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Abstract

Smart agriculture, or precision agriculture, leverages advanced technologies like IoT, sensors, drones, GPS, and AI to enhance farming efficiency, productivity, and sustainability. AI's role is pivotal, analyzing large data sets with machine learning and predictive analytics to improve decision-making and address challenges such as crop yield optimization and environmental impact reduction. However, integrating AI in agriculture faces technological, economic, social, and environmental challenges. The architecture involves sensors, communication technologies, robust data collection, and a web application interface. A specialized AI model diagnoses potato leaf conditions, demonstrating AI's practical utility in crop management and disease detection.

Key words :

Smart Agriculture - Artificial Intelligence - Yolo - Potatoes leaf diagnosis

Résumé

L'agriculture intelligente, ou agriculture de précision, utilise des technologies avancées telles que l'Internet des objets, les capteurs, les drones, le GPS et l'intelligence artificielle pour améliorer l'efficacité, la productivité et la durabilité agricoles. Le rôle crucial de l'intelligence artificielle réside dans son analyse de vastes ensembles de données à l'aide de l'apprentissage automatique et de l'analyse prédictive, visant à améliorer la prise de décision et à traiter des défis tels que l'optimisation des rendements des cultures et la réduction de l'impact environnemental. Cependant, l'intégration de l'intelligence artificielle dans l'agriculture rencontre des défis technologiques, économiques, sociaux et environnementaux. L'architecture proposée comprend des capteurs, des technologies de communication, des mécanismes robustes de collecte de données et une interface d'application web. De plus, un modèle développé spécialisé dans le diagnostic des conditions des feuilles de pomme de terre distingue entre les feuilles saines et malades. Cette application de l'intelligence artificielle démontre son utilité pratique dans la gestion des cultures et la détection des maladies au sein des cadres de l'agriculture intelligente.

Les mots clés :

Agriculture intelligente - Intelligence artificielle - Détection d'objets - YOLO - Diagnostic des feuilles de pommes de terre.

الملخّص

الزراعة الذكية، أو الزراعة الدقيقة، تستخدم تقنيات متقدمة مثل إنترنت الأشياء، وأجهزة الاستشعار، والطائرات بدون طيار، ونظام تحديد المواقع، والذكاء الإصطناعي لتعزيز الكفاءة والإنتاجية والإستدامة الزراعية.
دور الذكاء الإصطناعي جوهري، حيث يحلّل مجموعات كبيرة من البيانات بإستخدام التعلم الآلي والتحليل التنبؤي لتحسين عملية اتخاذ القرار ومعالجة التحديات مثل تحسين غلة المحاصيل وتقليل الأثر البيئي.
ومع ذلك، فإن دمج الذكاء الإصطناعي في الزراعة يواجه تحديات تكنولوجية وإقتصادية وإجتماعية وبيئية. تتضمن البنية التحتية أجهزة الإستشعار وتقنيات الإتصال وجمع البيانات بشكل قوي وواجهة تطبيق ويب.
نموذج الذكاء االصطناعي المتخصص يشخص حالات أوراق البطاطس، مما يظهر الفائدة العملية للذكاء الإصطناعي في إدارة المحاصيل والكشف عن األمراض.

الكلمات المفتاحية:

الزراعة الذكية - الذكاء الإصطناعى - التعرف على الكائنات - يولو - التعرف على أمراض الطماطم.

GENERAL INTRODUCTION

Smart Agriculture, also known as precision agriculture, represents the evolution of farming practices through the integration of advanced technologies. This innovative approach leverages cutting-edge tools such as the Internet of Things (IoT), sensors, drones, GPS, and, increasingly, Artificial Intelligence (AI) to enhance the efficiency, productivity, and sustainability of agricultural operations.

AI, with its capacity to analyze vast amounts of data and generate actionable insights, plays a pivotal role in the smart agriculture ecosystem. By employing machine learning algorithms, neural networks, and predictive analytics, AI transforms raw agricultural data into valuable information that can guide decision-making processes. This integration addresses numerous challenges in modern farming, from optimizing crop yields to minimizing environmental impact. While the integration of Artificial Intelligence (AI) in smart agriculture holds great promise, it also presents several challenges and issues that need to be addressed to realize its full potential. These challenges span technological, economic, social, and environmental domains. This work proposes a comprehensive architecture for Smart Agriculture, leveraging sensors, communication technologies, and data collection. Furthermore, a web application serves as the user interface, facilitating interaction between users and the Smart Agriculture system. Additionally, we have developed a model that can diagnose potato leaves, identifying whether they are healthy or diseased. Our work is presented as follows: In the first chapter, we provide an overview of Smart Agriculture. The second chapter introduces machine learning and deep learning models. The third chapter proposes the overall architecture of our system, including UML diagrams of the developed system and the models used to train and test local potato leaf data. Finally, we present the implementation and tools used in our work in chapter 4.

CHAPTER 1

SMART PRECISION AGRICULTURE

1.1 Introduction

Agriculture encompasses a range of activities and processes involved in the cultivation of land and the domestication of animals to produce food. In the context of this chapter on smart agriculture, our focus is specifically on the cultivation aspect. We delve into the innovative techniques and technologies that are transforming how crops are grown, managed, and harvested, highlighting the integration of advanced tools to optimize agricultural productivity and sustainability.

Modern day agriculture has undergone four revolutions that have significantly increased the production and quality of agricultural products[2] :

- The introduction of the first tractor by the Waterloo Gasoline Engine company in 1893 marked the first revolution, this technological evolution allowed a significant growth on the methods used until then based on the use of animals.
- The second revolution came from discoveries in chemistry, making it possible to use nutritious products for the crop, as well as to protect it from natural hazards with the introduction of pesticides.
- Norman Borlaug's work on plant genetic modification has led to a significant improvement in agricultural yields in several parts of the world, preventing millions of people from dying to starvation. These results earned him the Nobel Peace Prize in 1970.
- The fourth revolution in modern agriculture is precision agriculture, which will be discussed in the remainder of this chapter.

1.2 Definition of precision agriculture

Precision agriculture is a concept of agricultural plot management, based on the observation of the existence of intra-plot variability.

It is generally believed that precision agriculture originated in the United States in the 1980s. In 1985, researchers at the University of Minnesota varied the application of calcium amendments to agricultural plots.

The evolution of precision agriculture has been possible thanks to the emergence of technologies such as GPS, satellite imagery, affordable drones, sensor networks, and the grid computing environment. This allowed the acquisition of precise data on the existing variabilities on the soil and their treatment in order to draw useful recommendations for the farmer.

The development of variable-rate technology has also made it possible to act on the information obtained on a large scale.

The development of robotics also promises to improve efficiency in carrying out agricultural tasks.

Precision agriculture seeks to use new technologies to increase crop yields and profitability while lowering the levels of traditional inputs needed to grow crops (land, water, fertilizer, herbicides and insecticides). In other words, farmers utilizing precision agriculture are using less to grow more. GPS devices on tractors, for instance, allow farmers to plant crops in more efficient patterns and proceed from point A to point B with more precision, saving time and fuel. Fields can be levelled by lasers, which means water can be applied more efficiently and with less farm effluent running off into local streams and rivers. The result can be a boon for farmers and holds great potential for making agriculture more sustainable and increasing food availability.[14]

Figure 1.1: Modern Agriculture[2].

1.3 Technologies implemented

In recent years, there has been a growing interest in the application of different technological tools in precision agriculture. In this section, the various works carried out are divided into three main sub-groups :

- Remote sensing.
- Robots and autonomous machines.
- Wireless sensor networks.

1.3.1 Remote sensing

1.3.1.1 Definition

Remote sensing is the process of obtaining information about the object being measured without having to be in direct contact with the object. The carrier of information, in this case, is the electromagnetic wave at different frequencies. [9]

Two types of sensors exist for these applications:

- Passive sensors, i.e. sensors that capture, convert and detect incidental radiation, emitted or reflected by the object.Often, passive sensors are used.
- Active sensors, sensors that emit their own radiation and detect the reflection of these radiations by the object of interest.

1.3.1.2 Platforms used

Different platforms are used in remote sensing for their application in precision agriculture. There is remote sensing using satellites. The advantages of using satellites is the great spatial coverage. This allows the extraction of data over a long period of time with consistent and comparable data. There are also satellite platforms that offer multispectral images free of charge such as Landsat 7-8 or SPOT. However, the latter are low pixel resolutions ($30m^2$ per pixel for Landsat), long intervals between two visits to the same area (revisit time) and a long orbit period (16 days for Landsat and 26 days for SPOT).

More recently, new high-pixel resolution satellites have been launched, such as WorldView-2 and -3 (Digital Globe). WorldView-2 was the first high-resolution commercial satellite to provide spectral imagery in both the visible and near-infrared spectrum.

It should also be noted that high-resolution images from commercial platforms remain expensive for long-term application [9].

Another problem related to the use of satellite remote sensing is the revisit time, which remains very long, especially in relation to applications that aim to provide nutrients and irrigation to plants in optimal time, in addition to the fact that passive sensors cannot penetrate clouds, which reduces their efficiency.

There is also Planet Labs, which is an American company that manufactures and operates CubeSat-type nanosatellites that take images from orbit. It has a large number of satellites forming a constellation; This allows it to cover the entire surface of the earth and provide daily satellite images with a resolution of 3-5m.

One solution to the problems associated with the use of satellites for remote sensing is the use of manned aircraft, and more recently drones (Unmanned Aerial Vehicle UAVs), which have been used more frequently in recent years. this is due to the higher cost associated with the use of manned aircraft as well as technological advancements related to drones that are used with cameras that capture images in the visible, near-infrared, thermal infrared and LiDAR spectrum, which is referred to as Unmanned Aerial System (UAS).

The use of UAS makes it possible to obtain high-resolution images, enabling a large number of applications related to precision agriculture. Their disadvantages are the short flight time and limited ability to carry weight.

We also have remote detection on the ground, which is done using handheld sensors that are useful when it comes to a small area of interest [4], for the detection of biotic stress and abiotic stress or for the calibration of other measurements based on other platforms.

1.3.1.3 The most used applications of remote sensing in agriculture

❖ Yield Forecasting

The use of remote sensing for yield forecasting is based primarily on empirical-statistical relationships between yield and vegetation indices [4, 6].

This yield information is of great importance to government agencies, commodity traders and producers for harvest and transportation planning and marketing. This information helps to reduce economic risk. This would lead to better efficiency and improve the return on investment.

❖ Plant nutrient needs assessment

Research has shown that it is possible to measure the state of nitrogen in the crop with optical instruments [5]. Since the majority of the nitrogen in the leaf is contained in chlorophyll molecules**Ref**, this is the basis for predicting the state of nitrogen by measuring the reflection of the leaves. An increase in visual reflection is largely related to the decrease in chlorophyll content, which is the result of a lack of nitrogen.

An increase in near-infrared (NIR) reflection is largely due to the growth of the Leaf Area Index (LAI) and green biomass.

There are many examples of the use of satellite or aerial imagery to estimate the amount of nitrogen in crops [10].

❖ **Detection of diseases and pest damage**

The variability in the spectral reflection of plants resulting from the occurrence and severity of diseases or damage caused by pests allows the use of remote sensing to identify them.

The spectral characteristics of healthy and infected plants are significantly different in the visible spectrum (SIV). A healthy leaf reflects little radiation due to high absorption of photosynthetic pigments, whereas spectral reflection in the near-infrared (NIR) bands is relatively high which is determined mainly by the internal structure of the leaf and dry matter.

There are also numerous applications for infection identification in the literature, using ground-based (handheld) sensors [7], drones (UAVs) [14], and multispectral satellite imagery [6].

❖ **Assessment of plant water demands**

The development of infrared thermal remote sensing has made it possible to measure temperature changes and canopy dynamics. These changes are due to plant transpiration rate and stomatal conductance.

Therefore, the temperature of the plant leaves and the canopy was used for the determination of the water requirements of the plants.

In order to make the temperature of the canopy more consistent, the authors of [13] established the Crop Water Stress Index (SWSI) to monitor the water status of the crop

$$CWSI = \frac{T_{canopy} - T_{nws}}{T_{dry} - T_{nws}} \tag{1.1}$$

T_{canopy} : the temperature of the fully illuminated canopy leaves (C°) when the plant is well irrigated (no water stress).

T_{dry} : canopy leaf temperature (C°) completely sunny when the crop is severely water stressed due to low soil water availability.

T_{nws} and T_{dry} are the upper and lower bounds used to normalize CWSI to the effects of changing environmental conditions (air temperature, relative humidity, solar radiation, and wind speed) on the T canopy.

The $CWSI$ has two models, an empirical model and a theoretical model; However, the theoretical model involves too many parameters and these parameters are not easy to obtain.

Therefore, the theoretical model is used for research purposes only [4]. The empirical model can be obtained only by using canopy temperature, air temperature and air saturation difference, the empirical model has been further studied and has been used in many applications [7].

In addition to the use of infrared thermal radiation for the detection of plant water stress, the visible spectrum (VIS) has also been used for the early detection of water stress. This involves the use of indices focused on bands at specific wavelengths where photosynthetic pigments are affected by stress conditions such as chlorophyll. The Photochemical Reflectance Index (PRI) has been used as a stress index based on this principle, with initial developments to be applied to the detection of disease symptoms. It is expressed by :

$$PRI = (R_{531} - R_{570})/(R_{531} + R_{570}) \tag{1.2}$$

There is a close relationship between the Estimated Water Thickness (EWT), which is the weight of water per unit leaf area, and plant biomass and their Leaf Area Index (LAI). Considering this relationship, authors of [14] develop a model describing a relationship between EWT and a hyper-spectral aerial image, which proved to be a good predictor for broadleaf crops such as beans, corn, canola and peas, while it provided poor predictions for wheat. Several methods have been developed to estimate canopy water content (CWC) using NDWI (Normalized Difference Water Index) and NDII (Normalized Difference Infrared) [14].

Low-resolution satellite imagery is useful for estimating the water content of vegetation over large agricultural areas and can support efficient irrigation management by providing information on total evaporative water demand for crops [4].

❖ **Weed control**

Intensive research has been done on the use of hand-held radiometers for weed control in agriculture. Weed control involves identifying weed species and distinguishing between crop plants. The former is less complicated than the latter and would suffice for the application of herbicide specifically to the weed.

High efficiency has been achieved for the distinction of weeds from cultivated plants as well as their identification using machine vision, exploiting information on the colour and its saturation, shape and texture of the plants. The accuracy of this method is high, ranging from 80% to 97% [10].

Authors[9] investigated the possibility of using drones to optimize herbicide application based on aerial imagery.Drones low flight altitudes (40m) allowed the acquisition of aerial images with high spatial resolution, which allowed the detection of weeds with an accuracy of up to 90% , 50 days after sowing.

Weed recognition using high-resolution multispectral satellites such as QuickBird and GeoEye (ground resolution of 2.44m and 1.64m respectively), looks promising [9].

Medium-resolution (e.g. SPOT and LandSat) and low-resolution (NOAAAVHRR) satellites are only useful on a large scale.

1.3.2 Robots and autonomous machines

The advancement of robotics in precision agriculture enables their integration into forecasting and decision support systems, enhancing accuracy and significantly reducing the manpower needed to manage agricultural areas.

One example is the self-steering tractors produced by John Deere [5]. The tractor does most of the work autonomously with the ability to notify the farmer in case of emergency.

Recently, we have also seen the introduction of AgBots, robots that can take care of tasks traditionally done by a farmer; Advances in computer vision in recent years embedded in robots can produce robots that can automate tedious and expensive agricultural tasks in the future.

