error

/	K-Neighbors regressor	Linear regression	Decision tree regresso	FAO alternative calculation	Our model	Targets
predictions	8.410	8.859	8.480	10.462	8.605	8.880
	1.746	1.420	2.330	2.280	1.816	1.760
	2.389	2.139	1.930	2.754	2.112	2.180
	2.446	2.990	2.639	3.777	2.630	2.519
	5.830	6.065	6.950	5.783	6.117	5.030
	3.603	3.627	4.840	4.622	3.774	3.960
	8.406	8.268	7.560	8.634	8.029	8.129
	4.999	5.217	4.360	6.751	4.762	5.589
	7.303	7.984	8.400	8.554	7.593	7.260
	2.699	2.664	2.959	4.182	2.750	2.820
Mae	0.41	0.42	0.55	1.17	0.3	

Table 5.1: Results comparison

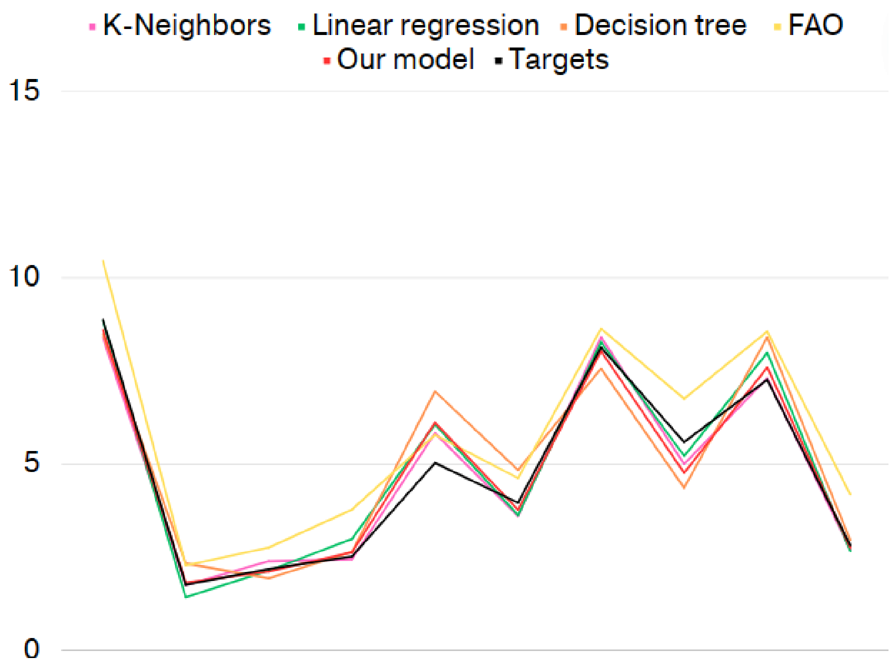

Figure 5.21: Results comparison graph

5.5 Conclusion

In conclusion, our model demonstrated superior performance, surpassing the alternative calculation procedure with the lowest Mean Absolute Error (MAE) of 0.3 among all models. This showcases the power of deep learning in achieving accurate predictions. Our system was thoughtfully designed, incorporating an optimal combination of hardware and software tools. The effectiveness of our system and architecture played a huge role in successfully achieving our goals.

Chapter 6

Conclusion and Perspectives

6.1 Conclusion

The agriculture industry is gradually adopting digital technologies, but it still lags behind other industries such as healthcare, manufacturing, mining, automotive, and energy. Despite this, our project has proven that incorporating digital twins ,deep learning and IoT technology into smart irrigation can yield promising results. Our innovative approach allowed for real time monitoring and control of the irrigation system while accurately predicting plant water requirements. This precision resulted in reduced water wastage and improved water use efficiency, especially in regions facing water scarcity. Furthermore, automating the irrigation process with our system significantly reduced the need for manual labor, ultimately reducing production costs. This feature makes our smart irrigation system an attractive option for farmers who aim to increase their yield while minimizing expenses.

In summary, our project demonstrates that smart irrigation can revolutionize the agriculture industry. Therefore, the integration of digital twins and IoT can provide an efficient and sustainable smart irrigation solution for agriculture.

6.2 Perspectives

As part of our future work, we aim to enhance our system with additional features. One of these features is the installation of weather stations in the field to help in collecting weather data. By providing the digital twin with more data from the weather stations, we aim to increase the system's efficiency and accuracy in predicting the required amount of water for irrigation, which will help us avoid the issues we have faced in the past due to a shortage of weather data.

Another feature we plan to incorporate is the monitoring of water quality used in the irrigation process. This addition will significantly improve crop health .we are also exploring the possibility of distributing fertilizers through the irrigation system This will increase productivity by ensuring that the crops receive the right amount of nutrients .

Overall, these planned developments aim to improve the effectiveness and sustainability of our smart irrigation system, providing farmers with more advanced tools to manage their irrigation systems with greater precision and efficiency while reducing the manual labor required.

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