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Detection of plant diseases using deep learning based on image recognition

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Dedicate

"I extend our heartfelt gratitude to my beloved family for their unwavering support and encouragement throughout the completion of this endeavor"

Achouak

"I express my appreciation to my best friends Rania, Achouak, Soulef and my cherished family, whose steadfast love, unwavering support and belief in my abilities have been instrumental in the successful realization of this work"

Fatima

Summary

Deep learning has been getting a lot of attention lately in computer vision as it is constantly evolving. The advancements of deep learning have been used in many fields, including the field of agriculture. Among the problems that agriculture suffer from it, is the plant diseases, and this is what we have presented in this thesis.

In this work, we present a mobile application for plant disease detection, providing farmers with a comprehensive tool to manage their crops. The application utilizes a Convolutional Neural Network (CNN) model to accurately detect and classify plant diseases from leaf images. In addition to disease detection, the application provides recommendations for appropriate treatments and offers a range of phytosanitary products tailored to each specific disease.

Keywords:

Machine learning, deep learning, plant diseases, Convolutional neural network, classification, prediction, mobile application, farmer, marketplace.

Abstract

L'apprentissage profond suscite beaucoup d'attention ces derniers temps dans le domaine de la vision par ordinateur, car il évolue constamment. Les avancées de l'apprentissage profond ont été utilisées dans de nombreux domaines, y compris celui de l'agriculture. Parmi les problèmes auxquels l'agriculture est confrontée, on trouve les maladies des plantes, et c'est ce que nous avons présenté dans cette thèse.

Dans ce travail, nous présentons une application mobile pour la détection des maladies des plantes, offrant aux agriculteurs un outil complet pour gérer leurs cultures. L'application utilise un modèle de réseau neuronal convolutif (CNN) pour détecter et classer avec précision les maladies des plantes à partir d'images de feuilles. En plus de la détection des maladies, l'application fournit des recommandations pour les traitements appropriés et propose une gamme de produits phytosanitaires adaptés à chaque maladie spécifique.

Mots-clés:

Apprentissage automatique, apprentissage profond, plant maladies des plantes, réseau neuronal convolutif, classification, prédiction, application mobile, agriculteur, marketplace.

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Abbreviation	Complete expression	Page
pH	hydrogen potential	8
CNN	Convolutional neural network	14
F	farenheit	15
AI	Artificial Intelligente	17
KB	Knowledge Base	20
MIT	Massachusetts Institute of Technology	20
ML	Machine Learning	22
DL	Deep Learning	22
JPEG	Joint Photographic Experts Group.	24
JPEG2000	New JPEG format developed in 2000.	24
TIFF	Tagged Image File Format	24
GIF	Graphics Interchange Format	24
PNG	Portable Network Graphics	24
WebP	Format developed by Google	24
SVG	Scalable Vector Graphics	25
GLCM	Gray Level Co-occurrence Matrix	32
ICSAI	International Conference on Systems and Informatics	34
BPNs	Back-Propagation Networks	35
RBF	Radial Basis Function	35

GRNN	Generalized Regression Neural Networks	35
trainLM	Training Algorithm LevenbergMarquardt	35
PNNs	Probabilistic Neural Networks	35
SVM	Support Vector Machines	36
r-fcn	Region-based Fully Convolutional Networks	36
API	Application Programming Interface	37
SDK	Software Development Kit	38

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General Introduction

Agriculture was and remains one of the most essential fields in the world. It is principal for human life not only as a source of energy but also plays an important role in the economic sector of the countries.

For thousands of years, agricultural development was very slow. But with time it kept developing especially with the appearance of artificial intelligence in the field of agriculture which has witnessed remarkable development.

Diseases cause severe damage to crop plants and result in biomass reduction, stunting growth and ultimately plant death. However, the damage depends upon pathogen prevalence at infection. The biggest challenge faced for food security by twenty-first-century scientists is to improve yield stability through the detection of plant diseases.

To minimize production losses and maintain crop sustainability, it is essential that disease management and control measures be carried out appropriately, so it is necessary to develop automated solutions, practical, reliable, and economically able to monitor the health of plants providing meaningful information to the decision-making process.

This study focuses on creating an application with an intelligent system for plant disease detection. It presents models designed using deep learning techniques. Specifically, the study seeks to:

- Create a reliable system for detecting plant diseases using Convolutional neural network (CNN).
- Detect and identify diseases of plants by using images of their leaf.
- Suggest the appropriate treatment for the infected plant and recommend certain products.

Chapter 1

Plant diseases

1.1 Introduction

The importance of agricultural production to economic development is undeniable, but crops are susceptible to pathogen infections during growth that can reduce production or cause plant death. To minimize economic losses, proper plant disease diagnosis is crucial and artificial intelligence is a widely used tool for this. Disease management and control measures, including regular crop monitoring and accurate diagnosis, are essential to reduce the negative impact of plant diseases on food production and economic productivity.

In this chapter, we will talk about agriculture, traditional and smart farming, plant diseases, symptoms, causes and treatment.

1.2 Agriculture

Since the beginning of human civilization, agriculture is the backbone of the world's economy. People depend on agriculture either directly or indirectly for food, shelter and clothes. Therefore, crop protection is of great concern for the world food security. The increase in the world population with a rapid pace will boost the demand of food and other raw materials. Crop protection is therefore important for food security.

Farming systems are an integrated set of activities that farmers perform in their farms to maximize the productivity and net farm income on a sustainable basis. The farming system considers the components of soil, water, crops, livestock, labor, capital, energy and other resources. [1]

Due to the rise of globalization and modernization, traditional farming methods and knowledge have become outdated and less dependable. Therefore, farmers began to implement precision agriculture to enhance the efficiency of farming. This trend has led to a move away from food systems that rely on a multitude of farmers to a system controlled by few agribusinesses.

The progression of agricultural systems across different regions of the world has been shaped by advancements in technology and expanding human understanding. These systems have progressed develops from primitive agriculture (conventional farming), traditional agriculture to modern agriculture (smart farming).

1.2.1 Traditional farming

Half of the world's farmers still rely on traditional farming, which is considered a primitive method of farming. This approach relies on indigenous knowledge, traditional tools, organic fertilizers, natural resources, and cultural beliefs of the farmers.

Traditional farming evolved over foremost thousands of years of agriculture as a sustainable system and in equilibrium with the surrounding ecosystems. With the passing years, the human population increased at a tremendous pace and food security became a major challenge. Although production multiplied several folds because of Green Revolution, it is still not enough to cover the population needs. [1]

1.2.2 Modern farming

Modern farming is an emerging approach to agricultural innovation and farming practices that helps farmers increase productivity and reduce the number of natural resources required to meet the world’s needs for food, fuel, and fiber, such as water, land ad electricity. [2]

It is widely recognized that modern farming has significantly enhanced the quality, viability, and sustainability of food supply, as well as ensuring its safety.

1.2.3 The difference between traditional and smart farming.

Although traditional agriculture is still practiced in some regions of the world, modernization has changed the face of agriculture. Traditional agriculture relies on outdated information, outdated tools, and organic fertilizers, whereas modern agriculture relies on technologically improved tools and machinery.

The traditional farming system focuses on the food needs of farmers, so it is not suitable to meet the needs of an increasing number of people. Nevertheless, modern agriculture focuses on efforts to meet human food needs and species breeding agriculture, aiming to optimize farming to produce quality food.

Table 1 - Difference between traditional and smart farming

Traditional Farming	Modern Farming
Traditional farming is mainly based on labor-intensive	Modern farming is entirely based on capital intensive.
Crop rotation, agroforestry, slash, and burn cultivation are some of the techniques which are practiced under traditional farming	Monocropping, and precision agriculture is some of the techniques practiced under modern farming.
The traditional method of farming is environment friendly as natural manure is used as fertilizers	Modern method of farming is not environment friendly as chemical fertilizers and pesticides are used.
Traditional farming takes a longer duration for a crop to yield as a result the rate of production is low	Modern farming is a fast method of farming as it yields the crop at a faster pace; as a result, the rate of production is high.

1.3 Plants

Plants are living organisms made composed of cells. They need air, water, soil and sunlight to live. Although plants cannot physically move from one location to another, their leaves may move to capture sunlight, while their roots may grow to reach water. Seeds of plants can be dispersed by animals and insects or through wind scattering.

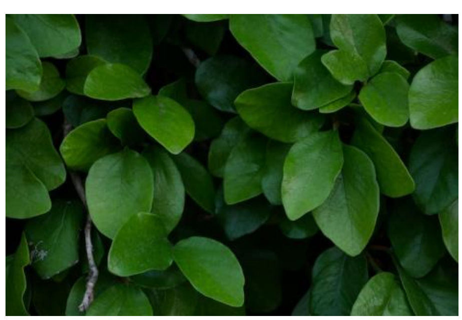

Figure 1 – A plant

Various parts of plants provide us with food, including flowers, fruits, vegetables, seeds, nuts, stems, and leaves. Additionally, some plants offer medicinal properties, and trees are commonly used in the production of furniture and paper.

1.3.1 Plant diseases:

Plants face biotic and abiotic stress resulting in significant crop losses, which poses a threat to global food security. Any professional plant pathologist needs to have theoretical as well as practical knowledge of plant diseases and contributing factors to identify effective control measures.

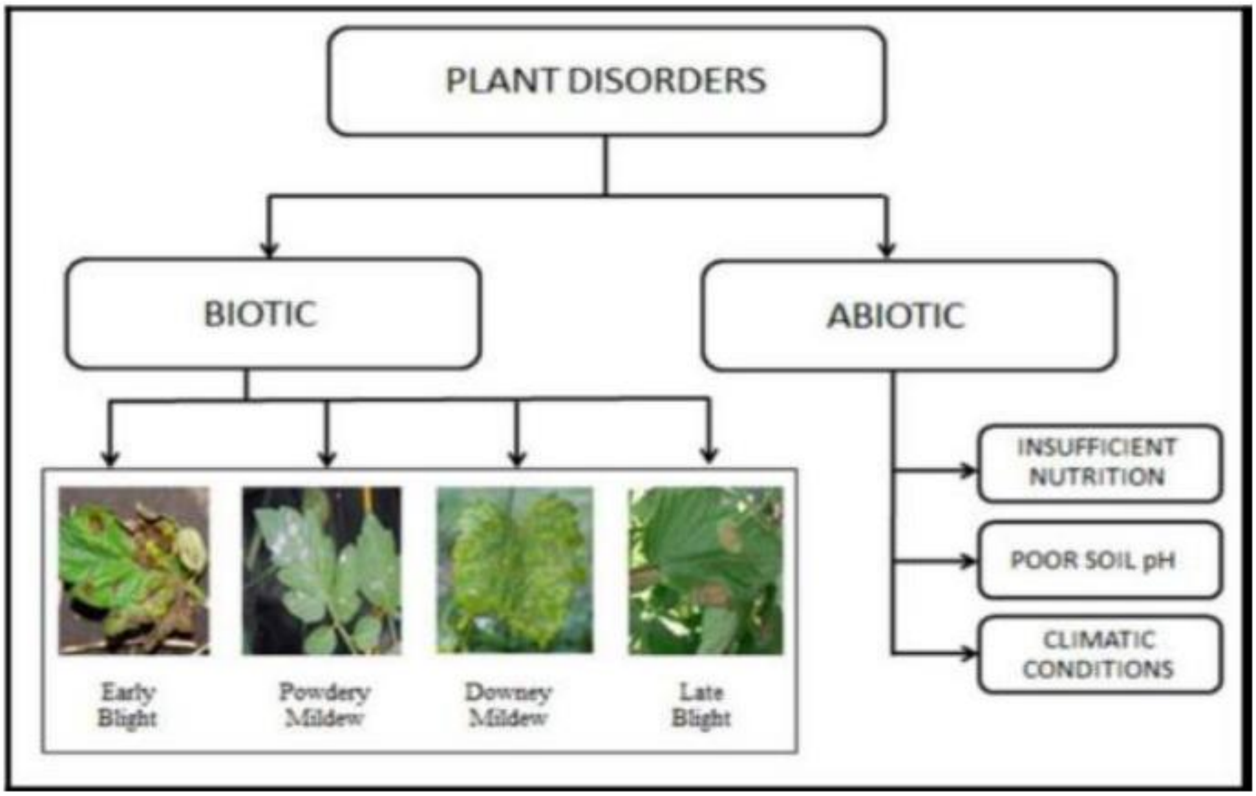

Figure 2- Types of agricultural diseases

Plant pathogens consist of microorganisms like fungi, bacteria, and viruses, as well as abiotic stressors such as adverse environments, nutrient imbalances, extreme temperatures, moisture levels, soil pH, pollution, light intensity, and chemical damage.

