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Presented by:

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Optimization of Machine Learning Models for Potato Disease Classification

Defended publicly on 04 /06 /2025 in Tiaret in front the jury composed of :

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Thank you

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I dedicate this humble work to the dearest people in my life...
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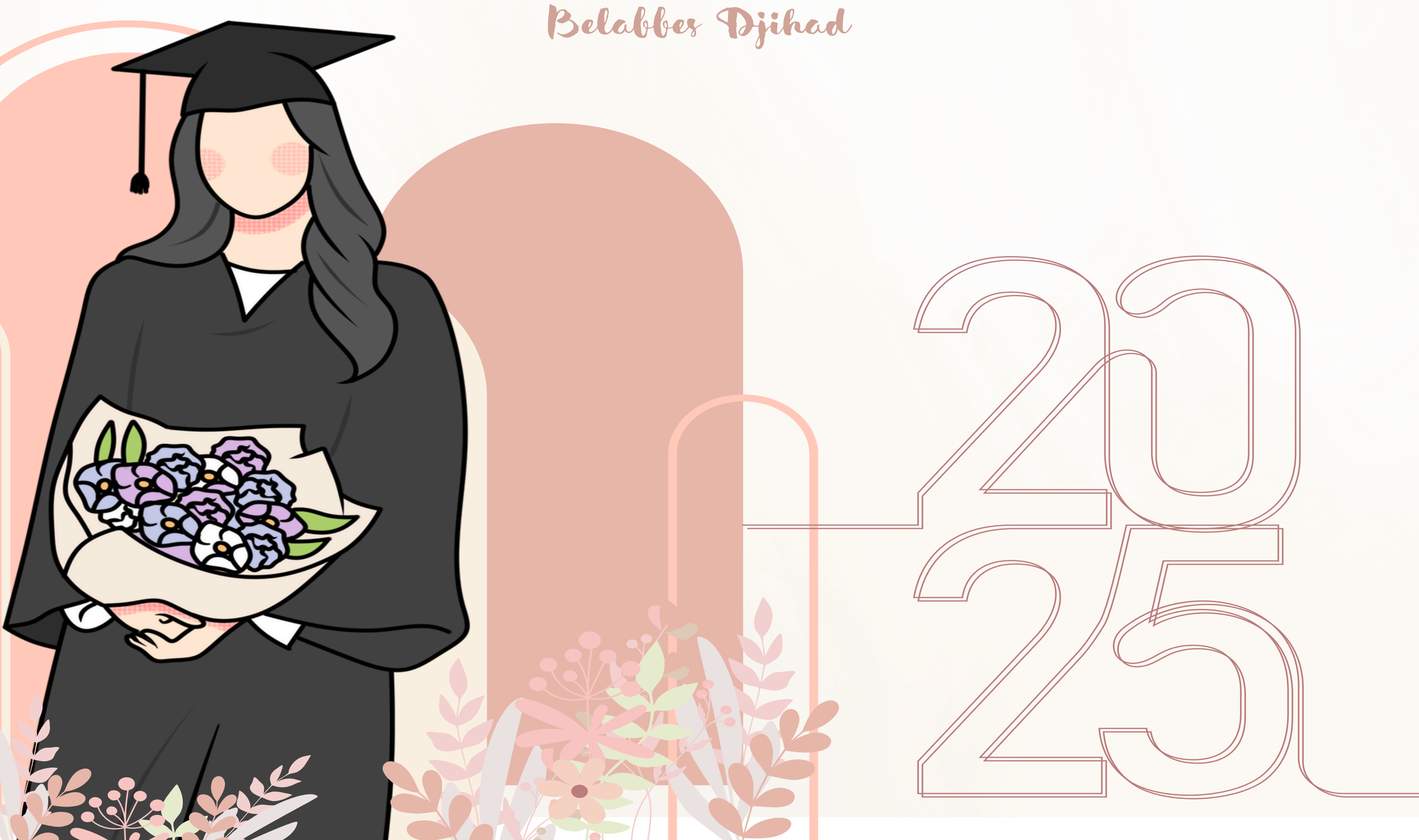


Resume

Ce projet se concentre sur la classification des maladies des feuilles de pomme de terre à l'aide de techniques de vision par ordinateur. Les cultures de pommes de terre sont particulièrement vulnérables à diverses maladies foliaires qui peuvent réduire considérablement le rendement et la qualité. Pour relever ce défi, nous avons développé un système qui utilise le traitement d'images et les méthodes d'apprentissage automatique pour identifier et classer automatiquement les feuilles infectées. Notre approche comprend la collecte de données, le prétraitement des images de feuilles, l'extraction de caractéristiques, ainsi que l'application de modèles d'apprentissage profond pour la classification. Les résultats démontrent une précision et une efficacité prometteuses, prouvant que de tels systèmes peuvent aider les agriculteurs et les experts agricoles à détecter les maladies précocement et à prendre des décisions éclairées. Ce travail contribue au domaine plus large de l'agriculture de précision, visant à améliorer la surveillance de la santé des cultures et à promouvoir des pratiques agricoles durables.

Mots-clés : Maladies des feuilles de pomme de terre, apprentissage automatique, apprentissage profond, classification d'images, réseaux de neurones convolutifs (CNN), vision par ordinateur, détection de maladies, agriculture de précision, technologie agricole, phytopathologie.

Abstract

This project focuses on the classification of potato leaf diseases using computer vision techniques. Potato crops are particularly vulnerable to various foliar diseases that can significantly reduce yield and quality. To address this challenge, we developed a system that leverages image processing and machine learning methods to automatically identify and classify infected leaves. Our approach involves data collection, preprocessing of leaf images, feature extraction, and the application of deep learning models for classification. The results demonstrate promising accuracy and effectiveness, proving that such systems can assist farmers and agricultural experts in early disease detection and decision-making. This work contributes to the broader field of precision agriculture, aiming to enhance crop health monitoring and sustainable farming practices.

Keywords: Potato leaf diseases, machine learning, deep learning, image classification, convolutional neural networks (CNN), computer vision, disease detection, precision agriculture, agricultural technology, plant pathology.

الملخص

يركز هذا المشروع على تصنيف أمراض أوراق البطاطا باستخدام تقنيات الرؤية الحاسوبية. تعتبر محاصيل البطاطا عرضة بشكل خاص لمجموعة متنوعة من الأمراض الورقية التي يمكن أن تؤدي إلى انخفاض كبير في المحصول والجودة. لمعالجة هذا التحدي، قمنا بتطوير نظام يعتمد على معالجة الصور وطرق التعلم الآلي للتعرف التلقائي على الأوراق المصابة وتصنيفها. تتضمن منهجيتنا جمع البيانات، ومعالجة الصور المسبقة، واستخراج الميزات، وتطبيق نماذج التعلم العميق من أجل التصنيف. أظهرت النتائج دقة وفعالية واعدة، مما يثبت أن مثل هذه الأنظمة يمكن أن تساعد المزارعين والخبراء الزراعيين في الكشف المبكر عن الأمراض واتخاذ القرارات المناسبة. يساهم هذا العمل في مجال الزراعة الدقيقة، ويهدف إلى تحسين مراقبة صحة المحاصيل وتعزيز ممارسات الزراعة المستدامة.

الكلمات المفتاحية: أمراض أوراق البطاطا، التعلم الآلي، التعلم العميق، تصنيف الصور، الشبكات العصبية الالتفافية (ث)، الرؤية الحاسوبية، الكشف عن الأمراض، الزراعة الدقيقة، التكنولوجيا الزراعية، أمراض النباتات.

Contents

List of Figures

List of Tables

Introduction

1 Context and Importance of Potato Cultivation

1.1 Importance of Potato Cultivation

Potatoes play a fundamental role in global food security and are among the most important crops economically and nutritionally. They are the leading non-cereal food crop and represent a vital source of carbohydrates and essential nutrients. According to the FAO, global potato production exceeded 300 million tons in 2007, cultivated on 18.5 million hectares [1].

Since 1991, potato cultivation has increased significantly in developing countries, while production has stabilized or slightly declined in industrialized nations. In Africa, this crop has grown by over 50% in ten years, mainly due to its high yield (20 to 30 tons/ha) and its ability to be cultivated outside the rainy season [1].

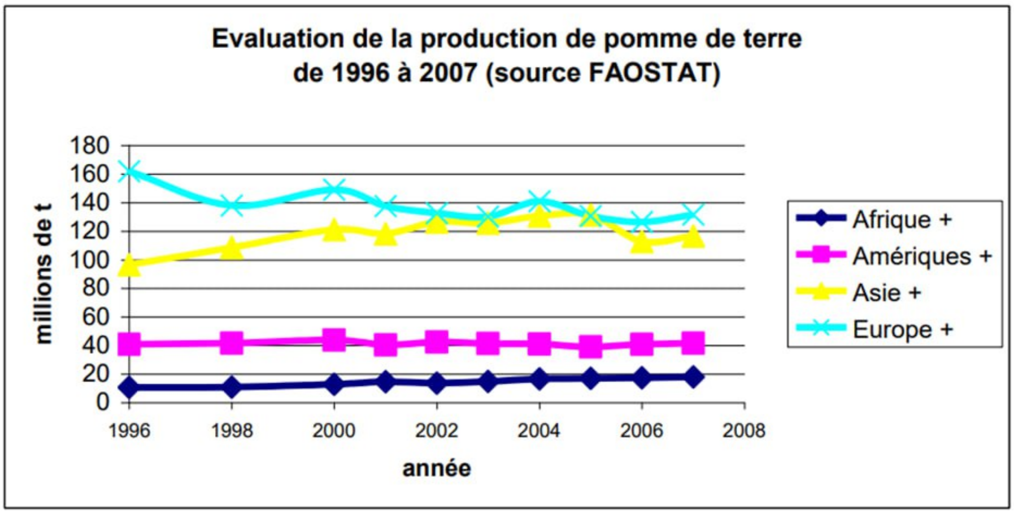


Figure 1: **Evolution of potato production across different continents (1996–2007)**

In Algeria, potato cultivation is a crucial component of the agricultural sector. With production exceeding 50 million quintals, the country is the second-largest producer in Africa, after Egypt. Potatoes are grown year-round in various regions, notably El Oued, Mascara, Mostaganem, Ain Defla, Bouira, and Skikda. The crop is often integrated into rotations with cereals, particularly wheat, to improve soil fertility and optimize yields [2].

Country	Total Production (Million Tons)	Average Yield (Tons/Ha)	Rank in Africa
Egypt	∼5.3	25	1st
Algeria	∼5.0	21–28	2nd
South Africa	∼1.88	35.45	3rd
Morocco	∼1.48	30	5th
Kenya	∼0.98	14	7th
Nigeria	∼0.77	12	8th
Cameroon	∼0.145	8	12th

Table 1: Comparison of Potato Production in Africa. Source: FAO, Cirad, ResearchGate.

