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Smart IoT and machine learning-based solutions for fertilization management system in the arid area

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Table of contents

Liste of figures

Liste of tables

Abstract

The agricultural sector is one of the major consumers of Earth's resources. The rapid growth in demand for food, driven by the expanding population in the MENA area, poses significant challenges.

However, climate change and poor soil fertility are factors that contribute to reduced crop yields. To address this issue, our plan is to integrate the Internet of Things (IoT) and machine learning (ML) algorithms to optimize fertilization management. The proposed system aims to ensure efficient fertilization planning by assessing soil nutrients and monitoring weather conditions in arid areas, thereby increasing productivity.

The intelligent system will schedule fertilization based on the specific needs of the plants while considering weather conditions and maintaining desired soil moisture levels.

This innovative approach holds great potential for enhancing agricultural outcomes.

Keywords : Internet of Things (IoT), Machine learning, Fertilization management, Agriculture 4.0.

Résumé

Le secteur agricole est l'un des principaux consommateurs des ressources de la Terre. La croissance rapide de la demande alimentaire, tirée par l'expansion démographique dans la région MENA, pose des défis importants. Cependant, le changement climatique et la faible fertilité des sols sont des facteurs qui contribuent à la baisse des rendements des cultures. Pour résoudre ce problème, notre plan est d'intégrer les algorithmes de l'Internet des objets (IoT) et de l'apprentissage automatique (ML) pour optimiser la gestion de la fertilisation.

Le système proposé vise à assurer une planification efficace de la fertilisation en évaluant les éléments nutritifs du sol et en surveillant les conditions météorologiques dans les zones arides, augmentant ainsi la productivité.

Le système intelligent programmera la fertilisation en fonction des besoins spécifiques des plantes tout en tenant compte des conditions météorologiques et en maintenant les niveaux d'humidité du sol souhaités. Cette approche innovante recèle un grand potentiel pour améliorer les résultats agricoles.

Mots clés :Internet des Objets (IoT),l'apprentissage automatique,Gestion de la fertilisation, Agriculture 4.0.

General Introduction

Context

Concerns for food security have arisen due to the growing human population and diminishing natural resources. In response, efforts have been made to enhance agricultural productivity and ensure sustainability. The concept of smart farming utilizes the Internet of Things (IoT) and Machine Learning to enable data-driven agriculture, replacing traditional practices with automated management systems and advanced technologies.

By integrating IoT and Information and Communication Technology (ICT), smart agriculture aims to optimize management models and production technologies, ultimately leading to reduced consumption of agricultural resources and increased production, fostering long-term sustainability.

Problematic and objectives

Smart and precision agriculture play a crucial role in achieving sustainable development in agriculture by optimizing resource utilization and increasing productivity. In this context, efficient fertilizer application is vital for supporting sustainable practices, as it conserves resources and prevents soil degradation.

Inadequate nutrient management poses concerns such as low productivity and soil deterioration. However, traditional soil chemical analysis methods for assessing fertility levels are expensive, time-consuming, and complex. To address this, there is a need for user-friendly solutions that enable farmers to assess fertility levels easily in the context of smart agriculture.

Fortunately, advancements in sensing and machine learning technologies offer promising opportunities to overcome the limitations of existing soil fertility assessment methods.

Outline

Our work is structured as follows :

In the 1st chapter, we have presented the state of the art of Smart Farming. Starting by introducing the traditional farming concept and defining the using techniques in smart farming, such as IoT, Machine learning, and Deep learning. We have also discussed related work concerning this concept.

In the 2nd chapter, we have defined the fertilization practice in agriculture as well as discussed some related works.

While the 3rd chapter detailed the proposed method, and the architecture of the system and explained our contribution. We have presented our proposal which is an automatic fertilization system.

Implementation and results are discussed in the 4th chapter. We present the development tools and frameworks, with screenshots of the system (the web application). Then we discuss and analyze the obtained results.

Lastly, Chapter 5 concludes the work and mentioned some future work.

Chapitre I

Technics used in smart agriculture

Technics used in smart agriculture

I.1 Introduction

Agriculture has been a mainstay of human life for thousands of years. However, agricultural production methods have changed considerably over time. Traditional farming practices have long been manual, using simple tools to plow fields and cultivate crops.

With the advent of technology, agricultural production methods have evolved, including the use of machinery to plant and harvest crops used to monitor agricultural areas and crops, furthermore to control the quantities of water as well as fertilizers needed in addition to identify crops that are in line with the quality of the soil.

Modern agriculture is a recent development that has been driven by the need to feed a growing world population while conserving natural resources and reducing environmental impact on the use of the innovative technologies such as artificial intelligence, the Internet of things, data collection and analysis, and the use of images taken by drones or satellites.

I.2 Agriculture

I.2.1 Definition

Agriculture [30] comprises a range of human endeavors centered around cultivating land, rearing animals, and generating essential resources to fulfill human requirements for sustenance, textiles, energy, medicine, and various other beneficial goods. It encompasses the management of soil, water, and ecosystems, along with the implementation of practices that ensure their sustainable use. Additionally, agriculture encompasses the establishment of efficient marketing and distribution systems to facilitate the trade of agricultural products.

FIGURE I.1 – Traditional Farming [30]

I.2.2 The purposes of agriculture

According to [23] and [27], The purpose of agriculture may vary according to the needs and priorities of different communities and regions of the world. Some of the common goals of agriculture include :

- Providing nutritious and affordable food to meet the growing needs of the global population.
- Supporting the economic development of rural communities.
- Protecting the environment by practicing sustainable agriculture and limiting negative impacts on ecosystems.
- Reduce poverty by increasing farmers' incomes and creating jobs in rural areas.
- Provide sufficient, nutritious, quality food for the world's growing population.
- Ensure food security for all, reducing poverty and improving access to food.
- Protect natural resources such as water, soil, and biodiversity through sustainable agriculture that does not compromise future generations.
- Promote resilience and adaptation of food systems to climate change, disease and economic disruption.
- Contribute to rural economic growth and poverty reduction by providing stable employment and income.

It can vary according to the needs and priorities of each society. According to the FAO [FAO 2021] (Food and Agriculture Organization of the United Nations), the main objectives of agriculture are :

agriculture must produce enough food to meet the needs of the population while ensuring that the food is safe and nutritious.

Agriculture can provide livelihoods and employment in rural areas, thereby helping to reduce poverty.

Agriculture can help improve infrastructure and services in rural areas, including providing health services, education, and access to clean water.

agriculture must adopt sustainable practices to minimize negative impacts on soil, water,and biodiversity.

Agriculture can help stimulate economic growth by providing raw materials for industries, creating jobs, and stimulating rural development.

I.2.3 Types of Agriculture

Here are some common types of agriculture that can be found in current publications :

Conventional agriculture : agriculture that uses traditional farming practices and chemical inputs to increase yields. [37]

Organic agriculture : agriculture that focuses on the use of sustainable and environmentally friendly farming practices to maximize yields. [37]

Precision agriculture : agriculture that uses technology to optimize farming practices, including soil management, water management, crop management, and input management. [44]

Urban agriculture : agriculture that takes place in urban areas to meet the growing demand for fresh, local food. [25]

Regenerative agriculture : agriculture that focuses on soil restoration and regeneration of natural ecosystems while increasing yields. [54]

Biodynamic agriculture : agriculture that focuses on the use of natural preparations and planetary calendars to regenerate soils and plants. [54]

Agroforestry : agriculture that integrates trees into crops to improve soil quality, biodiversity and productivity. [48]

Conservation agriculture : agriculture that focuses on protecting soils and natural resources by reducing soil disturbance and using sustainable farming practices.

Subsistence agriculture : agriculture that provides basic food for local communities and families, often practiced in developing countries. [2]

Mountain agriculture : agriculture practiced in high-altitude areas that faces challenges such as poor soils and extreme weather conditions. [4]

I.3 Smart Agriculture

I.3.1 Definition

Smart agriculture is a holistic farming approach that leverages digital technologies to maximize crop yields while minimizing harm to the environment. It integrates the expertise and wisdom of farmers with advanced tools such as geographic information systems, climate modeling, remote sensing, and sensors to deliver precise data on weather conditions, soil quality, and crop health. The primary objective is to enhance the adaptability of farms to climate change and mitigate risks for farmers by providing real-time information to support well-informed decision-making. [24]

FIGURE I.2 – A Prototype of a Smart Farming [24]

I.4 Smart agriculture techniques

I.4.1 Internet of Things

I.4.1.1 Definition

The Internet of Things (IOT) is a network of connections and communications between computing devices, physical things, mechanical and digital tools, and people that allows data to be transmitted across a communication network without requiring human-to-human or human-to-computer contact. An IOT platform may be applied in a variety of domain sectors, such as healthcare, transportation, agriculture, energy production and distribution, among others, that require objects to connect with each other through the Internet in order to carry out business projects intelligently and without human involvement. [5]

I.4.1.2 Essentials of IoT

The Internet of Things (IoT) refers to a network comprising interconnected devices capable of gathering and sharing data about their operations and surrounding environment. Various devices equipped with two-way data links, such as sensors, thermostats, cars, biometric devices, and luminaires, can be part of the IoT ecosystem. [8]

The IoT system comprises three fundamental levels : the device layer, network layer, and platform layer. The device layer consists of the interconnected ”things” involved in the IoT. The network layer encompasses the necessary infrastructure for connecting devices to one another and to the platform layer. An IoT system comprises four essential components, as illustrated in Figure I.3.

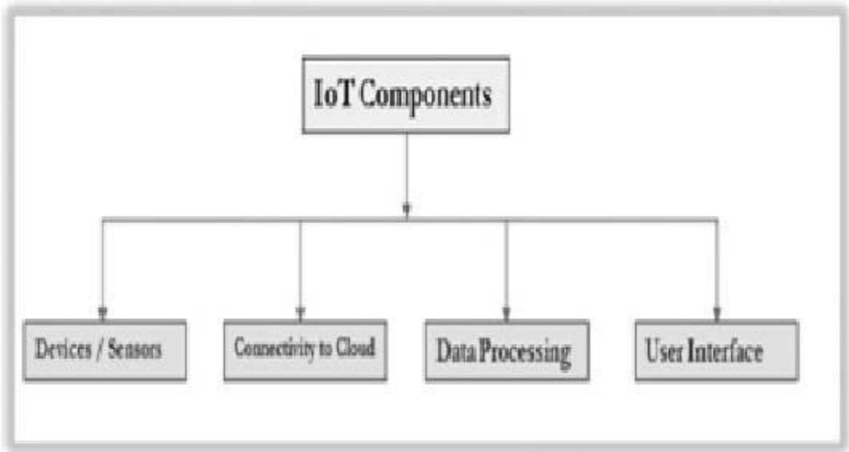

FIGURE I.3 – Four Basic Components of IOT [8]

Sensors/Devices : Collecting real-time data from the environment requires the use of sensors and devices. This data can come in various forms and complexities, ranging from basic temperature readings to intricate video streams. A single device may be equipped with multiple sensors that serve a broader purpose beyond simple sensing. Take, for instance, a smartphone, which includes diverse sensors like GPS and a camera. Despite having these capabilities, the smartphone itself is unable to perceive these features.

Data Transmission : The data collected from sensors is transmitted to a cloud infrastructure for processing and storage. To establish the connection between the sensors and the cloud, various communication methods can be employed. These methods include mobile or satellite networks, Bluetooth, Wi-Fi, WAN, and several others.

Data Processing : Once the data is captured and transmitted to the cloud, the software comes into play to process the information. This processing may involve simple tasks like monitoring temperature or readings from devices such as air conditioners or heaters. However, there are more challenging tasks that the software can handle, such as object recognition using computer vision on video streams.

User Interface : The end-user needs to have access to the information, which can be achieved through methods like sending email or text notifications or setting up alerts on their mobile devices. In some cases, an interface that actively monitors the user's IoT devices may be necessary. For instance, if the user has a camera installed in their home, they would like to access video recordings and live streams through a web server. [8]

I.4.1.3 Internet of Things Characteristics

The following are the IoT's basic characteristics [33] :

Interconnectivity : With the IOT, anything may be connected to the global infrastructure of information and communication.

Things-related services : Under the limitations of things, such as privacy protection and semantic coherence between physical things and their associated virtual things, the IOT is capable of offering things-related services. Both the technology in the physical world and the information world will alter in order to deliver thing-related services within the limitations of things.

Heterogeneity : The IOT devices are heterogeneous since they are built on many hardware platforms and networks. Using multiple networks, they may communicate with other gadgets or service platforms.

Dynamic changes : Dynamically changing states of gadgets include sleeping and waking up, being connected or disconnected, and their context, which includes location and speed. Also, the number of devices may fluctuate.

Enormous scale : There will be many more gadgets than there are currently linked to the Internet that will need to be monitored and coordinated with one another.

Safety : We must remember safety even while we profit from the IOT. We must design for safety since we are both the LOT's producers and users. This covers the security of our private information as well as the security of our physical safety. In order to secure endpoints, networks, and the data passing across them all, a scalable security paradigm must be developed.

Connectivity : Network compatibility and accessibility are made possible via connectivity. Accessibility involves joining a network, whereas compatibility gives everyone the same capacity to use and create data.

I.4.1.4 Internet of Things Architecture

Five layers make up the IOT's core architecture. The first layer is called The Perception layer or the 'Device Layer' It consists of tangible items and sensing technology. This layer primarily deals with the identification and gathering of information about specific objects via sensing devices.

The information gathered is subsequently given to the Network layer. The second layer is the Network layer whose duty is to safely send data from sensor devices to the Middleware layer. The third layer is the Middleware Layer This includes IOT devices that implement various types of services. Only other devices that use the same service type as the connected device can connect to it and communicate with it. This layer has a connection to the database and is in charge of managing the services.

It obtains the knowledge from the Network layer adds it to the database, etc. It processes data, does ubiquitous computation, and then automatically decides to depend on the outcomes. The fourth layer is the Application Layer which manages the program globally depending on the data processed by the object in the Middleware layer.

Finally, the fifth layer is the Business Layer which is in charge of managing the whole IoT system, including the apps and services. It bases its business models on the information obtained from the Application layer. This layer aids in deciding on future courses of action and corporate strategy. IoT five-layered architecture is shown in Figure I.4 [33].

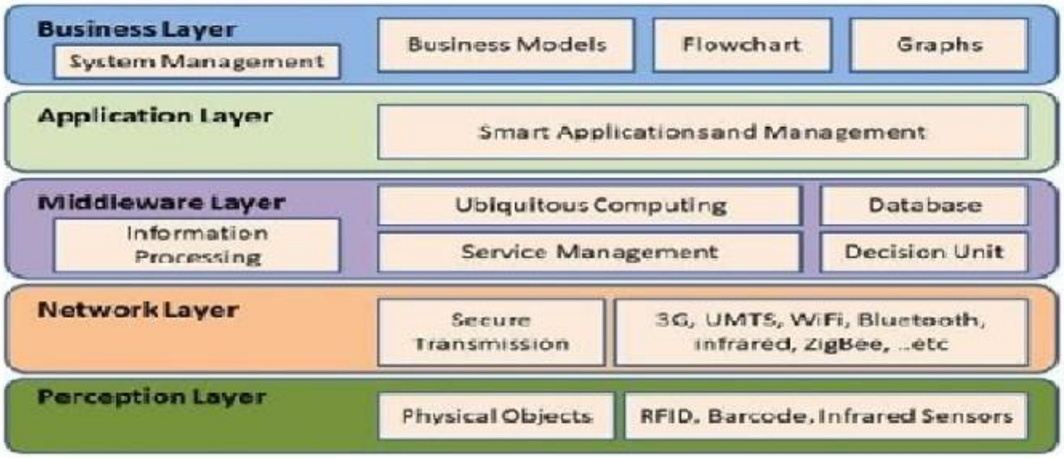

FIGURE I.4 – IOT Five-Layers Architecture [33]

I.4.1.5 Internet of Smart Agriculture

Greenhouses : Manage microclimates to increase the quantity and quality of fruits and vegetables produced there.

Compost : To avoid fungus and other microbial pollutants, humidity and temperature levels in alfalfa, hay, straw, etc. are controlled.

Animal farming and tracking : Locating and identifying animals in large stables or on open pastures, research on agricultural ventilation and air quality, as well as dangerous gas detection from feces.

Offspring Care : Monitoring the offspring's growth circumstances in animal farms to guarantee its survival and well-being.

field Monitoring : By improving monitoring, acquiring correct continuing data, and managing the agricultural fields, including improved management of fertilizer, energy, and watering, spoilage and crop waste may be reduced [33].

I.4.2 Artificial Intelligence

I.4.2.1 Definition

AI encompasses a range of methods used to develop intelligent machines capable of tackling intricate problems and executing tasks typically associated with human intelligence. Various categories of AI systems exist, such as machine learning systems, artificial neural networks, expert systems, autonomous robots, and multi-agent systems. The overarching objective of AI is to create systems that possess not only problem-solving capabilities but also the capacity to learn and adapt in response to their surroundings [58].