There is also the development of devices that make it possible to apply fertilizers or irrigate at variable rates; This makes it possible to take into account the variability of the soil deduced from the monitoring of the surface when applying irrigation or fertilizers [10].

Agricultural processes are systematic and repetitive chains of tasks that depend on time with some processes that differ depending on the type of crop, permanent crop or arable crop.

A study [21] on the economic feasibility of using robotic applications in agriculture showed a significant reduction in the cost of production. The introduction of robots in agriculture improves sustainability and adds consistency to agricultural processes. The precision of robots in tasks such as applying chemicals reduces the environmental impact and these harmful effects on humans [4].

There is also work on modifying existing tractors by adding the electronic part necessary for steering and communication for automated operations in agricultural fields.

Drones have a limited capacity to carry chemicals and batteries. It is also difficult to use them for certain soil tasks such as soil preparation and the application of plant-specific pesticides.

The complexity of developing a robot that can perform the different agricultural tasks has led recent research to focus on the development of robots that can perform a specific agricultural task.

The complexity of developing a robot that can perform the different agricultural tasks has led recent research to focus on the development of robots that can perform one of the agricultural tasks in a specific way.

In arable cultivation, a study [1] categorizes agricultural tasks into 5 major operations (Figure 1.2), with some differences depending on the country or crop concerned:

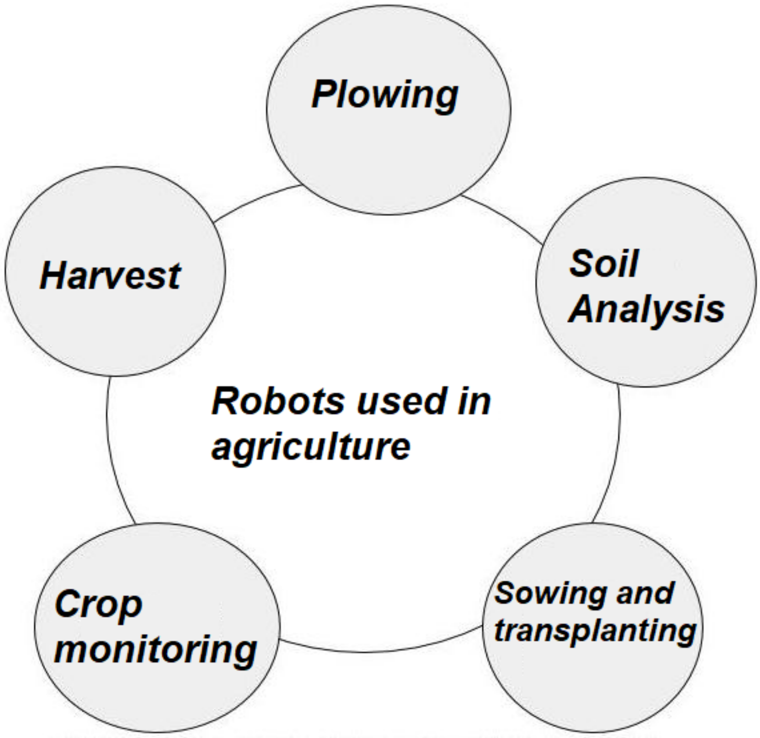

Figure 1.2: The Five Major Operations in Agriculture

1.3.2.1 Plowing robots

Ploughing is the first step in the farming process. The operations of ploughing consist of primary tillage which is a deep agitation of the soil producing a rough surface, followed by secondary ploughing which is the opposite of primary ploughing and produces a smooth surface.

Ploughing is a tedious and labor-intensive process, making it a goal for automation. Traditional tractors are heavy and have high torque; This allows them to have enough power to lift the ground up. Unlike small robots, tractors also tend to damage the soil through soil compaction.

Research has focused on modifying existing tractors by adding the necessary equipment to make them autonomous.

The authors of [4] modified a commercial tractor (Yanmar EG65) (Figure 1.3) by adding a GNSS (Global Navigation Satellite System) antenna, a DC motor for controlling the tractor's steering, and an Inertial Measurement Unit (IMU).

Figure 1.3: Yanmar EG65-based autonomous tractor

A study [14] showed that soil compaction by tractors in operation uses 80%-90% of the energy in conventional agriculture. This compaction requires other operations to loosen the soil.

Several studies [4] suggest that the use of small robots would reduce the frequency of ploughing required. It is also possible for robots to drill and place seeds or seedlings without having to plough the soil, or optimize the tilling process by micro-tilling around the seeding site, which has the most influence on the growth of the plant.

1.3.2.2 Soil analysis robots

Ploughing is followed by soil analysis, which involves measuring different physical and chemical properties of the soil to assess its fertility and physical conditions. Under certain conditions, soil testing is done at different stages of plant growth to assess the amount and composition of nutrients to be applied.

The analysis is traditionally done by taking samples from the field of interest that will be analyzed in a specialized laboratory. This is expensive and time-consuming

1.3.2.3 Robots for sowing and transplanting plants

Sowing involves planting the seeds in the ground so that they can germinate successfully. Transplanting (or transplanting) involves placing a small plant from a seedling that has germinated in a particular position in the soil based on the specific spatial requirements of each plant.

Food grains such as rice and wheat represent one of the main types of food consumed by people around the world. They are of interest for automating their sowing, such as the Iseki PZ60 for rice transplantation (Figure 1.4).

Figure 1.4: Iseki PZ60 transplantation du riz

1.3.2.4 Crop monitoring robots

✻ Crop condition monitoring robots

Recent advances in research in the field of plant phenotyping, which assesses plant growth status, yield and other parameters based on visual plant parameters such as leaf length, leaf area index (LAI).

These parameters can be estimated by using different sensors or by merging data from different sensors.

Various research projects are focused on the use of soil sensors worn on tractors; This raises the possibility of developing autonomous robots that perform the same operation, allowing for more automatic management of the agricultural field.

The authors of [67] equipped a robot, Bonirob (Figure 1.5), with sophisticated sensors, such as the 3D-TOF (3D-Time Of Flight) camera, multispectral imaging tools as well as GPS for the precise location of the data collection.

✻ Robots for monitoring and control of pests and diseases

Cases of diseases caused by pests or microorganisms affect the production of agricultural products worldwide. The majority of these diseases induce visible symptoms in plants. However, farmers can only identify a disease in a large field when a significant number of plants are infected.

Figure 1.5: Robot Bonirob

1.3.2.5 Robots for harvesting

When we talk about harvesting, we usually refer to the collection of ripened crops. However, the process differs for different crops. For example, harvesting horticultural crops, such as fruit and vegetable crops, refers to the collection of fruits or vegetables from plants, but this process is different for rice and wheat crops.

Harvesting requires many hours of work. In horticulture, fruits and flowers must be picked repeatedly as they ripen. A robotic harvester must therefore detect the properties of the product such as its position, size, surface type and shape.

In addition, the robot needs mobility to move in a reasonable position and a picking or harvesting mechanism for the harvesting process.

To solve these problems, several semi-automatic machines such as harvesters and combine harvesters were built. Many harvesters available on the market have the ability to interact with tractors by using a Power Take-Off (PTO) shaft that uses the power provided by the engine.

Combine harvesters, which are vehicles dedicated to harvesting and driven by humans, have been used to harvest various crops such as wheat, oats, barley, corn, soybeans and sunflowers. Iseki HFG 443 has been modified [9] for crops such as rice. The navigation methodology was similar to that of an automated tractor and rice transplanter.

In [10], the authors upgraded an AG1100 combine harvester with a Topcon AGI3 GNSS receiver and Topcon IMU for autonomous navigation guided by the global coordinates of the Sysetm-84 geodetic system (WGS-84) for rice and wheat harvesting.

Detection and picking of fruits, vegetables, or plant flowers is necessary for other types of crops such as horticultural crops. Robotic pickers that pick fruits or vegetables consist mainly of contact grippers that are operated by pneumatic, hydraulic or electric means. Other methods such as cutting the rod with a laser beam have been proposed [21] to minimize the size and complexity of end effectors. A focusing lens can focus a high-power 30W laser beam from a fiber-coupled laser diode to cut the stem of a single fruit or cluster.

More details are given on recent developments in this field as well as the trend of research undertaken in [16].

1.3.3 Wireless Sensor Networks (WSN)

Recent technological advances in the field of sensors, GPS, as well as the advent of wireless sensor networks (WSNs) have led to a new direction of research in the field of agriculture.

In this section, we will present a brief overview of applications and publications studying the application of sensor networks in agriculture, organized according to the agricultural process.

WSN and WSAN (Wireless Sensor and Actuator Networks) are often used with different technologies.

1.3.3.1 Irrigation

Irrigation is the application of water to agricultural land. It is considered one of the most important milestones in agriculture.

Several works have been carried out in order to apply water/irrigation in an efficient and optimal way, applying water only where it is needed and in measured quantities, using it with modern irrigation methods such as drip irrigation, sprinkler irrigation and center pivot irrigation.

In [10], the authors developed and tested a remote-controlled automatic irrigation system for irrigated areas in Spain. The area has been divided into seven sub-regions. Each sub-region was monitored and controlled by a control sector. The seven control sectors were connected to each other and to the central controller via a WLAN network. The results showed a significant water saving, i.e. up to 30–60%.

In [7], the authors worked on precision irrigation control using self-propelled, linear-displacement, and center-pivot irrigation systems. Wireless sensors were used in the system to aid irrigation planning using remote sensing and meteorological data.

1.3.3.2 Fertilization

The importance of fertilizers for plant growth, as well as their significant cost and the harmful effects that can be caused by their excessive application, have motivated several studies aimed at the optimal application of fertilizers in the agricultural field.

In [8], the authors constructed an automated fertilizer applicator consisting of input, decision support, and output modules using GPS technology, real-time sensors, and Bluetooth technology. The input module is used to provide GPS data values and sensor data to the decision support system that calculates the optimal amount and spread of the offered pattern based on real-time sensor data acquisition via Bluetooth communication modules. Calculations from the decision support system were used to regulate the fertilizer application rate.

1.3.3.3 Pest control

A lot of research focuses on developing better products for pest control with better efficiency and less ecological impact. for example, there is work on the use of WSNs for more precise application of pesticides.

In [6], the author worked on a project to treat Phytophtora disease that affects potato cultivation. The sensors were used to monitor humidity and temperature. Tracking these two parameters helped them reduce the disease.

Plant diseases often occur in crop plots that require fungicides at varying rates and uniform application throughout the field.

In [5] the author suggests the use of a variable flow field sprayer controlled by CROP-meter.

The information given by the CROP-meter and the spatial distribution data of the leaf area of the plants to be sprayed with pesticides were used by their algorithm to control the dosage of the fungicides to be sprayed.

Semios [10] markets a system consisting of sticky traps with cameras that allows the distribution of harmful insects to be known in real time and allows an appropriate pesticide application strategy to be adopted.

1.3.3.4 Horticulture

Horticulture deals with the cultivation, production, distribution, and use of flowers, fruits, greenhouses, ornamental plants, etc. It is also known as small-scale or low-intensity agriculture. In [89], the authors used a sensor network to monitor air temperature, humidity, ambient light, soil moisture, and soil temperature. These data allowed for an analysis of the current state of the nursery. This network can also assist in combating plant diseases.

In [90], the authors deployed a WSN (Wireless Sensor Network) of 65 nodes in a vineyard for 6 months. The collected information was used to improve significant aspects of production.

1.4 Conclusion

In this first chapter, we introduced the essential elements needed to understand the challenges and limitations of smart agriculture. Advances in technology now allow us to overcome these constraints through robotic systems and comprehensive data processing solutions, which handle everything from sensing and communication to data aggregation and analysis.

CHAPTER 2

MACHINE LEARNING AND DEEP LEARNING

2.1 Introduction

As a subset of artificial intelligence, machine learning is the process by which a system learns from its experience using self-learning algorithms. For example, the kind of data that is sent into the system helps it identify patterns and responds to those patterns at the output. In this instance, the system learns over time and becomes the smartest without human assistance. It makes use of an algorithm for statistical learning that learns and becomes better on its own without human assistance.

Conversely, a deep learning system gains knowledge not only from its incoming data but also from its vast database. In shallow neural networks, there are only ever two layers between the input and output of the neural network; in deep neural networks, there are several layers between the input and output.

These two subgroups of artificial intelligence differ greatly, but the primary one is that machine learning requires more constant human interaction in order to produce desired outcomes. Deep learning still takes more setup work but less ongoing involvement.

In this chapter, we will delve a lot into machine learning and deep learning, and we will be exposed to the most important modern methods in artificial intelligence and their efficiency in classification.

2.2 Artificial Intelligence

Artificial intelligence (AI) is a broad field of computer science and engineering focus on modeling a wide range of topics and functions in the domain of human intelligence. It is mostly about understanding and performing intelligent tasks such as acquire new skills, think and adapt to new situations and challenges. We explore different types of AI, including analytical, functional, interactive, textual, and visual.

2.3 Machine Learning

Machine learning is a field of study which allows machines (computers) to learn from data or experience and make a prediction based on the experience. It enables the computers or the machines to make data-driven decisions rather than being explicitly programmed for carrying out a certain task. These programs or algorithms are designed in a way that they learn and improve over time when are exposed to new data. Machine learning accesses vast amounts of data (both structured and unstructured) and learns from it to predict outcomes accurately. It employs various approaches to teach computers in order accomplish tasks where no fully satisfactory algorithm is available [4].

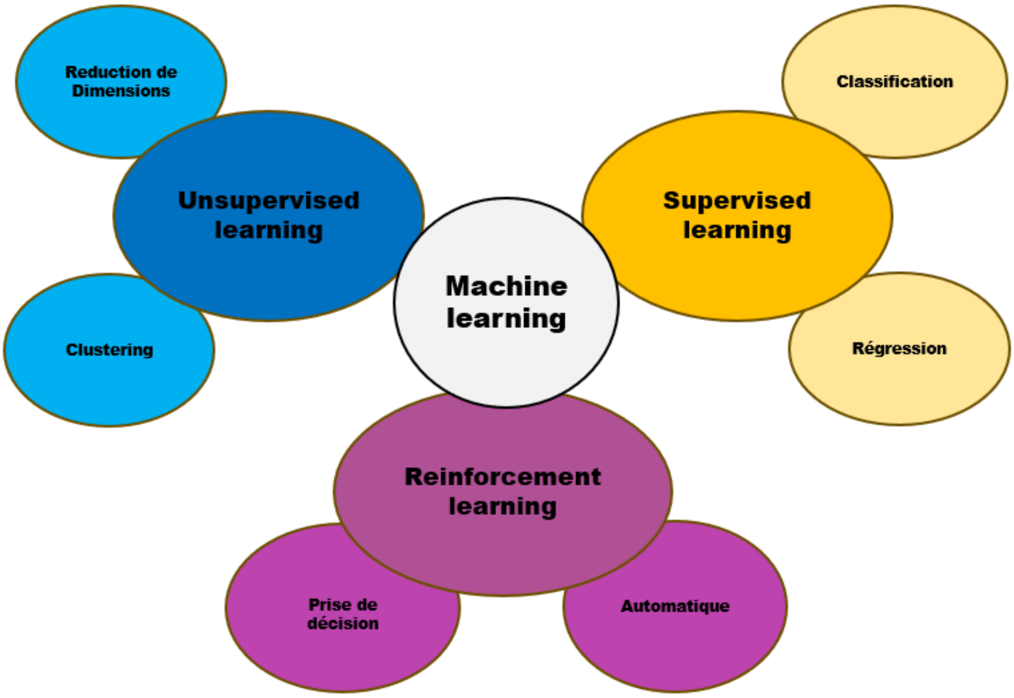

Figure 2.1: Machine Learning [5].