1.2 Productivity Comparison with Other Root Crops

Potatoes are highly efficient in terms of yield per hectare. Compared to other root crops such as cassava, yam, and sweet potatoes, potatoes provide the highest production per unit of land use. This makes them a strategic crop for ensuring food security in regions with limited arable land.

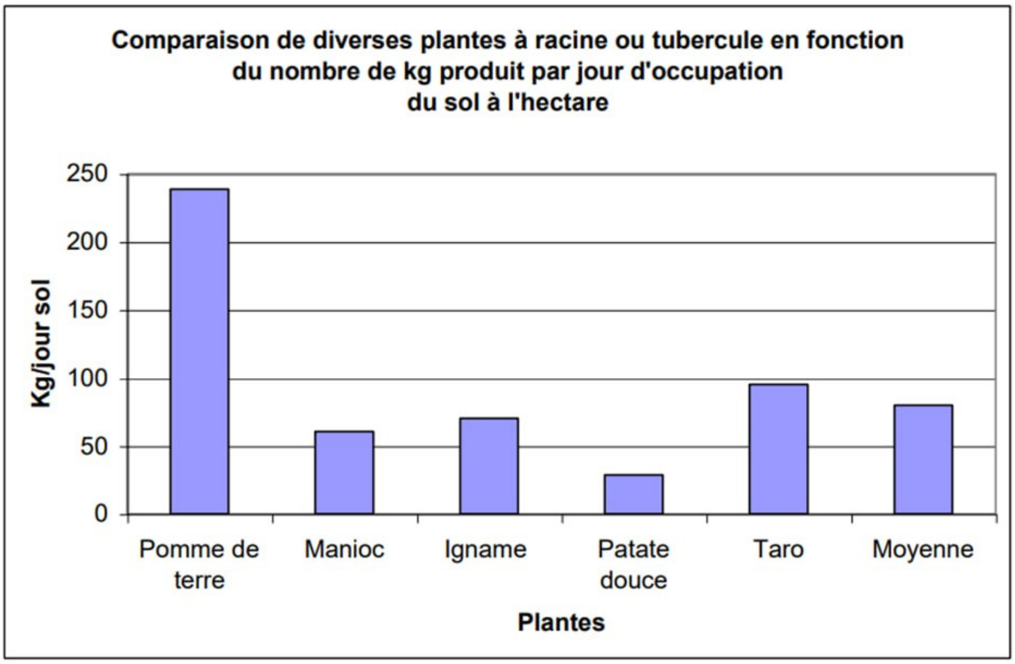


Figure 2: **Productivity comparison of various root and tuber crops in Algeria.**

1.3 Evolution of Potato Production in Algeria

The following graph illustrates the evolution of potato production in Algeria from 2010 to 2021.... as shown in [3].

The production has fluctuated over the years, peaking at 5.02 million tons in 2019, before slightly decreasing in 2021.... as shown in [3].

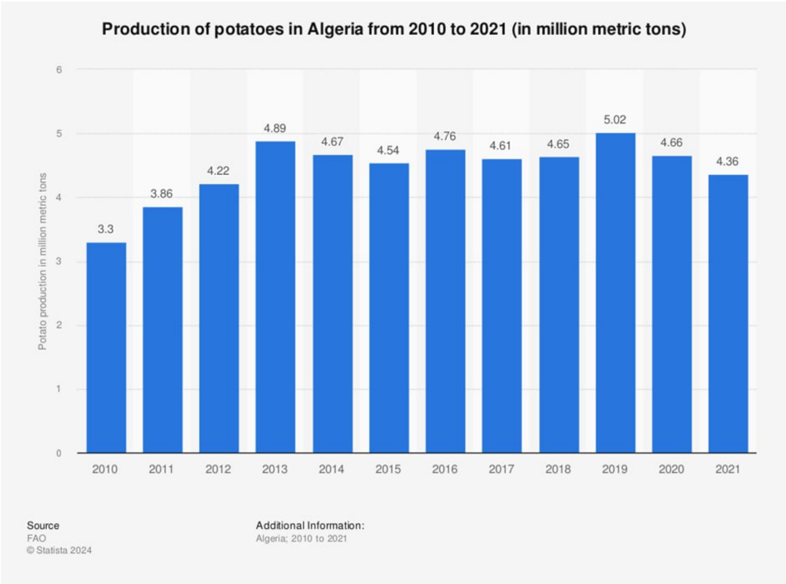


Figure 3: Potato production in Algeria (2010–2021)

1.4 Impact of Foliar Diseases on Potato Production

Potato crops are threatened by several foliar diseases that not only reduce productivity but also affect tuber quality. Among the most notorious are late blight (*Phytophthora infestans*) and early blight (*Alternaria solani*). These diseases can cause significant losses if not detected and controlled in time.

Disease	Effects on the Crop	Consequences
Late Blight	Brown lesions on leaves, reduced photosynthesis	Yield loss up to 100% in severe cases [?]
Early Blight	Black spots on tubers	Reduced market quality and storage life [?]

Table 2: **Major potato leaf diseases, their effects, and consequences**

Increased Production Costs: Farmers must invest in expensive fungicides and preventive treatments to limit the impact of foliar diseases. This leads to significantly higher production costs and lower profit margins [4].

Post-Harvest Losses: Some diseases continue to develop after harvest, reducing potato shelf life and causing economic losses for farmers and traders [5].

Food Security Threats: In regions where potatoes are a staple food, a disease outbreak can lead to local food crises, affecting availability and driving up prices [6].

1.5 Prevention and Management Strategies

To mitigate these challenges, several strategies can be implemented to reduce the impact of foliar diseases and ensure sustainable production:

Use of Resistant Varieties: Developing and adopting genetically resistant varieties to major foliar diseases can reduce reliance on fungicides and improve yields.

Integrated Pest Management (IPM): This approach combines various methods, such as biological treatments, and crop rotation, to minimize the risks of infection.

Monitoring and Early Detection: Smart sensors and drones detect crop infections early, enabling quick action to reduce spread and losses.

Good Agricultural Practices: Proper soil drainage, controlled irrigation, and adequate plant spacing help limit pathogen development and strengthen crop resilience.[6]

2 Problematic: Challenges in Classifying Potato Leaf Diseases

The classification of potato leaf diseases presents numerous challenges that hinder accurate identification and management. These challenges stem from factors such as symptom variability, pathogen diversity, diagnostic limitations, environmental influences, and technological constraints. Understanding these obstacles is crucial for developing effective classification models that enhance disease detection and improve potato crop management.

2.1 Variability in Symptoms

One of the primary difficulties in classifying potato leaf diseases is the similarity of symptoms across different diseases. Many infections cause overlapping visual signs, including yellowing, browning, wilting, and necrotic spots, making it difficult to distinguish between them. For instance, early blight and late blight both cause dark lesions on leaves, but they result from entirely different pathogens and require different treatments [7].

Additionally, potato cultivars exhibit varying degrees of resistance or susceptibility to specific diseases. Some varieties may develop milder symptoms, while others show severe manifestations for the same infection. This variability complicates the classification process, as symptoms alone may not be a reliable indicator of the exact disease affecting the crop [7].

2.2 Diversity of Pathogens

Potato plants are vulnerable to a wide range of pathogens, including fungi, bacteria, viruses, and nematodes. Each pathogen class presents unique diagnostic challenges:

- **Fungal infections:** Diseases such as *Phytophthora infestans* (late blight) and *Alternaria solani* (early blight) are among the most common and destructive fungal infections. They spread rapidly in humid conditions and can devastate crops if not managed promptly [7].
- **Bacterial infections:** *Ralstonia solanacearum* (bacterial wilt) and *Clavibacter michiganensis* (ring rot) cause severe losses by attacking the vascular system of the plant, leading to wilting and decay [9].
- **Viral infections:** Viruses such as Potato virus Y (PVY) and Potato leafroll virus (PLRV) are transmitted by aphids and cause stunted growth, leaf curling, and yield reduction [8].
- **Nematodes and insect vectors:** Some potato diseases are exacerbated by nematodes and insect vectors, which serve as carriers for bacterial and viral pathogens, making disease classification more complex [9].

Moreover, it is common for multiple infections to occur simultaneously, further complicating classification efforts. A potato plant may suffer from both fungal and bacterial infections at the same time, requiring precise diagnostic tools to differentiate between them [7].

2.3 Limitations of Diagnostic Methods

Visual diagnosis: Many farmers and agricultural experts rely on visual inspection, which is subjective and prone to errors. [7].

Molecular techniques (PCR, ELISA): These laboratory-based methods offer highly accurate disease detection but are costly and require specialized equipment and expertise, making them inaccessible to many small-scale farmers [9].

AI-based classification: Machine learning models have shown promise in automated disease detection, but they depend on large, well-labeled datasets. The lack of extensive, high-quality image datasets for potato leaf diseases limits the effectiveness of AI-based approaches [10].

3 Objectives

The primary objective of this thesis is to design, develop, and evaluate an optimized system for classifying potato leaf diseases using advanced deep learning techniques. The aim is to provide farmers with a reliable and practical tool to improve disease detection and crop management.

The specific objectives are:

- Understanding potato leaf diseases: Conduct a detailed review of major diseases, their symptoms, and their impact on potato yields.
- Exploring deep learning fundamentals: Study the core concepts of deep learning and identify the most effective approaches for plant disease detection.
- Developing a robust model: Design and implement a high-performing deep learning model tailored for the classification of potato leaf diseases, focusing on optimization techniques to enhance accuracy .
- Building a practical application: Develop an easy-to-use application, leveraging Python to ensure the model's accessibility and practical use in agricultural settings.

chapter 1

Foliar Diseases of Potatoes

chapter 1
Foliar Diseases of Potatoes

1.1 Introduction

Potato plant diseases pose a significant challenge to agriculture, the environment, and the economy in Algeria. These diseases result from various pathogens, including bacteria, fungi, viruses, and nematodes, which infect leaf tissues and can cause substantial damage to crops. Among these, late blight (*Phytophthora infestans*) and early blight (*Alternaria solani*) are particularly concerning, as they can lead to severe yield losses and deteriorate tuber quality [11].

The symptoms of potato leaf diseases vary widely, ranging from spots, necrosis, and discoloration to malformations and leaf drying. These infections hinder plant growth and productivity, ultimately reducing overall agricultural output. Furthermore, their rapid spread across vast cultivated areas can result in significant economic losses for farmers and pose risks to food security and public health [11].