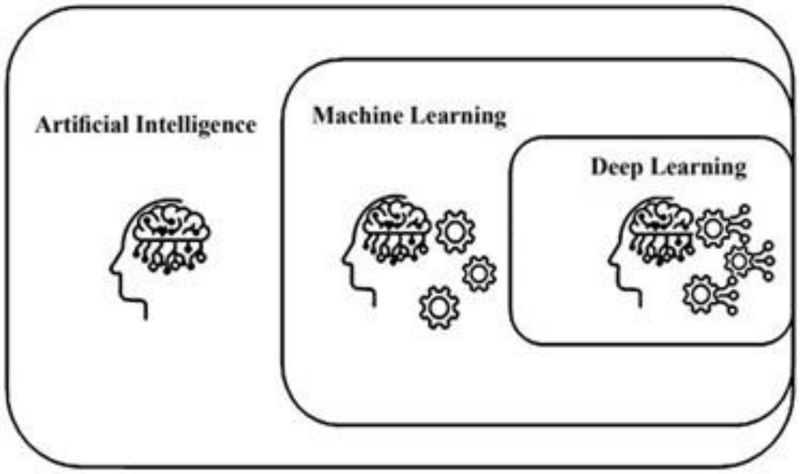

FIGURE I.5 – Connection of AI, ML, and DL [49]

I.4.2.2 Applications of AI in Agriculture

Artificial intelligence has a wide range of uses and is quite versatile in the agricultural sector. A great deal of information on temperature, precipitation, solar radiation, and wind speed is provided by agricultural fields, which may be evaluated to our advantage when it comes to harvesting from them. The nicest thing about applying artificial intelligence to agriculture is that it won't replace farmers' work ; instead, it will enable them to enhance the way they collect crops in the fields. Artificial intelligence finds extensive applications in the field of agriculture, some notable applications include [50] :

Artificial Intelligence Agriculture Bots : AI-powered agricultural bots have the capability to support farmers in discovering more efficient harvesting techniques for various types of agricultural fields, while also aiding in weed control. These bots can significantly enhance agricultural operations by enabling faster and higher-volume crop harvesting compared to human laborers. Consequently, farmers can increase their crop yield within shorter timeframes. Additionally, by integrating computer vision technology, these bots can identify crop diseases and apply pesticides at the appropriate times, contributing to improved crop health and protection.

Monitoring crop and soil health : Artificial Intelligence can be effectively harnessed to monitor and detect defects and nutrient deficiencies in the soil. By leveraging computer vision's image recognition capabilities, sophisticated systems can be created to identify crop defects. Furthermore, deep learning applications can analyze flora patterns in agriculture, enabling a comprehensive understanding of various crop aspects, such as defects, plant pests, and diseases. The implementation of these AI-enabled applications facilitates a more precise assessment of crop health and aids in the identification of potential issues affecting plant growth and productivity.

Agricultural Expert System : Expert systems are highly beneficial for farmers as they offer valuable guidance and expertise. By design, expert systems are equipped with a repository of expert-level knowledge obtained from diverse domain specialists. This knowledge is derived from various real-world situations and best practices employed by experts in the field. As a result, expert systems serve as a valuable resource, providing farmers with accurate and insightful recommendations tailored to specific contexts and scenarios.

Forecasted Weather data : By leveraging advanced Artificial Intelligence techniques, farmers can stay updated on sudden weather changes, enabling them to safeguard their crops from potential hazards. The system's analysis provides valuable insights that assist farmers in taking necessary precautions (need to think from here).

AI with Drones : Farmers can enhance agricultural yields and reduce costs with the assistance of drone technology. Prior to deployment, users can plan the drone's route, and once in the field, the airborne technology can be activated to perform various tasks. This includes capturing live crop imagery data, applying pesticides for disease diagnosis on specific crops, and more. Drones can be programmed to perform specific agricultural jobs, such as regular field inspections to identify damaged or infected crops. Equipped with image technologies, the drone's cameras aid in overall field management by providing insights into the crop's water, fertilizer, herbicide needs, and more. Utilizing machine learning, the collected data on crop and soil conditions can be analyzed to optimize agricultural yield through a comprehensive understanding of crop requirements.

Indoor Harvesting with AI : In recent times, indoor harvesting has gained popularity as a method to cultivate various crops in a limited space by providing artificial lighting tailored to their needs. The integration of Artificial Intelligence (AI) simplifies and streamlines the indoor harvesting process by analyzing all aspects within a controlled environment and automating the harvesting process, whether it involves hydroponics or aquaponics.

I.4.2.3 Advantages of AI in Agriculture

Artificial Intelligence (AI) offers numerous advantages across various fields, including agriculture. In the context of agriculture, the following benefits of AI have been discussed :

- AI provides more efficient methods for crop production, harvesting, and market analysis, enabling farmers to make informed decisions about selling essential crops based on market values.
- AI can be utilized to detect crop defects and enhance the yield of healthy crops, leading to improved harvest outcomes.
- The increased utilization of AI-based technologies strengthens agricultural businesses and markets, allowing them to operate more efficiently.
- AI can contribute to the improvement of crop management practices and harvesting techniques, optimizing agricultural processes.
- AI-based solutions offer opportunities to address traditional challenges faced by farmers, such as climate change, pest infestations, and weed control, ultimately enhancing the productivity of food crops [50].

I.4.3 Machine Learning

Machine learning (ML) is a field of study focused on computer algorithms that have the ability to learn and discover patterns through data-driven approaches. The primary goal of ML is to accurately and efficiently predict new items. It draws upon various theories and methods from computer science, including statistics, probability, and optimization. As a result, the data collected for ML undergoes preprocessing and analysis to enhance the accuracy of the algorithms [28].

I.4.3.1 Learning Paradigms

As suggested in [28], ML is well-suited for accomplishing certain types of tasks that demand specific learning mechanisms based on the given inputs and desired outcomes.

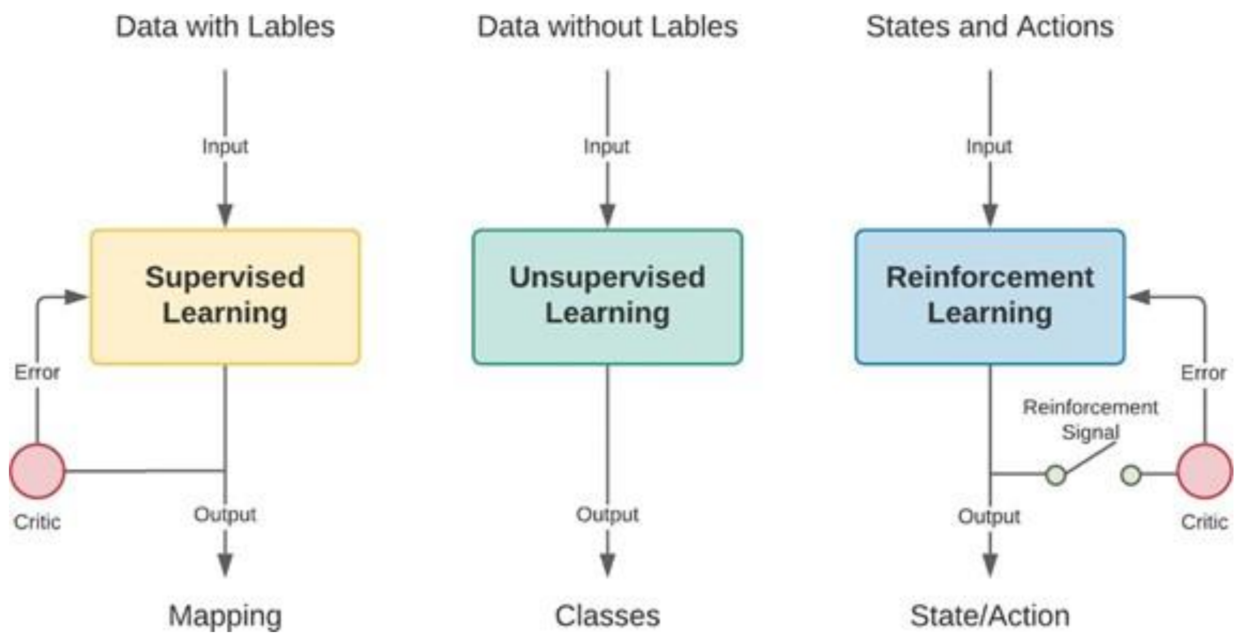

FIGURE I.6 – Common learning paradigms in ML [28]

Supervised learning : Supervised learning is a fundamental concept in machine learning where an algorithm learns to map input data to corresponding output labels based on a labeled training dataset. By analyzing patterns and relationships in the training data, the algorithm generalizes from known examples to make accurate predictions on unseen instances. It is widely used in various applications such as image recognition, natural language processing, and recommendation systems. The goal is to learn a mapping function that can predict output labels for new data points, enabling automated decision-making and pattern recognition based on known examples.

Unsupervised Learning : Unsupervised learning differs from supervised learning in that the training samples lack labels, and predictions are made on unseen data points. This learning method is commonly employed in tasks such as clustering and dimensionality reduction. Clustering aims to group numerous items into homogeneous subgroups or clusters, such as customer segmentation. Dimensionality reduction, on the other hand, focuses on reducing the complexity of an item by representing it with lower dimensions while retaining crucial information, such as visualizing big data.

Reinforcement Learning : Reinforcement learning involves an iterative process where training and testing phases work in conjunction to achieve desired outcomes. Within a predefined set of rules, the machine learning algorithm interacts with the observed environment. Predictions are made in the form of actions, which are subsequently assessed through rewards or penalties. The effectiveness of this model depends on maximizing rewards and minimizing penalties. Reinforcement learning finds frequent application in real-time scenarios such as robot navigation, real-time decision-making, and skill acquisition [28].

I.4.4 Deep learning

I.4.4.1 Definition

Deep learning is a specific subset of machine learning that revolutionizes the process of acquiring meaningful representations from data. Unlike other approaches, deep learning emphasizes learning multiple layers of progressively insightful representations. The term ”deep” does not signify a deeper comprehension achieved through this methodology, but rather denotes the notion of sequential layers of representations. The depth of a model refers to the number of contributing layers in its representation of the data. Alternatively, the field could have been named layered representations learning or hierarchical representations learning. In contemporary deep learning, models often consist of numerous successive layers, ranging from tens to hundreds, all of which are autonomously learned through exposure to training data. In contrast, other machine learning methods typically focus on learning only one or two layers of data representations, earning them the moniker of shallow learning [9].

Machine Learning	Deep Learning
Small amount of data is needed to provide accuracy	Large amount of data is needed for training.
It requires low system specifications.	It requires high system specifications.
The given problem is divided into multiple tasks and each task is solved independently. Finally, the results are combined.	The given problem is solved fully as a node tonode problem.
The time needed for training the model is low.	The time needed for training the model is high.
But for testing the data with the model the time required is high.	Here, less time is needed to test the data with the model.

TABLE I.1 – Differences between Machine Learning and Deep Learning [36]

I.4.4.2 Common Deep Learning Algorithms

Within this section, we provide a concise overview of the primary Deep Learning algorithms that are frequently employed [14] :

Convolutional Neural-Network (CNN)

CNN is a group of deep, feed-forward artificial neural networks (ANNs) that assess visual data rather than recurrent ones. Neurons that make up these networks contain biases and weights that can be learned. Each neuron receives a few inputs before producing a dot product. A CNN takes a two-dimensional input, such as an image or speech signal, and uses a series of hidden layers to output characteristics. For feature extraction, the structure consists of convolutional and pooling layers, and both of these linked layers function as classifiers. Moreover, CNN may be employed in agricultural fields such as fruit counting, plant recognition, weed identification, crop and plant leaf disease detection, and land cover categorization.

Recurrent Neural Networks (RNN)

RNNs are a network of nodes that resemble neurons and are built-in steps or ”layers.” Every node has a directed connection or a one-side connection to every other node in the layer below it. This connection is used in many agricultural fields, including soil cover classification, crop yield estimation, weather prediction, soil moisture content estimation, and animal research, among others. RNN is ideally suited to handle time series data.

Generative Adversarial Networks (GAN)

Essentially, GANs consist of a framework made up of two competing neural network models. These models may be used to examine, understand, and imitate data from the training dataset. Moreover, GAN has frequently been used to improve datasets. These two neural networks, one of which is generating and the other of which is discriminative, cooperate to provide high-quality data. Although GAN is a different type of neural network, it has been found to be very effective in image processing.

Long- Short Term Memory (LSTM)

Of the several deep learning algorithms, this one is the most common. It can handle individual data points (such as images) as well as entire data successions (for example, voice or video). They are appropriate for categorizing and basing forecasts on time series data. Crop type categorization, crop yield forecasting, and weather forecasting are all employed in agricultural applications of LSTM. LSTM may also be used for voice and handwriting recognition, among other things [14].

I.4.4.3 Deep Learning in Agriculture

The application of deep learning in agriculture entails utilizing machine learning algorithms to analyze extensive agricultural data, including aerial images, sensor readings, and weather data. Through deep learning models, predictions on crop yields, identification of plant diseases, and optimization of resource utilization like water and fertilizer can be made. Furthermore, deep learning techniques can enhance the quality of satellite and drone images for efficient monitoring of crop conditions [35].

I.4.5 Blockchain

I.4.5.1 Definition

The term “blockchain” refers to the way BC stores transaction data in “blocks” that are linked together to form a “chain.” The chain grows as the number of transactions increases. Since every entry is stored as a block on a chain, the care you receive is added to your personal ledger. At its core, blockchain is a distributed system recording and storing transaction records.

In a blockchain system, there is no central authority. Instead, transaction records are stored and distributed across all network participants. Rather than having a centrally located database that manages records, the database is distributed to the networks, and transactions are kept secure via cryptography [40].

I.4.5.2 Blockchain in agriculture

Crop insurance, traceability, smart farming, the food supply chain, managing weather emergencies, and the exchange of agricultural goods are all improved by blockchain technology [40].

Traceability : The most common application of blockchain in agriculture is here. The barcode and RFID tracking technologies are distinct from the blockchain tracking technology. Customers can confirm the route taken by their goods, tracking it from farm to table, thanks to blockchain technology. It makes information traceable across the food supply chain, enhancing food safety. In a couple of seconds, it also offers information on when a commodity was picked. Since the information stored on the blockchain cannot be changed, it may offer trustworthy information and is unforgeable [40].

Crop Insurance : Food security may be threatened by weather conditions that affect agricultural productivity. Agricultural insurance programs are frequently used to control risks associated with the weather. Farmers may insure their crops and file claims for agricultural damage using smart contracts. Weather abnormalities can produce losses that are difficult to accurately assess, which opens the door for fraud. Smart contracts protect a farmer’s harvest and allow for damage claims. The damage claim can be triggered by changes in weather conditions that fulfill specific requirements using customized smart blockchain contracts [40].

Food Supply Chain : The production and distribution of products and services from suppliers to clients are referred to as the supply chain. To guarantee consumer loyalty and confidence, it is always practical to disclose information about the sources of food goods. Food sellers do not have a reliable method of confirming that all items were grown under the required circumstances with existing supply chains. A traceable and transparent system is what blockchain technology in the food supply chain aims to achieve. Using real-time tracking technology, blockchain technology enables the tracking of people and things across the supply chain. Because of this, retail behemoths like Walmart turn to blockchain to track the origins of their food supplies. The amount of time needed to trace the source of food has been dramatically reduced to only 2 seconds. The use of blockchain technology in the food supply chain is still in its infancy [40].

Transactions : Blockchain technology enables direct network transactions between people and companies without the need for a middleman. The use of cryptocurrencies in the exchange of agricultural goods will significantly lower transaction costs. Each user has access to transaction data and a copy of the ledger. In these transaction records, the product information is tracked and documented. Agricultural producers may set pricing more effectively and efficiently thanks to blockchain technology. As a result, they may adjust their output to meet the market's demand for their goods [40].

Smart Agriculture : The term "smart agriculture" refers to the integration of cutting-edge technology with conventional farming in an effort to minimize labor-intensive tasks (such as the Internet of Things (IoT), cloud computing, global positioning system, artificial intelligence, and big data). It implies the wise use of natural resources and the reduction of environmental impact. Someone has claimed that : Blockchain + IoT = smart agriculture [40].

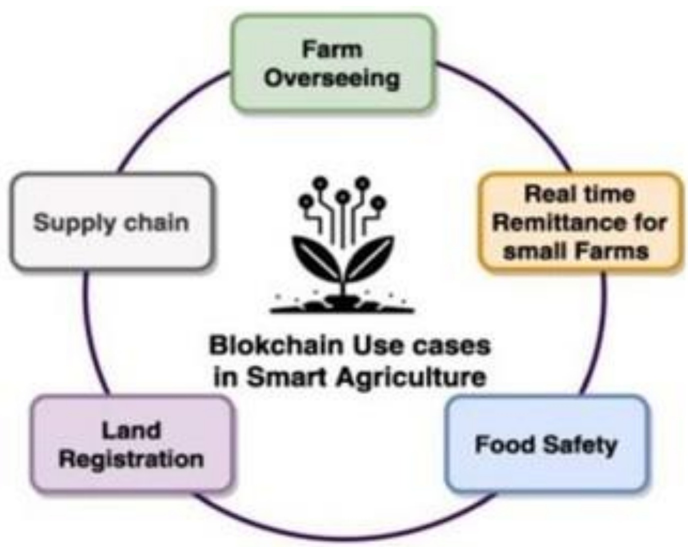

FIGURE I.7 – The uses of blockchain in smart agriculture [40]

I.4.5.3 Benefits

Blockchain technology is changing the way that the agriculture sector does business by speeding up transactions, assisting farmers in controlling and analyzing crops, etc. By improving an organization's ability to make decisions, it is transforming the agriculture industry.