2.3.1 Types of Machine Learning

Machine learning algorithms are classified into three main categories: Supervised Learning, Unsupervised Learning and Reinforcement Learning

2.3.1.1 Supervised Learning

Working with labeled datasets, the supervised learning category focuses on mapping patterns by determining the link between variables and known outcomes. Put simply, it's similar to having two variables: an input (x) and an output (y), and using an algorithm to teach it to discover a mapping function between the two.

In supervised learning, prior to the machine working on or learning the algorithm, it is already aware of the method's outcome. This implies that the training dataset will steer the algorithm back in the correct direction if things go awry and the algorithms produce results that are entirely at odds with expectations. Systems that use this learning approach may forecast future results by using historical data. It requires that at least an input variable be given to the model for it to be trained.

(Figure 2.2) present a basic supervised learning process. We input Raw Data to the algorithm, this algorithm will learn then make predictions using a given dataset and is corrected by the "supervisor". After generating a trained model, the model can then accept new input data; process it then give desired outputs according to what it's trained for. Supervised learning can

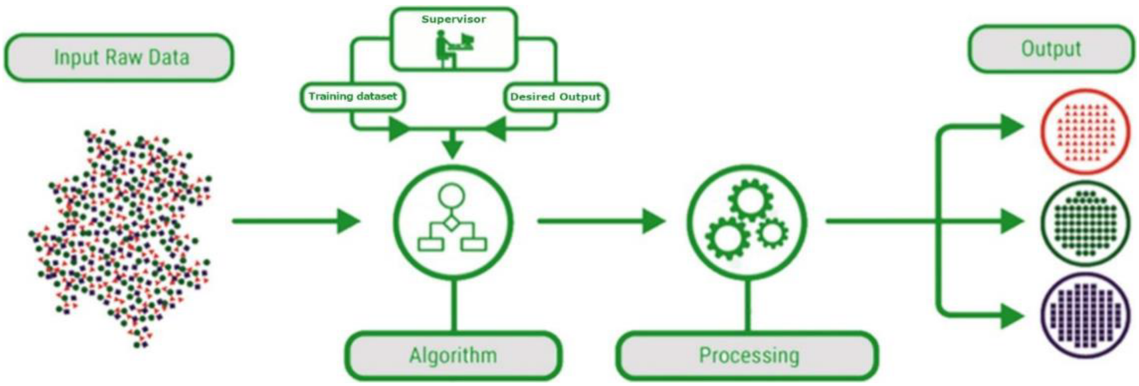

Figure 2.2: Supervised learning process[11]

further be divided into two types of tasks:

✻ **Regression :**

Regression problem is when the output variable is continuous and real value. For example, price, weight, etc.

✻ **Classification :**

Classification is a problem when the output variable is a category (ex. mask, no-mask, person, car…etc.) and can be used in applications such as speech recognition, handwriting recognition, biometric identification, document classification…etc.

Naive Bayes, decision trees, support vector machines (SVM), logistic regression, and linear regression are a few instances of supervised learning algorithms. The list of the most popular algorithms for classification and regression is shown in Figure 2.3

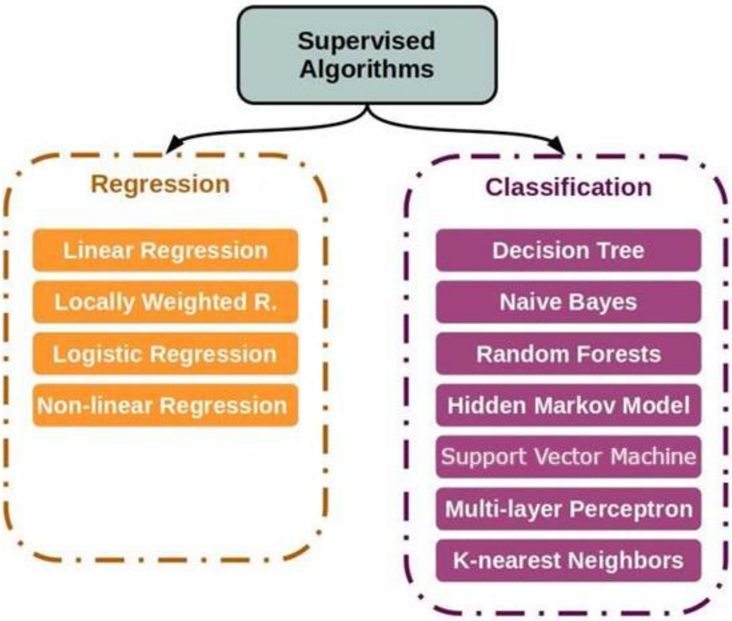

Figure 2.3: Regression and Classification algorithms [18]

2.3.1.2 Unsupervised Learning

Unsupervised Learning is a machine learning approach where users may learn without having to watch over the model. Rather, it lets the model do its own thing and find previously missed patterns and information. It addresses the unlabeled data (Figure 2.4) primarily. The systems have the ability to discern concealed characteristics from the given input data (interpretation). The patterns and similarities become more apparent as the data becomes easier to read. The model may now cluster any new data in accordance with its learned model.

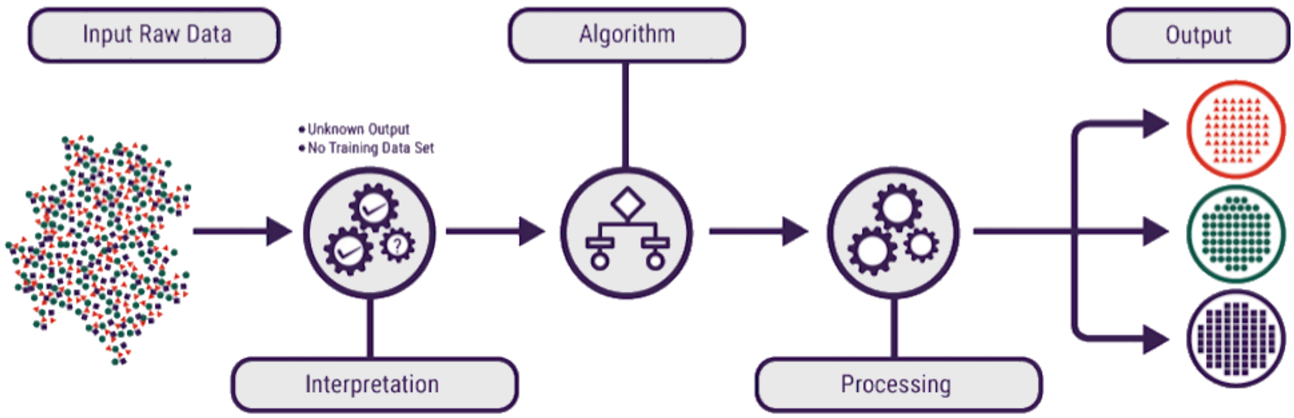

Figure 2.4: Unsupervised learning process [11]

Unsupervised learning can further be divided into two types of tasks :

✻ **Clustering :** A clustering problem is where you want to discover the inherent groupings in the data, such as grouping customers by purchasing behavior.

✻ **Association :** An association rule learning problem is where you want to discover rules that describe large portions of your data, such as people that buy X also tend to buy Y.

2.3.1.3 Reinforcement Learning

Reinforcement learning, in the context of artificial intelligence, is a type of dynamic programming that trains algorithms using a system of reward and punishment. A reinforcement learning algorithm, or agent, learns by interacting with its environment. The agent receives rewards by performing correctly and penalties for performing incorrectly. The agent learns without human intervention by maximizing its reward and minimizing its penalty.

Reinforcement learning differs from the supervised learning in a way that in supervised learning the training data has the answer key with it so the model is trained with the correct answer itself whereas in reinforcement learning, there is no answer but the reinforcement agent decides what to do to perform the given task. In the absence of a training dataset, it is bound to learn from its experience. Figure 2.5 shows how reinforcement learning works to train itself with rewards and penalties according to given policy.

The main points we should consider in Reinforcement learning :

- **Input :** The input should be an initial state from which the model will start;
- **Output :** There are many possible output as there are variety of solution to a particular problem;
- **Training :** The training is based upon the input, the model will return a state and the user will decide to reward or punish the model based on its output;
- The model keeps continue to learn;
- The best solution is decided based on the maximum reward.

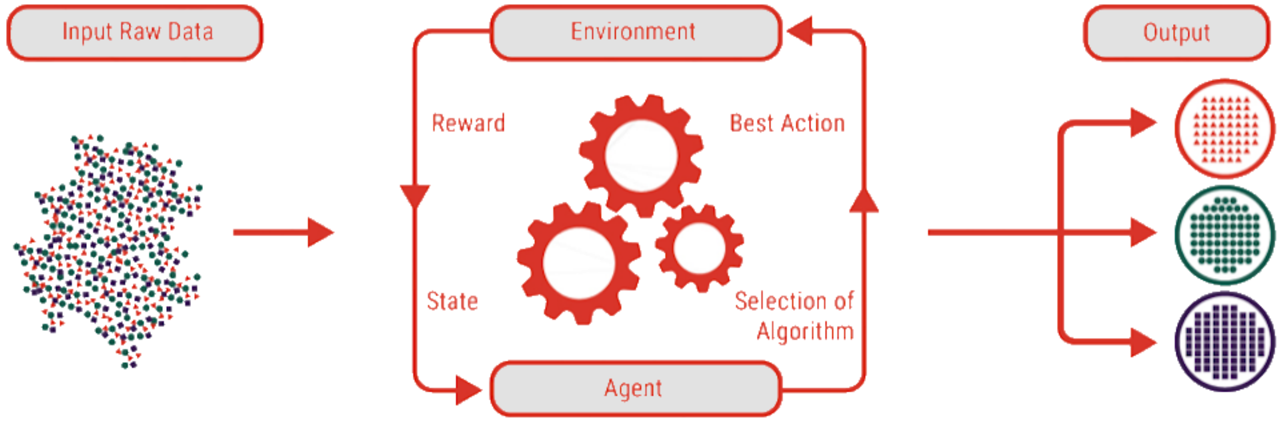

Figure 2.5: Reinforcement learning process [11]

Examples of reinforcement learning algorithms include: Q-learning and Deep Q-learning Neural Networks.

2.3.2 Machine Learning applications

Figure 2.6 shows different applications according to the type of machine learning :

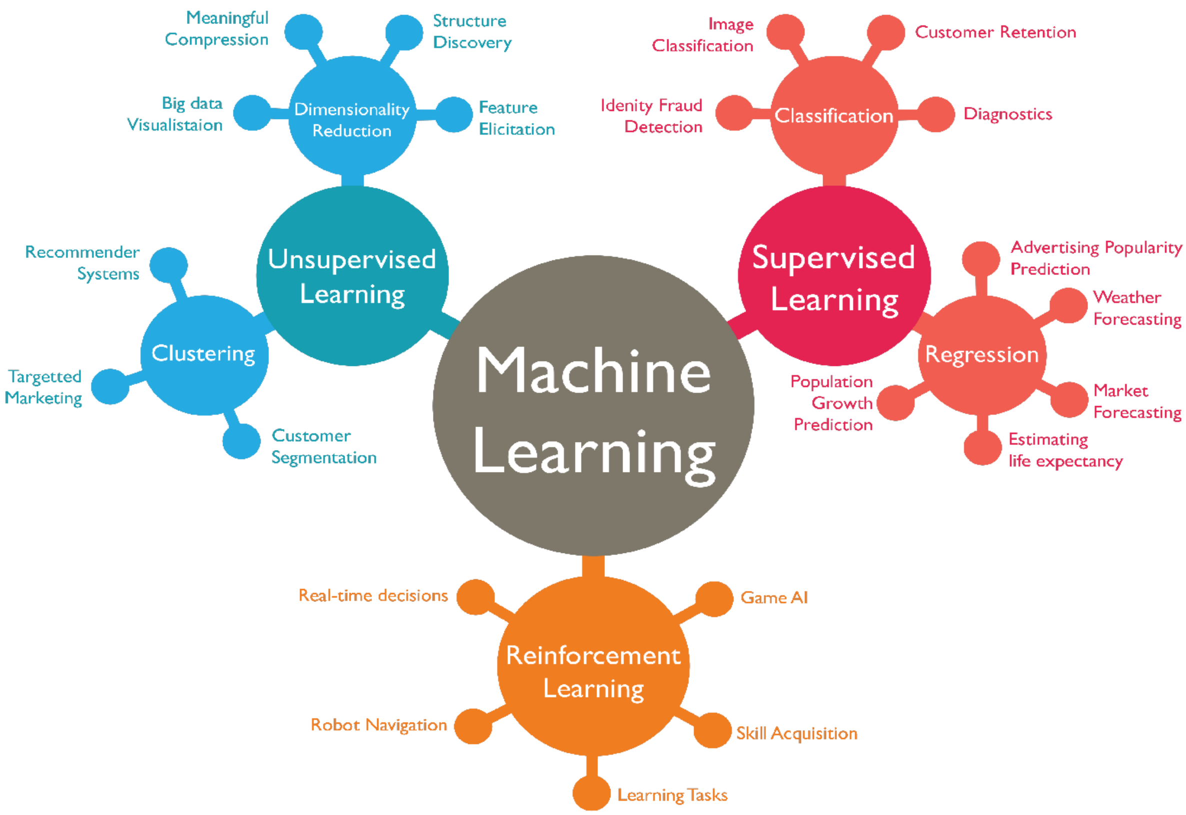

Figure 2.6: Different Machine-Learning applications according to their types[3]

2.4 Deep Learning

Deep learning is a subset of machine learning which itself is a subset of Artificial intelligence, it deals with algorithms inspired by the structure and function of the human brain.

Deep learning algorithms work with an enormous amount of both structured or unstructured data and its core concept lies in artificial neural networks, which enable machines to make decision.

Artificial neural network (ANN) is the piece of a computing system designed to simulate the way the human brain analyzes and processes information. It is the foundation of AI and solves problems that would prove impossible or difficult by human or statistical standards. Figure 2.7 describe a simple artificial neural network structure :

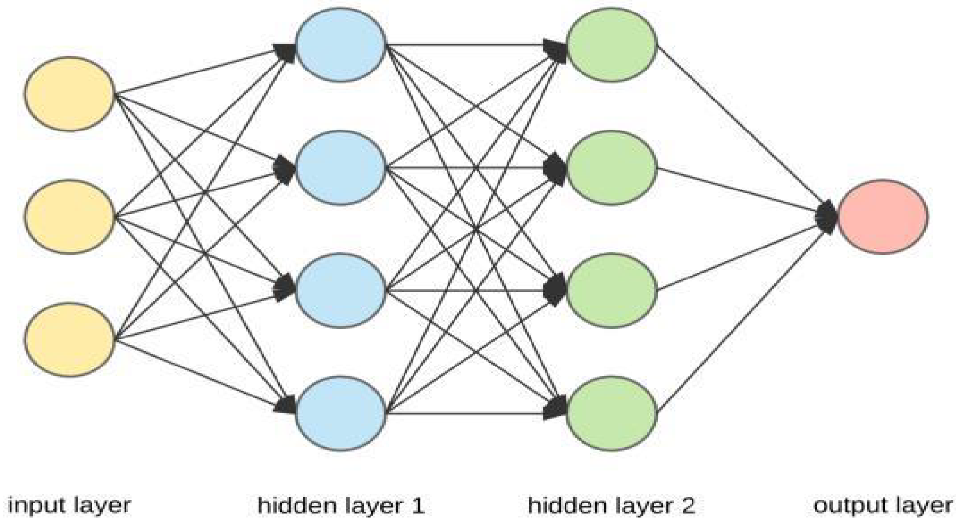

Figure 2.7: : Basic Artificial Neural Network structure

The ANN is constructed from 3 types of layers :

- **Input layer :** initial data for the neural network.
- **Hidden layers :** intermediate layer between input and output layer and place where all the computation is done.
- **Output layer :** produce the result for given inputs.