1.3.1.1 Examples of Plant Diseases

In 1840, an epidemic of potato late blight caused by an Oomycete (Phytophthora infestans) resulted in the Irish famine. This is still one of the most significant diseases of potato. The disease (potato late blight) was first observed in Belgium in 1845 and later spread to other countries i.e. England, Scotland, Ireland, France, Germany and Scandinavia. [3]

Figure 3 - Potato late bligh

Figure 4 - Brown spot of rice

The causal agent of the brown spot of rice is the fungus Helminthosporium oryzae. In favorable conditions, this disease can result in severe damages to rice crops. In 1942, it caused disastrous consequences in Bengal, with a dramatic impact on people. They faced starvation and many people died. The affected population number was two million. [3]

Cassava (Manihot esculenta) was cultivated approximately 4000–6000 years ago. This plant originated in South America, where it is the third carbohydrate source. Its per annum production is about 136 million tons. In Africa, it is an important crop and total yield reaches 57 million tons. Epidemics of the African Cassava Mosaic Virus in the continent are frequent, and prevalence may reach 80–100% of plants, with projected losses around 50% of yield. [3]

Figure 5 - African Cassava Mosaic Virus

Figure 6 - Bayoud on date palms

Bayoud is a fungal disease caused by Fusarium oxysporum. In Morocco about ten million date palms are affected, with three million trees also killed in Algeria. This disease not only causes production losses, but also speeds up the process of desertification. [3]

1.4 Detection of plant diseases

Plants face various biotic and abiotic and are affected by a variety of microorganisms like bacteria, viruses, insects and fungi, which can cause severe damage leading to reduced crop yields and quality. Detecting and identifying plant diseases is a significant challenge for food security scientists. It is crucial to detect plant diseases early, and develop automated and reliable solutions, it is necessary to monitor plant health and provide valuable information for decision-making processes, such as the correct use of pesticides, the specific treatment of particular diseases, etc.

1.5 Study case

In this study we will focus on one particular plant which is potato (Solanum tuberosum), Potatoes are typically planted in the spring and harvested in the late summer or early fall. They grow best in well-drained soils with a pH between 4.5 and 7.5. Water is an essential requirement for potatoes, especially during the flowering and fruiting phases.

1.5.1 Categories of potato diseases

1.5.1.1 **Potato Late Blight** Phytophthora infestans

Late blight is caused by the fungal-like oomycete pathogen Phytophthora infestans. The primary host is potato, but Phytophthora infestans can also infect other solanaceous plants, including tomatoes, petunias and hairy nightshade. These infected species can act as source of inoculum to potato. [4]

1.5.1.1.1 Symptoms

The first symptoms of late blight in the field are small, light to dark green, circular to irregular-shaped water-soaked spots as shown on figure 7. These lesions usually appear first on the lower leaves. Lesions often begin to develop near the leaf tips or edges, where dew is retained the longest. [4]

Figure 7 - light to dark, circular to irregular-shaped water-soaked spots

Under cool and moist conditions, these initial spots expand rapidly and develop into big, dark brown or black lesions that may have a greasy appearance, as shown in Figure 9. In addition, a yellow chlorotic halo frequently surrounds leaf lesions, as seen in Figure 8.

Figure 9 - Late blight lesions expand rapidly into large, dark brown or black lesions, often appearing greasy

Figure 8 - Leaf lesions frequently are surrounded by a yellow chlorotic halo

During active growth, particularly in cool and moist conditions, a white mildew-like region becomes apparent along the edge of the lesions (as shown in Figure 12) or along the petioles (as shown in Figure 11), indicating the active spore production by the late blight pathogen. When the weather turns warm and dry, the lesions become dry, stop producing spores, and turn tan, as depicted in Figure 10. [4]

Figure 12 - white mildew-appearing area visible at the edge of the lesions

Figure 11- white mildew-appearing area along petioles

Figure 10– Brown, dry lesions

1.5.1.1.2 Management

To control late blight, it is necessary to adopt an integrated approach to disease management. Given that late blight is a community disease, effective management requires the cooperation of the community Here are some methods that can help manage the disease: [4]

- Destroy all cull and volunteer potatoes.
- Plant late blight-free seed tubers.
- Use a seed piece fungicide treatment labeled for control of late blight. Recommended seed treatments include Revues, Reason and mancozeb.
- Avoid planting problem areas that may remain wet for extended periods or may be difficult to spray (the field near the center of the pivot, along powerlines and tree lines).
- Avoid excessive and/or night-time irrigation.
- Eliminate sources of inoculum such as hairy nightshade weed species and volunteer potatoes.
- Use foliar fungicides on a regular and continuing schedule. Once late blight is present, only foliar fungicide applications can manage late blight in the field.
- Quickly destroy hot spots of late blight.
- Applying phosphorous acid to potatoes after harvest and before piling can prevent infection and the spread of late blight in storage.

1.5.1.2 **Potato Early Blight** Alternaria solani

Early blight of potato is caused by the fungal pathogen Alternaria solani. The disease affects leaves, stems and tubers and can reduce yield, tuber size, storability of tubers, quality of fresh-market and processing tubers and marketability of the crop. [5]

The first symptoms of early blight appear as small, circular or irregular, dark-brown to black spots on the older (lower) leaves (Figure 13). These spots enlarge up to 3/8 inch in diameter and gradually may become angular-shaped.

Figure 13 – dark-brown spots on older (lower) leaves

Initial lesions on young, fully expanded leaves may be confused with brown spot lesions (Figure 14). These first lesions appear about two to three days after infection, with further sporulation on the surface of these lesions occurring three to five days later.

Figure 14 – Initial early blight lesions on older leaf tissue

Multiple lesions on the same leaf also may coalesce, or grow together, to form one mass (Figure 15). As lesions coalesce, chlorosis (yellowing of plant tissue) may be visible due to clusters of infection (Figure 16). Elongated, brown to black lesions also may develop on stems and petioles of infected plants (Figure 17).

Figure 15 - Chlorotic symptoms

Figure 16 - Elongated, brown to black lesions on the stems

Figure 17 - Multiple early blight lesions on the same leaf

Later in the growing season, numerous lesions may appear on the upper leaves, and leaves may drop, as the infection becomes more severe (Figure 18). Premature leaf senescence, reduced yield, and low dry matter content likely will result from severe foliar infection during the tuber bulking stage.

Figure 18 – Severe infection by early blight

The rate of early blight infection during the early part of the growing season is generally low but increases following flowering. During the tuber bulking stage later in the growing season, foliar infection can increase rapidly.

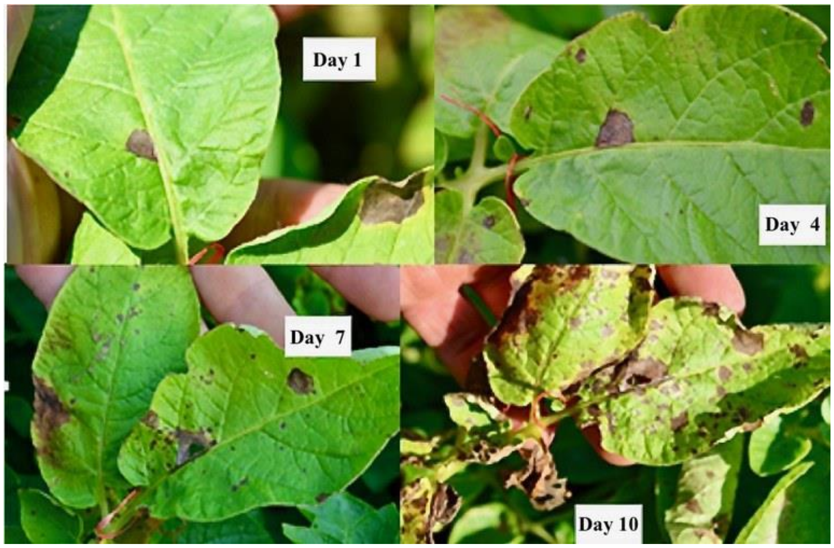

Figure 19 - the rate of early blight infection in 10 days

1.5.1.3 Management

- Time irrigation to minimize leaf wetness duration during cloudy weather and allow sufficient time for leaves to dry prior to nightfall.
- Avoid nitrogen and phosphorus deficiency.
- Rotate foliar fungicides.
- Kill vines two to three weeks prior to harvest to allow adequate skin set.
- Store tubers under conditions that promote wound healing (fresh air, 95 to 99 percent relative humidity, and temperatures of 55 to 60 F) for two to three weeks after harvest.
- Application of appropriate protective fungicide can reduce severity of foliar symptoms; reduce stress to plants by fertilizing and watering adequately; plant late varieties which are less susceptible to disease; store tubers in cool environment. [5]

1.5.2 Chemical Control

Early and late blight diseases affect potato varieties, and to manage this, the primary approach is to use foliar fungicides. While Mancozeb and chlorothalonil are commonly used protectant fungicides, they may not be effective enough when the disease pressure is high. In such cases, locally systemic and translaminar fungicides are necessary to achieve efficient control, especially under irrigation.

Fungicide selection and rotation should be approached with thought to obtain effective disease control and prevent the early and late blight pathogen from further fungicide resistance development. Rotate fungicides with different modes of action. Fungicides with the same mode of action should not be applied in consecutive applications. [5]

1.6 Conclusion

In conclusion, we discussed the evolution of farming systems from traditional to modern agriculture. we explored the distinction between traditional and smart farming, highlighting their differences in terms of labor intensity, techniques employed, environmental impact, and production rate. We provided an overview of plants, their various uses, and the significance of plant diseases in global food security. We presented examples of notable plant diseases and their impact on crops. Furthermore, we delved into the detection and management of plant diseases, emphasizing the need for early detection, automated solutions, and effective disease control measures. Lastly, we presented a study case on potato diseases, specifically late blight and early blight, discussing their symptoms and management strategies, including cultural practices and chemical control methods.

Chapter 2

Artificial intelligence and image recognition

2.1 Introduction

Humans can easily distinguish places, objects, and persons from images, but computers traditionally struggle to understand these images. Thanks to the new image recognition technology.

The essence of artificial intelligence is to use large amounts of data to make informed decisions. Image recognition is an essential element of artificial intelligence that is getting prevalent with every passing day.

Image recognition without Artificial Intelligence (AI) seems paradoxical. Effective AI image recognition software cannot only decode images, but it also has a predictive ability.

In this chapter, we discuss the artificial intelligence, its definition, advantages and disadvantages. We also present of brief history of the AI development and some of its applications such as machine learning and deep learning.

Finally, we will discuss image recognition, which is a part of artificial intelligence where we present some general definitions of image recognition tasks.

2.2 Artificial intelligence

Shortly after the emergence of the first computers, researchers have been interested in developing ‘intelligent’ systems that can make decisions and perform autonomously. Until then, most of these tasks were carried out by humans.

Transferring the decision process to an AI system might in principle lead to faster and more consistent decisions, additionally freeing human resources for more creative tasks. AI techniques, such as machine learning, have made tremendous progress over the past decades and many prototypes have been considered for use in areas as diverse as personal assistants, logistics, and surveillance systems, high-frequency trading, health care, and scientific research. [6]

2.2.1 Definition of Artificial Intelligence

The term ***“artificial”*** can be understood as the imitation of something that is not natural, which was modeled, manufactured or created according to a natural model by the use of technical means. Moreover, the word “artificial” can be derived from the word “art”, which implicates an artist or creator and cannot exist without him. [7]

The term ***“intelligence”*** derives from the Latin “*intelligentia*” and "*intellergere*" and means insight, cognitive ability or understanding. It also describes the ability to act abstractly and reasonably and to derive appropriate action from it. [8]

Intelligence also stands for the characteristics of learning ability, abstraction ability, adaptability and logical thinking. [9]

The term ***“artificial intelligence”*** is defined as systems that combine sophisticated hardware and software with elaborate databases and knowledge-based processing models to demonstrate characteristics of effective human decision making.

Artificial intelligence is a research field with the aim of creating artefacts, such as computer programs or machines. The objective of most applications is to solve problems by applying algorithms. Applications can address the imitation or extension of human intelligence. Another possible focus of AI application can be the learning from complex problem solutions and the extension of the functionalities of existing applications.