Agricultural producers can set pricing more effectively thanks to blockchain. The use of blockchain in agriculture offers the potential to improve supply chain efficiency, transparency, and trust. Transparency in decision-making along the supply chain is made possible by the usage of data dispersed on the blockchain network. The parties concerned have access to trustworthy information, enabling improved market management and planning [40].

I.4.6 Drone

I.4.6.1 Definition

Drones have become valuable tools in the field of agriculture, serving as unmanned aerial vehicles (UAVs) that gather data and carry out various agricultural tasks. These UAVs are equipped with a range of sensors, cameras, and other advanced technologies, enabling them to capture high-resolution images and data, as well as perform tasks like pesticide or fertilizer spraying. One of the primary applications of drones in agriculture is crop mapping and monitoring. By capturing aerial images of crop fields, drones facilitate the creation of detailed maps that provide valuable insights. These maps can identify potential issues such as nutrient deficiencies, pest infestations, or uneven crop growth. The gathered data plays a crucial role in making informed decisions regarding crop management, including optimal timing for planting, irrigation, fertilization, and harvesting [20].

I.4.6.2 Drone in soil fertility and vegetation mapping

Soil degradation resulting from erosion, whether caused by wind or water flow, is a prevalent issue in agricultural regions. Detecting and assessing the extent of this degradation, as well as determining necessary corrective measures, can be a time-consuming and costly process when relying solely on human scouts in large farms. Aerial photography and photogrammetry offer a more accurate and efficient means of assessing soil erosion compared to skilled farm workers. Remotely sensed data obtained from satellites and piloted aircraft are often used to create land and soil maps. Through satellite imagery, areas affected by soil issues and erosion can be clearly identified and marked. However, in recent years, the emergence of low-flying drones has enabled farmers to gather valuable data about their farmland, including topography, variations in fertility, and the presence of gully and sheet erosion. Digital data obtained from sensors can be leveraged to develop precise digital elevation models, providing high-resolution imagery that accurately depicts the extent of soil degradation and erosion [20].

I.4.6.3 Drones in precision farming

Precision Farming has garnered significant attention from farmers in various agricultural regions due to the numerous benefits associated with its adopted practices. Future predictions indicate that the success or failure of Precision Farming techniques may largely hinge upon the widespread utilization of drones to carry out various agronomic tasks. While farmers are already employing satellite-derived data for implementing variable-rate techniques, satellite-based methods lack the same level of accuracy and efficiency that unmanned aerial vehicles (UAVs) can offer on larger farms. As the name implies, Precision Farming relies heavily on precise data collection. Most soil and crop management practices are implemented based on data collected on the ground, through satellites, UAVs, handheld devices, sensor-equipped tractors, or stationary instruments strategically positioned in the field. The process of data collection for precision farming commences with the analysis of yield maps from previous crops cultivated in the same area. These maps provide insights into variations in grain harvests in response to soil fertility and agronomic practices employed by the farmer [20].

I.4.7 Robotics

I.4.7.1 Definition

Agricultural robots or Agri-robot could be autonomous or semi-autonomous equipment used for various procedures during agricultural crop production. Agri-robots are used mainly in land preparation, ridging, making channels, spraying liquid fertilizers, spraying pesticides, sprinkling irrigation water, and most importantly harvesting grains or picking fruits [20].

Robots are used when repetitive, hard labor and drudgery are essential to achieve results. In the horticultural gardens, tasks such as repetitive pruning of branches (e.g., grape vines), weeding the inter-row spaces among trees, spraying tree canopies with pesticides, irrigation, and fruit picking are tasks accomplished by driverless robots. Agri-robots are equipment that could replace human labor requirements during crop production or cattle ranching. Moreover, an agricultural robot comprises three fundamental components. They are :

(a) a sensing system for assessing the physical and biological characteristics of agricultural fields,

(b) a collection of decision-making tools, including a computer that utilizes programmed algorithms to process data acquired from sensors.

(c) a manipulative arm or device that carries out the designated tasks in the crop field through the reception of electronic signals.

I.4.7.2 Robots in soil management

The next generation of agricultural robotics envisions the utilization of small, compact, and lightweight farm vehicles capable of performing tasks like tillage, intercultural activities, and other soil management operations. These lightweight robots effectively mitigate issues such as soil compaction.

By employing laser technology for traction and swift movement, the frequency of tractor repairs and adjustments is significantly reduced. According to [20], lightweight robots maneuver on wide, low-pressure tires, thereby minimizing soil compaction to the greatest extent possible. During the seeding process, robots exhibit precise movements guided by GPS and laser-assisted traction. They navigate exclusively along designated rows with optimal moisture content, thereby avoiding undue soil disruption [20].

I.4.7.3 Robots in crop production

Crop production typically involves a sequence of agronomic practices aimed at improving soil conditions, such as plowing, cultivating, clod crushing, harrowing, and ridging. Subsequently, a set of procedures focuses on nurturing crops in the fields. These include precise and appropriate sowing to optimize plant density and spacing, thereby maximizing root development, photosynthetic efficiency, and biomass formation. Intercultural operations involving tools like hoes with tines are conducted periodically to loosen the soil for aeration, promote root growth, and apply fertilizers (top dressing) between rows or ridges. These tasks lend themselves well to automation through various types of robots. In fact, the tractor, which is one of the earliest and most successful agricultural robots, plays a crucial role in initiating crop production by performing tasks like deep or light plowing of the soil.

I.4.7.4 Agricultural robots and their influence on human farm labor

Tractors serve as essential farm vehicles capable of performing diverse functions, particularly those directly related to crop production in the field. Additionally, they can be employed for various other farm activities such as threshing, winnowing, grinding, and lift irrigation, depending on the attachments and hitches used. Transforming these versatile farm vehicles into autonomous robots yields significant effects on labor requirements, working hours, efficiency, and economic benefits. Consequently, the need for human labor per farm vehicle is drastically reduced, as well as the overall labor demand for crop cultivation. While certain aspects like GPS guidance, computer decision support, and machine tracking may require skilled personnel and maintenance costs, the transition from manned tractors to robotic counterparts generally leads to a 1.2-fold increase in vehicle costs while reducing human labor needs to 5 to 20 of the original levels. Moreover, the utilization of robotic tractors enables the extensive extension of farm working hours, potentially doubling from 8 hours with manned tractors to 16 hours. It is worth noting that robotic tractors can also operate during nighttime.

I.4.8 Precision agriculture

I.4.8.1 Definition

As per a report from the European Parliament regarding Precision agriculture and the future of farming in Europe, precision agriculture is described as the contemporary approach to farming management that utilizes digital techniques to monitor and enhance agricultural production processes [43].

The primary objective of precision agriculture is to optimize farm inputs, encompassing the precise application of fertilizers to specific areas of the field based on soil characteristics, efficient water usage, and accurate feeding of individual animals. This approach heavily relies on the integration of sensors, satellite navigation, and positioning technology. Precision farming emerged with the advent of publicly accessible GPS signals, which enabled its implementation [12].

I.4.8.2 Components of precision agriculture

The effectiveness of precision agriculture technologies relies on the level of technology employed, necessitating the utilization of the most advanced available options. The fundamental components of technologies utilized in precision agriculture can be categorized into three groups [32].

FIGURE I.8 – Basic elements of precision agriculture technologies [32]

The first group comprises data collection technologies that furnish farmers with essential spatial and temporal data. In the second group, data processing and decision-making technologies are employed to refine and interpret raw data. The third group encompasses application technologies that utilize created maps and comments to execute planned operations within the production area. Figure I.8 provides a comprehensive overview of the technologies and processes associated with precision agriculture [32].

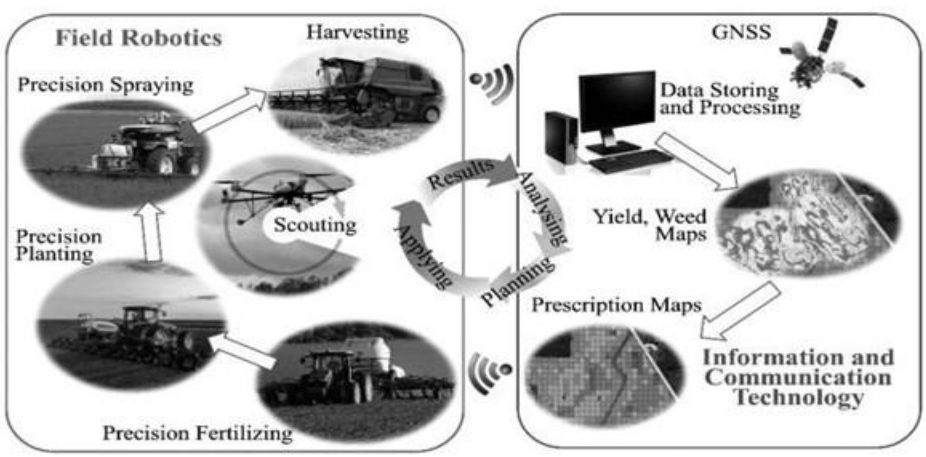

FIGURE I.9 – Technologies and processes involved in precision agriculture [32]

The utilization of remote sensing satellites, a fundamental component of precision agriculture, has experienced a recent surge in monitoring various aspects including crops, land use, vegetation indices, plant characteristics, diseases and pests, soil properties, fertilizer application, water status, and water resources. This has enabled the implementation of informed management decisions.

Notably, both the number and imaging resolutions of these satellites have witnessed significant advancements. Figure I.9 presents a case study illustrating the application of remote sensing in agricultural monitoring.

In today's precision agriculture applications, the integration of technologies such as artificial intelligence, robotics, the Internet of Things (IoT), autonomous vehicles, drones, advanced computers, cloud computing, and big data has propelled the transition to the Agriculture 4.0 era. These technologies have paved the way for more competitive, efficient, and sustainable agricultural practices.

They have also facilitated the instantaneous acquisition and evaluation of data in agricultural applications, enabling more informed decisions to enhance production quality. Figure I.10 illustrates the evolution from precision agriculture to Agriculture 4.0 through the incorporation of IoT.

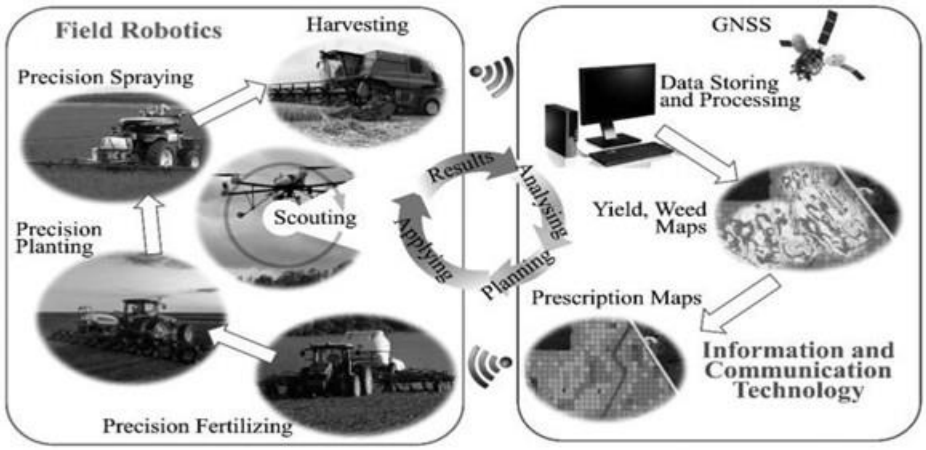

FIGURE I.10 – A case study of agricultural monitoring application with remote sensing [32]

I.5 Difference between traditional and smart agriculture

Traditional and modern smart farming are two distinct approaches to agriculture that differ in many ways. The differences are discussed below :

I.5.1 Traditional

It is based on age-old farming practices that have been passed down from generation to generation. It often uses manual labor methods and rudimentary tools. Crops are often planted in medium-sized fields, where farmers use proven seeds and crop rotation to maintain soil fertility. Yields are often limited due to the lack of use of modern technology.

According to [37] and [3], the form of agriculture is still practiced in many parts of the world, it has both advantages and disadvantages :

Advantages

Knowledge and experience : Traditional farmers often have extensive knowledge of their farming environment and farming techniques appropriate to their local context. This experience can be passed on from generation to generation, helping to preserve traditional agricultural practices and maintain biodiversity in agricultural ecosystems.

FIGURE I.11 – Traditional farming and Smart farming

Sustainability : Traditional agriculture can be sustainable if it is practiced in a balanced manner and in harmony with the environment. Traditional farmers can use farming practices such as crop rotation, use of compost and natural fertilizers, water conservation and crop diversification to improve soil health and reduce erosion.

Social cohesion : Traditional agricultural practices can foster social cohesion and solidarity among farmers. Traditional farming communities can share knowledge, skills and resources to help each other with farming activities and solve community problems.

Disadvantages

Low productivity : Traditional farming may have low productivity compared to modern farming practices. Traditional farmers may use inefficient production techniques that do not make optimal use of available land and resources.

Vulnerability to climate change : Traditional agricultural practices may be vulnerable to climate change and extreme events such as droughts and floods. Traditional farmers may not have access to modern agricultural technologies to adapt to climate change and improve their resilience.

Poverty : Traditional farmers may be more likely to live in poverty due to the low productivity of their agricultural activities. Traditional farmers may have difficulty accessing markets and obtaining fair prices for their products.

I.5.2 Smart Agriculture

Modern smart agriculture uses advanced technologies to increase yields, improve crop quality, and reduce losses. Farmers use precision techniques such as soil mapping, remote sensing, sensors, and data analysis to optimize inputs and yields. Technologies such as hydroponics, drones, and agricultural robots are also being used to improve efficiency and productivity [39].

Advantages

Improved agricultural productivity : Smart farming allows farmers to better understand their production environment and adapt their farming practices accordingly, which can increase productivity. the use of precision farming has increased corn yields by an average of 7.8 percent [62].

Reducing pesticide use : Smart farming can help farmers better monitor crop pests and diseases, which can reduce the need for pesticide use. using drones to monitor crops has reduced pesticide use by 30

Improving water quality : Smart farming can help farmers better manage water use in their fields, which can reduce water pollution from nutrients and pesticides. using sensors to measure soil moisture and temperature has reduced irrigation water use by 20

Reducing production costs : Smart agriculture can help farmers better manage resources and reduce production costs. using remote sensing to monitor crops optimized fertilizer use and reduced production costs by 11

Disadvantages

High costs : Adoption of smart agricultural technologies can be costly, which may limit access for small farmers and developing countries [15].

Dependence on technology : Farmers may become dependent on technology and lose their ability to use their own knowledge and experience to make decisions.

Safety risks : Smart agricultural technologies such as drones, sensors, and robots can pose safety risks for farmers and farmworkers, especially if they are not trained in their use.

Complexity : Smart agricultural technologies can be complex to use and maintain, requiring advanced technical skills and regular updates, which may limit their adoption.

Environmental impact : smart farming may result in increased water and energy use, as well as the generation of e-waste, which may negatively impact the environment.

It is important to note that these two approaches are not mutually exclusive and that farmers can use a combination of traditional and modern techniques to increase yields while maintaining environmental and social sustainability.

I.6 Related works

To achieve better results in our project, we have studied certain papers and related works that aim to find better results in the field of fertilization.

The study consists of summarizing the major issues and proposed solutions related to fertilization, which are based on different approaches such as organic and inorganic fertilizers, foliar feeding, and fertigation.

The reviewed works include those that have investigated the effects of fertilization on soil health and crop productivity, and those that have proposed innovative fertilization strategies to improve nutrient use efficiency and reduce environmental impacts.

I.6.1 A novel approach to optimize water and fertilizers in agriculture

[26] discusses the potential benefits of smart farming, which is a hi-tech system that uses wireless sensor networks (WSN) and the Internet of Things (IoT) to automate the agriculture process. By using various sensors, such as those for soil moisture, temperature, and humidity, farmers can obtain information about the soil and make informed decisions about irrigation and fertilization.

The proposed method uses WSN and IoT to automate the process of supplying nutrients to the soil. Soil moisture and humidity sensors are used to monitor soil properties, and the data is transmitted to an IoT server. Based on the values received, drip irrigation is turned on or off through a solenoid valve. The system also includes a quantitative analysis of the nutrient requirements for the plants to ensure they receive the proper amount of nitrogen, phosphorous, and potassium, which are essential for plant growth, fruit and flower development, and strong stems, the proposed system, is developed with an Arduino Uno open-source microcontroller board based on the Microchip ATmega328P microcontroller.