Given these challenges, the prevention, diagnosis, and management of potato plant diseases have become critical areas of agronomic research and resource management. This study aims to explore the different diagnostic and disease management methods, with a particular focus on leveraging modern machine learning techniques to enhance early detection and improve disease control strategies.

In Algeria, research on the evolution of fungal diseases affecting potatoes, particularly in the northwestern regions, has highlighted the necessity of continuous monitoring and effective disease control measures to sustain agricultural productivity [12].

1.2 Precision Agriculture: Technology and Its Role in Enhancing Agricultural Production

Agriculture has always been essential to human survival, providing food, raw materials, and economic stability. Over the centuries, farming techniques have evolved, moving from manual labor to mechanized systems. Today, agriculture faces new challenges, such as climate change, soil degradation, and increasing demand for food. To address these issues, farmers are turning to Precision Agriculture (PA)—a modern farming approach that uses technology to improve efficiency and sustainability.

Precision Agriculture relies on tools like remote sensing, artificial intelligence (AI), the Internet of Things (IoT), and data analytics to help farmers make smarter decisions. By accurately managing resources such as water, fertilizers, and pesticides, PA helps increase crop yields, reduce costs, and minimize environmental impact [13].

1.2.1 What is Precision Agriculture and How Does It Work?

Precision Agriculture is a data-driven agricultural management system that focuses on collecting, analyzing, and utilizing information to make informed decisions about resource application. This approach relies on several key technologies:

- **Advanced Sensors:** These devices measure soil moisture, temperature, and nutrient levels in real time.
- **Drones and Satellites:** These tools capture high-resolution images of crops, allowing farmers to monitor plant growth and detect potential issues.
- **Smart Software and Data Analytics:** This technology processes collected data to provide recommendations on irrigation, fertilization, and pest control.

1.2.2 Applications of Precision Agriculture in Potato Farming

Precision agriculture has significantly transformed potato farming, enabling farmers to manage crops more effectively and improve both plant health and yield. By employing advanced soil and nutrient management techniques, farmers can monitor variables such as moisture, pH, and nutrient levels in real-time. This allows for the targeted application of fertilizers and water, which reduces waste and enhances tuber quality.

Additionally, GPS-guided planting systems ensure potatoes are sown at optimal depths and spacing, fostering uniform growth and maximizing yield potential. Early disease detection through the use of drones and satellite imagery further aids in identifying plant stress or infections like late blight before they spread.

Smart irrigation systems also contribute by adjusting water distribution based on weather forecasts and soil moisture levels, preventing issues like over- or under-watering that can negatively affect potato quality.

In addition to optimizing resources and crop quality, precision agriculture reduces the environmental impact of farming practices. However, technological advances alone are not enough; a solid understanding of plant physiology and the potential threats they face is crucial for successful potato cultivation.

1.3 Presentation of the Potato Plant Leaf

The potato plant consists of several main parts that play an important role in its growth and production. The main tuber is the planted part that grows to produce the new plant, while the main stem branches out to carry leaves and sprouts. The roots extend up to 60 cm below the main tuber, and the underground stems, known as stolons, grow and produce new tubers. The process of tuber formation is called "tuberization," where these tubers grow and enlarge due to the stored nutrients.

1.3.1 Description of the Tuber

The tuber is a swollen part of the root stem, acting as a storage for nutrients. The tuber contains several parts, including the eyes, which are small indented areas containing buds that can grow into new stems. At one end of the tuber is the crown or apical end, while the other end connected to the root stem is known as the base. The tubers also contain lenticels, which are small pores that facilitate gas exchange, thus aiding respiration and growth.

1.4 Optimal Conditions for Growing Potatoes

potato farming requires careful planning and thorough market research. Before expanding potato cultivation, a market study should be conducted that includes local demand, pricing, production costs, and identifying possible marketing outlets.

1.4.1 Suitable Climatic Conditions

Potatoes grow optimally in temperatures ranging from 15 to 25°C. A daily variation between 10 to 15°C ensures good tuber formation. Altitudes above 700 meters are preferable for sustainable year-round cultivation. It is advised to plant potatoes during the cold and dry season in lower-altitude areas. Full sunlight exposure without shading is essential for healthy growth and good production.

1.4.2 Selection of Agricultural Land

Potatoes are best grown in sandy or light clay soils with good drainage, which helps reduce root and tuber rot issues. The pH level of the soil should range between 5 and 6.5 to ensure proper nutrient absorption. In sloped lands, it is preferable to arrange the planting lines perpendicular to the slope to reduce soil erosion. Crop rotation is also an important factor in potato cultivation. It is advised not to plant potatoes in the same soil used for growing crops from the same family, such as tomatoes or peppers, in the previous three to four years to avoid disease and pest transfer. However, in certain regions with specific environmental conditions, such as waterlogged areas, potato farming can be repeated annually due to the reduced pest spread in these environments.

1.4.3 Water Availability

Potato cultivation requires a sustainable water source, with quantities ranging between 5000 and 8000 cubic meters of water per hectare during the growing season. Regular irrigation is essential, especially during the tuber formation and enlargement stages. Both water scarcity and excess can negatively impact the quality of the crop and increase the likelihood of fungal diseases.

1.4.4 Crop Protection

Protecting the potato crop is essential for ensuring good production. Livestock and wild animals such as pigs may cause damage to the crop, so it is recommended to fence the fields to prevent these damages. Easy access to the fields facilitates irrigation, harvesting, and transportation, contributing to improved production efficiency..

1.5 Potato Leaf Functions

The potato leaves perform several key functions, including photosynthesis, which helps convert sunlight into energy, and the production of dry matter necessary for tuber growth. The leaves also contribute to regulating the distribution of energy and nutrients within the plant, and their significant impact on productivity is influenced by environmental factors such as temperature and humidity. Additionally, the leaves can be supplied with nutrients through foliar fertilization to support the plant in challenging environmental conditions.

1.6 Diseases Affecting Potato Leaves

This section explores the most common of these diseases, outlining their symptoms, the pathogens responsible, and their impact on crop productivity. Backed by reliable data and visual representations, this analysis provides an in-depth look at these diseases and their consequences for contemporary agricultural practices.

1.6.1 Late Blight in Potatoes

Late blight is a highly destructive disease affecting potatoes and tomatoes, caused by the microorganism *Phytophthora infestans*. This pathogen spreads rapidly in cold and moist conditions, leading to severe damage to plant foliage and tubers. It is responsible for significant agricultural losses worldwide, making its management crucial for sustainable potato production[14].

1.6.2 Symptoms of the Disease

Symptoms on Leaves and Stems

Initial Signs: Small, water-soaked spots appear on lower leaves, ranging from light to dark green in color. These spots are circular to irregular in shape and typically develop near the leaf tips or edges, where moisture from dew remains longer [15].

Figure 1.4: Initial symptoms of late blight: small, light to dark green, circular to irregular-shaped water-soaked spots

Progression: Under cool and moist conditions, these spots rapidly enlarge into large, dark brown or black lesions with a greasy appearance. A yellowish (chlorotic) halo often surrounds these lesions [15].

Figure 1.5: Late blight lesions expanding rapidly into dark brown or black greasy patches

Figure 1.6: Leaf lesions frequently surrounded by a yellow chlorotic halo

Spread: The lesions are not confined by leaf veins and, as they merge, entire leaves can become blighted and die within just a few days. Stems and petioles may also show similar lesions [15].

Figure 1.7: Late blight lesions present on petioles and stems, especially in moist new growth

Fungal Growth: During periods of cool, wet weather, a white mildew-like growth appears at the edges of lesions or along petioles, indicating active spore production. When the weather turns warm and dry, these lesions stop producing spores, dry out, and turn tan [15].

Figure 1.8: White mildew-appearing area at lesion edges during active late blight growth

Figure 1.9: Actively growing late blight can cause a white mildew-appearing area along petioles.

Figure 1.10: Brown, dry lesions can develop following warm and dry weather.

Distinct Odor: Severely infected fields may produce a characteristic, unpleasant odor.

Symptoms on Tubers

External Symptoms: Infected tubers develop irregularly shaped, slightly depressed spots that vary in size and color, ranging from brown to purplish. These symptoms may be less noticeable on russet or red-skinned potato varieties [15].

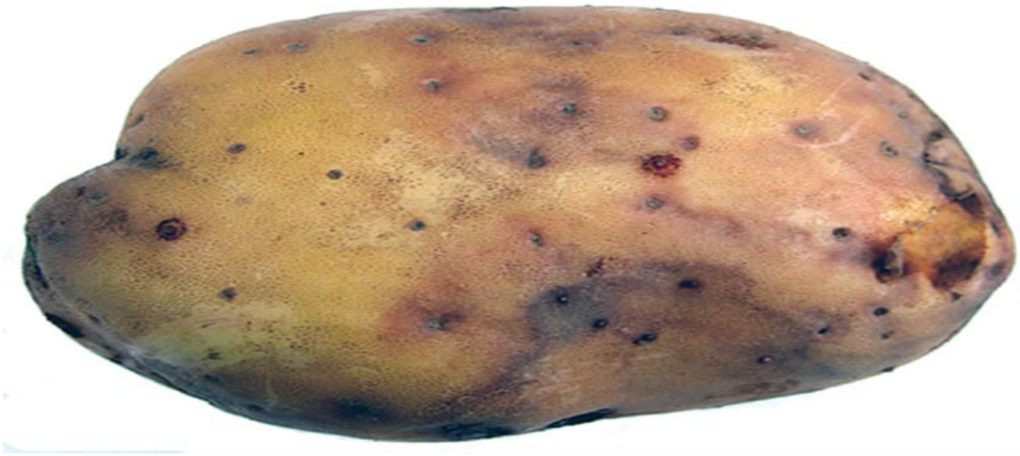


Figure 1.11: Late blight infection of tubers is characterized by irregularly shaped.

Internal Damage: Under the skin, affected areas show a tan to reddish-brown, dry, granular rot that usually extends less than $\frac{1}{2}$ inch into the tuber. The severity depends on variety, temperature, and time since infection [15].

Figure 1.12: Late blight causes a tan to reddish-brown, dry, granular rot found under the skin in the discolored areas and extending into the tuber.

Distinguishing Diseased Tissue: The boundary between infected and healthy tissue may not always be distinct. However, in some cases—especially in cold-stored seed potatoes—a clear brown "finger-like" pattern extends into healthy tissue [15].

Figure 1.13: The margin of the diseased tissue is not always distinct but can be, particularly in seed potatoes that have been stored at cold storage temperatures

Secondary Infections: Other tuber rot pathogens such as soft rot bacteria, pink rot, or leak may enter through late blight-infected areas and progress faster than *Phytophthora infestans*, complicating diagnosis [15].