Table 2 - definitions for artificial intelligence from 1955-2018

Source	Definitions of AI
[10]	The science and engineering of making intelligent machines, especially intelligent computer programs
[11]	Artificial Intelligence is the study of how to make computers do things at which, at the moment, people are better
[12]	To build artefacts - computer programs or robots - that can meet human targets in a rational and human-like and thus understandable way.

[13]	The modern definition of AI is the investigation and construction of intelligent agents that perceive and act in order to maximize their chances of success.
[14]	AI is typically defined as the ability of a machine to perform cognitive functions we associate with human minds, such as perceiving, reasoning, learning, and problem solving
[15]	AI generally describes the ability of a machine to independently interpret, solve and learn from complex problems.

2.2.2 A brief history of AI

The field of artificial intelligence is relatively young. The creation of Artificial intelligence as an academic discipline can be traced to the **1950**s, when scientists and researchers began to consider the possibility of machines processing intellectual capabilities similar to those of human beings. [16]

Alan Turing, a British mathematician, first proposed a test to determine whether or not a machine is intelligent. The test later became known as the ***Turing Test***, in which a machine tries to disguise itself as a human being in an imitation game by giving human-like responses to a series of questions. Turing believed that if a machine could make a human being believe that he or she is communicating with another human being, then the machine can be considered as intelligent as a human being. [16]

The term "***artificial intelligence***" itself was created in **1956** by a professor of Massachusetts Institute of Technology, John McCarthy. [16]

McCarthy created the term for a conference he was organizing that year. The conference, which was later called the *Dartmouth Conference by AI researchers*, established AI as a distinct discipline. The conference also defined the major goals of AI: to understand and model the thought processes of humans and to design machines that mimic this behavior. [16]

Much of the AI research in the period between 1956 and 1966 was theoretical in nature. The very first AI program, the Logic Theorist (presented at the Dartmouth Conference) was able to prove mathematical theorems. Several other programs were later on developed by taking the advantage of AI such as "Sad Sam"[1] that understood simple English sentences and was capable of drawing conclusions from facts learned in a conversation. The conclusions drawn depend on the data, which is called Knowledge Base (KB) in AI. [16]

Another was ELIZA, a program developed in **1967** by Joseph Weizenbaum at MIT that was capable of simulating the responses of a therapist to patients. With more and more successful demonstrations of the feasibility of AI, the focus of AI research shifted. [16]

Researchers turned their attention to solving specific problems in areas of possible AI application. This shift in research focus gave rise to the present-day definition of AI, that is, "*a variety of research areas concerned with extending the ability of the computer to do tasks that resemble those performed by human beings*," as V. Daniel Hunt puts it in his **1988** article "The Development of Artificial Intelligence". Some of the most interesting areas of current AI research include expert systems, neural networks, and robotics. [16]

2.2.3 Advantages and disadvantages of Artificial Intelligence

Like everything else in the real world, artificial intelligence comes with its own share of advantages and disadvantages. Its advantages make its patrons swear by it, and its disadvantages help the sceptics get more vocal about their arguments.

2.2.3.1 Advantages of AI

- **Reduction in Human Error:** One of the biggest advantages of Artificial Intelligence is that it can significantly reduce errors and increase accuracy and precision.
- **Zero Risks:** Another big advantage of AI is that humans can overcome many risks by letting AI robots do them for us.
- **24x7 Availability:** There are many studies that show humans are productive only about 3 to 4 hours in a day. Humans also need breaks and time offs to balance their work life and personal life. However, AI can work endlessly without breaks. They think much faster than humans and perform multiple tasks at a time with accurate results. They can even handle tedious repetitive jobs easily with the help of AI algorithms.

[1] Sad Sam program written by Robert K. Lindsay in 1960

- **Digital Assistance:** Some of the most technologically advanced companies engage with users using digital assistants, which eliminates the need for human personnel.
- **Unbiased decisions:** Human beings are driven by emotions, whether we like it or not. AI on the other hand, is devoid of emotions and highly practical and rational in its approach. A huge advantage of Artificial Intelligence is that it does not have any biased views, which ensures more accurate decision-making.
- **Perform Repetitive Jobs:** We will be doing a lot of repetitive tasks as part of our daily work, such as checking documents for flaws and mailing thank-you notes, among other things. We may use artificial intelligence to efficiently automate these menial chores and even eliminate "boring" tasks for people, allowing them to focus on being more creative.
- **AI in Risky Situations:** One of the main benefits of artificial intelligence is this. By creating an AI robot that can perform perilous tasks on our behalf, we can get beyond many of the dangerous restrictions that humans face.

2.2.3.2 Disadvantages of AI

- **High Costs:** The ability to create a machine that can simulate human intelligence is no small feat. It requires plenty of time and resources and can cost a huge deal of money.
- **No creativity:** A big disadvantage of AI is that it cannot learn to think outside the box. AI is capable of learning over time with pre-fed data and past experiences, but cannot be creative in its approach.
- **Unemployment:** One application of artificial intelligence is a robot, which is displacing occupations and increasing unemployment (in a few cases). Therefore, some claim that there is always a chance of unemployment as a result of chatbots and robots replacing humans.
- **Emotionless:** Since early childhood, we have been taught that neither computers nor other machines have feelings. Humans function as a team, and team management is essential for achieving goals. However, there is no denying that robots are superior to humans when functioning effectively, but it is also true that human connections, which form the basis of teams, cannot be replaced by computers

2.2.4 Application of AI

The following sections describe the functionalities of artificial intelligence. These include Machine Learning (ML) and Deep Learning (DL).

2.2.4.1 Machine learning

Machine Learning (ML) is an important technical approach of AI. ML forms the basis for the development of new solutions for a wide range of applications. [17]

ML is therefore a partial aspect of AI, which generates new knowledge from existing experience. Based on data or examples, an artificial system is trained to recognize patterns or repetitive characteristics. These are then used for an analysis of new, previously unknown data in order to draw the right conclusions for solving specific tasks. [18]

With Machine Leaning, a system learns from existing data and examples. Neural networks are a special form of these approaches. This AI technology uses simulated artificial neural networks in computers to understand the functioning of the human brain or to solve concrete application problems in statistics, economics and technology. [16]

Applications of ML include spam detection, content personalization, document classification, customer migration prediction, automated solution recommendation for customer service, transaction fraud detection, diagnostic systems, traffic jam prediction, medical diagnostics, chatbot applications, etc. Figure 20 shows the types of ML.

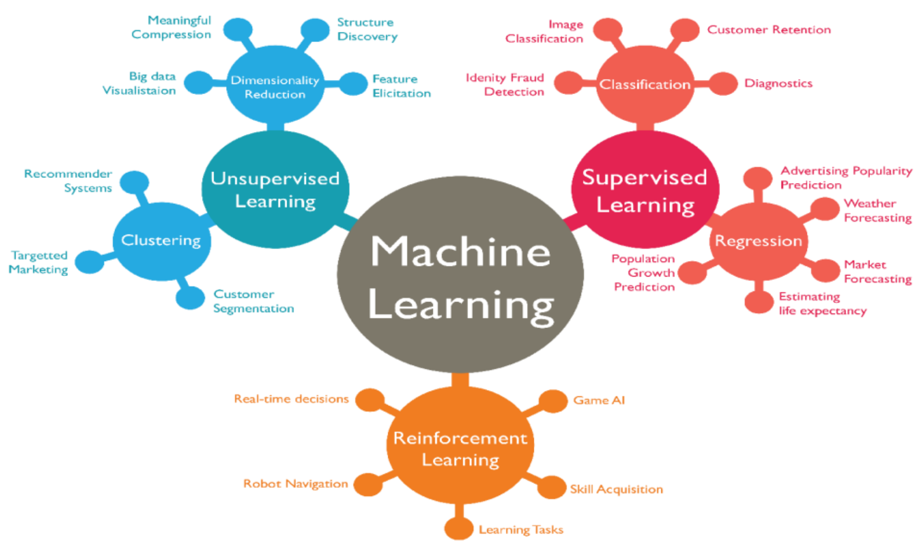

Figure 20 – Types of machine learning

2.2.4.2 Deep learning

Deep Learning, known as Deep Network Learning, is a specialized form of Machine Learning that uses statistical data analysis rather than an algorithm for input evaluation. The goal of DL is for a computer to learn an ability that people already own. [16]

Deep Learning is based on neural networks, which allow machines to understand more complex structures and complicated solutions through new applications than it is possible with ML. [19]

Simulated neurons, which are supposed to resemble the human brain, are modelled and arranged in many layers one behind the other or one above the other. [20] Each level of the network performs a single task, such as edge detection. This extraction of characteristics takes place separately within the individual layers. [21] The output of the individual layers then serves as input for the next layer. In combination with many high-quality training data, the network then learns to perform certain tasks.

Existing applications brought initial success, especially in the medical field, as the machines were able to diagnose cancer cells in images quick and efficient. These intelligent systems are used in particular for more complex problems, which are also associated with a large amount of data. These data records can contain both structured and unstructured data. They support decision-making, can interpret patterns, control processes or move autonomously in unknown use cases. Other known areas of application are the recognition of objects in images and videos, as well as speech recognition. [22]

2.3 Image recognition

The difference between computer vision and image recognition is that computer vision has been vigorously developed by Google, Amazon and many AI developers, and the two terms "computer vision" and "image recognition" may have been used interchangeably. Computer vision (CV) is to let a computer imitate human vision in achieving tasks such as image processing, image classification, object detection, object segmentation, image colorization, image reconstruction, and image synthesis and also to take action. In contrast, image recognition is about the pixel and pattern analysis of an image to recognize the image as a particular object. [23]

On the other hand, image recognition is a subfield of computer vision that interprets images to assist the decision-making process. Image recognition is the final stage of image processing which is one of the most important computer vision tasks.

2.3.1 Images

In the world of modern computers and smart phones, images are generally collected as digital information. There are a discrete number of pixels, and each pixel has a finite range of values. Today's common cameras can capture an image with a tremendous resolution with a few thousand pixels in both the vertical and horizontal dimensions.

2.3.1.1 Image File Formats

The following are some of the most widely used image formats, which are explained in Table 1:

Table 3 - Description and uses if different image format.

Format	Description	Use
JPEG	lossy compression of raw images	Photographs and paintings.
JPRG2000	Optimized form of JPEG better compression, both lossless and lossy compression	Surveillance
TIFF	Lossless compression can be stored and retrieved without losing information	Document storage
GIF	Bitmap image format, supports animation, lossless compression.	Gaming and animation
BMP	Independent of display device, lacks of compression.	In Windows
PNG	Lossless data compression supports different color spaces.	Image transfer over the internet.
WebP	Lossless and lossy compression small size but compatible image quality with JPEG	Stickers and massaging apps

SVG	For interactivity and animation, behaviors and images defined in XML format, they can be searched, indexed, and compressed.	Web site development.

2.3.1.2 Color Spaces

The organization of the colors of in an image in a specific format is called color space. The way in which a color is represented is called a color model. Images use one of the following color spaces for effective picture representation:

- **RGB:** red, green, blue
- **XYZ:** color in the x, y, and z dimensions
- **HSV/HSL:** hue, saturation, and value/hue, saturation, and lightness
- **LAB:** luminance, and green–red and blue–yellow color components
- **LCH:** lightness, chroma, and hue
- **YPbPr**: green, blue, and red cables
- **YUV:** brightness and chroma, or color
- **YIQ:** luminance, in-phase parameter, and quadrature

2.3.2 Definition of image recognition

Image recognition, a subcategory of Computer Vision and Artificial Intelligence, represents a set of methods for detecting and analyzing images to enable the automation of a specific task. It is a technology that is capable of identifying places, people, objects and many other types of elements within an image, and drawing conclusions from them by analyzing them. The best example of image recognition solutions is the face recognition – say, to unblock your smartphone you have to let it scan your face. Therefore, first, the system has to detect the face, then classify it as a human face and only then decide if it belongs to the owner of the smartphone. As you can see, it is a rather complicated process. [25]

Image recognition techniques may be based on the main features of the image. Each image has its characteristics, such as the letter A has a point, P has a circle, and Y has an acute angle at the center. The research on eye movement in image recognition shows that the line of sight always focuses on the main features of the image, that is, the places where the contour curvature of the image is the largest or the contour direction suddenly changes, and these places have the greatest amount of information.