2.4.0.1 Neurone process

A neural network is made up of neurons connected to each other at the same time, each connection of the neural network is associated with a weight that dictates the importance of this relationship in the neuron when multiplied by the input value as shown in Figure 2.8. Each neuron has an activation function that defines the output of the neuron. The activation function is used to introduce non-linearity in the modeling capabilities of the network. The formal representation of neuron: “wij” weights, “bj” biases, “xn” inputs, and ” yi” output

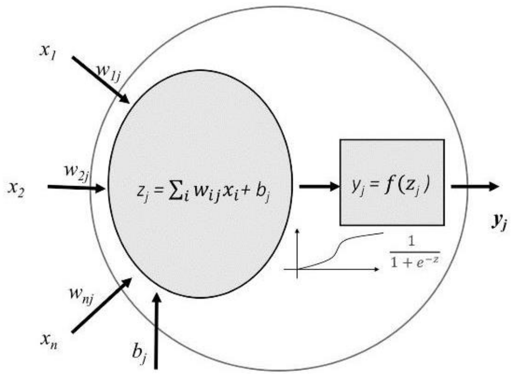

Figure 2.8: Neuon formal representation

Most essential element of Deep Learning is learning the values of parameters “wij”. The learning process in a neural network is an iterative process consisting of two phases (Figure 2.9):

- When the network is exposed to training data, the first stage of forward propagation takes place. These data travel across the whole neural network in order for the predictions (labels) to be computed. That is, the input data "xn" is routed through the network so that each neuron applies its transformation to the data it receives from the neurons in the layer above before giving it to the neurons in the layer below. The final layer will include the label prediction result for those input samples once the data has passed through all of the layers and all of the neurons have completed their computations.

- In the second phase of back propagation, the loss function is used to evaluate the loss (or error) and to compare and quantify the degree to which the neural prediction output was accurate compared to the label, or right result. To all the neurons in the hidden layer that directly contribute to the output, the mistake is transmitted backwards. Consequently, the weights of the neuronal connections will be gradually changed over the model’s training process until accurate predictions are made.

Following back-propagation, optimizers algorithms (such as gradient descent, stochastic gradient descent, momentum, AdaDelta, Adam, etc.) minimize errors to adjust the weights of neurons. In the case of the gradient descent method, this is done by computing the derivative

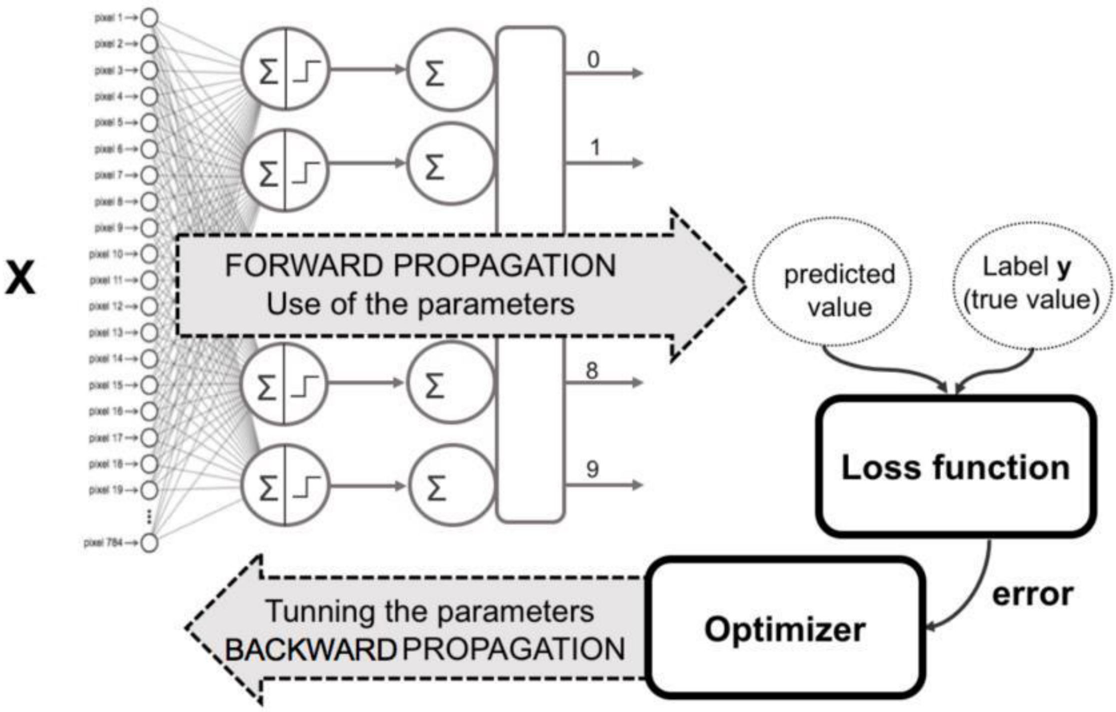

Figure 2.9: Back-propagation and forward-propagation process [19]

(or gradient) of the loss function, which allows for small weight adjustments. Generally, we achieve this by passing batches of data to the network in consecutive epochs, or iterations, of the whole dataset.

2.4.1 Deep Networks types

There are many types of neural networks in deep learning which are used for different purposes, but four of them are considered as major types of deep neural network :

- **Convolutional Neural Network (CNN)** - CNN is a class of deep neural networks most commonly used for image analysis.
- **Recurrent Neural Network (RNN)** - RNN uses sequential information to build a model. It often works better for models that have to memorize past data.
- **Generative Adversarial Network (GAN)** - GAN are algorithmic architectures that use two neural networks to create new, synthetic instances of data that pass for real data. A GAN trained on photographs can generate new photographs that look at least superficially authentic to human observers.
- **Deep Belief Network (DBN)** - DBN is a generative graphical model that is composed of multiple layers of latent variables called hidden units. Each layer is interconnected, but the units are not.

2.4.2 Convolutional Neural Network (CNN)

Convolutional neural networks are a subset of artificial neural networks that are mostly used for processing and image recognition. They are especially made to handle pixel data. CNN is a widely used deep learning technique that works well with both photos and videos.

2.4.2.1 Basic CNN architecture

Like other neural networks, a CNN is composed of an input layer, an output layer, and many hidden layers in between (Figure 2.11) :

a. Feature Detection Layers

These layers in the fundamental architecture operate on the data in one of two ways: pooling or convolution. Through a series of convolutional filters, each of which activates a different feature from the input pictures, convolution processes the images. By executing nonlinear downsampling, pooling reduces the amount of parameters the network needs to learn, simplifying the output. Tens or even hundreds of layers go through these procedures again, teaching each layer to recognize a new set of characteristics.

b. Classification Layers

The design of a CNN switches to classification after feature detection. The fully connected layer (FC), which comes in second to last, produces a vector with K dimensions, where K is the number of classifications the network can predict. The probabilities for each class in every image that is being categorized are contained in this vector. The classification output is produced by the CNN architecture's last layer using the determined class probabilities.

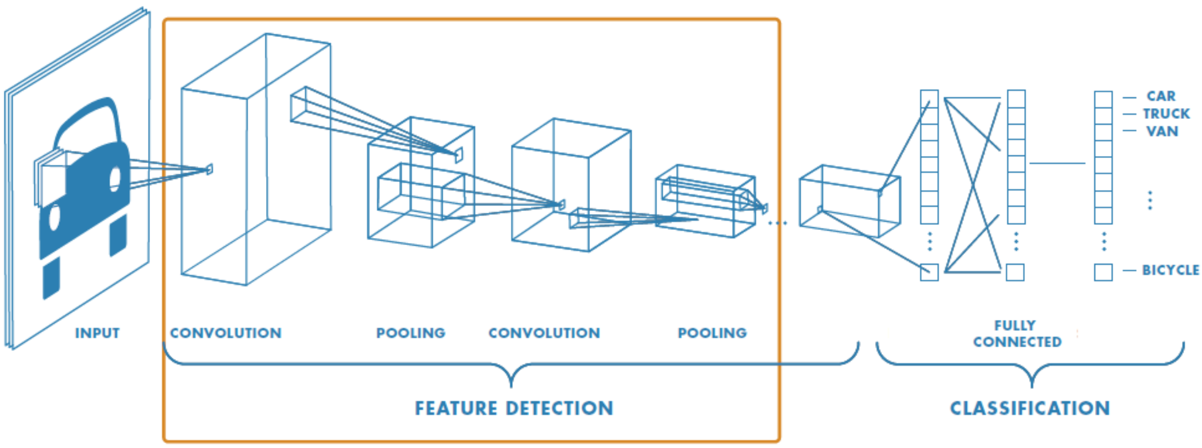

Figure 2.10: Basic CNN structure [6]

2.4.2.2 Deep learning techniques

Various techniques can be used to create strong DL models. These techniques include learning rate decay, transfer learning, training from scratch and dropout [4].

a. Learning rate decay

The learning rate is a hyperparameter – a factor that defines the system or set conditions for its operation prior to the learning process – those controls how much change the model experiences in response to the estimated error every time the model weights are altered. Learning rates that are too high may result in unstable training processes or the learning of a suboptimal set of weights. Learning rates that are too small may produce a lengthy training process that has the potential to get stuck. The learning rate decay method – also called learning rate annealing or adaptive learning rates – is the process of adapting the learning rate to increase performance and reduce training time. The easiest and most common adaptations of learning rate during training include techniques to reduce the learning rate over time.

b. Training from scratch

This method requires a developer to collect a large labeled data set and configure a network architecture that can learn the features and model. This technique is especially useful for new applications, as well as applications with a large number of output categories. However, overall, it is a less common approach, as it requires inordinate amounts of data, causing training to take days or weeks.

c. Dropout

This method attempts to solve the problem of overfitting in networks with large amounts of parameters by randomly dropping units and their connections from the neural network during training. It has been proven that the dropout method can improve the performance of neural networks on supervised learning tasks in areas such as speech recognition, document classification and computational biology.

2.4.3 Deep learning application

Because DL models process information in ways similar to the human brain, they can be applied to many tasks people do. DL is currently used in most common image recognition tools, natural language processing (NLP) and speech recognition software.

These tools are starting to appear in applications as diverse as self-driving cars and language translation services.

Use cases today for DL include all types of big data analytics applications, especially those focused on NLP, language translation, medical diagnosis, stock market trading signals, network security and image recognition.

Specific fields in which DL is currently being used include the following [4] :

- **Customer experience (CX) :** Deep learning models are already being used for chatbots. And, as it continues to mature, deep learning is expected to be implemented in various businesses to improve CX and increase customer satisfaction.
- **Text generation :** Machines are being taught the grammar and style of a piece of text and are then using this model to automatically create a completely new text matching the proper spelling, grammar and style of the original text.
- **Aerospace and military :** Deep learning is being used to detect objects from satellites that identify areas of interest, as well as safe or unsafe zones for troops.
- **Industrial automation :** Deep learning is improving worker safety in environments like factories and warehouses by providing services that automatically detect when a worker or object is getting too close to a machine.
- **Adding color :** Color can be added to black-and-white photos and videos using deep learning models. In the past, this was an extremely time-consuming, manual process.
- **Medical research :** : Cancer researchers have started implementing deep learning into their practice as a way to automatically detect cancer cells.
- **Computer vision :** Deep learning has greatly enhanced computer vision, providing computers with extreme accuracy for object detection and image classification, restoration and segmentation.

2.5 Deep Learning versus Machine Learning

Deep learning is a subset of machine learning, however Deep learning distinguishes itself from classical machine learning by the type of data that it works with and the methods in which it learns.

In order to generate predictions, machine learning algorithms use structured, labeled data, which is specified characteristics arranged in tables from the model's input data. This isn't to say that it doesn't employ unstructured data; rather, it only indicates that, in the event that it does, pre-processing is often used to arrange the data into a structured manner.

A portion of the data pre-processing that is usually required for machine learning is eliminated by deep learning. These algorithms automate feature extraction, reducing the need for human specialists, and can ingest and handle unstructured data, such as text and photos. For illustration, suppose we wished to classify a collection of pictures of various pets according to categories like "cat," "dog," "hamster," etc. Deep learning algorithms are able to identify which characteristics—like ears, for example—are most crucial in differentiating one species from another. This feature hierarchy in machine learning is created by hand by a human expert.

Then, through the processes of gradient descent and backpropagation, the deep learning algorithm adjusts and fits itself for accuracy, allowing it to make predictions about a new photo of an animal with increased precision.

Different forms of learning, which are often divided into supervised and unsupervised learning, may also be accomplished via machine learning and deep learning models. Labeled datasets are used in supervised learning to classify or predict; accurate labeling of incoming data necessitates human interaction. Unsupervised learning, on the other hand, groups the data according to any unique features it finds in the data by identifying patterns rather than requiring labeled datasets. [16]

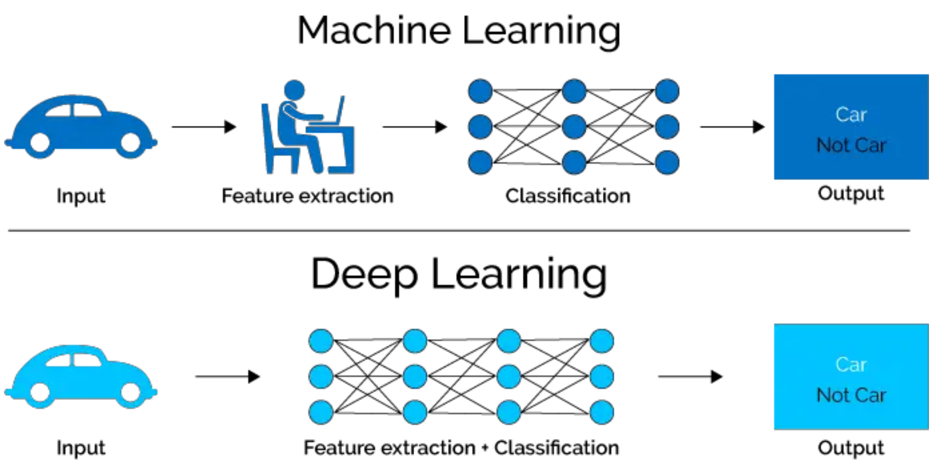

Figure 2.11: Machine Learning and Deep Learning Strategies[12]

2.6 Transfer leaning

In machine learning, transfer learning refers to the process of using a previously learned model on a novel issue. In transfer learning, a computer makes more predictions about a new task based on what it has learnt from an earlier assignment. For instance, while training a classifier to determine whether an image contains food, you may utilize the knowledge acquired during training to identify drinks.

Transfer learning occurs when a previously learned model is applied to a new situation. Due to its ability to train deep neural networks on little amounts of data, it is now quite popular in the field of deep learning. This is especially useful in data science as most real-world scenarios don't call for millions of labeled data points in order to train complex models.

Through transfer learning, the expertise of a machine learning model that has already been trained is applied to a distinct but related problem. For instance, you might utilize the model's training data to recognize additional things, like sunglasses, if you trained a straightforward classifier to determine if a picture has a backpack [5].