The disadvantages to consider in this article are :

Cost : The implementation of this system requires the use of various sensors, a microcontroller, a GSM module, and other components, which can add up to a significant cost.

Maintenance : The system requires regular maintenance, such as calibrating the sensors, checking the drip irrigation system, and replacing components as needed. This can be time-consuming and costly.

Complexity : The system can be complex to set up and operate, and may require technical expertise to troubleshoot any issues that arise.

Limitations : The system is designed to monitor and control specific parameters such as soil moisture and temperature, but it may not be able to account for other factors that can affect crop growth and yield, such as pest infestations, soil nutrient imbalances, and weather conditions.

Reliability : The system relies on a stable internet connection and reliable communication with the GSM module to send alerts to the farmer. Any disruptions or failures in these systems could result in delays in notifying the farmer to take action.

I.6.2 Solar-powered fertigation system optimizes irrigation cycles and crop growth

In [55], the author introduced a design and implementation of a remotely controlled solar-powered fertigation system based on a low-cost wireless sensor network (WSN). The system aims to optimize irrigation cycles and crop growth while reducing water and fertilizer consumption and minimizing the environmental impact. The system consists of three main components : the solar-powered control unit, the WSN, and the software platform for data acquisition and management.

The control unit is powered by a solar panel and consists of a microcontroller, a GSM module, a motor driver, and a relay. It controls the water pump and the fertilizer injector, based on the data received from the WSN. The WSN consists of sensor nodes that detect environmental and soil parameters such as temperature, humidity, and moisture. The nodes transmit the data to a coordinator node, which then sends it to the software platform for processing and analysis.

The disadvantages to consider in this article are :

Limited scope : The article focuses on a specific type of farming system, and the results may not be applicable to other agricultural practices.

Limited sample size : The study was conducted in a small agricultural area, and the results may not be generalizable to larger regions.

Cost : While the authors state that the WSN is low-cost, the cost may still be prohibitive for small-scale farmers who may not have the resources to invest in such technology.

Technical expertise : The use of advanced technology, such as WSN and on-cloud software, requires a certain level of technical expertise, which may not be readily available to all farmers.

Reliance on solar power : The system relies heavily on solar power, which may not be reliable in all regions or during periods of low sunlight.

complexity : it may require some technical expertise to understand the detailed technical specifications and implementation of the solar-powered fertigation system. This could make it less accessible to readers who are not familiar with the technical aspects of wireless sensor networks and agricultural technology.

I.6.3 Nitrogen fertilizer and cropping practices impact maize and soybean global warming potential

The work was conducted over three consecutive years in a long-term field experiment. Three cropping systems were studied : maize monoculture, soybean monoculture, and maize soybean intercrop. The nitrogen fertilizer was applied at four rates : 0, 150, 182, and 240 kg N ha-1. The researchers measured various parameters, including crop yield, nitrogen uptake, and greenhouse gas emissions, to calculate the GWP of each cropping system [47].

The results showed that maize monoculture and maize-soybean intercrop systems had higher net primary production and lower GWP than soybean monoculture. The C sink associated with CO_2 fixation by these crops exceeded the CO_2-eq losses from direct and indirect emissions during the cropping season. The N fertilizer inputs to maize-soybean intercrop should not exceed 150–182 kg N ha-1 because higher N fertilizer rates are associated with greater GWP, relative to maize monoculture that received 240 kg N ha-1.

Here are a few disadvantages of this article :

Limited scope : The study was conducted on a plot scale, which means that the results may not be fully representative of the entire North China Plain or the different agricultural systems used in the region.

Lack of data : The authors acknowledge that the study needs to be validated with realistic field- and farm-level data that accounts for the inherent heterogeneity of agroecosystems in the North China Plain, as well as the different levels of mechanization, efficiencies, and economies that operate at larger scales.

Limited analysis : The study focuses primarily on the impact of nitrogen fertilizer rates and cropping systems on global warming potential and does not explore other factors that could also affect greenhouse gas emissions, such as irrigation practices or soil management.

Lack of comparison : Although the study compares maize-soybean intercropping with maize and soybean monoculture, it does not compare these systems with other cropping systems that may have lower global warmings potential, such as agroforestry or conservation agriculture.

Narrow focus : The study focuses solely on global warming potential and does not consider other environmental impacts, such as water use, soil erosion, or biodiversity conservation.

limitation in the generalizability of the results : the study only focused on a specific region, the North China Plain, and the findings may not be applicable to other regions with different climates, soil, and crop management practice.

I.6.4 IoT-based sustainable irrigation and fertilization system

discusses the development and implementation of this solar fertigation system that utilizes photovoltaic solar energy and IoT technology for precision irrigation and fertilization purposes. The system monitors physical parameters such as temperature, radiation, humidity, and soil moisture, and uses an agronomic decision support system (DSS) platform to integrate soil, weather, and plant data and sensors. The study evaluates the sustainable estimation of reference evapotranspiration (ETo) and irrigation scheduling in a Mediterranean environment. The results demonstrate that the proposed system and Hargreaves-Samani (H-S) equation represented a nearby correlation to the standard FAO P-M model, and the hybrid agronomic DSS is suitable for smart fertigation scheduling [1].

There are a few disadvantages of the solar fertigation system :

Cost : While the solar fertigation system is designed to be a sustainable and cost-effective solution for irrigation, there may be significant upfront costs associated with the installation and setup of the system. This could make it difficult for small farmers or those with limited resources to implement the system.

Technical complexity : The solar fertigation system is a sophisticated solution that requires the integration of various technologies, including sensors, actuators, and software. This could make it challenging for some farmers to operate and maintain the system without adequate training or technical support.

Data limitations : The accuracy and effectiveness of the solar fertigation system depend heavily on the quality and availability of data from environmental sensors, soil moisture sensors, and other sources. If there are data gaps or errors, the system may not perform optimally, leading to lower crop yields and wasted resources.

Limited applicability : The solar fertigation system is designed primarily for use in agricultural settings, and may not be suitable for other applications or contexts. This could limit its broader impact and potential for adoption.

Lack of long-term data : While the article presents promising results from initial field tests of the solar fertigation system, it is unclear how the system will perform over the long term. Additional research and monitoring will be necessary to assess the system's durability, reliability, and ongoing impact on crop yields and resource use.

potential bias and misinformation : its limited scope of application. While the solar fertigation system and ETo modeling approach presented in the study have shown promising results in the specific regions and crops tested, their effectiveness may vary in different geographical locations or with different crop types. Thus, further research and testing may be necessary to determine the applicability of these methods on a broader scale.

I.6.5 IoT assisted context aware fertilizer recommendation

Presents a machine learning-based fertilizer recommendation system that uses the Internet of Things (IoT) to capture real-time soil fertility data. The system takes into account the soil type, crop type, and soil fertility level to recommend the appropriate fertilizer. The authors propose an IoT-assisted soil fertility mapping approach to capture soil fertility data, which was found to be in line with standard soil chemical analysis [19].

The authors begin by discussing the challenges of traditional fertilizer recommendation methods, which are often based on generic guidelines that do not consider specific soil and crop conditions. They then introduce the proposed system, which integrates IoT devices for real-time soil fertility monitoring and data collection, machine learning models for fertilizer recommendation, and a user interface for farmers to access the recommendations.

The authors describe the IoT devices used in the system, including soil moisture and temperature sensors, pH meters, and a microcontroller for data collection and transmission. They also discuss the data preprocessing steps, which involve filtering, outlier removal, and data normalization.

They focus on the machine learning models used for fertilizer, including logistic regression, Gaussian naive Bayes, and support vector machines. The authors explain how these models work and how they were trained and evaluated using accuracy, precision, recall, and F1 score metrics.

Also, the authors describe the experimental setup, which involved collecting soil samples from a rice field and analyzing them for nutrient content using standard laboratory methods. They then used the IoT devices to collect real-time soil fertility data over a period of two months, during which they also collected crop growth data.

Then, they present the results of the soil fertility mapping, which showed that the IoT-assisted system was able to provide accurate and reliable soil fertility data that was in line with the laboratory analysis. The authors also discuss the crop growth data, which showed that the system was able to improve crop yields and reduce fertilizer use compared to traditional methods.

After that gives an evaluation of the performance of the machine learning models for fertilizer recommendation. They report the accuracy, precision, recall, and F1 score metrics for each model and present confusion matrices and classification reports.

the authors conclude that the proposed system is a promising solution for context-aware fertilizer recommendation in agriculture. They recommend further research to expand the dataset and explore the use of deep learning models. They also acknowledge the support of the Department of Computer Science, College of Computing, Khon Kaen University, Thailand. Here are a few potential disadvantages of this article :

Limited dataset : The study was conducted with a limited dataset, which may not represent the diversity of soil types and crop types found in different regions. Therefore, the model's accuracy may not be applicable to all areas and crop types.

Dependency on IoT infrastructure : The proposed system is dependent on IoT infrastructure for real-time soil fertility mapping. This infrastructure may not be available in all areas, especially in remote regions with limited internet connectivity.

Cost of implementation : The implementation of the proposed system may require a significant initial investment, such as the installation of IoT sensors and other necessary equipment, which may not be affordable for small-scale farmers.

Maintenance and updates : The system may require regular maintenance and updates to ensure accurate soil fertility mapping and reliable recommendations. This may require additional costs and technical expertise.

Sustainability : The article does not discuss the long-term sustainability of the proposed system. It is essential to ensure that the system's implementation does not negatively impact the environment or cause other unintended consequences.

The study recommends using manual or threshold-based automatic irrigation and fertilization since it will guarantee data-driven farming, which will help to protect the environment and ensure the optimized use of water resources. This approach will result in lower operating costs, which will raise earnings. To predict when to irrigate, a deep learning model is used to analyze real-time information on soil moisture and soil nutrients collected by an ARM Cortex 4-based Arduino Nano 33 BLE sensing. Farmers receive text message alerts with recommendations for fertilizers to add if soil nutrient deficits are found. According to the forecasts and occasionally, the irrigation valve is automatically opened. This system's successful deployment will decrease water and fertilizer waste while boosting productivity [31].

Some possible disadvantages could be :

Limited scope : The study only focuses on one specific location, the Eastern province of Rwanda, and on a specific crop irrigation scheme. The results may not be generalizable to other regions or crops, and further research is needed to validate the model's performance in different settings.

Cost : The hardware components required to implement the system may be expensive, especially for small-scale farmers who may not have the resources to invest in such technology.

Technical expertise : The successful deployment of the system requires technical expertise in areas such as electronics, programming, and data analysis, which may be a barrier for some farmers.

Maintenance : The system may require regular maintenance and calibration of the sensors, which could be time-consuming and require specialized knowledge.

Dependence on technology : The system relies on technology, such as the Internet and the availability of electricity, which may not be reliable in some areas. This could limit the system's effectiveness and accessibility in certain regions.

I.6.6 IoT-based smart agriculture using machine learning

The proposed system architecture comprises temperature, soil moisture, and humidity sensors and a Raspberry Pi, which plays a central role in the system by providing storage to the datasets and hosting a web server. The decision tree algorithm is applied to the datasets to predict accurate results [38].

There are a few limitations to consider :

Cost : Implementing this system could require a significant investment in hardware and software components, as well as ongoing maintenance costs. This could make it less accessible for smaller-scale farmers who may not have the financial resources to invest in this technology.

Technical expertise : Setting up and maintaining the system would require a certain level of technical expertise, including knowledge of programming, data analysis, and sensor calibration. This could be a barrier for some farmers who may not have the necessary skills or resources to manage the system on their own.

Connectivity : The system relies on a stable internet connection to transmit data from the sensors to the Raspberry Pi and cloud storage. In areas with poor connectivity or unreliable internet access, the system may not function properly or may experience delays in transmitting data.

Limited scope for scalability and customization : it heavily relies on the accuracy and reliability of the sensors used to collect the data. If the sensors malfunction or produce faulty data, the decision tree algorithm may provide inaccurate results, leading to incorrect watering decisions for the crops. Additionally, the cost of implementing this system may be a barrier for small-scale farmers who may not have the financial resources to purchase the necessary equipment and sensors.

I.6.7 IoT-driven AI improves fertilizer recommendation model

This paper presents a smart agriculture system based on contemporary IoT communication technology, AI, and Wireless Networks. The system is designed to help farmers improve crop yield competitiveness and sustainability, by gathering and evaluating valuable data using IoT agricultural sensors. The system uses deep learning algorithms (GBRT, Random Forest, CNN, LSTM, and Bi-LSTM) to provide fertilizer recommendations that match the opinions of agricultural experts. The proposed approach has been analyzed and investigated to improve crop yield as an experiment [52].

There are a few limitations to consider :

Dependency on Technology : The proposed smart agriculture system relies heavily on technology, including IoT sensors, wireless networks, and AI algorithms. This can make farmers overly reliant on technology, potentially leading to issues if the system fails or malfunctions.

Cost : Implementing a smart agriculture system can be expensive, particularly for small-scale farmers who may not have the resources to invest in the required technology. The cost of purchasing and maintaining IoT sensors and other equipment can be a significant barrier to entry.

Technical Expertise : To use the system effectively, farmers may require technical expertise, including knowledge of AI algorithms and sensor calibration. This may be a challenge for farmers who are not tech-savvy or have limited access to training and support.

Data Privacy and Security : Collecting and analyzing sensitive agricultural data raises concerns about data privacy and security. Farmers may be hesitant to share their data with third-party systems, particularly if they are unsure about how the data will be used or protected.

Limited Scope : The proposed system focuses primarily on fertilizer recommendations based on soil and crop data. While this is an essential aspect of agriculture, it does not address other critical areas, such as pest management, irrigation, and climate monitoring

Financial and technical barrier to adoption : the potential for increased cost and complexity. Implementing IoT sensors, wireless networks, and AI technologies can be costly, particularly for small-scale farmers who may not have the financial resources to invest in such technologies. Additionally, the system may require specialized knowledge and technical expertise, which may not be readily available in all farming communities.

The following tables illustrate all the previously studied works :

Authors	Approach	Techniques	Services
[Louisa et al 2021] [26]	- Smart farming uses WSN, and IoT for automated soil nutrient supply.	-An algorithm calculates nutrient application quantity. - Utilizing RTC for time management and calendar, GSM module for user alerts.	- SMS alerts farmers about fertigation and pesticide spraying dates, reducing water waste and human intervention.
[Visconti et al 2020] [55]	- Remotely managed solar-powered automated fertigation system optimizes agricultural growth. -A low-cost wireless sensor network monitors soil and environmental parameters using a non-cloud software platform.	- Wireless sensor network technology utilizes solar power for data acquisition and transmission. - Software application optimizes fertigation cycles and supports decision-making for farmers using data analysis.	- Remotely managed solar-powered automated fertigation system optimizes crop growth. - Uses low-cost wireless sensor network, and offers on-cloud software for data analysis and decision-making support.
[Yawen et al 2018] [47]	- Ecosystem-level C balance approach to assess the impact of cropping practices and N fertilizer rates on GWP.	- Field experiments measure crop yields, N uptake, soil organic carbon, and GHG emissions. - Life cycle assessment calculates GWP, CO2-eq losses, and ANOVA compares practices.	- Supporting decision-making for farmers and policymakers to adopt low-carbon agriculture practices.
[Uzair et al 2022] [1]	- Solar-powered irrigation system and wireless sensor network developed for remote farmer control.	-Solar panels power system. - Low-power wireless communication transmits data. - Remote control via mobile app.	- Real-time monitoring, irrigation scheduling, crop growth optimization, remote farmer control.
[Arfat et al 2022] [19]	- IoT-assisted soil fertility mapping. - Fertilizer recommendation system.	- Machine learning models : Logistic Regression (LR), Gaussian Naive Bayes (GNB), and (SVM).	- IoT-based soil fertility mapping and machine learning-based fertilizer recommendation system.
[Nyakuri et al 2022] [31]	- IoT and AI integration for smart irrigation, nutrient assessment, and data-driven farming.	-Deep learning model predicts irrigated and recommended fertilizers using Neural Network classifier.	- Data collection, analysis, remote monitoring, and recommendations for fertilizers using Things Speak, Arduino(IDE), and GSM/GPRS shield.
[Kasara et al 2020] [38]	- Implementing an IoT-based system for smart agriculture, focusing on water management. - Uses sensors to collect temperature, moisture, and humidity data.	- The decision tree algorithm processes data for crop watering and utilizes cloud storage for future reference.	- The system decides the watering schedule for crops, reducing water consumption and improving yield, and sends email alerts to farmers.
[Swaminathan et al 2022] [52]	- IoT agricultural sensors and deep learning algorithms improve fertilizer recommendations.	- Four prediction models : GBRT, Random Forest, CNN, LSTM, and Bi-LSTM. -Kisaan Sasya Application for nutrient management and fertilizer recommendations.	- Providing farmers with data for improved crop yield and sustainability and potential for future integration.