1.6.3 Disease Life Cycle

Late blight typically originates from infected potato tubers, which serve as the primary source of disease transmission. *Phytophthora infestans* thrives in humid environments and moderate temperatures (10–20°C). The pathogen spreads through airborne or waterborne spores, which settle on leaves or soil, quickly infecting healthy plants. Under favorable conditions, the disease cycle can repeat every 5–7 days, leading to rapid expansion and severe damage to the crop [14].

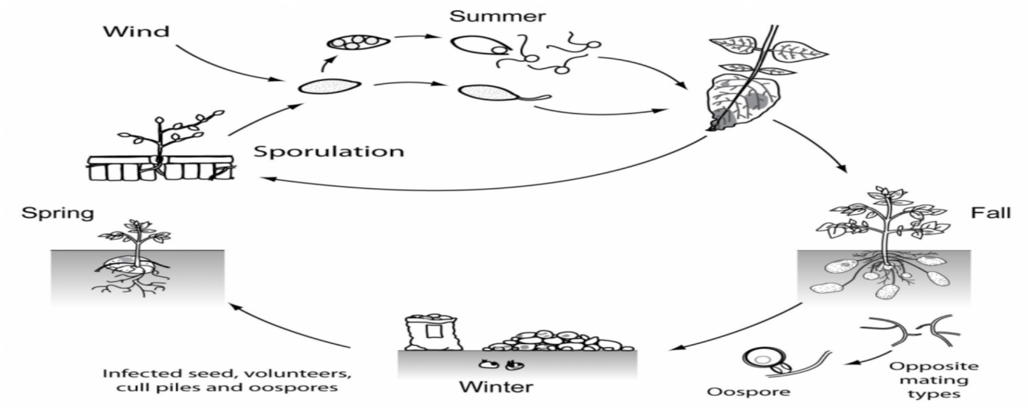


Figure 1.14: illustrating the disease cycle of Late Blight in potatoes.

1.6.4 Management and Control Strategies

Using Resistant Varieties: One of the most effective preventive measures against late blight is selecting resistant potato varieties. These varieties help reduce the risk of infection and limit disease spread within the field. Improved varieties with varying resistance levels are available, and farmers can refer to specialized databases such as the Potato Variety Database to choose the most suitable types based on local conditions [16].

Reducing Sources of Infection: The first step in managing the disease is eliminating infection sources. This includes early removal of infected plants and tubers to prevent the disease from spreading to healthy crops. Additionally, crop residues should be disposed of properly to prevent the pathogen from persisting in soil or water sources. Using certified disease-free seed potatoes further reduces the likelihood of introducing the disease into a new growing season [16].

Monitoring and Disease Forecasting: Continuous monitoring and disease forecasting play a crucial role in controlling late blight. This approach involves tracking environmental conditions such as temperature and humidity levels, which favor disease development. Modern forecasting systems use weather data to predict periods of high disease risk, allowing farmers to take preventive actions at the right time. Regular field inspections also help detect early infections and apply control measures before the disease spreads [16].

Chemical and Biological Control: Fungicides remain an effective tool in managing late blight, particularly when applied preventively before symptoms appear. However, they should be used as part of an integrated pest management strategy to prevent the pathogen from developing resistance. On the other hand, biological control methods can complement chemical strategies by using beneficial microorganisms that inhibit the growth of *Phytophthora infestans*. Additionally, implementing good agricultural practices such as proper crop rotation, balanced fertilization, and irrigation management helps minimize factors that promote disease development [16].

1.7 Early Blight in Potatoes (Alternaria solani)

Early blight, caused by *Alternaria solani*, is a widespread disease that affects potatoes annually in most growing regions. It infects leaves, stems, and tubers, leading to reduced yield, smaller tubers, decreased storability, and lower quality for both fresh-market and processed potatoes, ultimately affecting marketability [17].

Symptoms of Early Blight in Potatoes

Early blight, caused by *Alternaria solani*, affects the leaves, stems, and tubers of potato plants. The symptoms vary depending on the stage of infection and the part of the plant affected [18].

1 - Symptoms on Leaves **Early Stage:** Small, dark brown spots, ranging from irregular to circular in shape, appear on the lower, older leaves. These spots vary in size from tiny specks to about 1/8 inch in diameter [18].

Progression: The lesions gradually expand and take on an angular shape due to the restriction by leaf veins. Concentric rings develop within the lesions, giving them a target-like appearance [18].

Advanced Stage: Infected leaves turn yellow, wither, and die, yet often remain attached to the plant [18].

Severe Infection: In cases of heavy infection, large portions of the plant become covered with lesions, significantly reducing photosynthesis and weakening the plant [18].

Figure 1.15: Dark brown circular spots with concentric rings on potato leaves.

2 - Symptoms on Stems Elongated, superficial brown or black lesions may develop on stems and petioles. Infected stems can become weak, leading to plant collapse [18].

Figure 1.16: Dark, elongated lesions on potato stems.

3 - Symptoms on Tubers **External Symptoms:** Dark, sunken, irregular lesions appear, often surrounded by a raised purple to dark brown border.

Internal Symptoms: The infected tissue is dry, corky, and dark brown, reducing tuber quality and storability.

Processing Issues: Infected tubers require extra peeling due to damaged tissue [18].

Figure 1.17: Dark, sunken spots with corky texture on infected potato tubers.

Disease Cycle of Early Blight in Potatoes

The early blight fungus, *Alternaria solani*, survives between growing seasons by overwintering on infected potato debris, soil, tubers, and susceptible solanaceous crops or weeds, such as nightshade species. The overwintering spores can withstand a wide range of environmental conditions, allowing the disease to persist and re-emerge each year.

Primary Infection (Spring): In spring, fungal conidia spores serve as the primary inoculum. The infection begins when these spores land on susceptible potato leaves in the presence of free moisture from rain, dew, or irrigation. The optimal temperature range for spore development is between 41°F and 86°F, with 68°F being the most favorable for disease progression.

Disease Progression (Growing Season): As the growing season progresses, the spores germinate and penetrate plant tissue through different entry points, including direct penetration of epidermal cells, stomata, or wounds. Multiple infection cycles occur within a single season, with alternating wet and dry conditions accelerating spore production and dispersal.

Rapid Spread (Mid to Late Season): During mid to late season, the infection rate remains relatively low in the early stages but increases significantly after flowering, reaching its peak during the tuber bulking stage. Severe infections result in widespread defoliation, reducing plant vigor and negatively affecting tuber development.

This cycle repeats annually, making early blight a persistent and damaging threat in potato-growing regions worldwide [18].

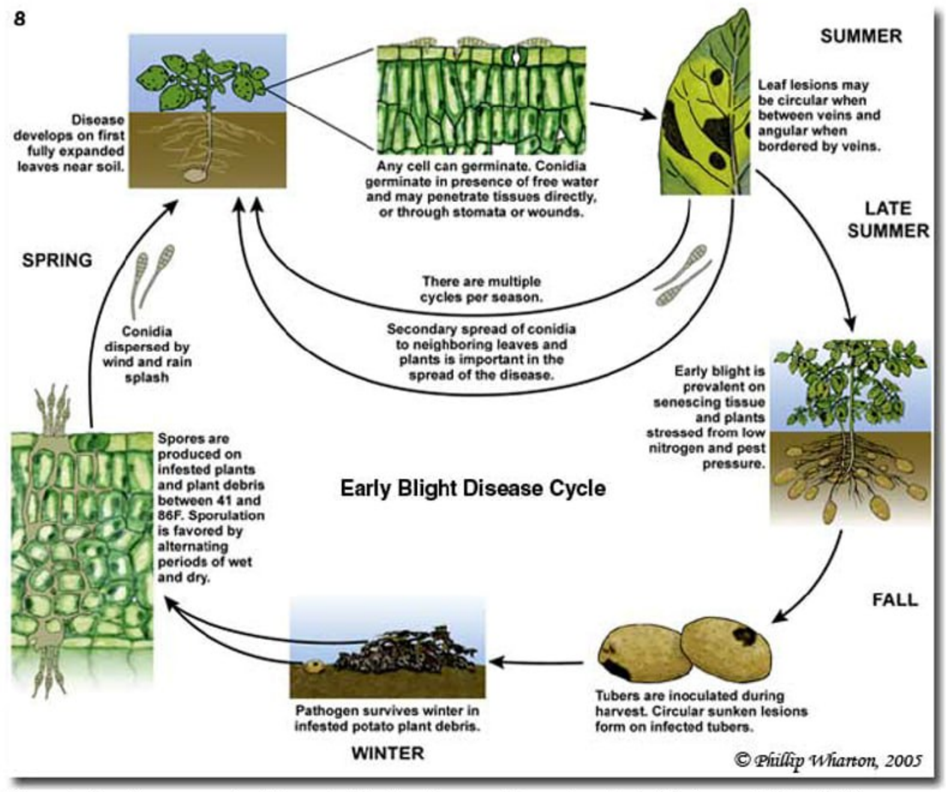


Figure 1. The diseases cycle of the early blight pathogen, *Alternaria solani*. (Warton and Kirk, 2012).

Figure 1.18: Early Blight Disease Cycle in Potatoes

Management Strategies for Early Blight in Potatoes

Managing early blight requires an integrated approach that combines cultural practices and fungicide applications to effectively control the disease and minimize its impact on potato crops.

Cultural Practices: Crop rotation is one of the most effective cultural strategies, as planting potatoes in rotation with non-host crops like corn, soybeans, or small grains for two to three seasons helps reduce the presence of disease-causing fungi in the soil. Weed control is also essential, as removing weeds such as nightshade and horsenettle minimizes potential sources of infection. Proper irrigation management plays a crucial role in disease prevention, and watering should be carefully timed to avoid prolonged leaf wetness, which creates favorable conditions for fungal growth. Ensuring proper soil and plant nutrition, particularly by providing sufficient nitrogen to the plants during the late growing season, helps strengthen plant resistance and reduce disease severity. Managing crop residues is another important practice, as plowing infected plant debris into the soil after harvest accelerates decomposition and reduces fungal survival. Additionally, selecting high-quality seeds is vital, and using certified disease-free potato seeds significantly lowers the risk of introducing the pathogen into the field.

Resistant Varieties: While no commercially available potato variety is completely resistant to early blight, late-maturing cultivars tend to be less susceptible than early-maturing ones. Young potato plants naturally exhibit a higher level of resistance, but as they mature, particularly after tuber formation, their susceptibility to infection increases. Selecting less susceptible varieties can contribute to better disease management and reduced reliance on chemical control methods.