Figure 21 - image recognition

2.3.2.1 Image recognition's tasks

2.3.2.1.1 Classification

Image classification is the identification of the "class", i.e., the category to which an image belongs. An image can have only one class.

It is the process of categorizing and labelling groups of pixels or vectors within an image based on specific rules. The categorization law can be devised using one or more spectral or textural characteristics. Two general methods of classification are '**supervised**' and '**unsupervised**'.

- **Unsupervised classification method** is a fully automated process without the use of training data. Using a suitable algorithm, the specified characteristics of an image are detected systematically during the image processing stage. The classification methods used in here are 'image clustering' or 'pattern recognition'. Two frequently algorithms used are called 'ISODATA' and 'K-mean'.
- **Supervised classification method** is the process of visually selecting samples (training data) within the image and assigning them to pre-selected categories (i.e., roads, buildings, water body, vegetation, etc.) in order to create statistical measures to be applied to the entire image.

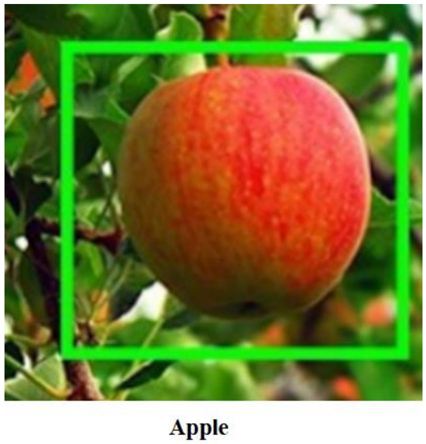

Figure 22 - image classification

2.3.2.1.2 Tagging

Image tagging in AI simply refers to search and image management. It allows computer programs to identify images as humans do. AI can be implored to search and better organize your image storage. Image tagging can also be defined as putting labels on images that makes it come highly searchable. It is the process of putting keywords on images based on figures within a picture. It is also a classification task but with a higher degree of accuracy. It can recognize the presence of several concepts or objects within an image. One or more tags can therefore be assigned to a particular image.

Tagging is the process of manually or automatically adding tags or annotation to various components of unstructured data as one step in the process of preparing such data for analysis. Tagging is different from categorization, as it adds more depth and benefits than categorization. [25]

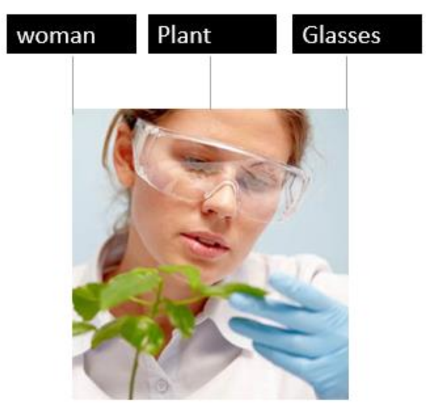

Figure 23 - Image tagging

2.3.2.1.3 Detection

This is necessary when you want to locate an object in an image. Once the object is located, a bounding box is placed around the object in question.

Image or Object Detection is a computer technology that processes the image and detects objects in it. People often confuse Image Detection with Image Classification. Although the difference is rather clear. If you need to classify image items, you use classification. But if you just need to locate them, for example, find out the number of objects in the picture, you should use Image Detection. [26]

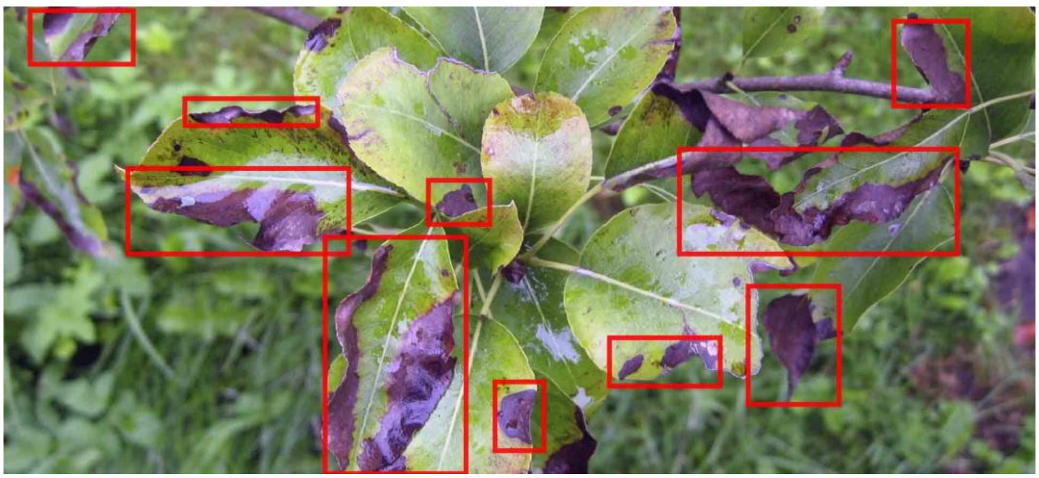

Figure 24 - Image detection

2.3.2.1.4 Segmentation

Image segmentation is the partitioning of an image into distinct regions or categories that correspond to different objects or parts of objects. Each region contains pixels with similar attributes, and each pixel in an image is allocated to one of these categories. A good segmentation is typically one in which pixels in the same category have similar intensity values and form a connected region, whereas the neighboring pixels that are in different categories have dissimilar values. The goal of this is to simplify/change the representation of an image into something more meaningful and easier to analyze. [19]

Segmentation techniques can be either non-contextual (do not consider spatial relationships between features in an image and group pixels only with regard to some global attributes, for example, color/gray level) or contextual (additionally exploit spatial relationships; for example, group spatially close pixels with similar gray levels). [19]

The following image shows the resulting segmented image.

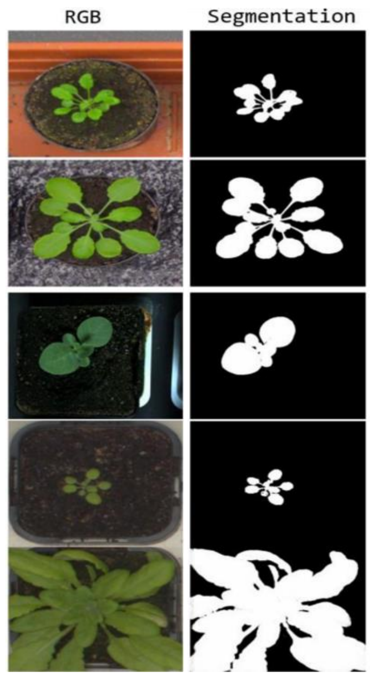

Figure 25 - Image segmentation

Felzenszwalb's algorithm takes a graph-based approach to segmentation. It first constructs an undirected graph with the image pixels as vertices (the set to be segmented) and the weight of an edge between the two vertices being some measure of the dissimilarity (for example, the difference in intensity).

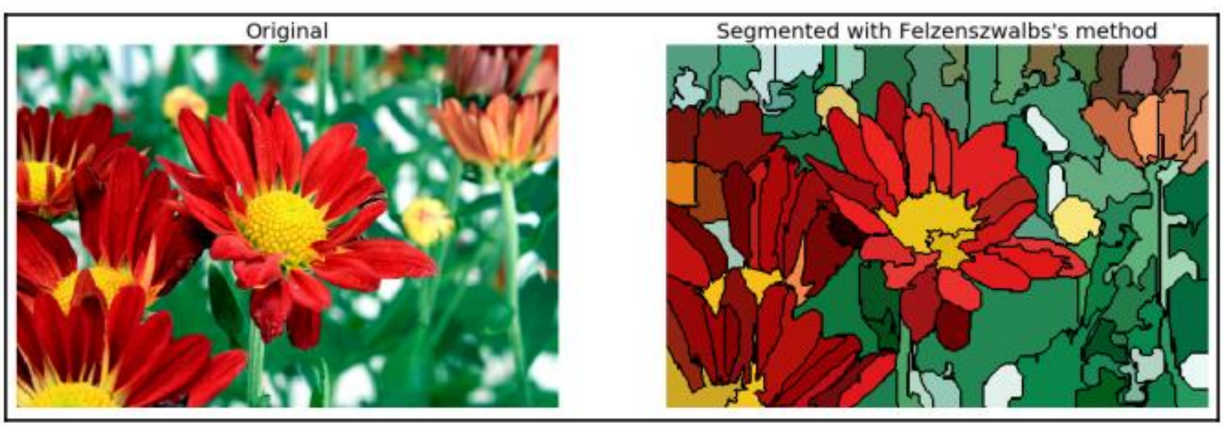

Figure 26 - segmentation using Felzenszwalb's algorithm

2.4 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a class of deep neural networks that are particularly effective in analysing visual data. They leverage specialized layers, such as convolutional and pooling layers, to automatically learn and extract relevant features from input images. [27]

Image recognition is a definitive classification problem, and CNNs, as illustrated in Figure 17, have a history of high accuracy for this problem. Basically, the main essence of a CNN is to filter lines, curves, and edges and in each layer to transform this filtering into a more complex image, making recognition easier

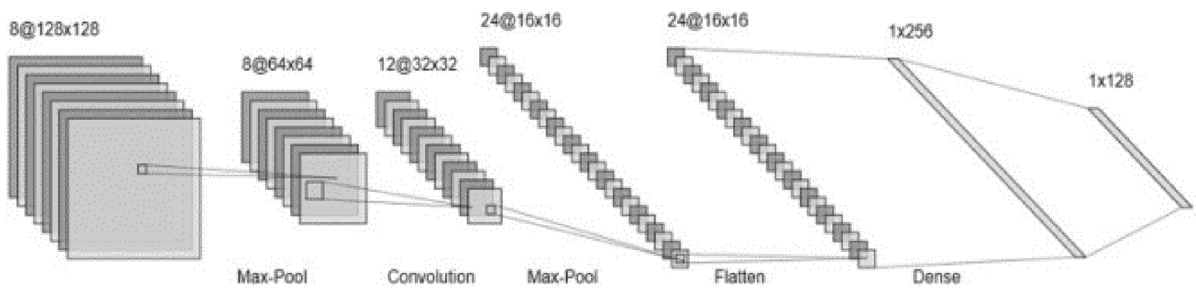

Figure 27 - Convolutional neural networks

2.5 Conclusion

In conclusion, this chapter introduces artificial intelligence (AI) and its applications in image recognition. It highlights the importance of image recognition as a subset of AI and its increasing prevalence in various industries. The chapter discusses the definition, advantages, and disadvantages of AI, along with a brief history of its development. It also delves into machine learning and deep learning as key components of AI. The concept of image recognition is explained, focusing on its tasks such as classification, tagging, detection, and segmentation. Additionally, the chapter introduces Convolutional Neural Networks (CNNs) as a powerful tool for image recognition, highlighting their ability to filter and transform images to facilitate accurate classification. The combination of AI and image recognition holds enormous potential for automating tasks and enabling decision-making in various domains.

Chapter 3

State of art

3.1 Introduction

In recent decades, computer technology has played a significant role in solving various real-life problems, such as farming, health care, etc. Machine learning has emerged as one of the most popular technologies widely used to solve the farmer's problems.

In previous studies, researchers often utilized traditional machine learning methods to classify different plant diseases. Among these methods, the support vector machine has been extensively employed for efficient classification of plant diseases. However, traditional machine learning models heavily rely on human-defined features of images, which may overlook important image features. To overcome this limitation, researchers have turned to deep learning methods based on Convolutional Neural Networks (CNNs) for detecting leaf diseases in various plants.

In agriculture, deep learning models are commonly used for plant disease classification and detection. Researchers frequently employ various deep learning models for classifying plant diseases. Deep learning-based methods often achieve higher accuracy compared to traditional machine learning models, particularly with larger datasets.

The Convolutional Neural Network (CNN) is the most popular deep learning model, and transfer learning with CNN is widely favored for addressing various real-world problems.

In this chapter, we will have a brief discussion about the state of art, followed by the development of a system based on CNN. We will then explain the materials and methods used in the research, including the image dataset, pre-processing techniques, our proposed architecture, the classification results and evaluation for the model. Finally, we will present the conclusion of the chapter.

3.2 State of art

3.2.1 Article 1

In 2015, Mrunmayee Dhakate, a PG student in Digital Systems, and Ingole A.B., an assistant professor, developed a neural network to diagnose diseases in pomegranate plants in India.