TABLE I.2 – Summary of related works based on three factors (approach, technique, and service).

Authors	Disadvantages
[Louisa et al 2021] [26]	Cost : High, Maintenance : High, Complexity : High, Limitations : Significant, Reliability : Moderate
[Visconti et al 2020] [55]	Reliance on solar power : High, Technical expertise : Moderate, Limited sample size : Moderate, Cost : Low, Complexity : Low, Limited scope : Low
[Yawen et al 2018] [47]	Limited scope : Moderate, Lack of data : Significant, Limited analysis : Moderate, Lack of comparison : Moderate, Narrow focus : Low
[Uzair et al 2022] [1]	Cost : Moderate, Maintenance : Moderate, Complexity : Moderate, Limitations : Significant, Reliability : Moderate
[Arfat et al 2022] [19]	Cost : High, Maintenance : High, Complexity : High, Limitations : Moderate, Reliability : Moderate
[Nyakuri et al 2022] [31]	Overreliance on AI : Low, Data privacy and security : Moderate, Bias and inequity : Moderate, Lack of transparency : Moderate, Cost : Moderate, Algorithmic bias and errors : Low
[Kasara et al 2020] [38]	Limited scope : Low, Lack of data : Moderate, Limited analysis : Low, Lack of comparison : Low, Narrow focus : Moderate
[Swaminathan et al 2022] [52]	Cost : High, Maintenance : High, Complexity : High, Limitations : Moderate, Reliability : Moderate

TABLE I.3 – Summary of the disadvantages of each related work.

I.7 Conclusion

In conclusion, the use of IoT with machine learning and deep learning in agriculture offers many benefits. Most notably, it allows for real-time data collection and analysis to improve crop productivity and sustainability, as well as water and natural resource management.

Automating agricultural processes with this technology can also help reduce costs and increase yields while minimizing environmental impact. However, it is important to emphasize that this technology must be used responsibly and ethically, taking into account the long-term social, environmental, and economic impacts.

Thus these technologies have great potential to transform agriculture and contribute to more sustainable food for all.

Chapitre II

Fertilization

Fertilization

II.1 Introduction

Soil characteristics have a crucial impact on maintaining fertility in agricultural production as they enable crops to develop optimally through efficient root nutrition with minimal energy requirements. Nitrogen (N), phosphorus (P), and potassium (K) are vital fertilizers extensively used in crops to ensure an adequate nutrient supply and maximize production levels. However, excessive fertilizer use poses negative effects that risk public health and the environment.

These effects include soil salinity, the accumulation of heavy metals, eutrophication of water bodies, and nitrate accumulation. Furthermore, nitrogen and sulfur-containing gases released into the air during fertilization can contribute to air pollution and exacerbate issues such as the greenhouse effect.

Thus, to tackle these challenges, there is a need to anticipate the appropriate nutrient requirements for different crops and provide recommendations for optimal nutrient levels. The rapid advancement of technology has led to the emergence of new and innovative approaches to agriculture. Technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have helped farmers and researchers optimize agricultural processes, including irrigation, pest control, and fertilization management, to improve crop yields.

In this chapter, we review related work on IoT, AI, ML, and DL, focusing on their application in the fertilization process to gain insights into the latest trends and advancements in this field and made a comparison between the used approaches. Our analysis includes a review of articles that discuss the use of these technologies, as well as an examination of the challenges and opportunities associated with their implementation

II.2 Crop cycle

The crop cycle includes many phases starting from Soil preparation to harvesting while the main objective of our work is the fertilization phase, we will discuss different works that aim to tackle the issues and challenges of this latter as Figure II.1 shows.

FIGURE II.1 – Crop cycle

II.3 Fertilization

II.3.1 Definition

Fertilization is the process of applying or adding essential nutrients to the soil or directly to plants to enhance plant growth, development, and productivity. These essential nutrients, including nitrogen, phosphorus, potassium, and others, are necessary for the proper functioning and balanced nutrition of plants.

Fertilization can be achieved through various methods, such as applying fertilizers to the soil, foliar application (spraying nutrients on the leaves), or fertigation (application of fertilizers through irrigation systems). Fertilization plays a crucial role in modern agriculture, ensuring that crops receive the necessary nutrients for optimal yield and quality, and it is vital for global food production.

The specific type and amount of fertilizers used depend on factors like soil conditions, crop requirements, and environmental considerations [51].

II.3.2 Types of Chemical Fertilizers

Chemical fertilizers are offered in three different varieties. These include fertilizers with nitrogen, phosphorus, and potassium. Chemical fertilizer is made up of components like potassium, phosphorous, and nitrogen. These are employed to raise land productivity. [10]

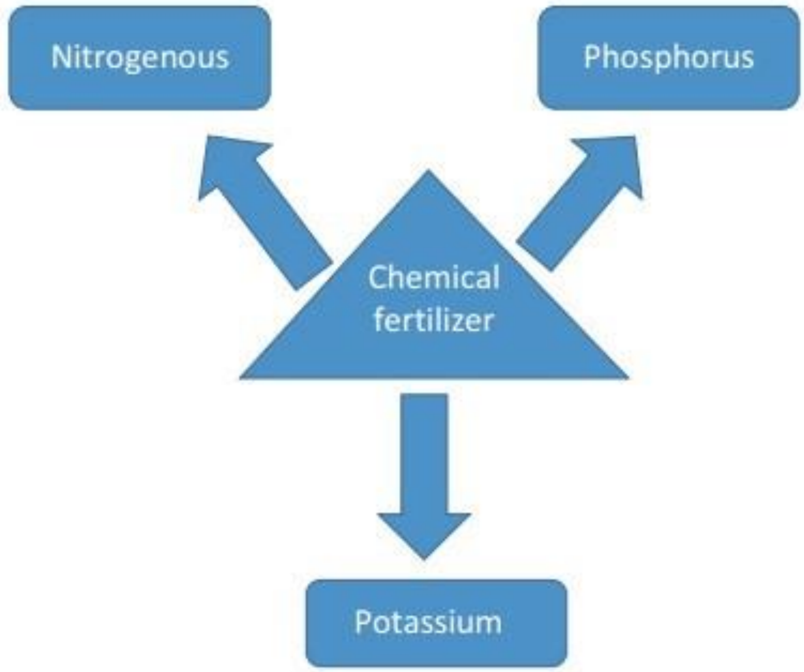

FIGURE II.2 – Types of chemical fertilizers [10]

II.3.2.1 Nitrogenous Fertilizer

Nitrogen is included in this type of fertilizer as ammoniacal nitrogen, such as ammonium chloride and ammonium sulfate, amide nitrogen, such as urea, and nitrate-nitrogen, such as calcium ammonium nitrate, which contains both ammoniacal and nitrate nitrogen. The nitrogen shortage in the soil is remedied by using this fertilizer. The plant will benefit the most from this fertilizer. Both plants and the earth receive nutrients from it [10].

Characteristics :

(a) Ammonium sulfate has substantially more strength than urea.

(b) Using nitric nitrogen at the beginning of the rice plant's reproductive phase increases its effectiveness.

(c) The paddy plant may absorb 30–35 of the total nitrogen after the application of ammonium nitrogen. But the nutrient is more readily available when fertilizers are applied at a depth of 5 to 10 cm.

(d) It is best to avoid using acid-producing fertilizers such as ammonium sulfate, urea, nitrate, and ammonium chloride continuously on soil that is low in calcium and acidic. Liming should be done at least 15 days before the crop is sown.

(e) It is water soluble and spreads out swiftly in all directions from the site of application. Application of nitrogen fertilizer should be done in accordance with crop needs.

(f) During the rainy season, any nitrogenous fertilizer is equally helpful [10].

II.3.2.2 Phosphorus Fertilizer

Phosphorus is found in phosphorus fertilizers as accessible phosphate. This fertilizer is essential for use on land. When compared to nitrogen fertilizer, it requires less [10].

Characteristics :

(a) The plant's ability to absorb nutrients is increased when phosphate and nitrogen fertilizer are used together.

(b) The best fertilizers for acidic soils are phosphate fertilizers like rock phosphate and basic slag.

(c) Phosphate compost, such as superphosphate, should be put in the soil or close to the crop roots.

(d) In soil ranging from neutral to alkaline, superphosphate should be used.

(e) It should be buried deep in fruit plants like citrus and apple trees [10].

II.3.2.3 Potassium Fertilizer

Muriate (potassium chloride) and sulfate of potash can be used to meet the potassium requirement. A healthy plant needs potassium sulfate to flourish.

With the aid of potassium, plants are able to produce carbohydrates. Potash comes in two subtypes : non-chloride potash and chloride potash. Examples of potash in non-chloride nature and potash in chloride form include sulfate potash and muriate of potash, respectively [10].

Characteristics

(A) It works with all types of crops.

(b) It may be applied to a variety of soil types.

(c) It increases plants' capacity for resistance.

(d) For a range of crops, including fruit trees and potatoes, potassium sulfate is preferred to potassium nitrate.

(e) It is water soluble.

(f) It breaks down into K+ ions and is ingested by the soil. Later, the plant absorbs it.

II.3.2.4 Advantages of Chemical Fertilizer

Chemical fertilizer is used to restore the fertility of the soil. The massive amount of crops grown throughout the year causes the ground to lose its fertility. When used properly, fertilizers are extremely important for the growth of the crop, quality criteria, and yield. They are also important for the health of the soil. By supplying the nutrients it requires, fertilizer improves the soil's nature and nutrient condition. Following are a few interesting points :

1. It increases plants' capacity for resistance.
2. Producing superior harvests.
3. Plant growth quickens.

4. Chemical fertilizer provides all the nutrients that plants need in equal amounts.
5. Chemical fertilizer is easily absorbed by soil since it is water soluble.
6. Chemical fertilizer does not include any extraneous ingredients.
7. Accurate measurements of plant development are made [45].

II.4 Important Nutrients in Fertilizers

The primary macronutrients for plants, such as nitrogen, potassium, and phosphorus, as well as a variety of micronutrients and additions, are found in chemical fertilizers [17].

ELEMENT	CHEMICAL FORMS OF ELEMENTS ABSORBED BY PLANTS
Primary nutrients	
Nitrogen (N)	NO_3^-, NH_4^+
Phosphorus (P)	$H_2PO_4^-$, HPO_4^{3-}, PO_4^{3-}
Potassium (K)	K^+
Secondary nutrients	
Magnesium (Mg)	Mg^{2+}
Calcium (Ca)	Ca^{2+}
Sulfur (S)	SO_4^{2-}
Micronutrients	
Boron (B)	BO_3^{3-}
Chlorine (Cl)	Cl^-
Copper (Cu)	Cu^+, Cu^{2+}
Zinc (Zn)	Zn^{2+}
Manganese (Mn)	Mn^{2+}
Molybdenum (Mo)	MoO_4^{2-}

FIGURE II.3 – Important nutrients and their chemical forms [17]

In addition to oxygen, carbon, and hydrogen, plants also require appropriate amounts of other nutrients. Primary, secondary, and micronutrients are the several types of nutrients.

II.5 Related work

Author	Year	Objective	Technique	Dataset	Results
[Thorat] [53]	2023	developing an intelligent recommendation system for insecticide and fertilizer selection in smart farming.	Machine learning techniques, (Transition Probability Function with Convolutional Neural Network (TPF-CNN), KNN, SVM, and ANN)	Not mentioned	TPF-CNN showed the highest accuracy 94ANN accuracy is 74 and 62 , SVM accuracyis78 and 71 , and KNN accuracy is 75 and 71
[Jayashree] [18]	2022	Developing a system to provide accurate and efficient fertilizer recommendations based on crop parameters.	Machine learning (Na¨ıve Bayes, Random Forest, and Decision Tree)	Kaggle dataset	RF achieves the best accuracy is 98, Na¨ıve Bayes and Decision Tree accuracy is 85
[Boris Kuzman .et al] [21]	2021	the impact of various factors (temperature, humidity, moisture, etc.) on the prediction of fertilizers.	Adaptive neuro-fuzzy inference system (ANFIS)	Kaggle dataset	Not mentioned
[Dr.B. Ratnakath et al] [16]	2021	Recommending the most profitable crop and suggest the optimal timing for fertilizer application	Machine learning techniques, (Decision Tree, Na¨ıve Bayes, Support Vector Machine, Logistic Regression, Random Forest, and XGBoost).	Not mentioned	Accuracy, where XGBoost achieves the best accuracy result
[Devdatta A. Bondre , Mr. Santosh Mahagaonkar] [7]	2019	the recommendation of suitable fertilizers for specific crops.	Machine learning : Support Vector Machine Random Forest	Dataset of 44 samples.	For Soil Classification RF accuracy is 86.35 SVM is 73.75. For crop yield prediction SVM accuracy is 99.47, RF accuracy is 97.48.
[Rafael Hernández Moreno.et all] [29]	2018	identifying the basic nutrients in the soil((N), (P), (K)) determining the required fertilizers and amendments for pasture cultivation	MLP (Multilayer Perceptron) Artificial Neural Network (ANN), backpropagation algorithm.	Dataset of 44 samples.	a threshold of 0.75 and k-fold = 3.
[Lavanya.et all] [22]	2018	to monitor and analyze soil nutrients	IoT, A Mamdani fuzzy inference system.	Iot based sensors Data set	Lower Cost of sensors

TABLE II.1 – Summary of related works.

II.6 Conclusion

We have studied various documents and related works aimed at achieving better results in the field of fertilization.

The study involved summarizing the major issues and proposed solutions related to fertilization. Based on our findings, most authors have focused on predicting the optimal timing for fertilization, while others have investigated the effects of fertilization on soil health and crop productivity. Additionally, some works have proposed innovative fertilization strategies to improve nutrient use efficiency and reduce environmental impacts.

However, the majority of these studies relied on machine learning algorithms applied to recommended datasets, with only a few utilizing datasets collected from the field through IoT sensors specific to different crop types.

Based on these results, our intention in this work is to propose an automatic fertilization system based on real datasets collected in the field, covering various crop types. We aim to compare the results obtained from this approach with those achieved by applying the same machine learning and deep learning algorithms. By utilizing actual field data, we hope to provide valuable insights into the effectiveness and applicability of these algorithms in realworld fertilization practices.

Chapitre III

Proposed method

Proposed method

III.1 Introduction

In this chapter, we will introduce the methods, tools and processes, and steps undertaken in the research. The research architecture is in the first term presented then the AI model training steps and lastly, the machine learning method used in developing the fertilization system.

III.2 Remote sensing farming system

Generally, IoT sensors demonstrate a high level of accuracy in converting input or external signals into scaled output values.

The equipment associated with IoT sensors facilitates the conversion of macroscopic scale factors such as soil moisture, temperature, and humidity to a measurable range for electronic systems. The quality of sensors can be quantitatively adjusted either directly or indirectly through the use of analytical expressions or by responding to environmental changes.

Nevertheless, the implementation of smart fertilization systems faces complexity due to the absence of models that guide practitioners in key areas, such as IoT-based fertilizer prediction systems. However, the adoption and deployment of this latter can be expedited by a well-designed framework that incorporates advanced IoT and AI techniques. The main elements of a monitoring system encompass sensing agricultural parameters, identifying suitable sensing locations, collecting data, routing information from agricultural fields, making informed decisions and controlling actions based on the sensed data, and generating visual reports through smart applications. Our model's architectural framework follows the OSI Model, which divides communication systems into four levels of abstraction.

The integration of IoT technology and artificial intelligence capabilities has facilitated the establishment of core agricultural layers, as illustrated in Figure III.1.