2.6.1 Models That Have Been Pre-Trained

Numerous well-liked pre-trained machine learning models are accessible. One of them is the Inception-v3 model, which was created for the ImageNet "Large Visual Recognition Challenge." In this challenge, participants had to group 1,000 images into subcategories, such "dishwasher," "Dalmatian," and "zebra." At this point, you might be asking what kinds of tasks you can utilize pre-trained models for. While there are a lot of plug-and-play models available, the most well-liked ones tend to be the ones that might perhaps aid you with your specific issues [5]:

- VGG (VGG-16 or VGG-19)
- GoogLeNet or InceptionV3
- Residual Network (ResNet50)

2.6.2 VGG-16

VGG-16 is a convolutional neural network that is 16 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database.

The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224. For more pretrained networks in MATLAB®, see Pretrained Deep Neural Networks.

You can use classify to classify new images using the VGG-16 network. Follow the steps of Classify Image Using GoogLeNet and replace GoogLeNet with VGG-16.

To retrain the network on a new classification task, follow the steps of Train Deep Learning Network to Classify New Images and load VGG-16 instead of GoogLeNet [10].

2.6.2.1 VGG-16 Architecture

Of all the configurations, VGG16 was identified to be the best performing model on the ImageNet dataset. Let's review the actual architecture of this configuration.

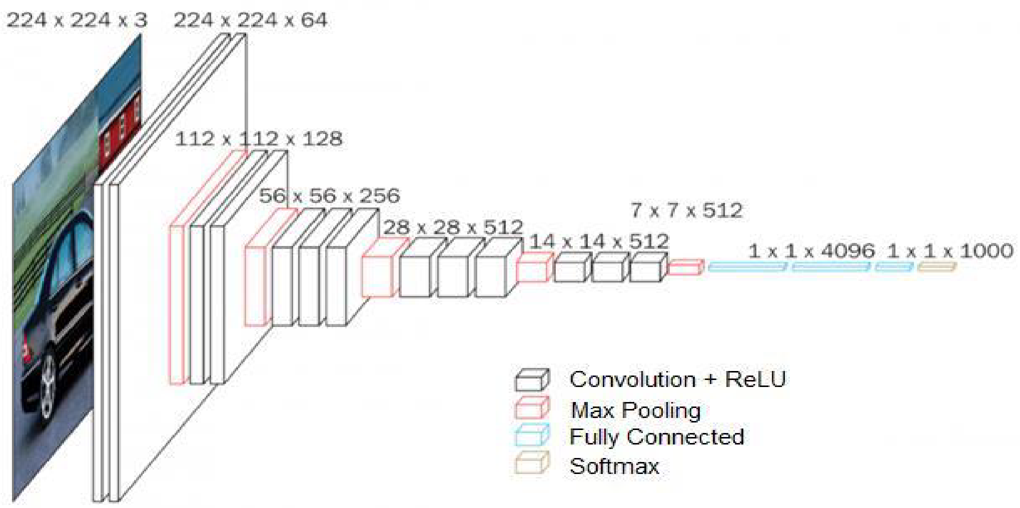

Figure 2.12: VGG-16 Architecture [17].

An RGB picture with a fixed size of 224 by 224 is the input for the cov1 layer. The picture is processed using a series of convolutional layers, where filters are applied with a minuscule 3x3 receptive field—the lowest size that can effectively capture left/right, up/down, and center—in the image. It also makes use of 1×1 convolution filters in one of the configurations, which is equivalent to a linear transformation of the input channels (followed by non-linearity). The convolution stride is set at one pixel, and the convolution layer input's spatial padding is designed to maintain the spatial resolution even after convolution—that is, for a 3x3 convolution, the padding is one pixel. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers (not all the conv. layers are followed by max-pooling). Max-pooling is performed over a 2×2 pixel window, with stride 2.

Following a stack of convolutional layers (which varies in depth across different architectures) are three Fully-Connected (FC) layers: the first two have 4096 channels apiece, while the third performs 1000-way ILSVRC classification and so has 1000 channels (one for each class).

The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks.

Every concealed stratum possesses the rectification (ReLU) non-linearity. It should be noted that all but one of the networks lack Local Response Normalization (LRN), which lengthens calculation times and increases memory use while having no effect on performance on the ILSVRC dataset [10].

2.7 Conclusion

In this chapter, we provided a concise introduction to machine learning, covering its various types and algorithms. We then discussed the principles of deep learning and its diverse models, supplemented with examples to highlight the differences between machine learning and deep learning.

CHAPTER 3

ARCHITECTURE DESIGN AND EXPERIMENTATION

3.1 Introduction

The agricultural sector is undergoing a radical transformation with the adoption of artificial intelligence applications, enhancing the efficiency and effectiveness of agricultural operations. Integrating AI into agriculture opens up vast opportunities for improving farm management and increasing crop productivity.

This advanced technology provides innovative solutions that help farmers tackle the challenges of traditional farming with greater precision and effectiveness. In this chapter we present our architecture of the system,design with UML our experimentation used to illustrate and validate our work.

3.2 Architecture of the system

The general architecture of an agricultural application utilizing artificial intelligence (AI) consists of several interconnected layers and modules to ensure data collection, processing, analysis, and decision-making.

3.2.1 Sensors and Data Collection

3.2.1.1 Internet of Things (IoT) Sensors

- ❖ **Environmental Sensors :** Measure temperature, humidity, light, etc.
- ❖ **Soil Sensors :** Measure moisture, chemical composition, soil temperature.
- ❖ **Drones and Satellites :** Provide aerial imagery and geospatial data.

3.2.1.2 External Data Sources

- ❖ **Weather Data :** Information about climate and weather forecasts.
- ❖ **Market Data :** Crop price trends and agricultural product trends.

3.2.2 Communication Infrastructure

3.2.2.1 Communication Networks

- **Wireless Networks (Wi-Fi, LoRa, NB-IoT) :** For transmitting sensor data.
- **5G :** For faster and more reliable connectivity.

3.2.3 Data Processing Nodes

3.2.3.1 Edge Computing

- Local data processing near sensors for real-time responses.

3.2.3.2 Cloud Computing

- **Data Storage :** Cloud databases for large storage capacity.
- **Advanced Processing :** Utilizing high computing capabilities for complex analytics.

3.2.4 Analysis and AI Modules

3.2.4.1 Data Preprocessing

- Cleaning and transforming raw data for use by AI algorithms.

3.2.4.2 AI Models

- **Predictive Analysis :** Crop yield prediction, early disease detection.
- **Machine Learning :** Supervised and unsupervised learning models for data analysis.
- **Computer Vision :** Using drone and satellite images for crop monitoring.

3.2.5 User Interface

3.2.5.1 Mobile and Web Applications

- **Dashboards :** Data and analytics visualization.
- **Alerts and Notifications :** Real-time warnings about crop conditions and actionable recommendations.
- **Information Portals :** Access to historical data and trends

3.2.6 Data Security and Management

3.2.6.1 Data Security

- ❖ Data encryption in transit and at rest.
- ❖ Access controls to ensure only authorized individuals can access sensitive data

3.2.6.2 Data Management

- ❖ Backup and recovery strategies.
- ❖ Compliance with data protection regulations (e.g., GDPR).

3.2.7 Integration and Interoperability

3.2.7.1 APIs and Web Services

- ❖ Application programming interfaces for integration with other systems (e.g., farm management systems, trading platforms).

3.2.7.2 Standards and Protocols

- ❖ Adoption of industry standards to ensure interoperability between different system components.

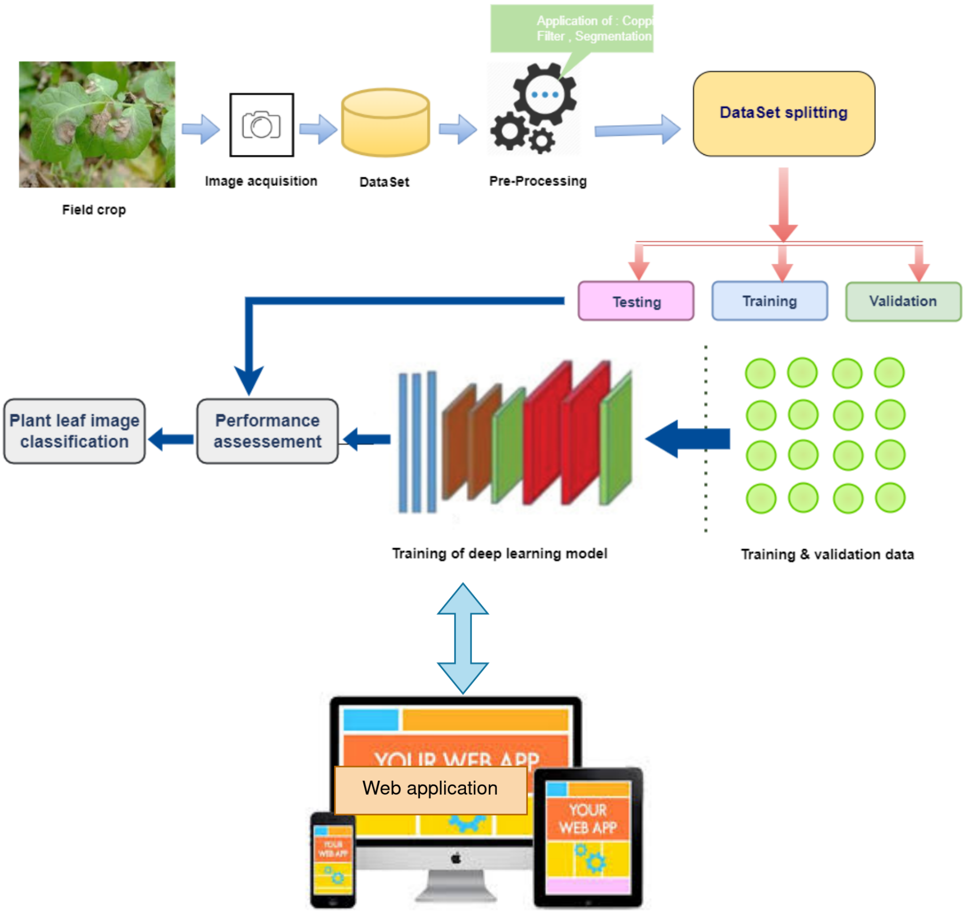

Figure 3.1: Architecture of the system

3.3 Unified Modeling Language (UML) diagrams of our system

The Unified Modeling Language (UML) is a crucial tool in both software development and various non-software industries. It provides a visual representation of a system's behavior, processes, and structure, aiding in the identification of potential errors in application architecture, system behavior, and business processes. UML is particularly effective for creating class diagrams and use case diagrams, which help to clarify and streamline complex systems.

3.3.1 Use Case Diagram

The use case diagram illustrates the interactions between different types of users and the system functionalities. Actors of the system are:

- Admin: An administrator who has comprehensive access to various system functionalities.

- User: A general user who interacts with the system.
- Customer: A user who has specific interactions related to account management and participation requests.
- E.Agriculer: Likely an agriculture specialist or a user with specific roles related to agriculture.
- Farmer: A user involved in farming activities.
- Authentication: Involves verifying the identity of users. This is typically accessed by the general user (User).
- CRUD Product: Stands for Create, Read, Update, Delete operations on products. This functionality is managed by the Admin.
- Browsing Users: Allows users to view other users' information. Admin has access to this use case.
- Confirming Participation Requests: Involves verifying and approving requests for participation in certain activities. This is handled by the Admin.
- Create an Account: Enables users to register and create a new account. Customers interact with this functionality.
- Login / Logout: Manages user sessions by allowing them to log in and out of the system. Customers and Admins use this feature.
- Browsing Participation Requests: Allows users to view requests made by others to participate in activities. Admin has access to this.
- Participation Requests:Users (Customers) can send requests to participate in certain activities or services.
- Sends an Email: Users (Customers) can send emails, possibly for communication or confirmation purposes.
- Product Promotion: Involves promoting products, likely a feature used by the Admin.
- Examination: The farmer can examine their plants or crops; in our experimentation, we focused on potato leaves.

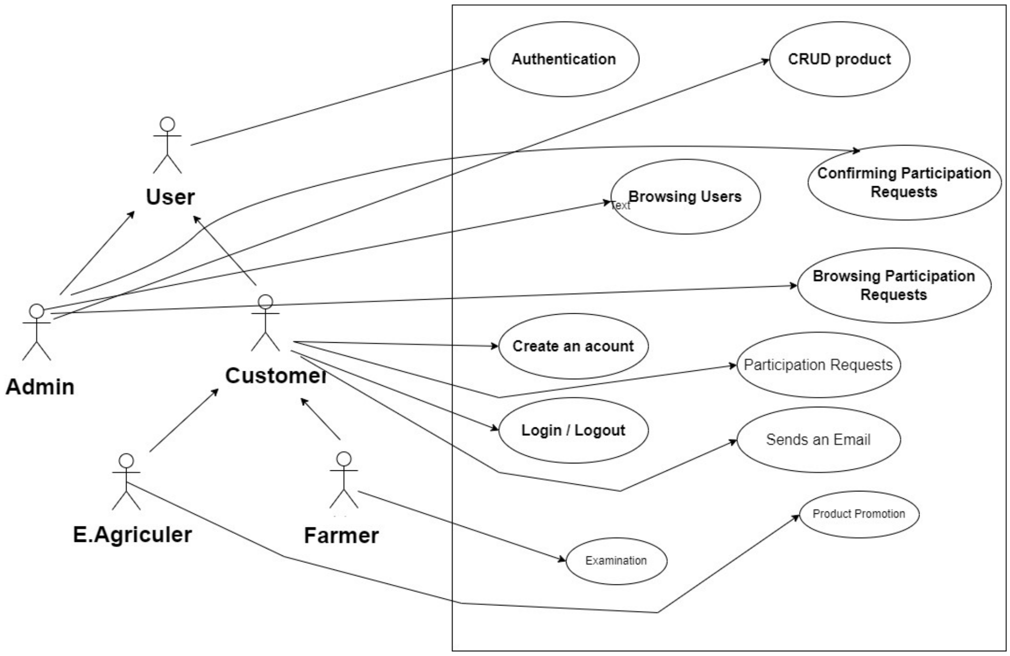

Figure 3.2: Use case diagram

3.3.2 Class Diagram Overview

A Class Diagram is used to represent the blueprint of a system by showing its classes and the relationships between them. It provides a visual representation of the different classes and their interactions, resembling a flowchart. Each class is depicted as a box divided into three sections:

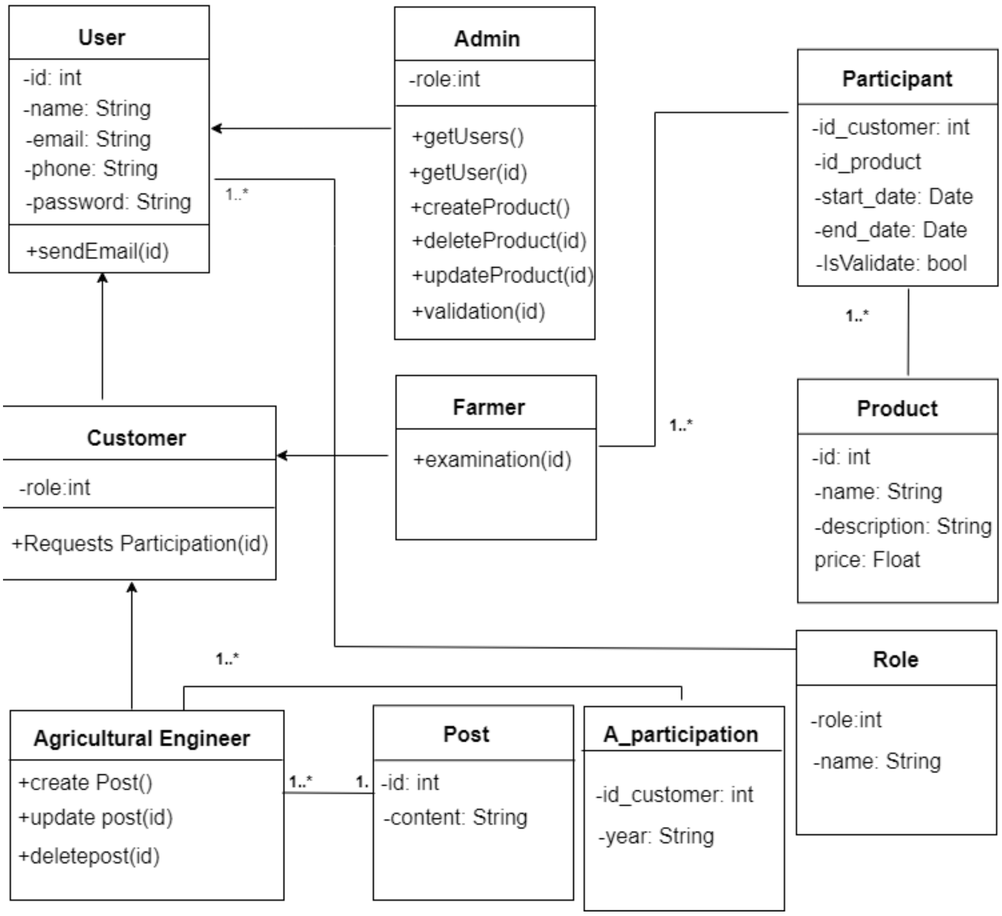

Figure 3.3: Class diagram

3.4 Artificial intelligent integration in our system

One of the major challenges in our proposition is the integration of deep learning models into our system. This integration will allow users to diagnose and consult on their plants. The process of integration as follows:

- Data Collection and Preparation
- Model Building
- Model Deployment

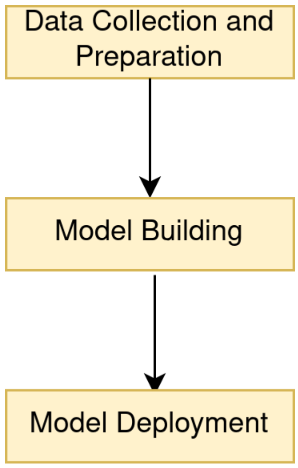

Figure 3.4: Process of artificial integration

3.4.1 Data Collection

Data collection involves gathering the necessary data to build our model. We capture images with a camera equipped with specific properties **Redmi9 and SAMSUNG** mobiles, particularly from various farms in El-Oued. The collected data are potatoes images,with two classes leaf disease and healthy leaf.

3.4.1.1 Leaf diseases Object detection

Leaf diseases Object detection is a pivotal technique in modern agriculture, revolutionizing the way plant diseases are identified and managed. Leveraging the power of computer vision, this technology enables automated detection and classification of diseases affecting plant leaves.

3.4.1.2 Annotated leaf data set

The annotated Potato's leaf dataset have two classes, healthy and diseased, consists of leaf images that have been labeled to distinguish between healthy leaves and those affected by disease. Each image in the dataset is annotated to indicate whether the leaf is healthy or diseased, providing ground truth labels for deep machine learning models

Figure 3.5: Annotation images 2 disease leaf and 03 healthy leaf

3.4.1.3 Data augmentation

Data augmentation is a crucial technique in the context of leaf images object detection for several reasons. Object detection involves identifying and localizing objects (in this case, leaves) within an image, which requires robust models that can generalize well across various conditions. Data augmentation is important[22]:

1. Enhances Model Generalization:

   - Variety in Training Data: By artificially increasing the diversity of the training dataset through augmentation, the model is exposed to a wider range of scenarios, helping it generalize better to unseen data.

- Handling Overfitting: Augmentation reduces the risk of overfitting, where the model performs well on training data but poorly on new, unseen data. This is especially critical in cases where the dataset is small or lacks variety.

2. Simulates Real-World Variability:

   - Lighting and Weather Conditions: Leaf images can vary significantly due to changes in lighting, shadows, and weather conditions. Augmenting data by altering brightness, contrast, and adding noise helps the model learn to recognize leaves under different environmental conditions.
   - Leaf Orientation and Position: Leaves can appear in various orientations and positions. Augmenting images through rotations, translations, and flips ensures that the model can detect leaves regardless of their orientation or placement within the image.

3. Improves Detection of Small and Occluded Objects:

   - Scaling and Cropping: Techniques like scaling and cropping can help the model learn to detect leaves of different sizes and those that are partially obscured. This is particularly useful for detecting small leaves or leaves partially covered by other foliage.
   - Adding Occlusions: Introducing occlusions in the training data can help the model learn to identify leaves that are not entirely visible, improving its robustness in real-world scenarios where leaves are often occluded by other leaves or branches.

Facilitates Robust Feature Learning:

- Noise and Distortions: Introducing random noise and distortions during augmentation can help the model learn more robust features that are less sensitive to minor image imperfections. This enhances the model's ability to detect leaves in suboptimal conditions.

3.4.2 Model building

This is the crucial phase in which we select the model that can resolve the object detection problem. We present,models and technique used to build and enhance the models for evaluation of models we use metrics of classification: precision, recall f1-score and confusion matrix. Furthermore the following diagrams use to present changes of the model during train validate and test phase:

- mAP: a crucial metric in evaluating the performance of object detection models, representing the precision-recall tradeoff across different classes.
- mAP@50:95, also known as the mean Average Precision at different Intersection over Union (IoU) thresholds, is a metric used to evaluate the performance of object detection models. It calculates the average precision (AP) across multiple IoU thresholds ranging from 0.5 to 0.95 in increments of 0.05.
- Box loss, also known as localization loss or bounding box regression loss, is a critical component in object detection models that measures the error between predicted bounding box coordinates and ground truth coordinates. It ensures accurate localization of objects within an image. Typically, box loss includes errors in the coordinates (such as center coordinates, width, and height) and is often computed using Smooth L1 Loss (Huber Loss), which balances sensitivity to outliers by combining L1 and L2 losses. The goal is to minimize this loss, leading to more precise bounding box predictions. During training, a steadily decreasing box loss indicates that the model is effectively learning to localize objects accurately.
- Class loss, or classification loss, is a fundamental component in object detection models that measures the error in predicting the class labels of detected objects. This loss helps the model improve its ability to correctly identify and classify objects within an image. Typically calculated using methods like cross-entropy loss or focal loss, class loss penalizes incorrect predictions and rewards correct ones. Cross-entropy loss assesses the difference between the predicted class probabilities and the true class labels, while focal loss extends this by focusing more on hard-to-classify examples, addressing class imbalance issues. A decreasing class loss during training signifies that the model is becoming more proficient in accurately classifying detected objects, enhancing its overall performance in object detection tasks.

3.4.2.1 YOLO (You Only Look Once)

YOLO (You Only Look Once) is a family of state-of-the-art object detection models known for their speed and accuracy. Developed by redmon et al. [15] and others, YOLO models have evolved through multiple versions, each improving upon the previous ones in various ways.

- Core Principles of YOLO:
  1. Single-Stage Detection:Unlike two-stage detectors like R-CNN and Faster R-CNN, which first generate region proposals and then classify them, YOLO treats object detection as a single regression problem. It directly predicts bounding boxes and class probabilities from full images in one evaluation.
  2. Unified Detection Framework:YOLO divides the input image into an $S \times S$ grid. Each grid cell is responsible for detecting objects whose center falls within it. For each grid cell, YOLO predicts a fixed number of bounding boxes, confidence scores for those boxes, and class probabilities.
- YOLOv1:
  1. Input Image Division: The image is divided into an $S \times S$ grid. Each grid cell predicts B bounding boxes and confidence scores for those boxes. Additionally, each cell predicts C class probabilities.
  2. Bounding Box Prediction: Each bounding box is defined by 5 predictions: x, y, w, h, and confidence. x and y are the coordinates of the box center relative to the bounds of the grid cell. w and h are the width and height of the box relative to the whole image. The confidence score reflects the confidence that the box contains an object and the accuracy of the box's location.
  3. Class Prediction: Each grid cell also predicts class probabilities for the object. These probabilities are conditional on the grid cell containing an object.
  4. Loss Function: The loss function in YOLOv1 includes terms for classification loss, localization loss (errors in bounding box coordinates), and confidence loss.
- YOLOv2 (YOLO9000)
  1. Batch Normalization:Introduces batch normalization to the convolutional layers, which helps in faster convergence and regularization.
  2. Anchor Boxes:YOLOv2 introduces anchor boxes, predefined bounding boxes of different shapes and sizes. The model predicts adjustments to these anchors instead of predicting bounding boxes from scratch, making it easier to detect objects of varying scales.

3.4.2.2 Roboflow 3.0 Object Detection (Fast) without data augmentation

Roboflow 3.0 Object Detection (Fast) is a streamlined and efficient solution for developing object detection models quickly. This service leverages the latest advancements in computer vision and machine learning to provide users with a robust and user-friendly platform,It is characterized by lightweight architectures that ensure rapid training and inference without significantly compromising accuracy.

The first experimental model is Roboflow 3.0 Object Detection (Fast) **without data augmentation** with input shape of image 640×640.

Total images	Train set	valid set	test set
284	201	56	27

Table 3.1: Images number, train valid and test split

Figure 3.6: Robotflow3 fast results mAP Box Loss Class loos and Object loss

The figure illustrate the training progression of an object detection model over 300 epochs. The primary graph depicts the mean Average Precision (mAP) and mAP@50:95 metrics, with the dark purple line representing the mAP and the light purple line showing the stricter mAP@50:95. Both metrics indicate a steady improvement in model performance, stabilizing around 0.4 to 0.5. The lower three graphs show the respective losses for bounding box prediction (Box Loss), object classification (Class Loss), and object presence confidence (Object Loss). Each loss graph demonstrates a rapid initial decrease, indicating effective early learning, followed by a gradual stabilization, reflecting the model's convergence. Overall, the graphs suggest that the model is learning effectively and improving its object detection capabilities over time.

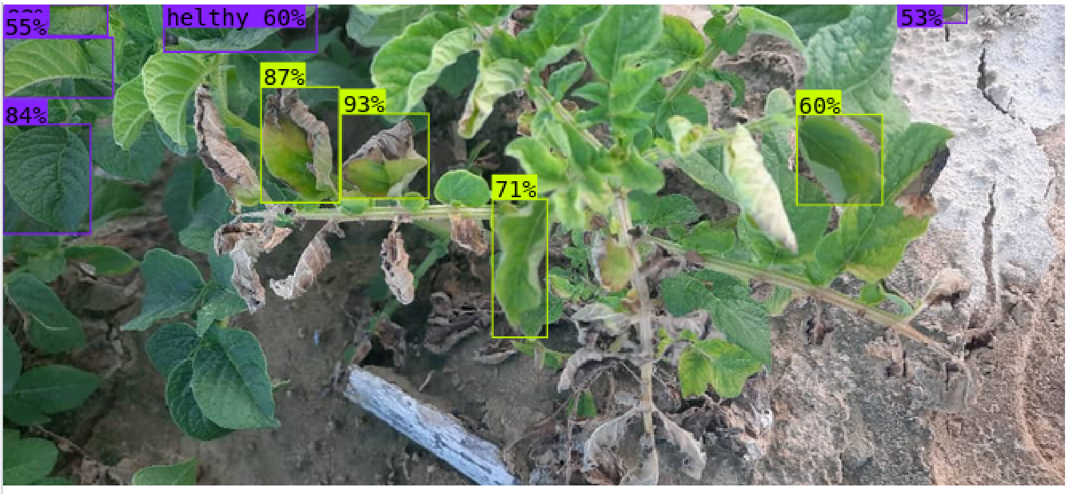

Figure 3.7: result of Robotflow3 fast without data augmentation

The figure illustrate the test result of this model predict 08 objects 04 healthy with 55%,60%,84% et 53% and 04 diseases 87%,93%,71% et 60%.

3.4.2.3 Roboflow 3.0 Object Detection (Fast) with data augmentation

We use the following data augmentation techniques:

Technique	values
Flip	Horizontal
Rotation	Between -15° and 15°
Grayscale	Apply to 15% of images
Hue	Between -15° and 15°
Noise	Up to 0.1% of pixels

Table 3.2: Augmentation technique

Data set augmented until 875 images divided on 768 train,72 valid and 35 test. the result describe in the diagram.

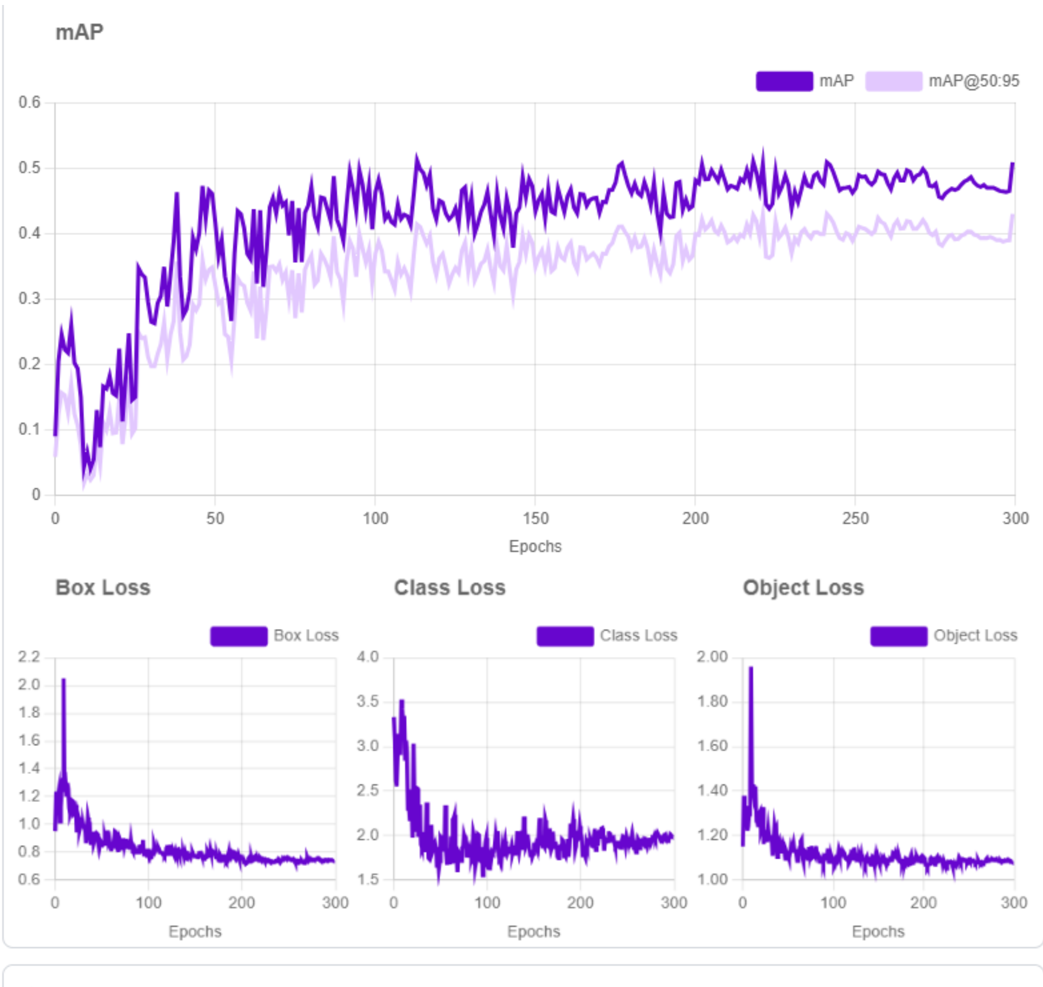

Figure 3.8: Result of robotflow with data augmentation

The training results of the object detection model over 300 epochs show significant improvement in performance metrics. The mean Average Precision (mAP) steadily increases and stabilizes around 0.4 to 0.5, indicating enhanced precision and recall capabilities. The stricter mAP@50:95 metric also improves but remains slightly lower, stabilizing around 0.3 to 0.4. In terms of losses, the box loss decreases and stabilizes around 0.6, the class loss reduces to around 1.5, and the object loss diminishes to about 1.2. These trends demonstrate effective model training, with notable reductions in errors related to bounding box predictions, object classification, and object presence confidence.