Field Monitoring and Risk Prediction: Regular field scouting is essential for detecting early infections before they spread extensively. Monitoring potato fields, especially once plants reach 12 inches (30 cm) in height, allows farmers to identify symptoms in the early stages and take timely action. The P-Day model is a predictive tool that helps assess disease risk based on plant growth. When 300 physiological days (P-Days) have accumulated after crop emergence, the likelihood of early blight increases, signaling the need for protective measures.

Fungicide Application: Chemical control remains the most effective method for managing early blight in potatoes. Systemic fungicides, such as those containing fluopyram, help protect plants by moving through the tissues and covering new growth. Resistance management is a crucial factor in ensuring the long-term effectiveness of fungicides, and this can be achieved by rotating and mixing fungicides from different chemical groups, identified by their FRAC codes, to reduce the risk of pathogen resistance. The timing of fungicide application is also critical, as treatments should begin when environmental conditions become favorable for disease development and continue throughout the growing season to provide consistent protection.

By implementing a combination of these management strategies, farmers can significantly reduce the incidence of early blight, protect their potato crops, and improve overall yield quality [17].

1.8 Brown Rot in Potatoes (Ralstonia solanacearum)

Brown rot, or bacterial wilt, is a severe potato disease caused by the soil-borne bacterium *Ralstonia solanacearum.* It disrupts the plant's vascular system, leading to wilting, stunted growth, and eventual tuber decay. The disease thrives in tropical, subtropical, and some temperate regions, significantly impacting global potato production. Its spread occurs through contaminated soil, water, infected plant debris, and agricultural tools, making effective monitoring and control measures essential for managing outbreaks.[19]

1.8.1 Symptoms of Brown Rot in Potatoes

Brown rot symptoms are predominantly favored by warm temperatures and high soil moisture. This disease impacts both the above-ground plant structures and the tubers, with the manifestation of symptoms varying according to environmental factors.

Symptoms on Potato Plants

The early symptoms of the disease in potato plants often begin with the wilting of the youngest leaflets at the tips of the leaves, particularly during the hottest part of the day. However, affected plants may seem to recover at night when temperatures drop. In cooler climates, wilting may not always be apparent, making early detection more challenging. As the disease progresses under favorable conditions, it leads to stunted growth, reduced plant vigor, and a general decline in health. The foliage gradually turns yellow and wilts, eventually leading to the plant's death due to severe vascular blockage. A distinctive diagnostic feature of this disease is the presence of a white bacterial slime oozing from the cut stem, indicating the bacterial infection of the plant's vascular tissues.[19]

Symptoms on Tubers

The most distinctive symptom of the disease appears in the potato tubers, where a brown discoloration develops in the vascular ring, typically beginning at the stolon end. As the infection progresses, the vascular tissue undergoes complete decay, severely affecting the tuber's internal structure. In advanced stages, a pale-colored, sticky bacterial ooze may seep from the eyes, lenticels, or stolon end, creating a moist environment that often causes soil particles to adhere to the affected areas.[20]

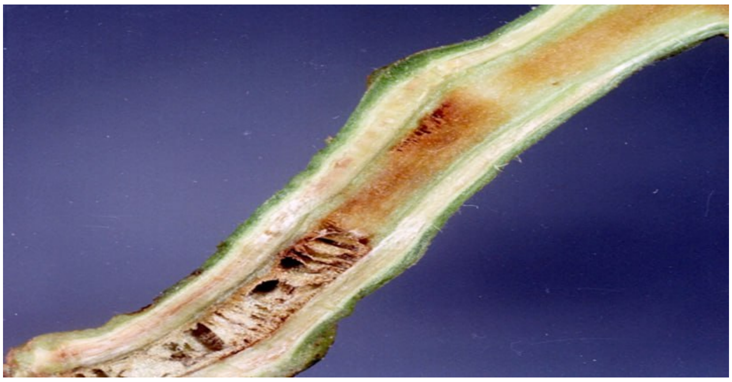


Figure 1.19: Wilting symptoms of Brown Rot showing vascular discoloration in the stem.

Figure 1.20: Symptoms of Brown Rot in potato tubers, showing vascular discoloration and decay.

1.8.2 Disease Cycle of Brown Rot

The bacterium *Ralstonia solanacearum*, which causes brown rot, is a serious plant pathogen, classified as a quarantine organism in Europe and a bioterrorist threat in the United States. It thrives in warm and humid environments, spreading through infected seed potatoes, contaminated soil, water, and plant cuttings. Different types exist, with Race 3 primarily affecting potatoes and tomatoes, making it a concern in temperate regions as it can survive at lower temperatures (around 27°C). The bacteria enter plants through wounds or natural openings, spreading via the xylem vessels and causing systemic infection. In potatoes, it can be tuber-borne, enabling transmission through seed potatoes. The disease spreads through roots, irrigation water, and soil, with the highest risk occurring during rainy periods. At low temperatures, the bacteria can remain dormant until favorable conditions allow disease development, making early detection challenging.[22]

4.4.1 - Symptoms of White Mold in Potatoes

Initial Symptoms: The first signs of white mold appear as water-soaked lesions on the lower leaves and stems, typically 10 to 20 days after row closure. These lesions commonly develop at stem branch points or in areas where the stems come into contact with the

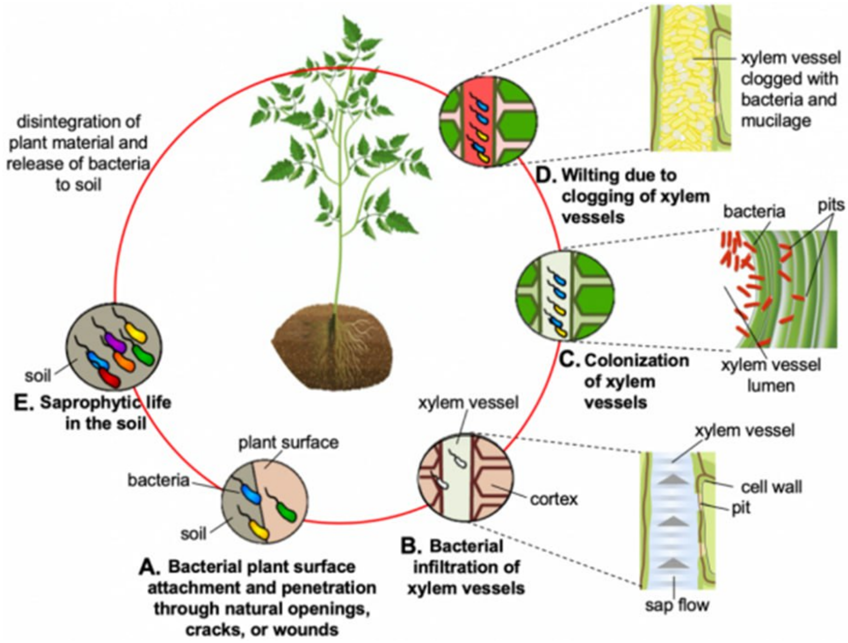


Figure 1.21: Life Cycle of *Ralstonia solanacearum*, the Causal Agent of Brown Rot and Bacterial Wilt in Potatoes.

soil, providing an ideal environment for fungal growth.[22]

Fungal Growth: As the disease progresses, the lesions become covered with a white, cottony fungal mat. If moisture levels remain high, this fungal growth can rapidly spread to nearby stems and leaves, worsening the infection and increasing its impact on the plant.[22]

Figure 1.22: White mold infection on a potato stem (*Sclerotinia sclerotiorum*), showing characteristic cottony fungal growth and developing sclerotia.

Stem Damage: The lesions continue to expand, girdling the stem and leading to wilting of the affected foliage. Infected stems may become hollow and split open, revealing tan to beige, papery tissue. This structural weakening disrupts the plant's ability to sustain healthy growth and contributes to further decline. [23]

Sclerotia Formation: One of the most distinctive signs of white mold is the formation of sclerotia—black, hard, irregularly shaped structures ranging from 0.25 to 0.5 inches in diameter. These sclerotia develop on or within infected stems and act as resting bodies for the fungus, allowing it to persist in the soil for years and cause future infections.[22]

Advanced Symptoms: In the later stages of infection, severely affected plants may collapse and die. Over time, the lesions dry out and take on a tan or bleached-white appearance with a brittle texture. The severity of these symptoms is often aggravated by high humidity, excessive irrigation, and dense canopies that retain moisture, creating an environment that favors the spread of the disease. As the infection advances, sclerotia formation becomes evident on potato tubers (Figure 2), contributing to long-term fungal survival in the soil.[22]

Figure 1.23: White mold infection on potato tubers, showing sclerotia formation and tissue decay.

4.4.2 - Disease Cycle of White Mold in Potatoes

White mold in potatoes, caused by *Sclerotinia sclerotiorum*, is a soil-borne fungal disease affecting over 400 plant species. The fungus survives in the soil as sclerotia, which can persist for years and germinate under cool, moist conditions. In late spring, sclerotia produce apothecia, which release ascospores that spread through wind and infect potato blossoms and senescing plant parts. The fungus then moves to healthy stems and leaves, forming water-soaked lesions with white cottony growth. Under warm, dry conditions, sclerotia may germinate directly and infect nearby plants. The disease cycle continues as new sclerotia develop in infected tissue, making moisture control and removal of infected debris essential for management.[23]

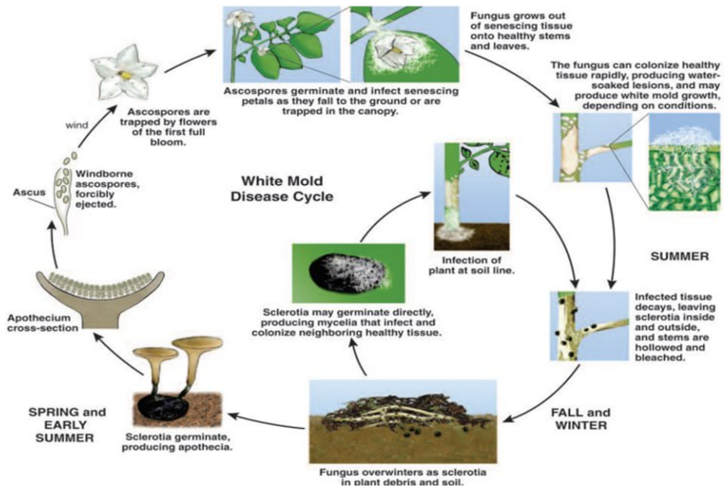


Figure 1.24: The disease cycle of the white mold pathogen, *Sclerotinia sclerotiorum*.

4.4.3 - Management of White Mold in Potatoes

Recordkeeping and Monitoring: Regular field inspections and thorough documentation of infections are essential in managing white mold. Since sclerotia can persist in the soil for up to eight years, tracking the disease over multiple seasons is crucial. Mapping affected areas allows for more targeted fungicide applications and enables farmers to make informed decisions about adjusting planting density to minimize disease spread.