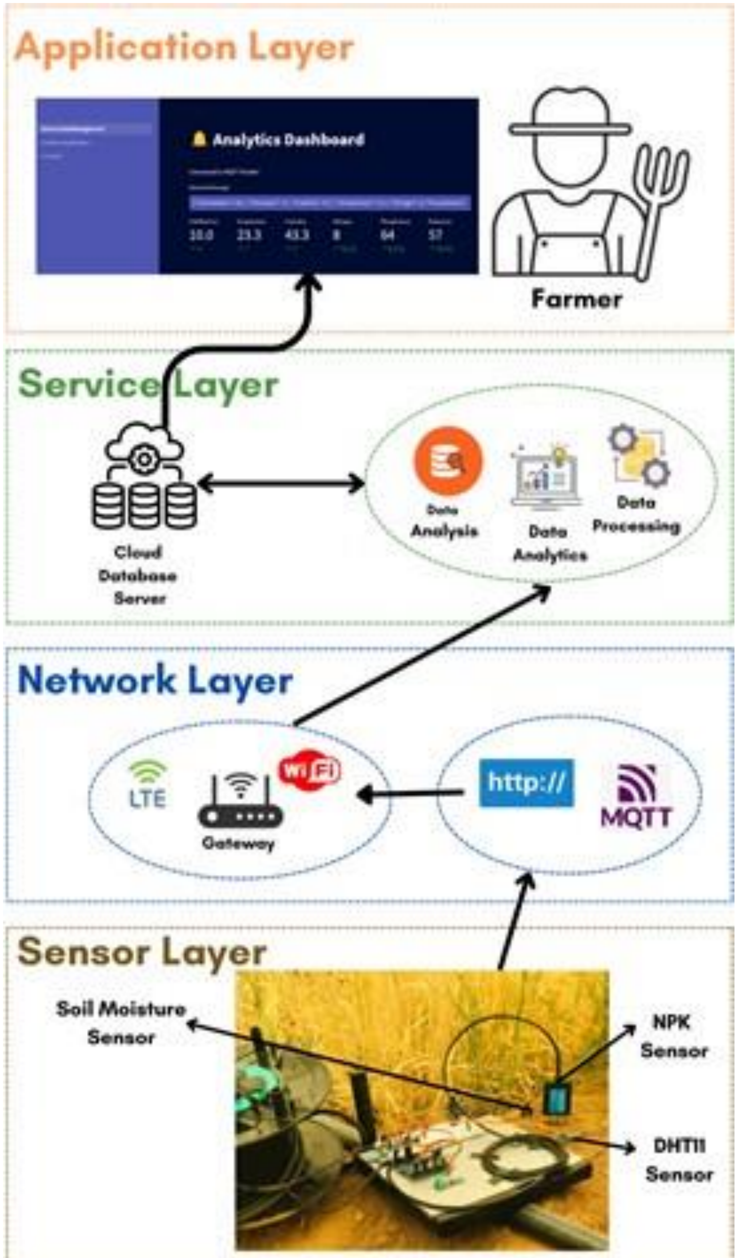

FIGURE III.1 – The architecture of the smart fertilization system

III.3 Architecture description

III.3.1 Sensing Layer

The sensing layer forms the physical component of the system and is tasked with monitoring the farm's environment and relaying information to the server. It utilizes various sensors, including a soil moisture sensor, humidity sensor, temperature sensor, and NPK sensor, all strategically positioned across the field.

These sensors are under the control of a Raspberry Pi Pico W and Arduino Uno that communicate using the I2C commination protocol, which serves as the central hub for data collection.

The Raspberry Pi collects data from the sensors and efficiently forwards it to the MQTT server for further processing.

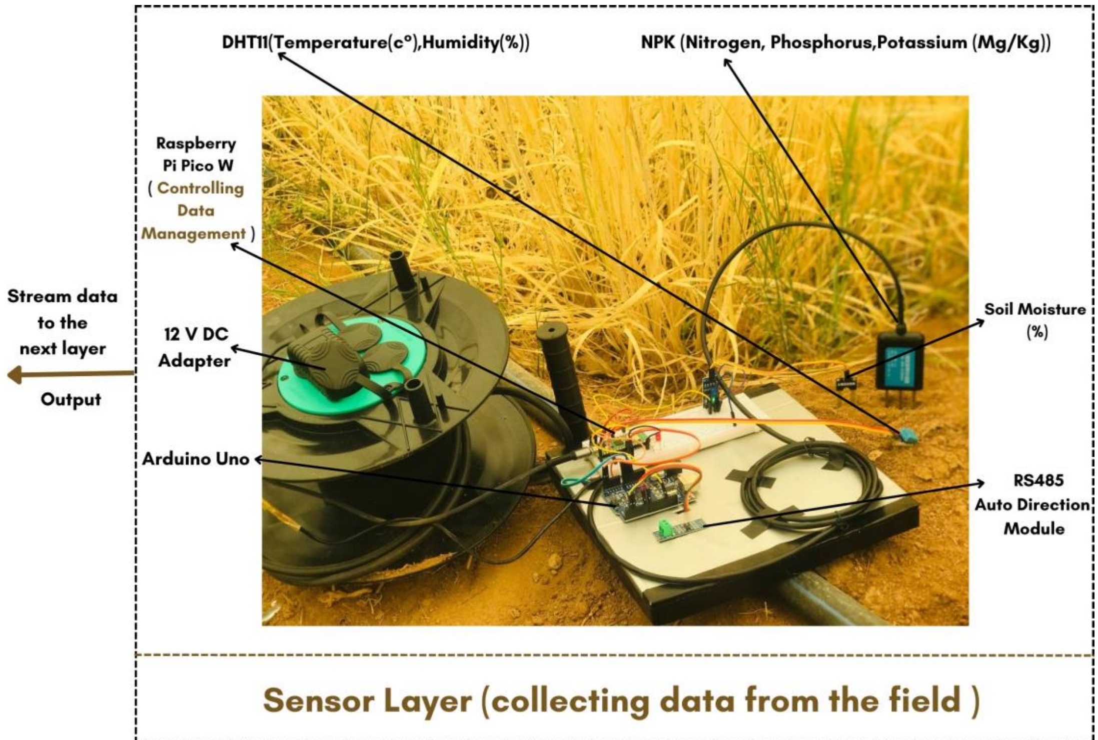

FIGURE III.2 – The components of sensor layer

The following are the used sensors in our model :

Soil Moisture Sensor

The soil moisture sensor comprises of a pair of probes employed for gauging the volumetric water content in the soil. By passing current through the soil, the two probes provide a resistance value that can be utilized to determine the moisture level. As Figure III.3 showed.

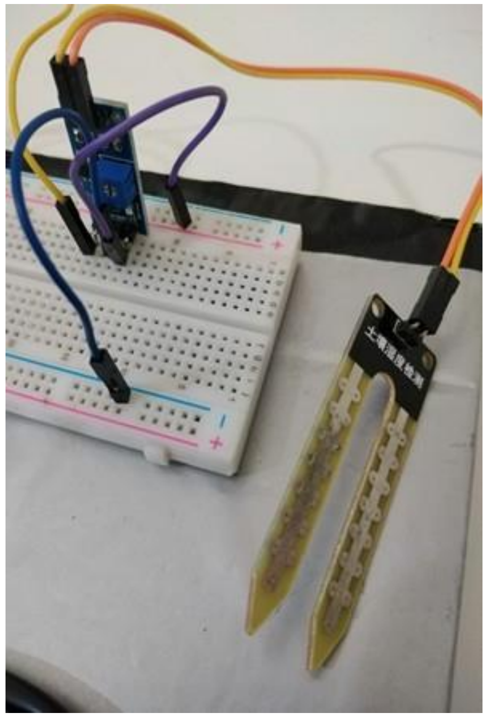

FIGURE III.3 – Soil Moisture Sensor [31]

DHT11

Is a humidity and temperature sensor that generates enhanced yield that is aligned. Microcontrollers like Arduino, Raspberry Pi, Pico W, and others can be used with DHT11. A low-effort temperature and wetness sensor are the DHT11. Long-term dependability and excellent, unwavering quality are provided as shown in Figure III.4 [46].

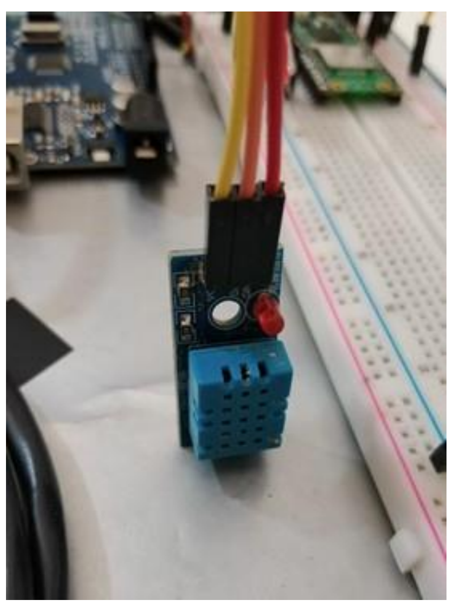

FIGURE III.4 – DHT11 Sensor [46]

Soil NPK Sensor

The NPK sensor designed for soil analysis is capable of detecting the levels of nitrogen, phosphorus, and potassium present in the soil. It operates within a measurement range of 0-1999 mg/kg and can be powered within the range of 5V-30V. As shown in Figure III.5. This sensor is connected to the Arduino Uno using the RS485 Auto Direction Module [31].

Figure III.6 shows the RS485 Auto Direction Module

FIGURE III.5 – Soil NPK Sensor [31]

The NPK is connected to the RS485 Auto Direction Module as follows :

VCC : Brown wire, connected to a 12V Power Supply.

GND : Black wire, connected to the GND of Arduino.

B Pin : Blue wire, connected to the B pin of RS485.

A PIN : Yellow Wire, connected to the A pin of RS485.

FIGURE III.6 – RS485 Auto Direction Module

Arduino UNO

The Arduino ATMega328P board has 14 digital I/O pins (6 of them for PWM) and 6 analog inputs. It includes a 16 MHz quartz crystal, reset button, ICSP header, and power jack. It can be powered via USB, AC-to-DC adapter, or battery. The Arduino is an 8-bit microcontroller with low-power CMOS technology and enhanced RISC architecture. Figure III.7 illustrates the Arduino implementation board.

We used the Arduino along with the Raspberry Pi Pico W to handle the Analog outputs from the NPK sensor with the Arduino and subsequently relay them back to the Raspberry Pi Pico W for further processing and analysis [34].

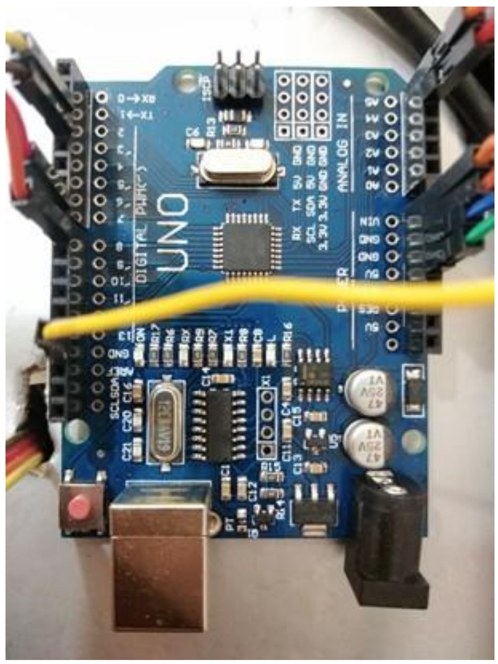

FIGURE III.7 – Arduino UNO implementation board [34]

Rasbperry Pi Pico W

The Raspberry Pi Pico, named after its compact size, is a microcontroller board presented as a small green printed circuit board, resembling a stick of gum in dimensions. It features GPIO pins along both of its longer sides, while one of the shorter ends hosts a micro-USB connector.

The opposite end contains a set of debugging pins, which can be utilized for advanced diagnostic purposes. The used sensor in this work has an additional option which is Wi-Fi chip to support networking as shown in Figure III.8.

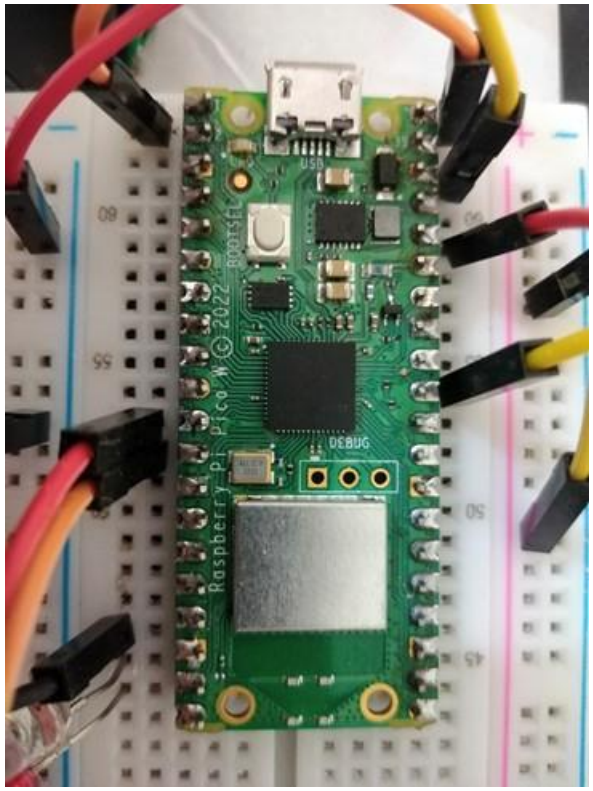

FIGURE III.8 – Raspberry Pi Pico W

The connection between the Raspberry Pi Pico W and sensors is established with electricity wires, using the Breadboard as an intermediary linking tool.

Figure III.9 shows the system prototype image. All the components were connected and the functionality of the system was tested in the Agricultural Department. [6]

FIGURE III.9 – System prototype [6]

III.3.2 Network Layer

Is a crucial component responsible for the seamless transmission of data from field devices to the server. Its primary objective is to ensure efficient and reliable communication within the system.

To achieve this, we rely on the MQTT (Message Queuing Telemetry Transport) protocol.

MQTT

IBM developed MQTT (Message Queue Telemetry Transport), a lightweight messaging protocol suitable for IoT applications. It operates at the application layer of the OSI model in the TCP/IP protocol stack and has minimal overhead with a fixed 2-byte header size.MQTT is an OASIS-based standard and follows an asymmetric architecture [59].

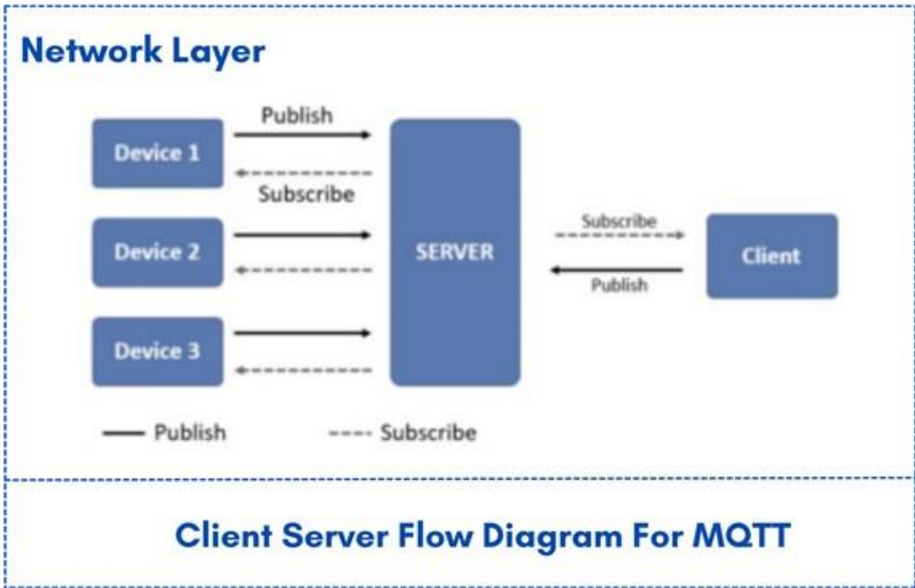

FIGURE III.10 – Network layer architecture including MQTT protocol

- MQTT is not only suitable for IoT but also for M2M (machine-to-machine) and WSN (Wireless Sensor Networks).
- It utilizes a Publish/Subscribes model, where publishers and subscribers are MQTT clients, and the broker serves as the MQTT server. The broker stores published topics, and subscribers subscribe to these topics of interest.
- Clients can exchange messages related to the subscribed topic.
- This protocol is advantageous when there is a need to exchange small messages with minimal bandwidth usage.
- MQTT is particularly useful in wireless network scenarios with latency issues caused by limited bandwidth.
- The establishment of an MQTT session involves four stages : connection, authentication, communication, and termination.

Integrating MQTT with the network layer

The collected data from various sensors is transmitted to the server using the MQTT protocol. This protocol operates on a publish-subscribe model, where field devices act as publishers and the server acts as a subscriber.

The server subscribes to relevant topics to receive the published data for further processing and analysis.

MQTT messages containing the collected data are then transmitted from the field devices to an MQTT message broker, which acts as an intermediary. The broker forwards these messages to the server based on the subscribed topics, ensuring efficient message delivery.

By leveraging the MQTT protocol and implementing a robust network layer, the smart fertilization system establishes efficient and reliable communication.

III.3.3 Service Layer

This layer includes a cloud server to enhance the platform's capabilities. One of the key functionalities provided by the cloud server is data storage. As the sensing layer generates large volumes of data that cannot be efficiently stored on a local server alone, the presence of a cloud server expands the storage capacity of the platform. This enables the farmer to securely store and manage the collected data in the cloud, ensuring its availability and accessibility from anywhere through the internet.

Then the stored data is processed and fed to different machine-learning models Figure III.11.