The following example show the result of the this model it can predict 06 object,healthy 94%,77%,71% and 67% diseases 90% and 88%.

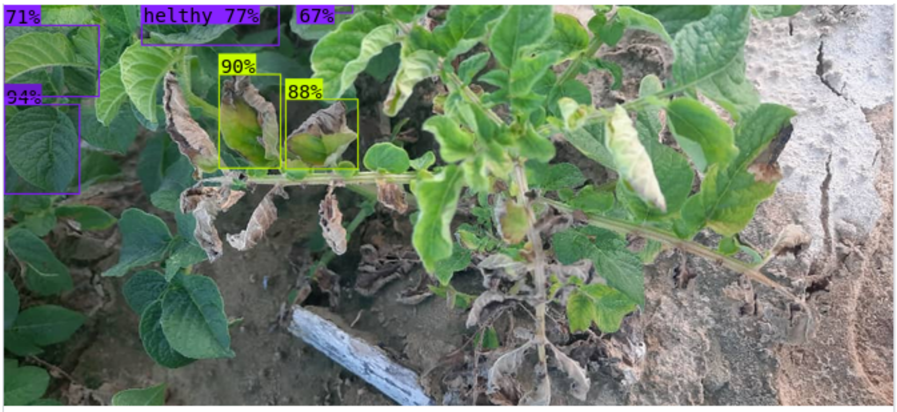

Figure 3.9: Robotflow boject detection model with data augmentation model object detection

3.4.2.4 Yolo5

YOLOv5 [20], developed by Ultralytics, is a cutting-edge object detection model known for its remarkable balance between speed and accuracy, making it highly suitable for real-time applications. As a continuation of the YOLO (You Only Look Once) series, YOLOv5 builds on its predecessors with significant improvements in performance and ease of use. It comes in various sizes, from small to extra-large, to cater to different computational capacities and performance needs. Built on the PyTorch framework, YOLOv5 includes advanced features such as CSP (Cross Stage Partial connections) and PANet (Path Aggregation Network) for enhanced feature extraction and fusion, as well as innovative training techniques like mosaic data augmentation and self-adversarial training. This model's user-friendliness, with pre-trained weights and straightforward commands for training, validation, and inference, makes it a popular choice for applications ranging from real-time video surveillance to autonomous driving and medical imaging. We use 284 images.

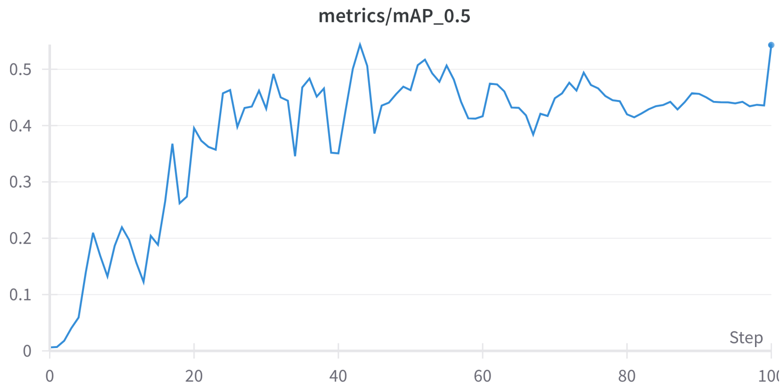

Figure 3.10: mAP0.5

The figure 3.10 display the training progress of a YOLOv5 model, illustrating its performance using mean Average Precision (mAP) metrics. The first chart, labeled metrics/mAP0.5, tracks the mAP at an IoU (Intersection over Union) threshold of 0.5, a standard measure for evaluating object detection accuracy. Initially, the mAP@0.5 rises quickly, indicating rapid learning, before leveling off with some fluctuations as the model fine-tunes its predictions. By the end of the training, the mAP@0.5 reaches slightly above 0.5, showcasing the model's capability to correctly identify objects with at least 50% overlap.

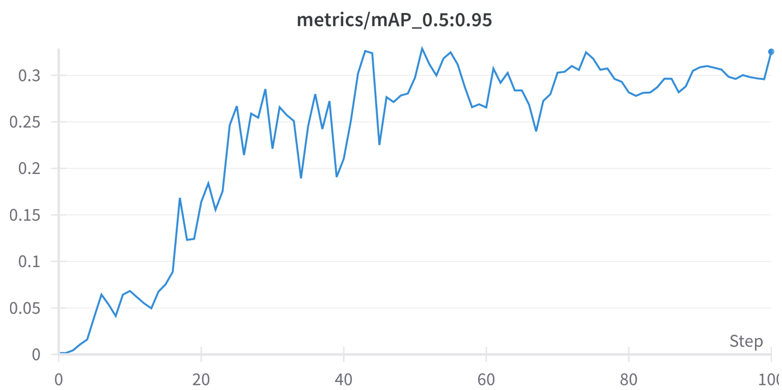

Figure 3.11: mAP0.5:0.95

Figure 3.11 metrics/mAP0.5:0.95, presents the mAP averaged across a range of IoU thresholds from 0.5 to 0.95. This metric is more stringent, assessing the model's precision under varying conditions. Similar to the first chart, the mAP improves rapidly initially, then stabilizes with some variability. The final value, slightly above 0.3, reflects the model's consistent performance across different IoU thresholds, although it is naturally lower due to the more rigorous evaluation.

Overall, both charts demonstrate the model's learning curve, highlighting its initial rapid improvement and subsequent stabilization, with the final metrics indicating effective training and reasonable detection performance.

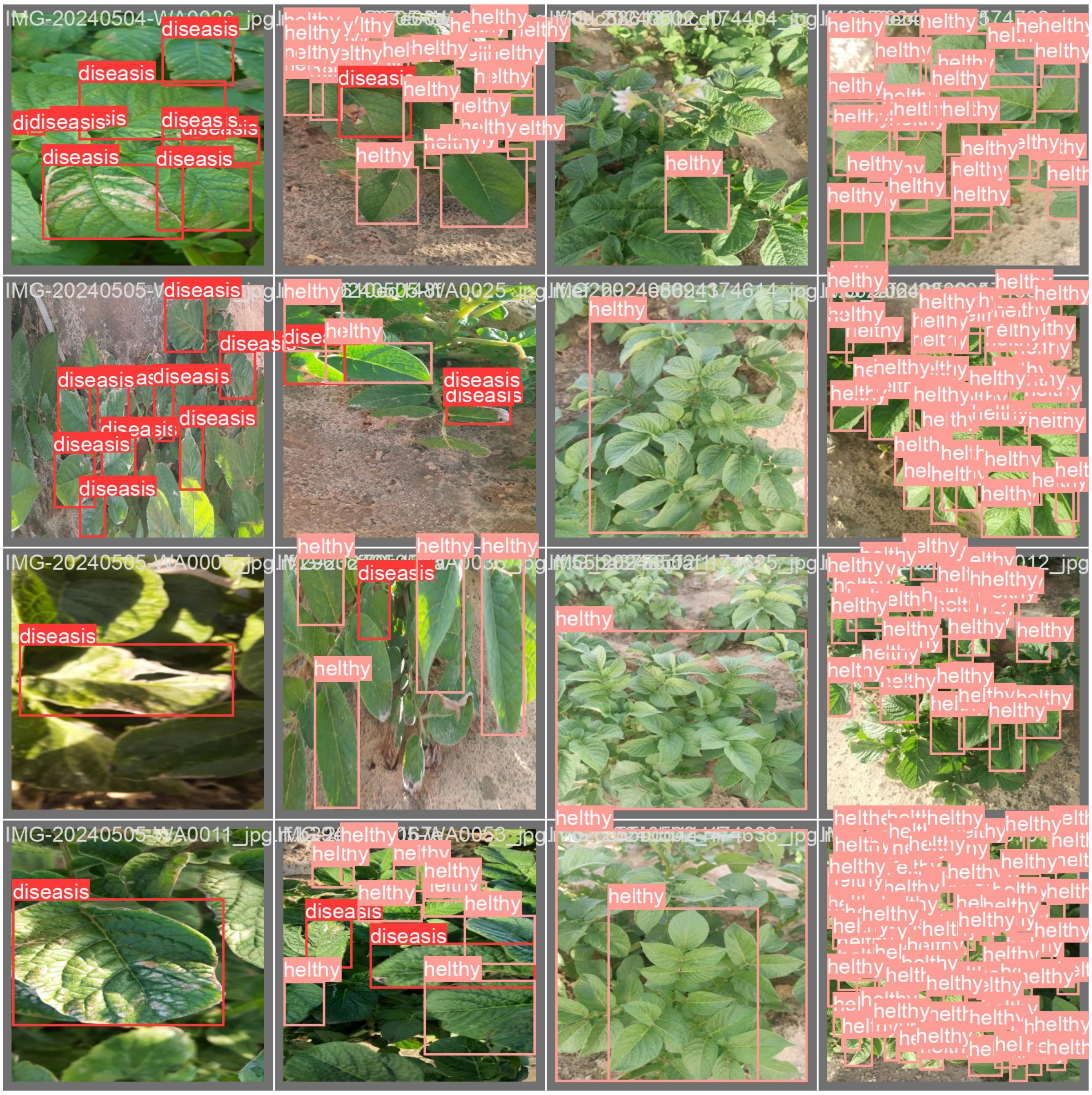

Figure 3.12: Example of results

3.4.3 Model deploy

Deploying a model involves transitioning it from a development environment to a production-ready state where it can be used to make predictions on new data. Roboflow cloud can supports the deployment of various popular model architectures and fine-tuned models. It provides an easy-to-use interface and natively integrated SDKs for optimized model performance across different devices.

The QR Code deployment feature in Roboflow is a practical tool for distributing models for testing or field use cases. It allows you to quickly get your model into the hands of anyone with a mobile phone, making it easier to test models or benefit from your trained model for any use case.

(a) Model without data augmentation

(b) Model with data augmentation

Figure 3.13: QR Model deploy

3.5 Conclusion

In this chapter, we presented an architecture designed for smart agriculture that utilizes YOLO (You Only Look Once) object detection to predict the health of potato leaves, marking a significant advancement in agricultural technology. By integrating state-of-the-art computer vision techniques, this architecture facilitates real-time disease detection, providing farmers with critical insights for timely intervention and enhanced crop management. YOLO ensures efficient and precise identification of leaf health conditions, underpinned by robust data collection and preprocessing pipelines. Looking ahead, ongoing improvements in model optimization, integration with IoT for advanced environmental monitoring, and wider adoption across farming communities hold promise for increasing productivity and sustainability in agriculture. This chapter underscores technology's pivotal role in empowering farmers with actionable data, fostering resilient agricultural practices amidst ever-changing challenges.

CHAPTER 4

IMPLEMENTATION

4.1 Introduction

After completing the theoretical and design stages, we move into the practical implementation phase of the project. In this chapter, we will discuss the tools and programming languages used realize the project. We will also describe the motivations behind our choices and explain our selection of the framework, including Node.js, JavaScript, CSS, and HTML. Utilizing development environments such as Visual Studio Code and Sublime Text, we created a database using MySQL.

Additionally, we will discuss robotflow cloud used for annotating data and developing our models.

4.1.1 Work environment

4.1.1.1 Visual studio code

Visual Studio Code is an open-source, cross-platform text editor used for web and software development.

- It provides a user-friendly interface tailored to meet developers needs and supports multiple programming languages and extensions that enhance developer productivity and facilitate the process of writing and debugging code.
- Stands out with its integration feature with popular development tools and version control systems like Git, making collaboration and source code management easier.
- It also supports providing an integrated runtime and debugging environment for web and software applications, helping to quickly identify and fix errors

4.1.1.2 My SQL

MySQL is a popular open-source database management system.

- It is known for its ease of use and integration with the Structured Query Language (SQL), and it provides powerful tools for managing and analyzing data.
- It is used for storing and retrieving project-related data, such as user information, reservation details, comments.

- It provides tools for managing the database, including creating and modifying tables, executing queries, and performing storage, update, and retrieval operations to meet the needs of our application.

4.1.1.3 JavaScript Programming Language

JavaScript is a high-level programming language that adds interactivity and dynamic behavior to web pages. It is primarily used for client-side scripting, running directly in the web browser of the user. JavaScript allows developers to manipulate HTML elements, handle events, create interactive features, validate forms, perform calculations, make HTTP requests, animate elements, and more. It is a versatile language that can also be used on the server-side (e.g., with Node.js) and for developing web applications and complex software systems [**?**].

4.1.2 CSS Programming Language and HTML Technology

HTML is the standard markup language used for creating the structure and content of web pages. It consists of a set of tags and elements that define the different parts of a web page, such as headings, paragraphs, images, links, tables, forms, and more. HTML provides the foundation for displaying content on the web and serves as a structural backbone for web documents[**?**].

CSS (Cascading Style Sheets): CSS is a style sheet language used to describe the presentation and visual appearance of HTML and XML documents. It allows web developers to control the layout, design, and styling of web pages.

CSS works by associating style rules with HTML elements, defining properties like colors, fonts, sizes, margins, padding, positioning, and more. It enables

the separation of content and presentation, making it easier to maintain and update the visual aspects of a website. The users can create or login into account.