Cultural Control: Implementing cultural practices plays a significant role in reducing white mold infections. Crop rotation with non-host crops such as corn, wheat, barley, and oats helps break the disease cycle, whereas avoiding broadleaf hosts like legumes, sunflowers, and potatoes minimizes reinfection risks. Tillage practices can influence disease management; while deep tillage buries sclerotia, it does not eliminate them, and no-till systems may accelerate their decomposition. Proper plant density management is also critical, as high populations encourage dense canopies, increasing humidity and favoring fungal growth.

Irrigation Management

Proper water management is crucial in controlling white mold development. Reducing irrigation frequency after vine closure can help prevent prolonged leaf wetness, which favors fungal infection. Opting for infrequent but deep watering instead of frequent, light irrigation can significantly lower disease risks by minimizing excessive moisture on plant surfaces.

Chemical Control

Fungicide applications remain a critical component in white mold management. The first fungicide treatment should be applied at full bloom, followed by a second application approximately 14 days later to ensure continued protection. Additionally, some herbicides, such as lactofen, can influence plant canopy structure, reducing the number of potential infection sites. The effectiveness of fungicides is highest at the R1 growth stage (early bloom), making precise application timing essential. Digital tools such as the *Sporebuster* and *Sporecaster* apps can assist in optimizing fungicide use by analyzing weather conditions and predicting periods of high disease risk.[24]

5.2 Potato Leafroll Virus (PLRV) in Potatoes

Potato Leafroll Virus (PLRV) is a serious viral disease affecting potato crops worldwide. It belongs to the *Polerovirus* genus in the *Solemoviridae* family and is mainly transmitted by aphids, particularly the green peach aphid (*Myzus persicae*). As a phloem-limited virus that spreads persistently, PLRV poses a significant threat to potato production, leading to reduced yields and poor tuber quality.[25]

Symptoms of PLRV Infection

PLRV symptoms vary depending on whether the infection is primary or secondary. In cases of primary infection, where aphids introduce the virus during the growing season, young leaves develop an upward rolling of the margins, particularly at the base. These leaves become thick, leathery, and may take on a pale, reddish, or purple hue. The plants also show signs of stunted growth and reduced vigor.[25]

In contrast, secondary infection occurs when infected seed tubers are planted. This results in more severe symptoms in older plants. Affected leaves exhibit extreme rolling, becoming rigid and leathery, while new growth appears upright and lighter in color. Additionally, tubers from infected plants may develop net necrosis, a condition characterized by brown discoloration in the vascular tissues, which significantly affects tuber quality and marketability.[28]

Disease Cycle and Transmission

PLRV is primarily spread by aphids, which acquire the virus while feeding on infected plants. The virus remains in the aphid's body for 24 to 48 hours before it can be transmitted to healthy plants. Winged aphids contribute to the long-distance spread of the virus, leading to widespread infection within and across fields. Another major source of infection is the use of infected seed tubers, which can carry the virus into the next growing season, perpetuating its presence in potato crops.[25]

Economic Impact of PLRV

The impact of PLRV on potato production is severe, with infected plants experiencing yield losses of over 50%. On a global scale, the virus is responsible for an estimated reduction of 20 million tons of potatoes annually due to decreased tuber size, compromised quality, and diminished market value.[26] The economic burden of PLRV extends beyond direct yield losses, as affected potatoes often fail to meet quality standards for both fresh consumption and processing, further limiting their commercial potential.[27]

Management Strategies for PLRV

To mitigate the impact of PLRV, an integrated management approach is essential. One of the most effective strategies is the use of certified, virus-free seed tubers, which helps prevent the introduction of PLRV into potato fields (Wikipedia, 2023) [27]. Aphid control plays a crucial role in limiting disease spread, and this can be achieved through early application of insecticides, the use of reflective mulches, and planting resistant potato varieties (PlantwisePlus Knowledge Bank, 2023) [28]. Additionally, cultural practices such as the removal of infected plants, elimination of volunteer potatoes, and controlling solanaceous weeds can significantly reduce alternative virus hosts, thereby limiting disease spread (PlantwisePlus Knowledge Bank, 2023) [28].

Early harvesting of potatoes can also help minimize late-season infections and reduce the viral load in stored tubers, ultimately improving overall crop health and productivity (Wikipedia, 2023) [27]. Moreover, continuous monitoring and testing through field inspections and laboratory diagnostic methods, such as ELISA and PCR, enable early detection of infections and allow for timely intervention to curb further spread of the virus (PlantwisePlus Knowledge Bank, 2023) [28].

By implementing these comprehensive management strategies, farmers can effectively control the spread of PLRV, minimize yield losses, and enhance the quality and marketability of potato crops. Given the persistent nature of the virus, sustained vigilance and proactive measures remain essential to ensuring long-term protection against PLRV infections.

1.8.3 Septoria Leaf Spot (*Septoria malagutii*) in Potatoes

Septoria leaf spot is a fungal disease primarily affecting tomatoes, but certain *Septoria* species, such as *Septoria malagutii*, can also infect potatoes. This disease weakens plants by reducing their photosynthetic capacity, ultimately leading to lower yields. The pathogen is particularly concerning in humid environments where it thrives and spreads rapidly, making effective management crucial for maintaining potato crop health [31].

Symptoms of Septoria Leaf Spot

The disease is characterized by distinct leaf lesions that first appear as small, circular to irregular dark spots with grayish centers. These lesions typically develop on the lower leaves before spreading upwards as the infection progresses [29]. As the disease advances, infected leaves turn yellow or brown and drop prematurely, a process known as defoliation. This premature leaf loss significantly weakens the plant, reducing its ability to produce energy through photosynthesis, which ultimately impacts yield [30]. In severe cases, prolonged infection leads to stunted growth, further decreasing plant vigor and productivity [31].

Disease Cycle and Environmental Conditions

The *Septoria* fungus overwinters in plant debris and soil, serving as a persistent source of reinfection in subsequent growing seasons. The spores are primarily dispersed through wind, rain splashes, and irrigation water, allowing the disease to spread quickly in favorable conditions [29]. Warm and humid environments provide optimal conditions for fungal growth, with temperatures around 20°C (68°F) being particularly favorable for *Septoria malagutii* infections in potatoes [31].

Management Strategies for Septoria Leaf Spot

Effective management of Septoria leaf spot requires an integrated approach that combines cultural, chemical, and genetic control measures. Sanitation practices, such as removing infected plant debris, are essential to reducing fungal survival in the soil and minimizing the risk of reinfection in future planting cycles [1]. Crop rotation is another key strategy, as rotating potatoes with non-host crops helps reduce the build-up of *Septoria* inoculum in the soil. Additionally, improving air circulation by properly spacing plants can create unfavorable conditions for fungal development and slow disease progression [30].

When environmental conditions favor disease outbreaks, fungicide applications can help protect crops. Protective fungicides such as chlorothalonil or mancozeb have been shown to be effective in managing Septoria leaf spot when applied as a preventive measure or at the first signs of infection [30]. Lastly, using resistant or tolerant potato cultivars, where available, provides a long-term solution to reducing disease susceptibility and minimizing yield losses [31].

By implementing these strategies, farmers can effectively control *Septoria malagutii*, mitigate its impact on potato crops, and maintain higher yields. As the disease thrives in specific environmental conditions, continuous monitoring and preventive measures are necessary to ensure long-term management success.

1.8.4 Powdery Mildew (*Erysiphe cichoracearum*) in Potatoes

Powdery mildew, caused by *Erysiphe cichoracearum*, is an occasional fungal disease in potatoes. Although it is not as widespread or destructive as other potato diseases, it can still lead to economic losses, particularly in humid environments where furrow irrigation is commonly used. The disease is characterized by its distinctive white, powdery fungal growth on leaves and stems, which can weaken the plant and reduce yield potential [32].

Symptoms of Powdery Mildew

The first visible symptoms of powdery mildew appear as white, powdery patches on both the upper and lower surfaces of potato leaves. These lesions gradually expand, sometimes covering large portions of the leaf surface and impeding photosynthesis. As the disease progresses, light brown flecks may develop on the petioles and stems, eventually darkening and causing structural weakness [32]. Infected plants also exhibit foliage decline, with lower leaves turning yellow, blackening, and prematurely dropping. Severe infections can lead to complete defoliation, significantly reducing plant vigor and, in extreme cases, causing plant death [33].

Disease Cycle and Environmental Conditions

The *Erysiphe. cichoracearum* fungus overwinters in plant debris or as spores on host plants, allowing it to persist between growing seasons. Wind plays a major role in the spread of spores, dispersing them to nearby healthy plants under favorable conditions [32]. Unlike many fungal pathogens that require wet conditions for infection, powdery mildew thrives in warm temperatures ranging between 20–25°C, combined with high humidity but relatively low soil moisture. These conditions are often present in regions with dense crop canopies and limited air circulation [33].

Management Strategies for Powdery Mildew

Controlling powdery mildew in potatoes requires a combination of cultural, chemical, and alternative treatments. Proper cultural practices, such as using center-pivot irrigation instead of furrow irrigation, can help lower humidity around the plants and reduce infection rates. Adequate plant spacing improves air circulation, making conditions less favorable for fungal growth. Additionally, removing infected plant debris minimizes the risk of overwintering spores and reinfection in the following season [32].

For severe infections, fungicide applications are necessary to limit disease spread. Sulfur-based fungicides, such as Microfine Sulfur, have proven effective against powdery mildew. Additionally, strobilurin-based fungicides like Quadris FL provide preventive protection against fungal expansion. Organic options such as neem oil can also serve as preventative treatments in early stages of infection [32].

Alternative treatments have also been explored for managing powdery mildew in an environmentally friendly way. A milk spray mixture containing 40% milk and 60% water, applied every 10–14 days, has shown effectiveness in reducing mildew growth. Similarly, a baking soda solution made from 1 tablespoon of baking soda and $\frac{1}{2}$ teaspoon of liquid soap mixed into 1 gallon of water can serve as an early-stage treatment to suppress fungal activity [34].

1.9 Traditional and Modern Methods for Disease Detection in Potatoes

The early and accurate detection of potato diseases is crucial for implementing effective management strategies and reducing crop losses. Various traditional and modern methods are used to diagnose plant diseases, ranging from visual inspection to advanced molecular techniques.

1.9.1 Traditional Methods for Disease Detection

Historically, farmers and researchers have relied on visual inspection and field diagnosis to identify symptoms of plant diseases. This method involves observing characteristic signs such as leaf spots, wilting, and discoloration. However, visual assessment can sometimes be misleading, as different diseases may exhibit similar symptoms [35].