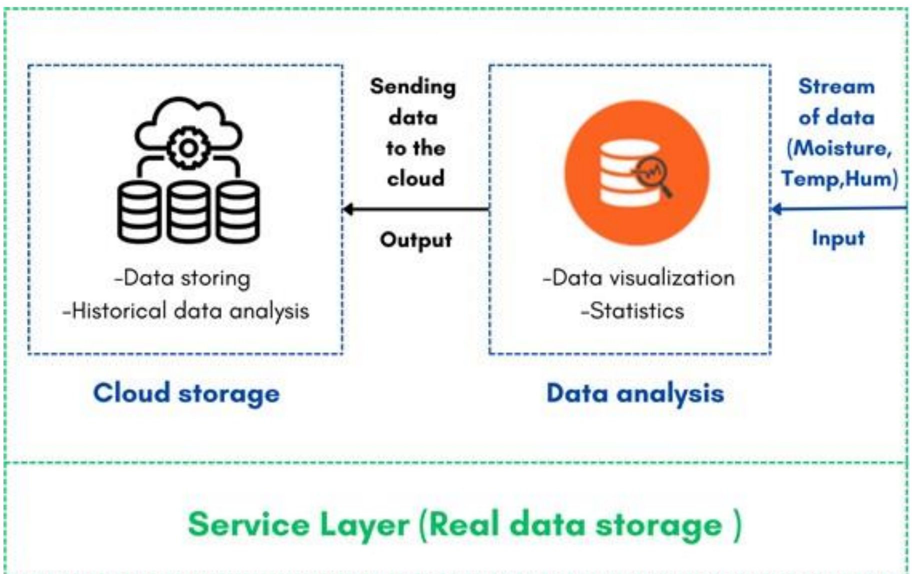

FIGURE III.11 – Service Layer architecture

III.3.3.1 Data analysis

Machine learning workflow

The standard steps employed in any machine learning algorithm were followed during the machine learning process. Figure III.12 illustrates these steps.

FIGURE III.12 – Machine learning steps

A- Data Collection

The initial phase of the machine learning process involved data collection, where the accuracy of the model depended on the quality and quantity of the data gathered. The data collection period was relatively brief, and regular calibration of the sensors was performed to uphold data quality throughout the process.

B- Data Pre-processing

In preparation for training, the collected data underwent a cleaning process. Unnecessary fields were removed, missing values were addressed, errors were corrected, and duplicates were eliminated. Subsequently, the data were transformed from JSON into CSV format and uploaded onto the cloud-based machine learning platform. To facilitate training, the data was divided into validation sets and training sets.

C- Model Design

After the preprocessing stage, the machine learning model was constructed. The selected inputs for model training were the raw features of soil moisture, humidity, temperature, Nitrogen, Phosphorus, and Potassium. Several machine-learning algorithms were chosen as the training framework such as Random forests (RF), Gradient boosting (GB), ADA boost, and Stacking with the intended output being a prediction for the required values of NPK.

D- Model Training

Subsequently, the model underwent training, during which various ML models were tested to determine the optimal training algorithm.

E- Evaluation and Optimization

The test data was used to evaluate the performance of the model. Furthermore, we have evaluated the model using the real data captured from the field to prove its effectiveness.

III.3.4 Application Layer

The application layer facilitates remote management of the fertilization process through web applications. The application layer ensures that farmers have a seamless and intuitive interface for accessing and visualizing data collected from various sensors in the field and predicting the right amount of fertilizer to use.

First, the data was captured from the sensors, then this latter have been sent and displayed in the web application. In addition, the farmer can predict and manage the right amount of fertilizers by entering the soil and weather parameters.

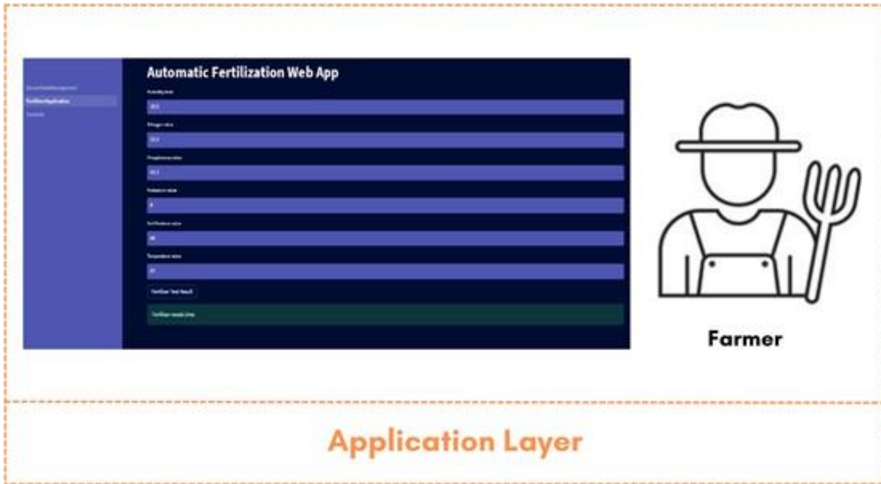

FIGURE III.13 – Application layer architecture

III.4 Used machine learning algorithms

III.4.1 Random Forest

The random forest is a supervised learning model that comprises a large number of decision trees. These decision trees serve as the base classifiers within the random forest, operating together as an ensemble. Therefore, random forests are often referred to as Classifier Ensembles.

Breiman and Cutler introduced the concept of random forests in 2001. One key characteristic of this model is that each decision tree is constructed using a randomly selected set of parameters. This randomness in parameter selection introduces diversity within the ensemble of base classifiers.

Consequently, each decision tree is independent and uncorrelated with the others. The outcome of each decision tree is considered as a vote, and the class with the highest number of votes is chosen as the model's prediction [11].

III.4.2 Gradient boosting

XGBoost is an enhanced version of the gradient-boosting decision tree (GBDT) model, featuring boosted trees that encompass both regression and classification trees. The fundamental principle behind this algorithm is to optimize the objective function's value. In the context of n-labeled samples with m features, the tree ensemble method utilizes K additive functions to make predictions for the labels.

$$\hat{y}_i = \sum_{k=1}^{k} f_k(x_i) \ , f_k \in F \qquad (1)$$

In the given context, represents the space of regression trees, while q represents the structure of each tree having T leaves. Each f k corresponds to an individual tree structure q and its associated leaf weight w. In order to acquire the set of functions within the model, XGBoost aims to minimize the following regularized objective.

$$L = \sum_{i} l\left(\hat{y}_i , y_i\right) + \sum_{k} \Omega(f_k) \ where \ \Omega(f_k) = yT + \frac{1}{2}\lambda\|w\|^2 \qquad (2)$$

In addition, the loss function is represented as l, and the regularized term is denoted as . The regularized objective in XGBoost demonstrates slight enhancements compared to the previous gradient tree-boosting algorithm. The prediction of the i-th instance at the t-th iteration is denoted as y l((t)). The ensemble model operates more effectively in an additive fashion. Furthermore, a second-order approximation is employed to accelerate the optimization process.

$$L(t) = \sum_{i=1}^{n} l\left(y_i , \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \qquad (3)$$

$$L(t) = \sum_{i=1}^{n} \left[l\left(y_i , \hat{y}_i^{(t-1)} + g_i\, f_t(x_i) + \frac{1}{2}\, h_i\, f_t^2(x_i)\right)\right] + yT + \frac{1}{2}\lambda \sum_{i=1}^{T} w_j^2 \quad (4)$$

The first-order gradient statistics on the loss function are denoted as g(i), while the second-order gradient statistics are represented as h(i). Given a fixed structure q(x), the optimal weight W and its corresponding optimal value can be determined by assessing the split candidates.

To efficiently identify the optimal split, the algorithm iterates through feature values in a sorted manner, accumulating the gradient statistics mentioned in (4). To avoid the need for a greedy enumeration of all potential splits, an approximate algorithm is outlined to streamline the process [60].

III.4.3 AdaBoost

A weak learner refers to a single decision tree with limited capabilities. Researchers have explored the idea of combining multiple weak learners to create a strong learner. Schapire [41] proved this concept in 1990, laying the groundwork for the boosting algorithm, which sequentially combines multiple weak learners.

As depicted in Equation (3), each iteration involves adding a new tree model while eliminating the weaker ones, thereby gradually improving the overall model performance through iterative calculations. However, a challenge arises after obtaining the initial basic tree model. Some samples in the dataset are correctly classified, while others are misclassified.

The AdaBoost algorithm addresses this issue by iteratively improving the classification ability through continuous training. The first weak classifier is obtained by training on the initial samples, and the misclassified samples are combined with the untrained data to create a new training sample.

This process is repeated to obtain subsequent weak classifiers. By iterating this process multiple times, an improved and robust classifier is ultimately obtained. The AdaBoost algorithm assigns different weights to the samples [13] to increase the number of correct classifications. Correctly classified samples are assigned relatively low weights, while the weights of misclassified samples are increased. This compels the model to focus more on the misclassified samples [61].

Figure 2 illustrates the overall computation process of the AdaBoost algorithm. During the training of each basic tree model, the weight distribution of each sample in the dataset needs to be adjusted. As each training data point changes, the training results also vary, and their summation yields the final result [42] [56].

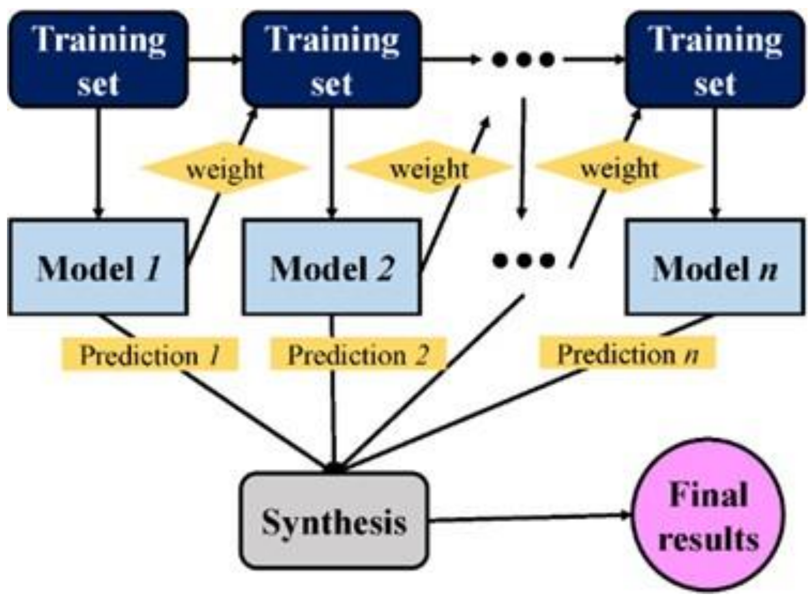

FIGURE III.14 – AdaBoost algorithm calculation process [56]

$$F_n(x) = F_{n-1}(x) + argmin_h \sum_{i=1}^{n} L\big(y_i, F_{n-1}(x_i) + h(x_i)\big) \qquad (4)$$

In this context, the overall model is represented as Fn (x), while the overall model obtained in the previous round is denoted as F(n-1) (x).

The prediction result of the i-th tree is represented as Yi, and h(Xi) corresponds to the newly added tree.

III.4.4 Stacking algorithms

Stacking, also known as ensemble learning is a technique that involves constructing a meta-classifier or meta-regression to combine multiple classification or regression models.

The initial level model undergoes cross-validation training using a comprehensive training set. Subsequently, the Meta-model is trained using the output from the base-level model, yielding the outcome. As the basic level typically consists of diverse learning algorithms, the stacking ensemble-learning algorithm is typically heterogeneous. Figure 5 depicts the model structure [57].

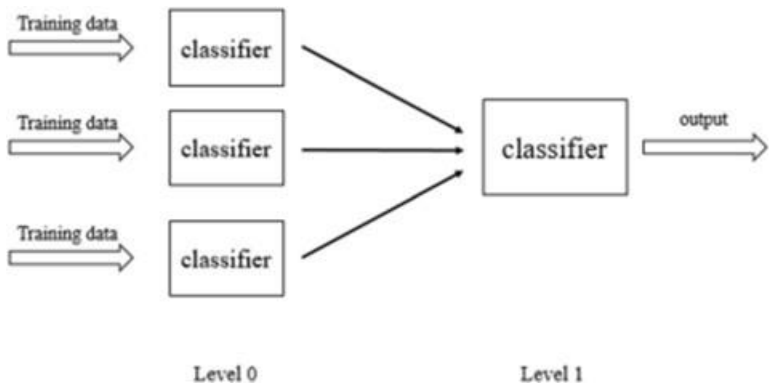

FIGURE III.15 – The stacking model [57]

III.5 Conclusion

This chapter explains the used OSI architecture for our work ; we have mentioned the different types of using sensors as well as the main machine learning workflow including the definition of the utilized algorithms. With the aim of enhancing farming practices. In the next chapter, we will discuss and results and the implementation of our proposal.

Chapitre IV

Implementation and results

Implementation and results

IV.1 Introduction

After presenting and discussing the theory and the details about the used approaches in the previous chapter, we will examine the main developed idea behind this proposal as well as the obtained results. In this chapter, we present the used tools including the platforms used to implement our system. In addition, we show the obtained results. Lastly, we give some discussions and analyses of the results of the model.

IV.2 Data collection

Due to the limited time, data used for the study was collected in collaboration with the Agricultural Department at the University of Biskra in Algeria. The data was collected for a brief period of 2023 ; of interest were soil moisture data, Humidity data, NPK data, and temperature. Microsoft Excel was used to format the data. This data was collected from the open field of the department on different planting crops such as (Melon, Barley, and Beetroot).

	Crop Type	Humidity	Nitrogen	Phosphorous	Potassium	Soil moisture	Temperature
2	Melon	53	171	186	181	24.48	37.9
3	Melon	54	171	185	180	25.09	38
4	Melon	51	242	93	90	44.46	39.9
5	Melon	43	46	233	231	45.65	43.8
6	Melon	43	184	215	211	36.27	41
7	Melon	41	184	216	212	45.45	40.4
8	Melon	50	193	236	232	82.57	42.4
9	Melon	49	190	53	54	50	41.9
10	Melon	65	139	111	106	78.3	37
11	Melon	52	194	238	234	52.03	42.3
12	Melon	64	237	83	80	82.9	37.6
13	Melon	65	235	78	74	83.24	37.6
14	Melon	61	2	131	128	48.3	37.6
15	Melon	59	175	195	190	34.5	37.7
16	Melon	58	174	192	188	51.32	37.7
17	Melon	61	52	247	245	57.44	38
18	Melon	62	95	90	89	62.33	38.5
19	Melon	60	221	45	41	38.63	38.5
20	Melon	55	136	185	184	36.24	38.9
21	Melon	63	245	4	11	73.52	38.5
22	Melon	72	249	14	21	80.94	38.5

FIGURE IV.1 – Real dataset file

Real dataset file

Figure IV.1 shows a simple view of the real dataset file

IV.3 Software

Google Colab

To train a machine learning model, a substantial amount of CPU/GPU processing power is often necessary. That's why we opted to utilize the Google Colab cloud platform for this purpose. Google Colab is a research project developed by Google to facilitate the dissemination of machine learning education and research. With the Google Colab service, This platform offers high performance in terms of RAM and disk space.

FIGURE IV.2 – Google Colab

Python

To develop the machine learning model, we utilized the Python programming language. Python is a high-level programming language with an interpreted nature, object-oriented design, and dynamic semantics. Its extensive range of libraries, dynamic typing, and high-level data structures make it an ideal choice for programming in the domains of AI and IoT. Here are some of the crucial libraries we employed :

- Tensorflow Keras : are used for machine/deep learning to create and train the model.

- Pandas : used for various data-related tasks, including data pre-processing, data analysis, and data analytics.

FIGURE IV.3 – Python

MicroPython

To develop the sensor model we have used micro python which is adequate for the type of sensors. Is a compact version of the Python standard library that is designed to run efficiently on different microcontrollers used in embedded applications It includes specific libraries tailored for various functionalities. For instance, there are libraries for Bluetooth, machine control, and networking.

Within the MicroPython ecosystem, the machine module is particularly noteworthy as it provides a collection of specialized classes and functions related to hardware interactions on embedded boards.

FIGURE IV.4 – MicroPython

IV.4 System interfaces

IV.4.1 Dashboard

Real-time data visualization

Real-time visualization allows the farmer to monitor the soil parameters from the deployed sensors in the field. The Raspberry Pi Pico W sends sensors' collected information through the MQTT protocol to the MQTTX server. When the server receives data it stores it in the databases and then the obtained file is converted to a CSV file. The code snippet below indicates how Pi Pico W is programmed to send the data to the server :

```python
    mqttClient = MQTTClient(CLIENT_ID, MQTT_BROKER, keepalive=60)
    mqttClient.set_callback(sub_cb)
    mqttClient.connect()
    mqttClient.subscribe(SUBSCRIBE_TOPIC)
    print(f"Connected to MQTT  Broker :: {MQTT_BROKER}, and waiting for callback function to be called!")
    while True:
            # Non-blocking wait for message
            mqttClient.check_msg()
            global last_publish
            current_time = time.time()
            if (current_time - last_publish) >= publish_interval:
                # collect data from sensors
                readings = {"Soilmoisture": Hum, "Temperature": t ,"Humidity": h ,
                            "Nitrogen": N, "Phosphorous": P, "Potassium": K}
                # send data to consumer
                mqttClient.publish(PUBLISH_TOPIC, ujson.dumps(readings).encode())
                last_publish = current_time
```

FIGURE IV.5 – Raspberry Pi Pico W producer code

The collected data is then displayed on the dashboard. This last receives data from the field by listening to the MQTTX broker, then the server automatically displays and updates the data in real-time, this task is illustrated in the code below :

```python
def on_message(client, userdata, msg):
    received_message = msg.payload.decode()
    st.session_state["message"] = "Save message received from MQTT broker"
    widget_key = f"mqtt_text_input_{msg.topic}_{random.randint(0, 100000)}"
    st.text_input("Received Message", received_message, key=widget_key)

    # Parse payload as JSON
    try:
        payload_json = json.loads(received_message)
        # Access specific fields in the payload
        field1 = payload_json["Soilmoisture"]
        field2 = payload_json["Temperature"]
        field3 = payload_json["Humidity"]
        field4 = payload_json["Nitrogen"]
        field5 = payload_json["Phosphorous"]
        field6 = payload_json["Potassium"]
        col1, col2, col3, col4, col5, col6,= st.columns(6)
        col1.metric(label="Soil Moisture", value=field1, delta="%")
        col2.metric(label="Temperature",value=field2, delta="c°")
        col3.metric(label="Humidity",value=field3, delta="%")
        col4.metric(label="Nitrogen",value=field4, delta="Mg/Kg")
        col5.metric(label="Phosphorous",value=field5, delta="Mg/Kg")
        col6.metric(label="Potassium",value=field6, delta="Mg/Kg")
        st.markdown("""---""")
```

FIGURE IV.6 – Real-time data model

The web application

- The data is visualized on the first page of the application as shown in Figure IV.7.