3.2.1.1 Introduction

Pomegranate is a fruit that grows with a very high yield in many states in India and is one of the most profitable fruits in the market. However, due to various conditions, the plants are infected by various diseases, which destroy the entire crop leaving very less product yield.

It becomes necessary to maintain the highest level of export quality, mainly carried out by visual inspection by experts. This is expensive and time-consuming due to the distant location of farms.

3.2.1.2 Methodology

The proposed approach starts with the image collection (database), pre-processing of those images, feature extraction using the k-means, clustering-based, color, segmentation technique, feature extraction using the GLCM (Gray level co-occurrence matrix) method, and finally the training. Firstly, some images are used to train the neural network and other images are used as test images to check the accuracy of the results.

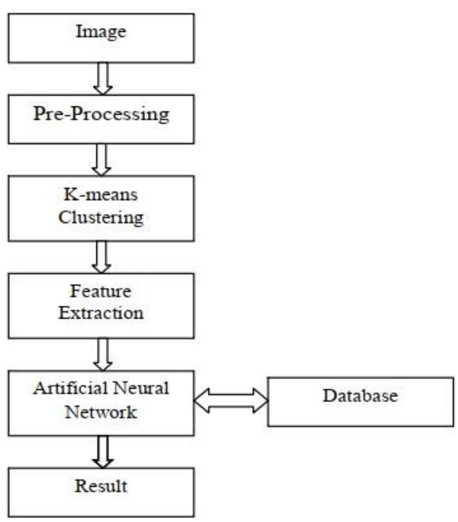

Figure 28 - The block diagram

3.2.1.3 Results

For the experimental work, a database of 500 images is created. The K-means clustering segments the image into 4 clusters. k=4 is considered because it gives proper clusters than k=3 or k = 5. From these images, the texture features are extracted using the GLCM method. From these features, the neural network is trained and it helps to classify the images into different categories namely, good fruit, fruit spot, bacterial blight, fruit rot, good leaf, and leaf spot.

Five sample images of each category are used for testing purpose; the obtained average accuracy is 90%.

The good fruit and good leaf yield a 100% result; leaf spot gives 87.50%, bacterial blight gives 85.71% while fruit spot and fruit rot give 83.33% result. The proposed approach gives the accurate and satisfactory results and with a 90% average accuracy.

3.2.2 Article 2

The Moroccan Journal of Plant Protection published an article in 2020, titled "Experimentation of model for early detection of tomato diseases by deep learning" by AIT ELKADI K., BAKOURI S., BELBRIK M., HAJJI H., and CHTAINA N.

3.2.2.1 Introduction

Early diagnosis of plant diseases plays an important role in improving agricultural yield. In recent years, deep learning used in image processing, offers many new applications related to precision agriculture.

Through this work, the authors built a model that is used to detect diseases affecting tomatoes from images of infected leaves. The images used are from the PlantVillage Database. The exploitation of these images as input information allowed the learning model, based on CNN convolutional neural networks, to guide a new approach to the diagnosis automation. With the experimentation of their code and model, they achieved a predictive accuracy level of tomato diseases equal to 94%.

3.2.2.2 Method

In order to develop accurate image classifiers for the diagnosis of plant diseases, they needed a dataset of images of healthy and diseased tomatoes. The database includes 37 varieties of plants. They extracted images of tomatoes from this database. These images are those of 8 Diseases, 200 images for each disease. The images are taken using an RGB ground camera with an image size of 256 × 256 pixels.

The authors of the article presented the methodology they used to create a model for the early detection of tomato diseases. Firstly, the authors prepared the data by using images from the PlantVillage database without segmentation. Then, they performed image transformation and increased the number of images through pre-treatment. Next, the authors chose the convolutive network architecture and fed models by embedding images, followed by adjusting the hyper-parameters and training the model. Finally, the authors evaluated the results of the model by making predictions and analyzing the outcomes. Overall, the presented methodology demonstrated the potential of deep learning techniques for improving the accuracy and speed of identifying tomato diseases, which can lead to better disease management and higher crop yields.

3.2.2.3 Results

The study developed models for early detection of tomato diseases using deep learning techniques on RGB images of leaves, achieving a high accuracy rate of 94.35% in disease prediction. Adequate training data, appropriate network structures, hyper-parameters, and learning conditions were found to be crucial in determining model accuracy.

3.2.3 Article 3

The paper "Application of Neural Networks to Image Recognition of Plant Diseases" by Haiguang Wang, Guanlin Li, Zhanhong Ma, and Xiaolong Li, was presented at the 2012 International Conference on Systems and Informatics (ICSAI 2012), the authors are affiliated with the Department of Plant Pathology at the China Agricultural University in Beijing.

3.2.3.1 Introduction

In order to find out an image recognition method for plant diseases, image recognition of plant diseases was conducted with two kinds of wheat diseases (wheat stripe rust and wheat leaf rust) and two kinds of grape diseases (grape downy mildew and grape powdery mildew) as the objects in this study.

The recognition performances of different neural networks including Back-Propagation networks, radial basis function (RBF) neural networks, generalized regression networks (GRNNs) and probabilistic neural networks (PNNs) were compared and the roles of extracted color features, shape features and texture features played in image recognition of the plant diseases were evaluated.

3.2.3.2 Method

This study aimed to recognize four important plant diseases using digital images. 185 digital images of wheat stripe rust, wheat leaf rust, grape downy mildew, and grape powdery mildew were obtained by image compression, cutting, and enhancement. K_means clustering algorithm was used to segment the plant disease images, and 50 features were extracted from the segmented images. BP networks, RBF neural networks, GRNNs, and PNNs were used as classifiers to recognize the diseases. The networks used the default backpropagation training algorithm LevenbergMarquardt (trainlm) as training functions and learngdm as learning functions. The study obtained a high recognition rate for the diseases.

3.2.3.3 Results and analysis

The study achieved high recognition results of neural networks with fitting accuracy and prediction accuracy of at least 75%. The four types of neural networks all provided perfect results for recognizing plant diseases from images. The prediction accuracy ranged from 82.05% to 85% when RBF neural networks were used as classifiers, and the fitting and prediction results were the same when GRNNs and PNNs were used as classifiers.

This study used BP networks, RBF neural networks, GRNNs, and PNNs to recognize plant diseases based on color, shape, and texture features. The study found that neural networks were effective in identifying and classifying plant diseases with good fitting and acceptable prediction accuracy. The study suggests that the choice of appropriate neural network models is important for different types of plant diseases and that excessive characteristic features can affect image recognition performance.

3.2.4 Other studies

Table 4 – State of art

Ref	Architecture	Accuracy	Dataset	year
[28]	k-means +svm	90%	collected	2015
[29]	k-means + bpnn	92%	collected	2016
[30]	Faster r-cnn+vgg16 r-fcn+resNet-50	83% 82.53%	collected	2017
[31]	LeNet	93%	PlantVillage dataset	2017
[32]	Inception-v3	94.32 %	PlantVillage	2019
[33]	AlexNet	89,90 %	Collected	2019
[34]	svm	95.56%	collected	2019
[35]	googleLeNet	84%	COCO dataset	2019
[36]	ResNet50	94,12 %	Collected	2020
[37]	ResNet101	96,46 %	PlantVillage	2021
[38]	VGG16	89,12 %	Olive leaf images	2021

3.3 Platform used for implementation

3.3.1 Hardware

The hardware used in our implementation is Type:

- laptop HP
- RAM: 12GO
- Processor: AMD A9-9425 RADEON R5, 5 COMPUTE CORES 2C+3G 3.10 GHz

- Graphic card: Radeon Graphics r5
- Operation system: windows 10

3.3.2 Software and libraries

- **Python 3.11.3**

Python is an object-oriented, and open source computer programming language with dynamic semantics. Its syntax is simple and readable, making it easy to learn and maintain programs. The Python interpreter and the extensive standard library are available in source without charge for all major platforms. [39]

- **Jupyter notebook 6.5.4**

Jupyter Notebook was published in 2015. an interactive environment for running code in the browser. It is a notebook authoring application, under the Project Jupyter umbrella. Jupyter Notebook offers fast, interactive new ways to prototype and explain your code, explore and visualize data. The Jupyter Notebook makes it easy to incorporate code, text, and images, [40]

- **Tensorflow 3.2.2**

TensorFlow was released in November 2015, TensorFlow is a Python-based, free, open source machine learning platform, developed primarily by Google. the primary purpose of TensorFlow is to enable engineers and researchers to manipulate mathematical expressions over numerical tensors. [41]

- **Keras**

It was released in March 2015, Keras is a deep learning API for Python, built on top of TensorFlow, that provides a convenient way to define and train any kind of deep learning model. [41]

- **Scikit-learn 1.2.2**

Scikit-learn is an open source project. scikit-learn is a very popular tool, and the most prominent Python library for machine learning. [42]

- **Matplotlib**

Matplotlib is a desktop plotting package designed for creating (mostly two-dimensional) publication-quality plots. The project was started by John Hunter in 2002 to enable a MATLAB-like plotting interface in Python. [43]

- **FastApi**

FastAPI is a modern, high-performance web framework for building APIs with Python. It is designed to be easy to use, efficient, and to provide automatic validation and documentation of API endpoints. [44]

- **Tf-serving**

TensorFlow Serving is a flexible and scalable open-source serving system that allows to deploy and serve machine learning models built with TensorFlow. It is a lightweight, standalone server that can be deployed in a variety of environments, including on-premises, in the cloud, or at the edge. [45]

- **Docker**

Docker is an open-source platform that automates the deployment and management of applications using containerization. Containers are lightweight, isolated environments that package applications and their dependencies together. This ensures that applications will run consistently across different environments and allows for easy portability. [46]

- **Flutter**

Flutter is an open-source UI software development kit (SDK) created by Google that allows developers to build natively compiled applications for mobile, web, and desktop platforms from a single codebase. [47]

- **Dart**

Dart is a programming language, developed by Google, which is known for its simplicity and efficiency. It utilizes a reactive and declarative programming paradigm, allowing developers to express the user interface and behavior of their applications in a clear and concise manner. [47]

- **Firebase**

Firebase is a comprehensive mobile and web application development platform provided by Google. It offers a set of backend services, tools, and libraries that help developers build and scale their applications more easily. Firebase provides a range of features, including data storage, real-time database, authentication, and more, making it a powerful and all-in-one solution for building modern applications. [48]

- **Vscode**

Visual Studio Code (VS Code) is a free and open-source code editor developed by Microsoft. It is a lightweight and customizable code editor that supports a wide range of programming languages and frameworks. VS Code includes a number of features that boost productivity and improve the overall developer experience. [49]

3.4 Methodology

In this study, we used a recent database from PlantVillage[2], which is an open repository containing over 54 thousand images, encompassing 14 crops and 38 disease classes for different types of plants.

3.4.1 Data description

For our experiments we used only potato related classes. The dataset contains 2152 images samples of potato leaves. All images were divided into 3 different classes, where one class is healthy and the other two classes are unhealthy. All the images used in this study were already resized to (256x256) pixels, which is the input size of our system. Table 5 provides a summary of the database used in this study.

Table 5 - the disease name and number of corresponding images in plant village dataset

Class designation	No of samples	Percentage
Potato___Early_blight	1000	46.47

[2] https://github.com/spMohanty/PlantVillage-Dataset/tree/master/raw/color

Potato___Late_blight	1000	46.47
Potato___healthy	152	7.06
Total	2152	100

We have loaded our dataset of images into batches by using image_dataset_from_directory function it is a convenient way to load images for training and testing a deep learning model.

The image_dataset_from_directory function has a number of parameters that can be used to control how the images are loaded. These parameters include:

- directory: The directory that contains the images.
- target_size: The size of the images to load.
- batch_size: The number of images to load in each batch.
- shuffle: Whether to shuffle the images before loading them into batches.