Another traditional approach is microscopic examination, which allows for the identification of fungal spores, bacterial cells, or viral inclusion bodies. This technique remains useful in laboratory settings but is time-consuming and requires expertise [36].

Additionally, pathogen isolation and culturing on selective media help confirm the presence of specific pathogens. This method is frequently used for bacterial and fungal diseases, but it requires several days to obtain results, delaying disease management decisions (Scholthof et al., 2011) [37].

Advancements in technology have introduced more accurate and rapid molecular and imaging-based techniques to detect plant diseases. Polymerase Chain Reaction (PCR) and Real-Time PCR (qPCR) are widely used to detect plant pathogens at the genetic level. These techniques allow for early diagnosis before symptoms become visible, improving disease control efficiency (Miller Martin, 2020)[38].

Enzyme-Linked Immunosorbent Assay (ELISA) is commonly used to detect viral infections such as Potato Leafroll Virus (PLRV). It is cost-effective and widely implemented in seed certification programs (Clark Adams, 1977) [39].

Remote Sensing and Spectral Imaging techniques, including drone-based and satellite imagery, allow for large-scale disease monitoring. These technologies can detect early-stage infections by analyzing changes in plant reflectance (Mahlein et al.., 2012) .

Artificial Intelligence and Machine Learning are increasingly integrated into plant disease detection. Computer vision models trained on large datasets can classify diseases based on leaf images, offering fast and automated diagnosis (Singh et al., 2021).

Traditional methods, while still valuable, have limitations in accuracy and speed. Modern techniques, especially molecular diagnostics and AI-based approaches, offer earlier and more precise detection, enabling farmers to implement control measures efficiently. Integrating both approaches enhances the ability to manage potato diseases effectively and reduce economic losses.

1.10 Techniques for Disease Classification

1.10.1 Traditional Techniques for Plant Disease Classification

Traditional techniques refer to manual or conventional methods used in agriculture before the emergence of modern technologies. These methods rely on visual inspection, laboratory testing, and agricultural practices to diagnose and manage plant diseases. While they are often effective and cost-efficient, they can be time-consuming and heavily dependent on the user's expertise, making them susceptible to errors and subjective assessments.

Visual Inspection

Farmers and plant pathologists examine plants for symptoms such as spots, discoloration, or wilting. Although this method is simple, it requires extensive experience to accurately differentiate between various diseases. Some common examples include:

- Powdery Mildew (Oïdium) – Appears as a white or gray powdery coating on leaves and other plant parts [40].

- Loose Smut (Charbon nu) – Characterized by abnormal greenish-olive formations on grains [41].

Laboratory Analysis

To accurately identify the causative agent, laboratory analyses are conducted, including microbial culturing and microscopic examination. These techniques help in detecting pathogens such as:

- Bacteria – Includes genera such as *Agrobacterium*, *Pseudomonas*, and *Xanthomonas*, which are responsible for various plant diseases [42].
- Fungi – Pathogens responsible for diseases like powdery mildew and loose smut [41].

Plant Disease Classification

Plant diseases can be categorized into two main types:

- Biotic Diseases – Caused by living organisms such as fungi, bacteria, and viruses [42].
- Abiotic Diseases – Not caused by pathogens but rather by environmental factors such as drought, pollution, or nutrient deficiencies [41].

Despite the importance of these traditional techniques, they face limitations in terms of accuracy and speed. This has led to an increasing reliance on modern technologies such as artificial intelligence and image analysis for plant disease detection and classification.

1.10.2 Modern Techniques for Plant Disease Classification

Modern techniques have revolutionized plant disease classification by integrating artificial intelligence, machine learning, and remote sensing. These advanced methods enhance diagnostic accuracy compared to traditional approaches, helping improve agricultural productivity and reduce crop losses caused by disease outbreaks [43].

Computer Vision and Convolutional Neural Networks (CNNs)

This technique relies on analyzing digital images using convolutional neural networks (CNNs) to detect and classify plant diseases based on specific patterns such as color changes and spots. Mobile applications utilizing CNNs enable farmers to diagnose diseases quickly, saving both time and effort [44].

Machine Learning (ML)

Machine learning is used to predict the emergence of plant diseases based on climate, soil conditions, and agricultural history. Algorithms like Random Forest and Support Vector Machines (SVM) help in making precise farming decisions to mitigate the spread of diseases [44].

Remote Sensing and Multispectral Imaging

Drones and satellites equipped with advanced sensors are used to monitor subtle changes that are invisible to the naked eye, such as water stress or chlorophyll deficiencies. This technology facilitates early disease detection and improves irrigation and disease management strategies [45].

1.10.3 Conclusion

The early detection of potato leaf diseases plays a vital role in ensuring crop productivity and reducing economic losses. Traditional methods, such as visual inspection and microscopic analysis, have long been used for disease diagnosis, but they often lack precision and efficiency. In contrast, modern technologies, including molecular diagnostics , remote sensing, and artificial intelligence, have revolutionized disease detection.

Despite the advantages of advanced technologies, integrating them with conventional agricultural practices remains essential for a comprehensive and effective disease management strategy.

Chapter 2

Deep Learning and Machine Learning

chapter 2
Deep Learning and Machine Learning

2.1 Introduction

Deep Learning and Machine Learning are two fundamental branches of Artificial Intelligence (AI), each with a distinct approach to data analysis. Machine Learning relies on algorithms to identify patterns, learn from data, and make predictions. This field has been evolving since the 1950s, continuously improving with advancements in computational power and data availability [46]. Deep Learning, a subset of Machine Learning, distinguishes itself by using artificial neural networks inspired by the human brain. This technology enables machines to automatically extract relevant features from raw data, eliminating the need for manual feature engineering [47].

Both approaches have a wide range of applications across various industries. Machine Learning is commonly used for tasks such as classification, trend analysis, and predictive modeling. In contrast, Deep Learning excels in more complex problems, including image and speech recognition, natural language processing, and autonomous systems [48].

2.2 1. Machine Learning

Machine learning is a branch of artificial intelligence that focuses on developing algorithms capable of learning and improving from data without being explicitly programmed. This process involves feeding a computer system with a large volume of data and using statistical and mathematical techniques to extract meaningful patterns and relationships. These models can then be used to make predictions, detect anomalies, or automate various tasks [49] [50].

Machine learning is widely applied across multiple fields, including image and speech recognition, natural language processing, recommendation systems (such as those used by Netflix or Amazon), fraud detection in banking, and predictive analytics. There are three main types of machine learning: supervised learning, where the model learns from labeled data; unsupervised learning, which explores hidden structures in unlabeled data; and reinforcement learning, where an agent learns through trial and error by interacting with its environment [49] [50].

2.2.1 Applications of Machine Learning

Machine learning enhances agriculture by optimizing irrigation, predicting crop yields, and monitoring plant health. It helps farmers manage resources efficiently by analyzing weather, soil moisture, and historical data. Additionally, machine learning detects early signs of diseases or pests through drone or satellite images, enabling timely intervention and reducing crop loss.

2.2.2 Types of Machine Learning [51]

1. Supervised Learning

Supervised learning is based on labeled data, meaning examples containing inputs associated with expected outputs. The algorithm adjusts its parameters to minimize prediction errors by identifying relationships between inputs and outputs. Commonly used algorithms include linear regression, logistic regression, support vector machines (SVM), and k-nearest neighbors (k-NN).

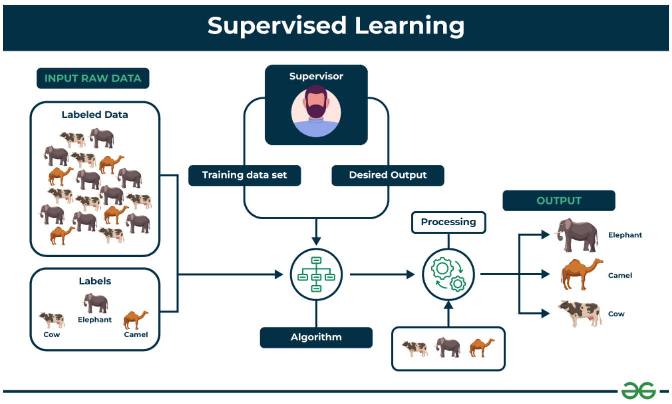


Figure 2.25: Visual representation of the Supervised Learning process, where labeled data is used to train a model to produce desired outputs.

2. Unsupervised Learning

In unsupervised learning, the data is unlabeled, and the algorithm must detect underlying structures such as clusters or trends. It allows for data exploration and the identification of relationships without human intervention. Commonly used algorithms include K-means, principal component analysis (PCA), and Gaussian mixture models (GMM). This type of learning is mainly used for customer segmentation, dimensionality reduction, and anomaly detection.

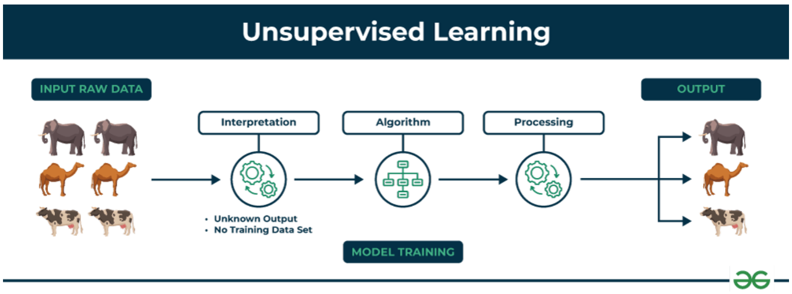


Figure 2.26: Illustration of the Unsupervised Learning process, where unlabeled input data is grouped based on inherent patterns without predefined outputs.

3. Reinforcement Learning

Reinforcement learning is based on the interaction of an agent with an environment. The agent makes decisions and receives rewards or penalties based on its actions. The goal is to learn an optimal strategy that maximizes cumulative rewards. Commonly used algorithms include Q-learning, SARSA, and Deep Q-Networks (DQN). This type of learning is applied in fields such as robotics, video games, and autonomous vehicles.

4. Semi-Supervised Learning

Semi-supervised learning combines labeled and unlabeled data, allowing the use of a large volume of unlabeled data while utilizing a small amount of labeled data to guide learning. It is particularly useful when data annotation is expensive or difficult. Its main applications include medical image classification, facial recognition, and natural language processing (NLP).

2.3 2. Deep Learning

Deep Learning is a field of artificial intelligence that enables machines to learn from complex data such as images, sound, or text. It relies on deep artificial neural networks capable of automatically extracting meaningful features from these data. This technology is widely used in various applications, including facial recognition, automatic translation, speech recognition, sentiment analysis, and trend prediction. It is particularly effective for handling large, unstructured, and noisy datasets.