Figure 4.1: Create or login into account

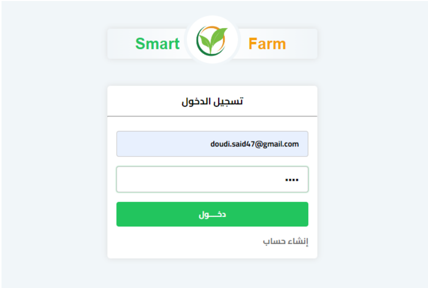

Figure 4.2: Login into account

Users can add crop

Figure 4.3: Add crop

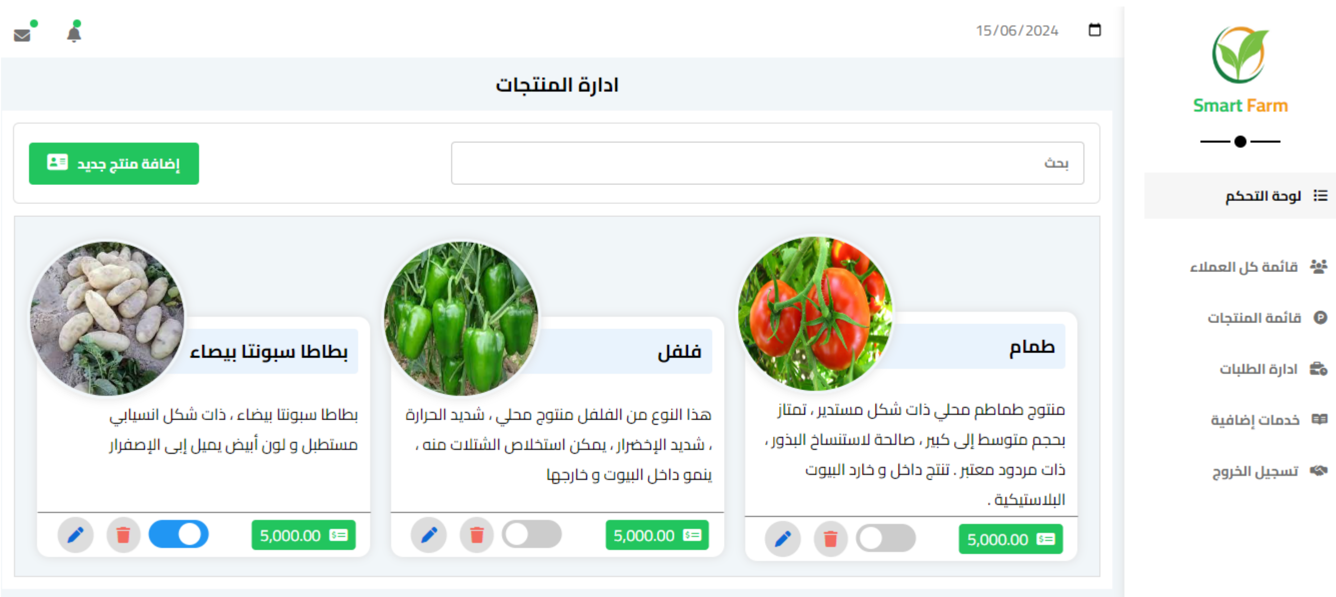

Figure 4.4: Crop manager

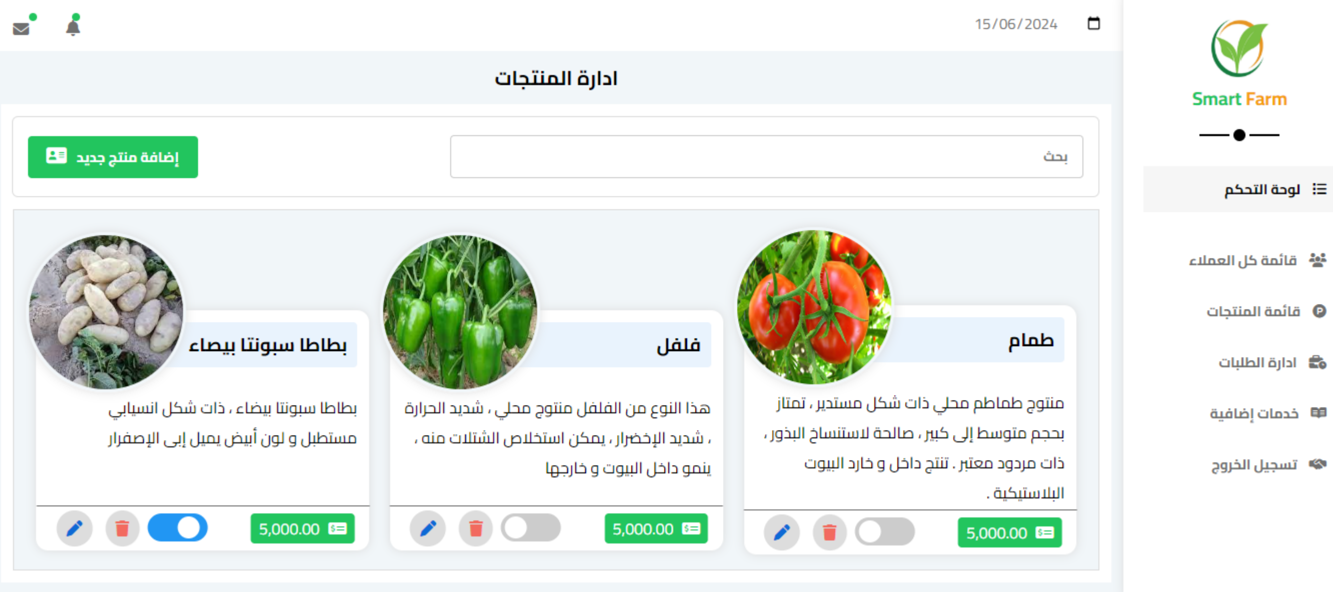

Figure 4.5: Administration of crops

4.1.3 Annotation Data set and building models

For data annotation we work with robotflow cloud to annotate data after upload it.

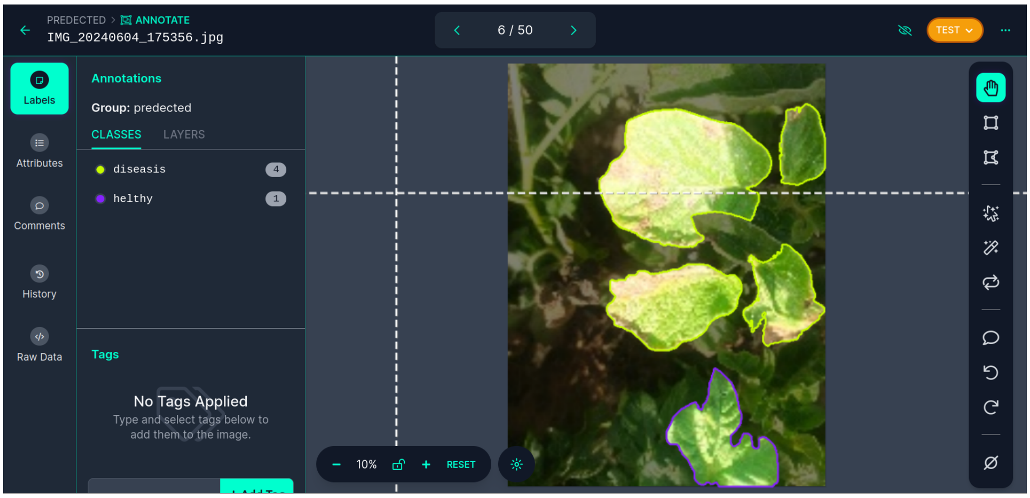

Figure 4.6: Annotation interface robotflow

After the step of data annotation. The model creation with create in robotflow for example Model Type: Roboflow 3.0 ObjectDetection (Fast) Checkpoint: COCO.

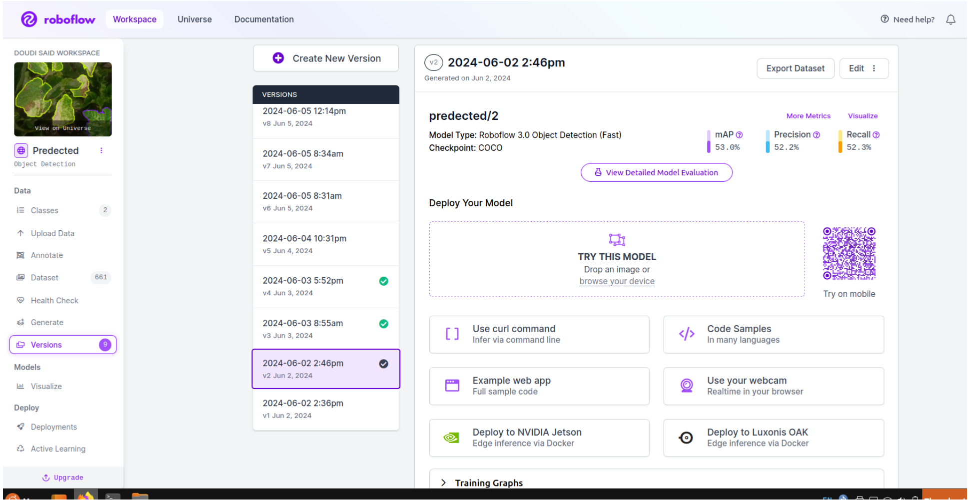

Figure 4.7: Model creation interface

4.2 Conclusion

This chapter has detailed the practical implementation of our project, covering the tools, programming languages, and frameworks used. We have also discussed the development environments and database management system employed to bring our project to fruition

GENERAL CONCLUSION

The integration of Artificial Intelligence (AI) into Smart Agriculture marks a significant advancement in the agricultural sector, offering transformative solutions to longstanding challenges. By leveraging AI technologies, farmers can achieve higher precision in crop management, optimize resource use, and enhance overall productivity.

This technological evolution not only promises increased efficiency and profitability for farmers but also contributes to sustainability by minimizing environmental impact and promoting resource conservation.

Throughout this work, we have outlined the key components of a Smart Agriculture system, including the use of sensors for data collection, communication technologies for seamless data transfer, and advanced AI models for data analysis and decision-making. The development of a web-based user interface further bridges the gap between technology and end-users, making these sophisticated tools accessible and user-friendly for farmers and agricultural workers.

Our work has demonstrated the potential of AI to revolutionize agriculture by providing practical insights and robust models for diagnosing potato leaf health. This serves as a testament to the broader applicability of AI in various agricultural contexts. As we move forward, continued research and innovation will be essential to fully harness the capabilities of AI, ensuring that smart agriculture becomes a cornerstone of modern farming practices.

Looking forward, future work in the realm of integrating AI with Smart Agriculture holds immense potential for innovation and impact. One crucial area of advancement lies in the refinement and enhancement of AI models tailored specifically for agriculture. Future research could focus on developing more sophisticated algorithms capable of handling a broader range of crops and agricultural conditions with increased accuracy and efficiency. This includes advancing techniques for disease detection, pest management, and yield prediction, leveraging advancements in Machine learning and Deep learning.

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Attachments :

Business Model Canvas

✓ Target Segments:

- Individual Farmers: Small and medium-sized farmers.
- Large Commercial Farms: That require advanced disease management solutions.
- Researchers and Educational Institutions: For using data and tools in research and education.

✓ Customer Relationship

- Continuous Technical Support: Via phone, email, or live chat.
- Education and Training: Through workshops and online training courses.
- Regular Updates: Providing users with periodic updates on new diseases and best treatment practices.

✓ Data Sources

- Private Farms: Plant images
- Model Farms: Plant images

✓ Core Value:

- Early and Accurate Diagnosis: Identifying plant diseases at early stages allowing for effective treatment.
- Providing Customized Remedial Solutions: Based on data analysis and optimal agricultural practices.
- Increasing Productivity: By reducing losses caused by plant diseases.
- Continuous Support: Offering ongoing consultations and updates to farmers.

✓ Key Activities

- Platform development and maintenance: building and updating the software and applications used.
- Data analysis: collecting and analyzing plant disease data from the fields.
- Training and Education: Providing training courses for farmers on how to use the platform.
- Marketing and Sales: Promoting the platform and attracting new users.

✓ Delivery Channels:

- Mobile Applications
- Website: For detailed information and reports.
- Partnerships with Agricultural Authorities

✓ Key Partners

- Agricultural researchers: to develop the knowledge and algorithms used in plant disease diagnosis
- Farmers and large farms: as a source of real information and use cases.
- Technology companies: to provide cloud infrastructure and modern technologies (such as artificial intelligence and data analytics).

✓ Cost Structure:

- Software Development and Maintenance: Costs of developing and updating the platform.
- Cloud Infrastructure: Costs of cloud storage and processing.
- Marketing and Sales: Costs of marketing campaigns and promotions.
- Research and Development: Costs of research and algorithm improvement.

✓ Revenue Sources:

- Monthly/Annual Subscriptions: Fees for using the platform on a subscription basis.
- Customized Consulting Services: Fees for providing tailored consulting services.
- Advertisements and Sponsorships: Revenue from in-app advertisements or sponsorships from agricultural companies.
- Data Sales: Selling agricultural disease analysis data to interested companies.

نموذج العمل التجاري

✓ الشركاء الرئيسيين

- الباحثون الزراعيون: لتطوير المعرفة والخوارزميات المستخدمة في تشخيص الأمراض النباتية.
- المزارعون والمزارع الكبيرة: كمصدر للمعلومات الحقيقية وحالات الاستخدام.
- شركات التكنولوجيا: لتوفير البنية التحتية السحابية والتكنولوجيات الحديثة (مثل الذكاء الاصطناعي وتحليل البيانات).

✓ الأنشطة الرئيسية

- تطوير وصيانة المنصة: بناء وتحديث البرمجيات والتطبيقات المستخدمة
- تحليل البيانات: جمع وتحليل بيانات الأمراض النباتية من الحقول.
- التدريب والتعليم: تقديم دورات تدريبية للمزارعين على استخدام المنصة.
- التسويق والمبيعات: الترويج للمنصة واستقطاب المستخدمين الجدد.

✓ قنوات التوصيل

- التطبيقات المحمولة: لسهولة الوصول في الميدان.
- الموقع الإلكتروني: للمعلومات المتعمقة والتقارير.
- الشراكات مع الهيئات الزراعية: للوصول إلى المزارعين من خلال القنوات الرسمية.
- المعارض الزراعية والمؤتمرات: لتعريف المنصة وجذب عملاء جدد.

✓ القيمة الأساسية

- التشخيص المبكر والدقيق: تحديد الأمراض النباتية في مراحل مبكرة مما يسمح بالعلاج الفعال.
- تقديم حلول علاجية مخصصة: بناءً على تحليل البيانات والممارسات الزراعية المثلى.
- زيادة الإنتاجية: من خلال الحد من الخسائر الناتجة عن الأمراض النباتية.
- دعم مستمر: تقديم استشارات وتحديثات مستمرة للمزارعين.

✓ العلاقة مع العملاء

- الدعم الفني المستمر: عبر الهاتف، البريد الإلكتروني، أو الدردشة المباشرة.
- التعليم والتدريب: من خلال ورش العمل والدورات التدريبية عبر الإنترنت.
- التحديثات المنتظمة: تزويد المستخدمين بتحديثات دورية حول الأمراض الجديدة وأفضل طرق العلاج.

✓ مصادر البيانات

- مزارع خاصة صور نباتات
- مزارع نموذجية صور نباتات

✓ الشرائح المستهدفة

- المزارعون الفرديون: المزارعون الصغار والمتوسطون.
- المزارع التجارية الكبيرة: التي تحتاج إلى حلول متقدمة لإدارة الأمراض.
- الباحثون والمؤسسات التعليمية: لاستخدام البيانات والأدوات في الأبحاث والتعليم.

✓ مصادر الإيرادات

- اشتراكات شهرية/سنوية: رسوم استخدام المنصة على أساس الاشتراك.
- الاستشارات والخدمات المخصصة: رسوم تقديم خدمات استشارية مخصصة.
- الإعلانات والرعايات: إيرادات من الإعلانات داخل التطبيق أو الرعايات من الشركات الزراعية.
بيع البيانات: بيع بيانات تحليل الأمراض الزراعية للشركات المهتمة.

✓ هيكلية التكاليف

- تطوير وصيانة البرمجيات: تكاليف تطوير وتحديث المنصة.
- البنية التحتية السحابية: تكاليف التخزين والمعالجة السحابية.
- التسويق والمبيعات: تكاليف الحملات التسويقية والعروض.
- البحث والتطوير: تكاليف الأبحاث وتحسين الخوارزميات.