Figure 29 shows ample images of healthy and different unhealthy potato leaves from the database

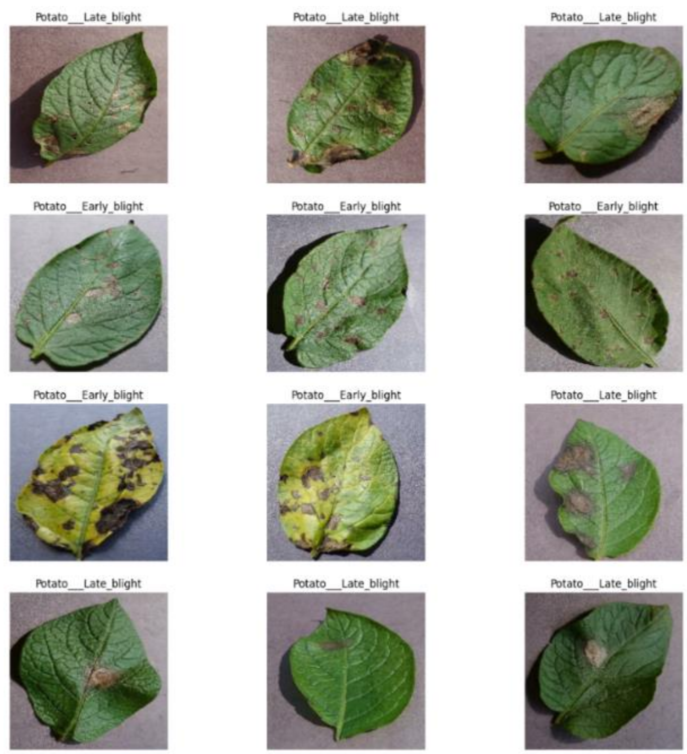

Figure 29 - Sample images of healthy and different unhealthy potato leaves from the plant village database

3.4.2 Dataset split

Dataset was split into training and test datasets with a ratio of 15% for test data, 15% for validation data and 70% train data. So, each disease class split to 15% test, 15% validation and 70% training.

3.4.3 Pre-processing

Although the images that we have in Database are all the same size and free of noise which make the recognition of the disease easy for the model, but we face a problem when the user enters images from his phone, it is possible that those images have a different size from the dataset or contain noise, then It causes difficulty in recognizing the disease. To solve this problem, we need pre-processing for the images before feeding it into the model.

Pre-processing refers to a set of operations aimed at resizing and normalizing images, as well as enhancing their features. Examples of these operations include the following:

Resizing: Resize the images to a specific size (256x256) that matches the input requirements of the model. This ensures consistency in image dimensions and prevents issues arising from different image sizes,

Normalization: Normalize the pixel values of the images to a consistent range. This can involve scaling the pixel values to a specific range (e.g., 0-1).

Rescaling: Rescaling involves adjusting the size or scale of the images to meet the requirements of the model's input size.

3.4.4 Data augmentation

The data augmentation techniques can be used to artificially increase the size of the dataset by generating new images from the existing images. This can help to improve the performance of the deep learning model. For example:

RandomFlip performs horizontal flipping, *RandomRotation* applies random rotations within the specified range, and *RandomZoom* scales the images by zooming in or out.

3.4.5 Presentation of CNN model for plant disease detection

The section provides detail on the potato leaf disease detection and classification model.

3.4.5.1 CNN architected model

Our CNN architecture is specially designed to identify the disease form of the potato plant leaf image. We have proposed a model that is composed of four convolutional layers, three maxPooling layers and three fully connected layers. At first, we have the resize_and_rescale layer that pre-process our inputs, and at the end we have the fully connected layer with an output size of 3 classes.

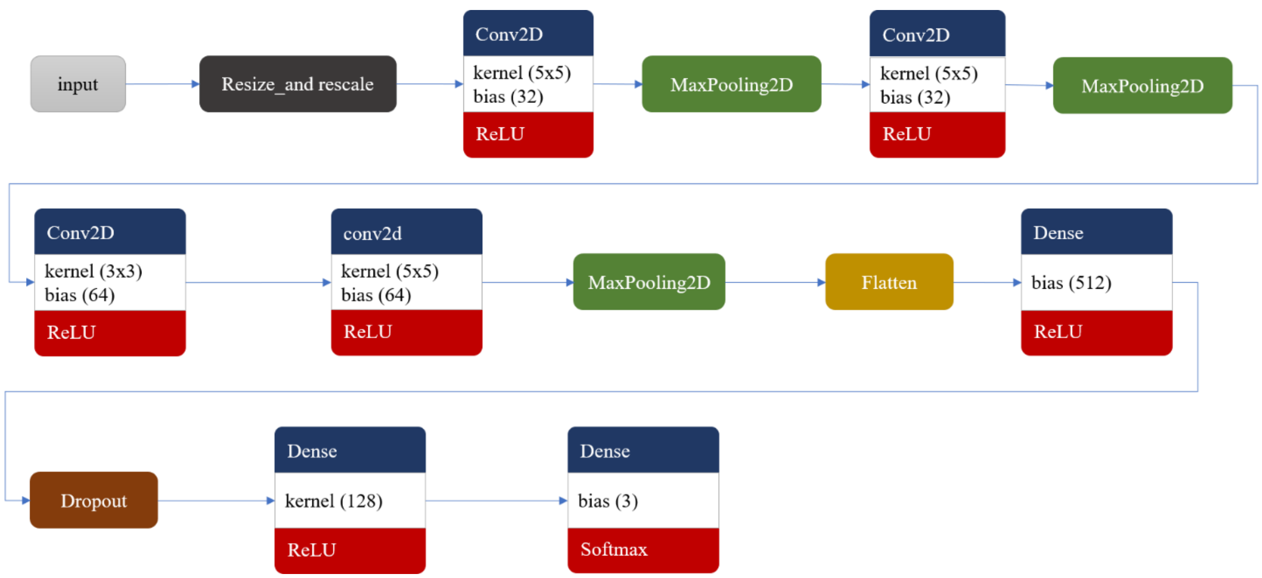

Figure 30- Architecture of the model CNN

3.4.5.2 Create model

In this model we used 4 convolution layers with a 32/32/64/64px filter and a kernel of size 3x3 and 5x5, the activation function is the rectifier function '*ReLU*', each of these 4 layers is followed with a Pooling layer, with size 2x2 and 3x3, the classification part consists of a Flatten layer and 3 hidden layers, with 512 neurons for the first layer,128 neurons for the second, the last one is an output layer with 3 neurons and an activation function of type '*Softmax*'.

After creating our model, we have executed '*model.summary()*' that allows us to see our model's summary and give us the number of parameters that we've got in our model, and as we can see in the Figure 28 the model has 1,821,219 parameters which is the sum of the parameters for each layer.

```
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential (Sequential)     (24, 256, 256, 3)         7

 conv2d_30 (Conv2D)          (24, 252, 252, 32)        2432

 max_pooling2d_30 (MaxPoolin  (24, 84, 84, 32)         0
 g2D)

 conv2d_31 (Conv2D)          (24, 80, 80, 32)          25632

 max_pooling2d_31 (MaxPoolin  (24, 40, 40, 32)         0
 g2D)

 conv2d_32 (Conv2D)          (24, 38, 38, 64)          18496

 max_pooling2d_32 (MaxPoolin  (24, 19, 19, 64)         0
 g2D)

 conv2d_33 (Conv2D)          (24, 15, 15, 64)          102464

 max_pooling2d_33 (MaxPoolin  (24, 7, 7, 64)           0
 g2D)
 flatten_7 (Flatten)         (24, 3136)                0

 dense_21 (Dense)            (24, 512)                 1606144

 dropout_9 (Dropout)         (24, 512)                 0

 dense_22 (Dense)            (24, 128)                 65664

 dense_23 (Dense)            (24, 3)                   387

=================================================================
Total params: 1,821,226
Trainable params: 1,821,219
Non-trainable params: 7
_________________________________________________________________
```

Figure 31 - model summary

3.4.5.3 Model result

After creating the model, we used the fit function to train the model and evaluate its accuracy and loss. The training and validation accuracy obtained through this model is 47% and 47% respectively.

```
Epoch 1/50
72/72 [==============================] - 301s 4s/step - loss: 0.9412 - accuracy: 0.4797 - val_loss: 0.8216 - val_accuracy: 0.
4722
Epoch 2/50
72/72 [==============================] - 304s 4s/step - loss: 0.8517 - accuracy: 0.5500 - val_loss: 0.6841 - val_accuracy: 0.
6991
Epoch 3/50
72/72 [==============================] - 309s 4s/step - loss: 0.6726 - accuracy: 0.6919 - val_loss: 0.5643 - val_accuracy: 0.
7454
Epoch 4/50
72/72 [==============================] - 339s 5s/step - loss: 0.6746 - accuracy: 0.7058 - val_loss: 0.3723 - val_accuracy: 0.
8472
```

Figure 32 - Results of the first four epochs of the mode

By the time, after each epoch the model experienced training and the exactness of the result improved as well. After completing 50 epoch the training and validation accuracy become 96% and 96% respectively.

```
72/72 [==============================] - 448s 6s/step - loss: 0.0596 - accuracy: 0.9797 - val_loss: 0.0605 - val_accuracy: 0.97
69
Epoch 49/50
72/72 [==============================] - 435s 6s/step - loss: 0.1044 - accuracy: 0.9645 - val_loss: 0.1855 - val_accuracy: 0.91
20
Epoch 50/50
72/72 [==============================] - 384s 5s/step - loss: 0.1040 - accuracy: 0.9618 - val_loss: 0.0795 - val_accuracy: 0.96
76
```

Figure 33 - Results of the last three epochs of the model.

And For better reading and understanding, the results of loss and accuracy were presented using graphs. The Figure 34 displays the loss result through all epochs. At the start, there were a lot of errors and as the number of training steps increased, the errors decreased to 0,1.

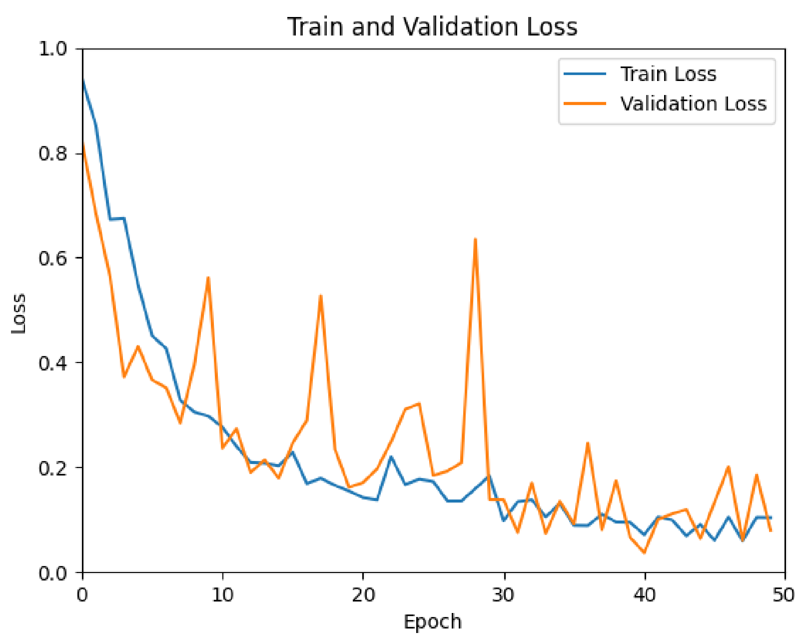

Figure 34 - train and validation loss

The Figure 35 Displays the accuracy result through all epochs. At the start, the accuracy was low and as the number of training steps increased, it increased to 96%

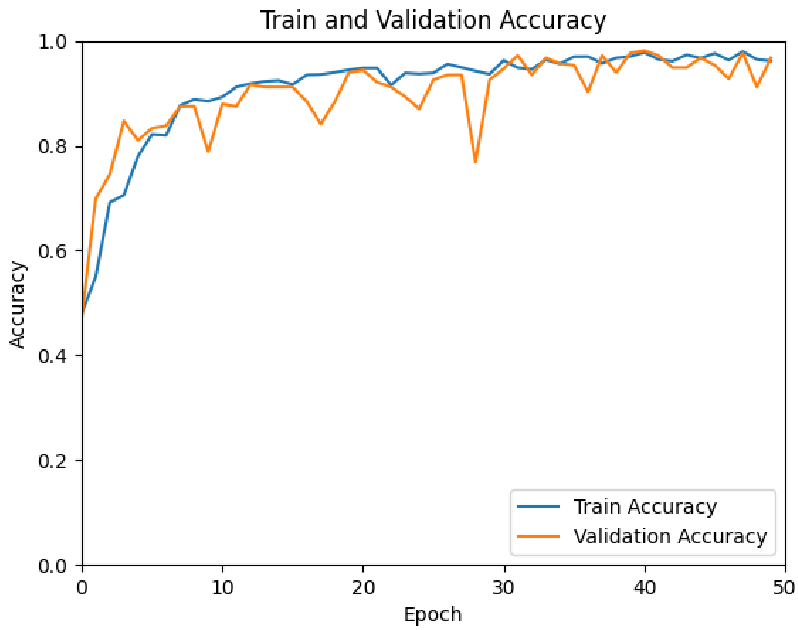

Figure 35 - Train and validation Accuracy

3.4.6 Evaluating the model

After training the model, we used the evaluate function to assess its performance on a separate test ana train dataset. The evaluate function calculates various metrics, such as accuracy and loss, to provide an objective evaluation of the model's performance. We also calculated recall and precision scores. Figure 36 shows the results.

```
Train Accuracy: 97.91%
Test Accuracy: 97.60%
Precision Score: 98.15%
Recall Score: 98.15%
```

Figure 36- result of evaluating the model

In the section below are some predicted samples with the confidence.