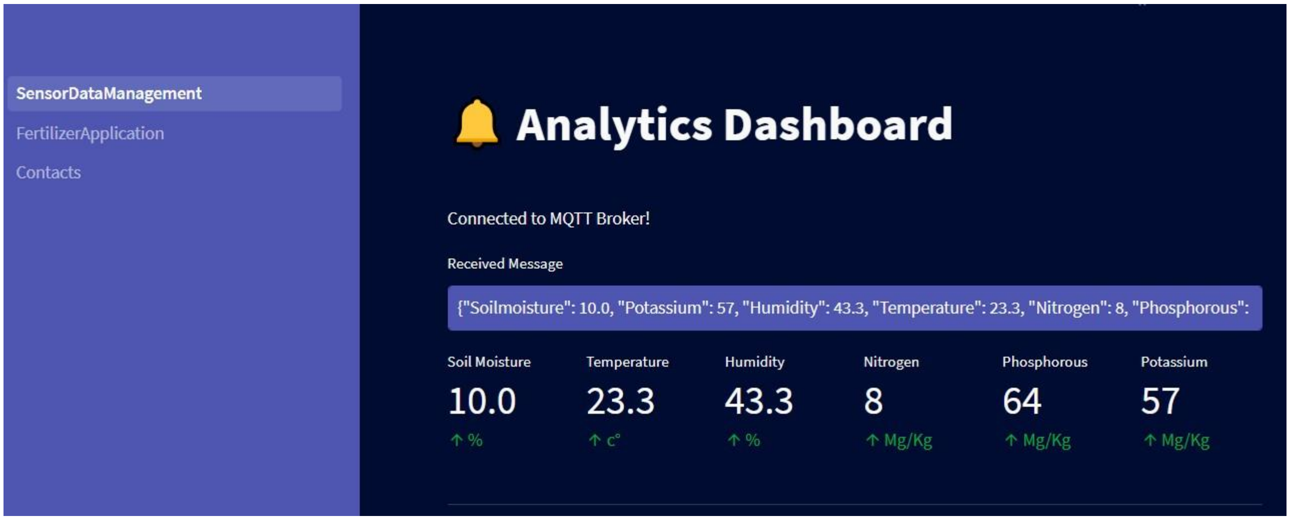

FIGURE IV.7 – Fertilization System Dashboard

- Fertilizer prediction application is managed with the machine learning model where the input were entered by the user then the model predicts the right amount of fertilizer to be added, and finally the prediction is displayed in the application as shown in Figure IV.8.

FIGURE IV.8 – Fertilizer prediction System

IV.5 Fertilizer prediction

IV.5.1 Experimental Results for the First Dataset

In the first step, we have built a Predictive fertilization model using the recommended Kaggle dataset of fertilizers.

Three machine learning algorithms are used, such as Random Forest, Gradient Boosting (GBoost), Adaptive Boosting (AdaBoost), and the Ensemble machine learning algorithms indeed the Stacking algorithm, for predicting the fertilizer type based on the input parameters.

These algorithms are used to classify data and generate a confusion matrix. Additionally, precision, recall, f1-score, average values, and accuracy percentage are provided as output at the end. The ML model will predict the fertilizer based on the current input. The data preprocessing workflow is demonstrated as :

1. Data cleaning by removing the NULL values.
2. Data visualization and correlation study as shown in Figure IV.9.
3. Data preparation by splitting it to train and test.

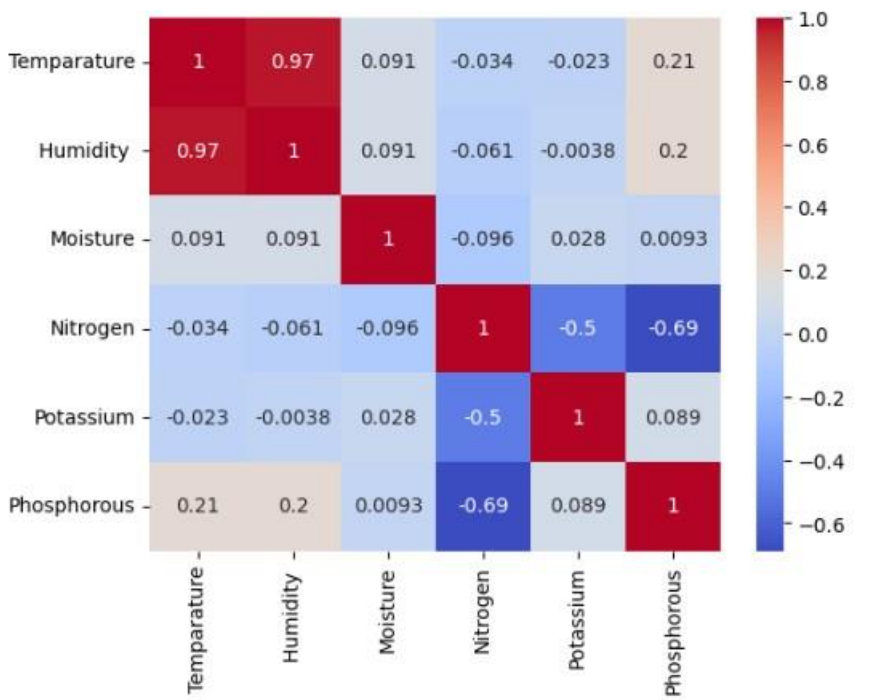

FIGURE IV.9 – The heatmap of correlation between features

After training the dataset using various algorithms based on previous research, the choice of these algorithms was motivated by the fact that many researchers commonly employed simple machine learning techniques such as K nearest neighbor (KNN), Decision Tree Algorithm (DT), and Na ıve Bayes Algorithm. However, a smaller number of researchers utilized advanced techniques such as XGBoost, ensemble machine learning, and stacking machine learning. The XGBoost algorithm as seen from the graph in figure8 produces the most accurate result, the accuracy of XGBoost is higher than the other used algorithms, and thus, the given data in the project will use the XGBoost algorithm for the fertilizer prediction as shown in Figure IV.11.

The Gradient Boosting algorithm exhibits robustness against outliers, making it a suitable choice for addressing problems involving differentiable loss functions.

This technique proves effective for both classification and regression tasks. Additionally, Gradient Boosting demonstrates its capability to handle heterogeneous feature datasets proficiently

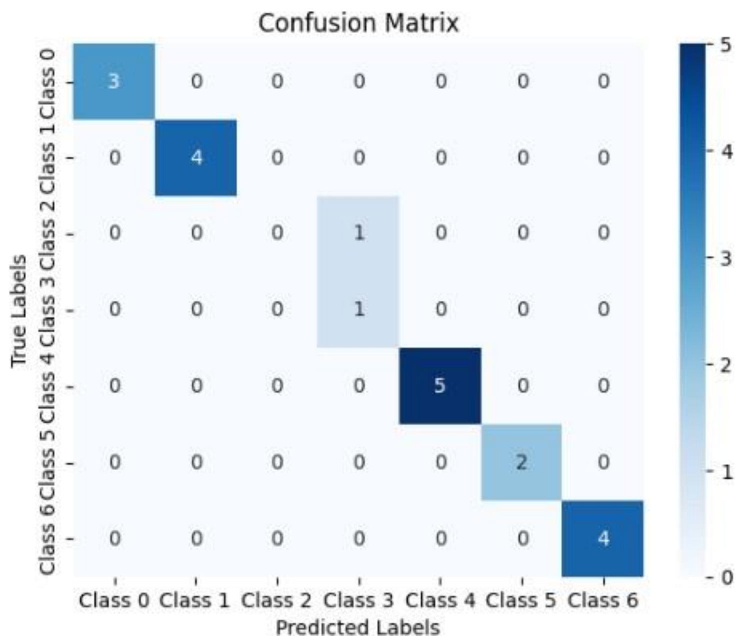

FIGURE IV.10 – The accuracy results of different algorithms

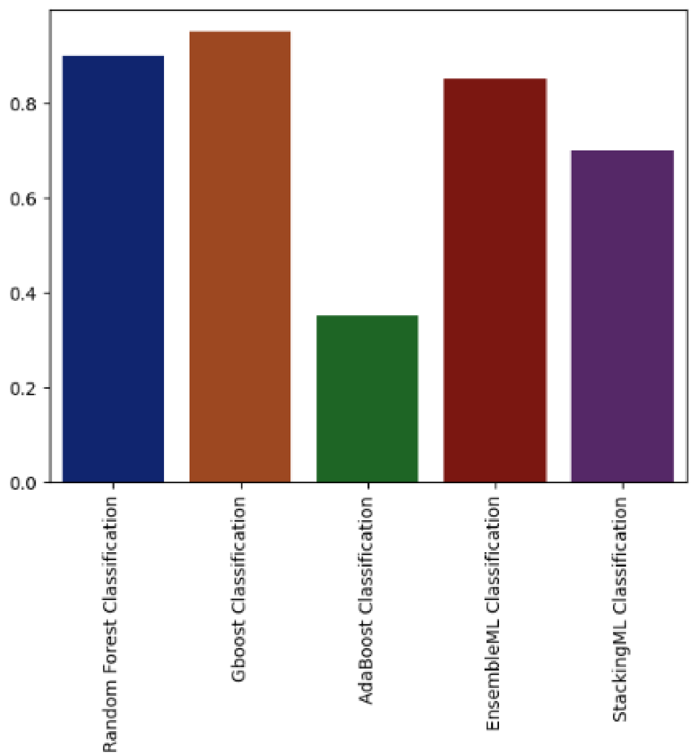

FIGURE IV.11 – Confusion matrix of the XGBoost algorithms

IV.5.2 Experimental Results for the Collected Dataset

As we have mentioned before that due to the lack of available datasets, we intend for this work to collect data from the field, in addition, to comparing the obtained results of both the first experiments and the second one.

- First the data was collected and stored in the cloud.
- Then data preprocessing is applied to the obtained dataset.
- Afterward correlation and data visualization are performed.
- Finally data preparation is to be fed to several networks.

The findings of the models trained on the gathered dataset are outlined. Notably, the used machine learning algorithms have demonstrated superior performance in fertilizer prediction unless the AdaBoost algorithm compared to the results obtained before demonstrates the effectiveness of our models and the validity of the gathered data.

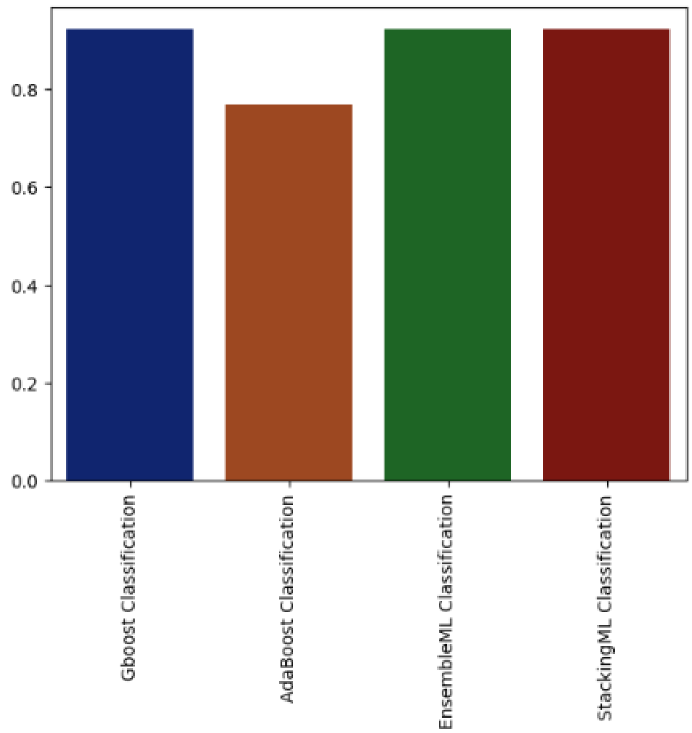

FIGURE IV.12 – The accuracy results of different algorithms

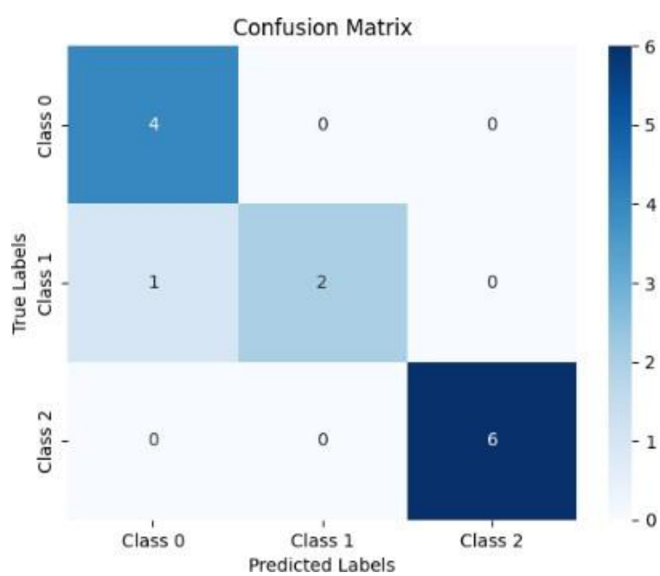

FIGURE IV.13 – Confusion matrix of the XGBoost algorithms

Due to the obtained results where the Gradient Boosting algorithm exhibits robustness and high accuracy values with Random Forests, we have used this latter as a saved model to build the automatic fertilization web application.

This technique proves effective results for both recommended dataset and the gathered dataset.

IV.6 Discussion

The show results in this chapter prove the effectiveness of our proposal where the Gradient Boosting algorithm results outperformed the other using machine learning algorithms in both experiments.

Indeed the collected dataset has proven its validity in terms of results compared to the recommended dataset which suffers from the lack of precision, as well as the proposed application leads the farmers to accurate prediction of the right amount of nutrients to avoid excessive or underuse of these nutrients and to manage soil and weather parameters.

IV.7 Conclusion

In this chapter, we have presented the obtained results in terms of machine learning algorithms as well as discussed them for both experiments. In addition, an explanation of the web application with its interfaces is examined. To conclude the chapter we have made a discussion of the results to prove the effectiveness of the proposal regarding predicting fertilizers and managing soil parameters.

General conclusion

This project presents a proposal that utilizes machine learning algorithms to recommend appropriate fertilizer usage. The recommendation system optimizes the results by considering various parameters.

This model is designed to assist farmers in obtaining specific fertilizer requirements based on different parameters. By utilizing this proposed system, farmers can benefit from fast and accurate fertilizer recommendations in the most cost-effective manner. The research collects agricultural data from the field and integrates it into a real-world agricultural dataset.

Subsequently, a machine learning model is constructed using different algorithms for fertilization prediction. The predictive model leverages real input information captured from sensors and incorporates inputs from the recommended dataset to achieve accurate prediction results.

The predictive model enables the computation of optimal fertilizer application amounts for various types, effectively preventing environmental harm caused by excessive fertilization.

By promoting rational and productive fertilizer usage, this model aids farmers and managers in reducing fertilizer pollution while simultaneously maintaining or enhancing agricultural production. The predictive model enables the computation of optimal fertilizer application amounts for various types, effectively preventing environmental harm caused by excessive fertilization.

By promoting rational and productive fertilizer usage, this model aids farmers and managers in reducing fertilizer pollution while simultaneously maintaining or enhancing agricultural production. As a future extension, we aim to expand the scope of our project by developing a mobile application that incorporates image processing techniques.

This application will serve as a valuable tool for farmers, enabling them to diagnose crop diseases accurately. Furthermore, we intend to incorporate other essential agricultural factors, including irrigation and pest management, into the application. This comprehensive approach will provide farmers with a holistic solution to address various challenges in crop cultivation and management.

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