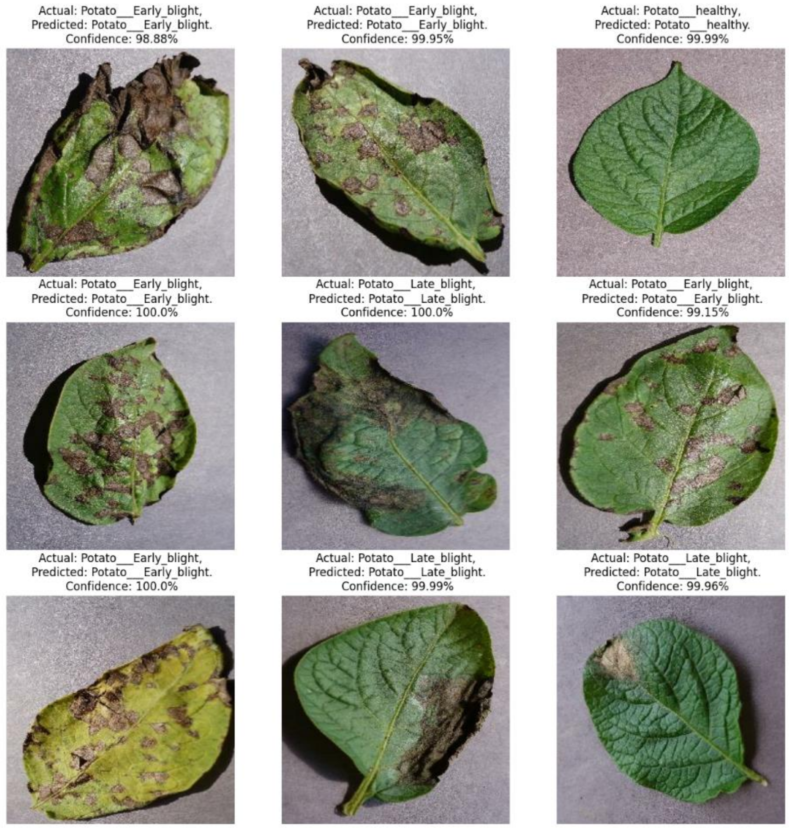

Figure 37 - Test with confidence

3.4.7 Saving the model

Saving the model after training is an important step to preserve its learned parameters and architecture for future use. It allows to reuse the trained model, make predictions on new data.

```
import os

# create version of the model
model_version=max([int(i) for i in os.listdir("../saved_models") + [0]])+1
model.save(f"../saved_models/{model_version}")
```

Figure 38- saving the model

3.5 Conclusion

This chapter provided an overview of the state-of-the-art techniques and methodologies used in the field of plant disease recognition using deep learning. In the proposed work, we have presented the developed and the ameliorate CNN model to detect the disease in potato crops. Also, we indicate the tools and datasets that we used, as well as the steps we followed to get the result.

Chapter 4

Development of a prototype

4.1 Introduction

In this chapter, we present the interfaces of “Napta” our mobile application, an innovative tool designed to enhance plant care and disease management.

Our app includes various screens:

- Splash screen.
- On boarding screens
- Welcome page.
- Login page.
- Forgot password.
- Email verification screen.
- OTP screen.
- Sign up page.
- Home page.
- Search page.
- Plant diseases screen.
- Disease details screen.
- Profile screen.
- Edit profile screen.
- Information screen
- Market place screen.
- Products screen.
- Product details screen
- Cart screen

- ♣ Check out screen

4.2 Splash screen and on boarding screens.

Splash screen shows our app name and our logo with our application tag.

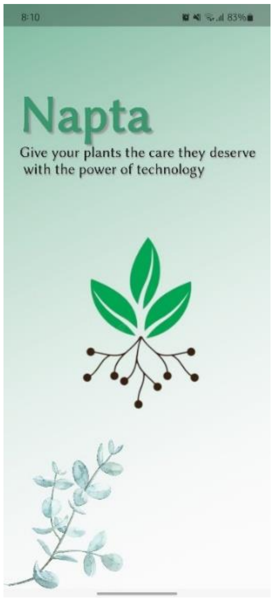

Figure 39 - Splash

The onboarding screens provide an insightful overview of the app's key features and functionalities, ensuring that our users are fully aware of the benefits our app “Napta” brings to their experience.

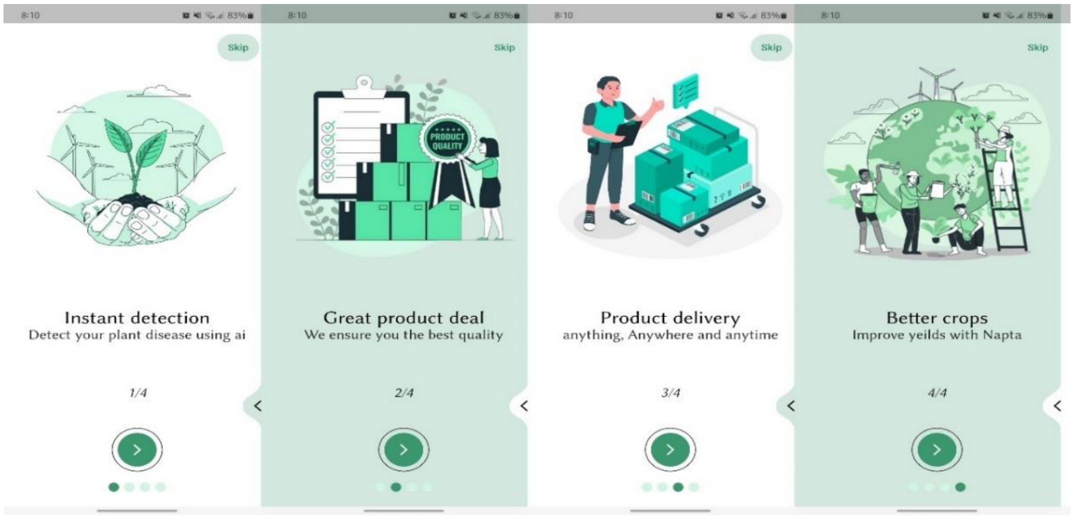

Figure 40 - overview screen

4.3 Authentication

4.3.1 Welcome Page:

After skipping the on boarding screens users will be greeted with a welcoming page, where they can login, sign up or even try the app and explore it without requiring prior registration.

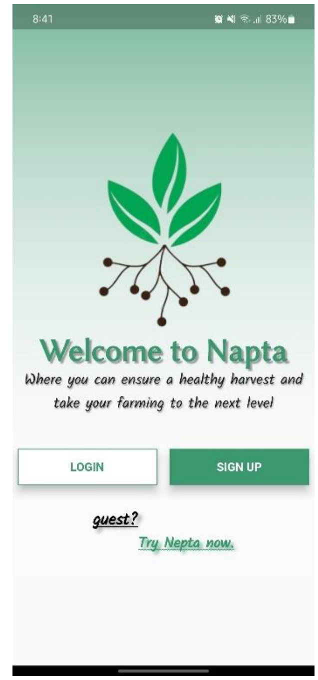

Figure 41 - welcome page

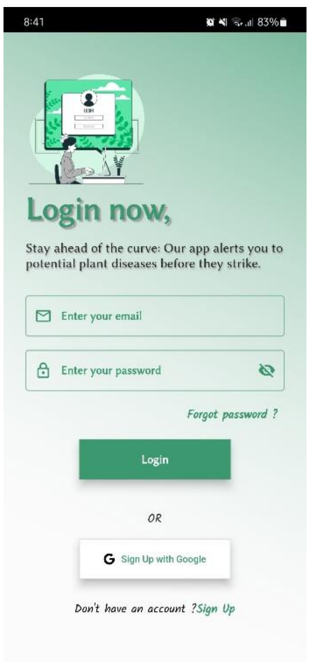

Figure 43 - Login page

4.3.2 Login page:

By clicking ‘LOGIN’ on the welcome page, users will be directed to this login page which provides them a secure access to their account.

4.3.3 Sign up page:

By selecting 'SIGN UP' on the welcome page, users will be redirected to the signup screen, where they can create a new account securely. This enables them to unlock a personalized experience and gain access to a wide range of features and services tailored to their preferences.

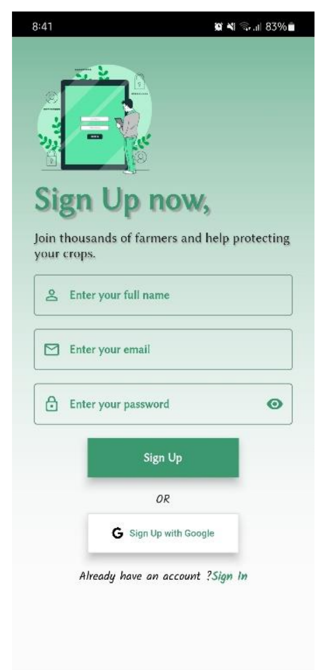

Figure 42 - sign up page

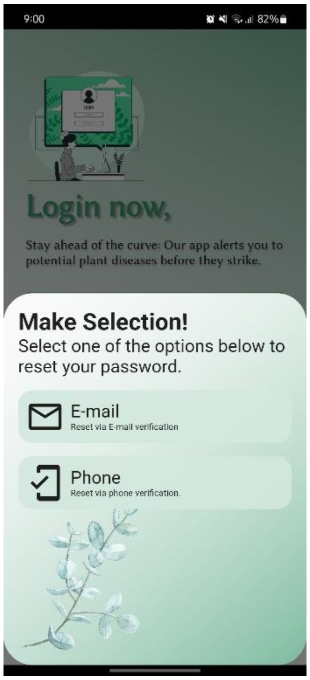

Figure 44 - forgot password screen

4.4 Forgot password, email verification screen and Otp screen.

4.4.1 Forgot password

When users click on the "Forgot Password" option, a user-friendly window will appear, allowing them to initiate the password recovery process.

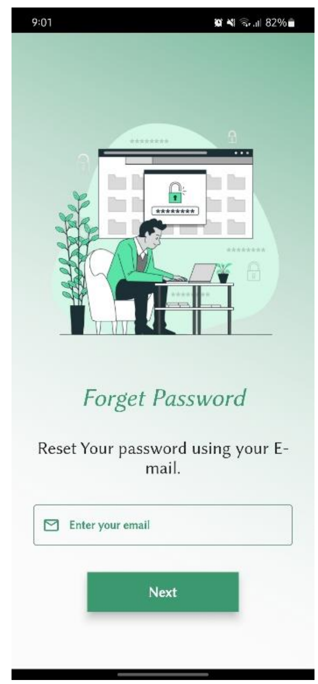

Figure 45 - Email verification screen

4.4.2 Email verification screen

Upon selecting the "Email" option, users will be directed to this page where they can securely enter their email address. Subsequently, they will await the arrival of an email verification in their designated email account to complete the necessary steps for account recovery.

Figure 46 - OTP screen

4.4.3 OTP screen

Another way of account recovery is using the phone number, upon choosing this option, users will be prompted to enter their phone number and subsequently receive a unique verification code via SMS.

4.5 Home screen

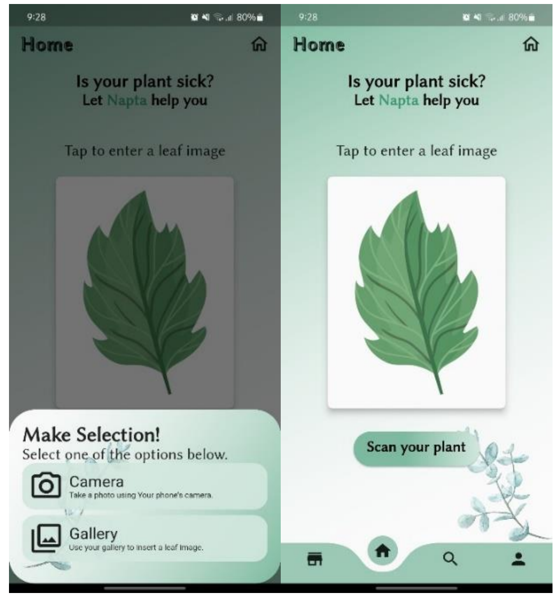

Figure 47 - Home Screen

Within this screen users have the ability to capture or upload a leaf image from their mobile device's camera or gallery. Our app will then utilize powerful algorithms to assess the image and provide a clear determination of whether the plant is infected or not. This allows users to instantly diagnose and address any issues affecting their plants with precision and efficiency.

4.5.1 Prediction screen

this screen is a user-friendly interface designed to help farmers and gardeners in predicting and managing diseases in plants. It is divided into several sections, each providing valuable information and recommendations for effective disease control.

Figure 48 - Prediction Screen

4.6 Search page

Within this page, users can delve into a diverse array of plants. By tapping on a particular plant of their choice, they will be seamlessly directed to the diseases screen of that particular plant which will be shown next.

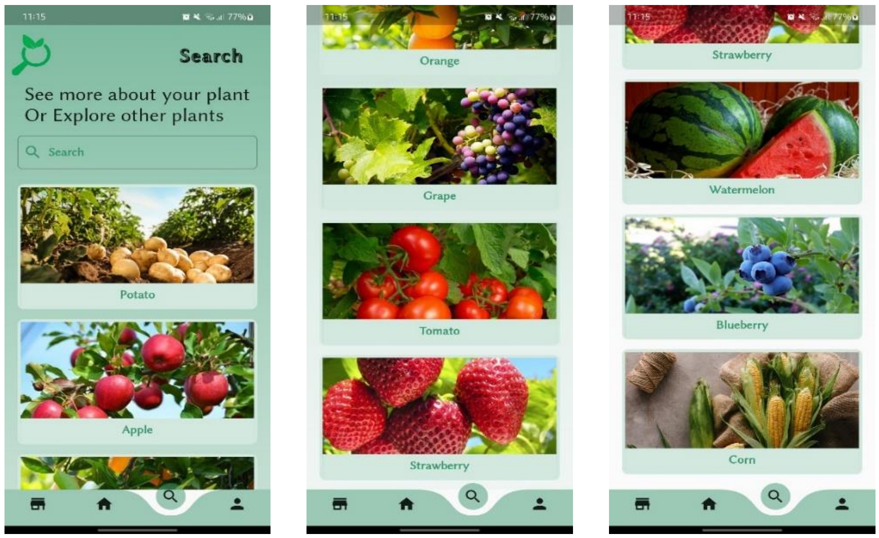

Figure 49 - Search page

4.7 Plant diseases screen

This screen shows each plant's particular diseases.

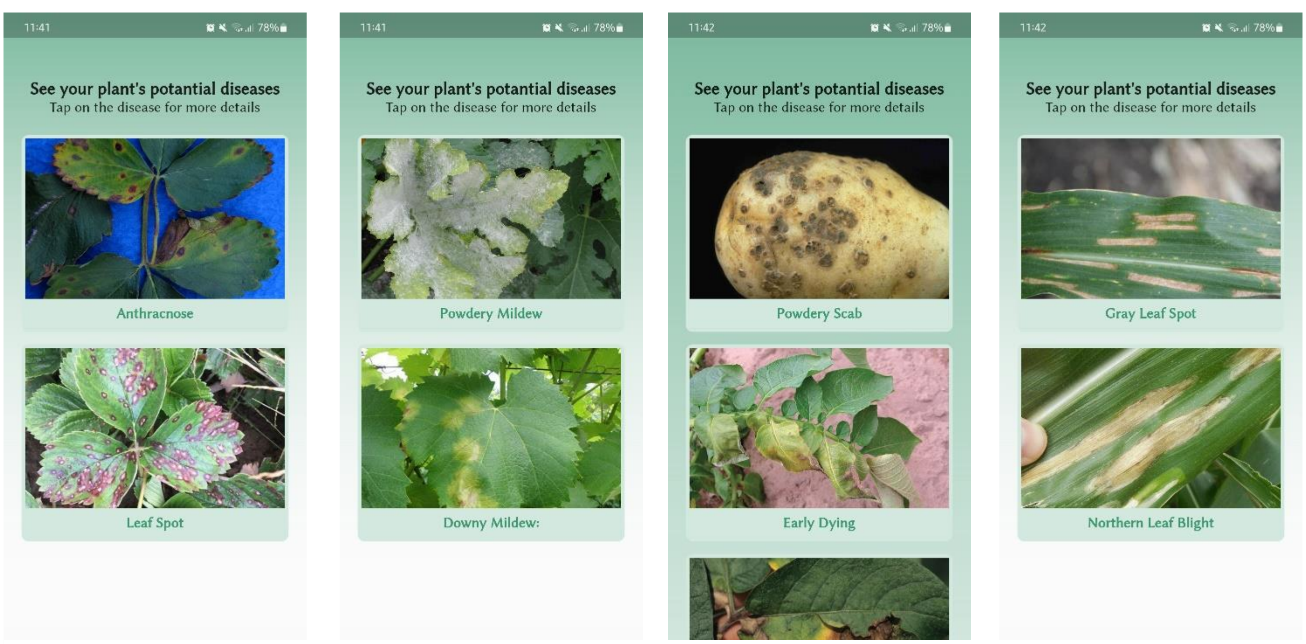

Figure 50 - Plant diseases screen

4.8 Diseases detail screen

This screen shows the details of each disease, when a user taps on a particular disease from the previous page, a comprehensive interface unfolds, presenting in-depth information about the selected disease. Let's take anthracnose, a common disease affecting strawberries, as an example. It’s a neatly organized layout that provides all the essential details. The page begins with a large, clear image of the disease. followed by a concise section that provides details about the disease. As the user scrolls down, they will find additional information about the disease, including its scientific name, a brief description highlighting the key characteristics and finally symptoms of the disease.

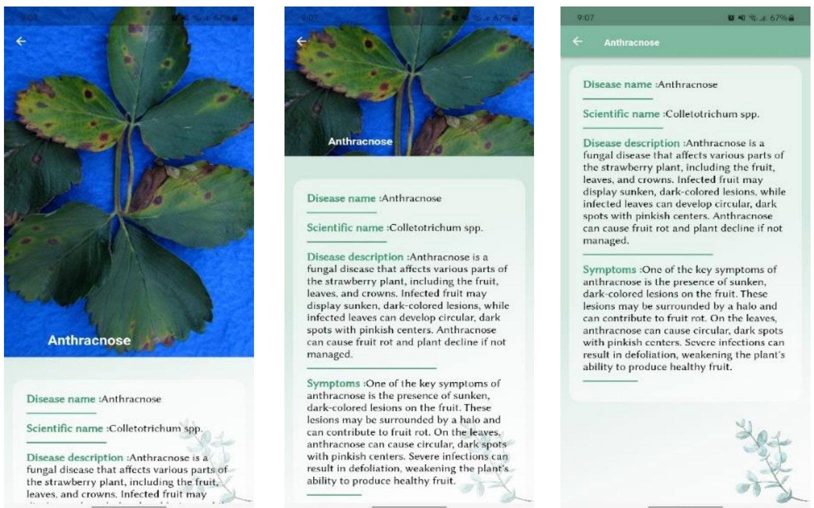

Figure 51 - Diseases detail screen

4.9 Profile screen

This page integrates the essential user-centered features and information, it allows users to edit their profile, customize their settings and securely log out when needed.

It additionally grants him the ability to access pertinent information regarding his plant, including temperature, humidity, and moisture levels, by selecting the 'My Plant' option.

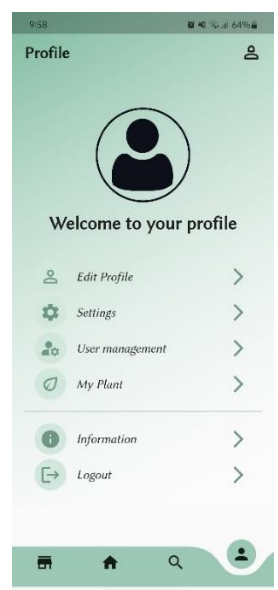

Figure 52 - Profile screen

4.9.1 Edit profile screen

This screen allows users to customize and update their personal information. It provides a convenient and user-friendly interface in order to manage their profiles and ensure that their information is accurate and up-to-date.

Users can access this page to modify various aspects of their profile, such as their name, contact information, password and their localization.

Users also may delete their account in this page.

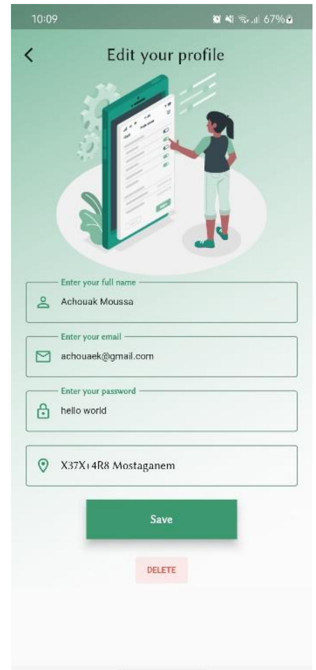

Figure 53 - Edit Profil screen

Figure 54 - Information screen

4.9.2 Information screen

This screen serves as a platform for users to access important contact details and address information about us. It offers a convenient and user-friendly interface, allowing users to easily find and access the necessary information to get in touch with us.

4.10 Market place screen

This interface presents our users with an extensive array of agricultural products, contributed by a diverse group of esteemed product sellers and suppliers. It not only showcases an expansive catalogue but also offers insightful recommendations for the finest and most widely utilized products available.

Figure 55 - Market place screen

4.10.1 Product detail screen

This screen serves as a comprehensive resource, offering users essential details pertaining to the specific product they intend to purchase. By providing a wealth of information, it enables users to make informed decisions based on a deeper understanding of the product's specifications. This screen serves as a vital tool for customers, empowering them to assess the product's suitability for their needs and preferences, thereby enhancing their overall shopping experience.

Figure 57 - Product detail screen

Figure 56 - cart screen

4.10.2 Cart screen

This screen allows users to conveniently manage their selected items before finalizing their purchase. It displays a summary of all the products the user has added to their cart. Users can easily review the quantity and the price of each item. Additionally, the cart screen offers seamless functionality, enabling users to modify quantities, remove items, the cart screen enhances the overall shopping experience, empowering users to make informed decisions before proceeding to the checkout process.

4.10.2.1 Checkout screen

In this screen users can securely finalize their purchases by confirming their personal information it offers a streamlined process for users to enter essential details, including their delivery address, name, and phone number. By providing a dedicated section for each piece of information, users can easily input and review their personal data before proceeding.

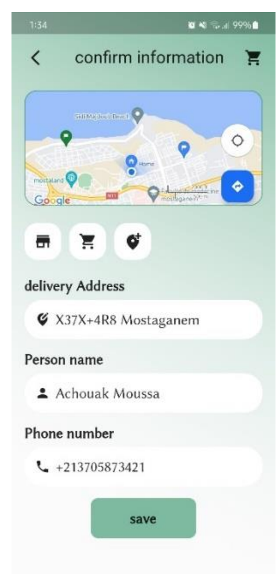

Figure 58- Checkout screen

4.11 Conclusion

In conclusion, this chapter provides a comprehensive overview of the development of the "Napta" mobile app prototype. The chapter introduces the app's various interfaces and discusses how they showcase the app's diverse features and functionalities. Overall, the development of the prototype highlights the "Napta" app's user-friendly interface and its ability to provide valuable assistance in plant care and disease management.

General Conclusion

The development of a machine learning model and a mobile app for detecting potato plant diseases is a significant advancement in agricultural technology. The model accurately classifies and detects diseases in potato leaves with a 97% accuracy rate. Through image preprocessing, augmentation techniques, and Convolutional Neural Networks (CNNs), the model distinguishes between healthy leaves and different diseases, providing prompt diagnoses.

The mobile app enhances accessibility and usability for farmers, allowing them to capture leaf images and receive immediate disease analysis. This technology has the potential to revolutionize plant disease detection, support farmers in mitigating crop losses, and contribute to sustainable agriculture.

Overall, these advancements provide valuable tools for agriculture, helping to conserve crops and improve yields.

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