The learning process involves training neural networks on large datasets. The algorithm gradually adjusts the connections between neurons to minimize the gap between its predictions and the expected results. Deep Learning plays a crucial role in the evolution of artificial intelligence, allowing machines to solve increasingly complex problems with remarkable autonomy.

2.3.1 Deep Learning Architecture

2.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a specialized deep learning architecture primarily used for image processing. They can automatically extract local features from data, enabling the recognition of complex patterns. CNNs were introduced by Yann LeCun in 1989 for handwritten character recognition and have since demonstrated outstanding performance in computer vision. Today, they are widely applied in various fields, including facial recognition, medical image analysis, 3D vision, and even speech recognition. Their ability to learn directly from data makes them a crucial technology in artificial intelligence [52].

The architecture of a convolutional neural network is shown in the figure below:

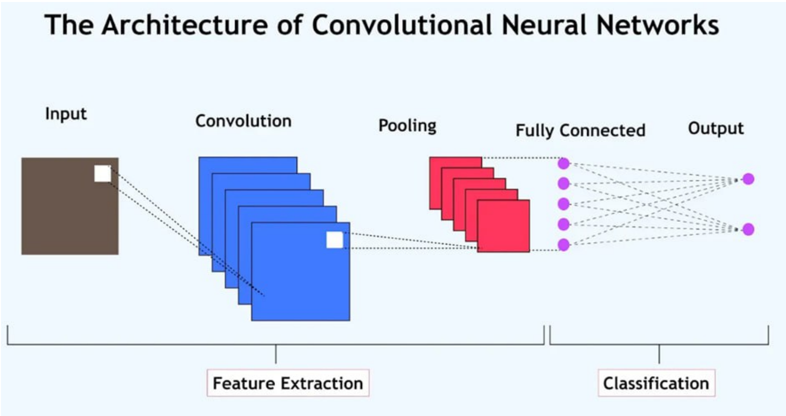


Figure 2.27: Classical architecture of a convolutional neural network (CNN)

Convolutional neural networks (CNNs) consist of four main types of layers: the convolutional layer, pooling layer, ReLU correction layer, and fully connected layer. Each plays a crucial role in feature extraction and classification.

1. Convolutional Layer

This is the fundamental layer of a CNN, responsible for extracting essential features from input data. It applies filters (kernels) that slide over the input image, detecting patterns such as edges, textures, and shapes. The result of this operation is a feature map, which highlights important regions in the image.

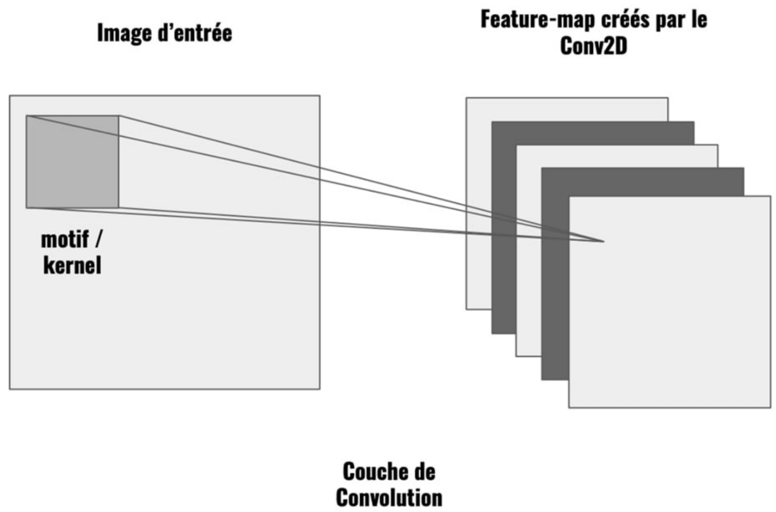


Figure 2.28: Convolutional Layer in CNN: Feature Extraction with Conv2D

2. Pooling Layer

The pooling layer reduces the dimensionality of the feature maps, making the model more efficient and less prone to overfitting. There are two main types of pooling:

- **Max pooling:** Retains the highest value in each region of the feature map, preserving the most prominent features.
- **Average pooling:** Computes the average value in each region, maintaining more general information.

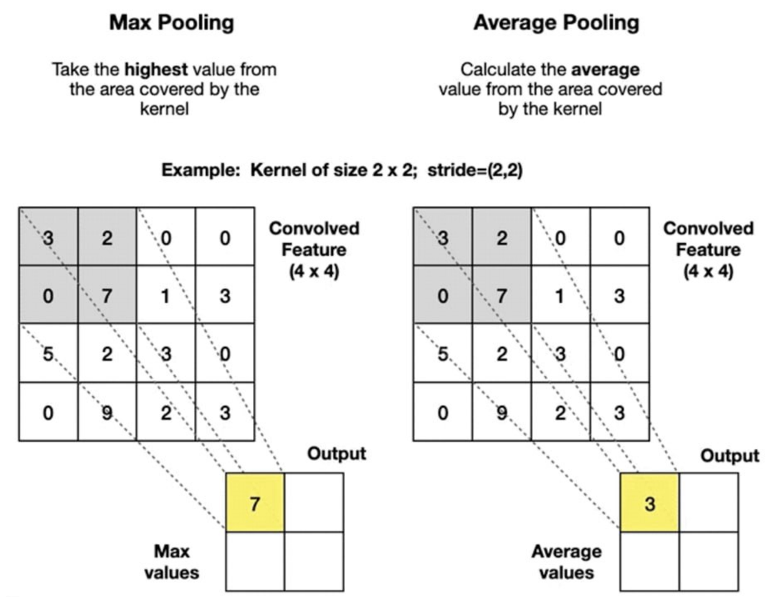


Figure 2.29: Comparison of Max Pooling and Average Pooling in CNN

3. Fully Connected Layer

After feature extraction, the fully connected layer interprets the extracted information and performs classification. Each neuron in this layer is connected to all neurons from the previous layer, allowing the network to make predictions based on learned patterns.

2.4 Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) are an advanced type of artificial neural network designed to process sequential data or time-series information. Unlike traditional Feed-forward Networks, which struggle to retain past information during learning and prediction, RNNs incorporate an internal memory mechanism that allows them to store and recall previous inputs. This capability enables them to understand temporal context, making them particularly well-suited for applications such as natural language processing, speech recognition, machine translation, and time-series forecasting. By leveraging sequence-dependent learning, RNNs can make more accurate and context-aware decisions, significantly enhancing performance in tasks that require understanding the order and relationships between data points.[53]

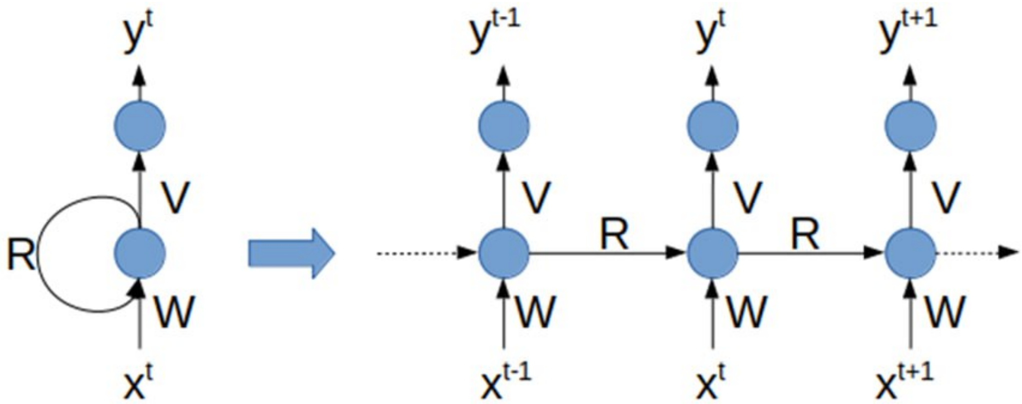


Figure 2.30: Extensions of Recurrent Neural Networks (RNN)

2.4.1 Long Short-Term Memory (LSTM)

LSTM networks are designed to address the vanishing gradient problem found in traditional RNNs. They incorporate memory cells that store information over long periods, allowing them to retain past data efficiently. Their architecture includes three gates (input, forget, and output) that regulate the information flow. [53]

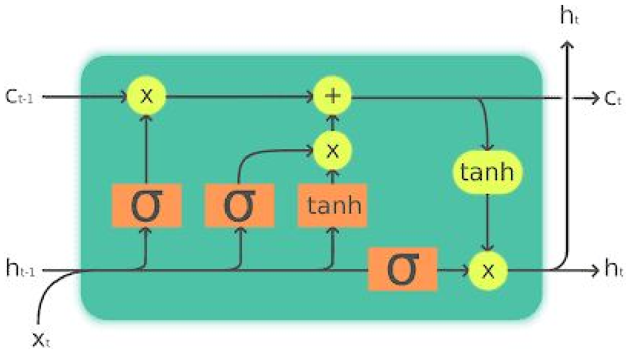


Figure 2.31: Internal Structure of a Long Short-Term Memory (LSTM) Unit

Conclusion

To conclude, this chapter has provided a clear and in-depth overview of Machine Learning and Deep Learning—two essential pillars of Artificial Intelligence. We explored the basic concepts, main types, and practical applications of Machine Learning, emphasizing its transformative role in sectors like agriculture, healthcare, and finance. We also examined the structure and functioning of Deep Learning, particularly through Convolutional Neural Networks (CNNs) for image analysis and Recurrent Neural Networks (RNNs) for sequential data, including their enhancement through Long Short-Term Memory (LSTM) networks.

While these two approaches differ in their architecture and complexity, they both offer powerful solutions for analyzing data and solving real-world problems. Machine Learning is well-suited for pattern recognition and prediction, whereas Deep Learning excels in processing large, complex, and unstructured datasets with high levels of autonomy. Together, they represent a major step forward in the development of intelligent systems capable of performing tasks once limited to human intelligence.

Chapter 3

Methodology

3 Methodology

3.1 Introduction

This chapter outlines the methodology used to study potato leaf diseases and early detection techniques. It covers the research methods, sample selection criteria, and experimental procedures followed to ensure valid and reliable results. The goal is to provide a clear understanding of the approach taken to assess the impact of leaf diseases and explore optimal management solutions.

3.2 Data Collection

Data collection is a fundamental step in building an efficient machine learning model capable of accurately classifying potato diseases. To ensure the reliability and accuracy of the results, we relied on one well-established dataset available on Kaggle.[54] These datasets provide a diverse set of images captured under different conditions, enhancing the model's ability to generalize and recognize disease patterns effectively.

The datasets used in this study were carefully selected for their quality and the accuracy of their annotations:

3.2.1 Potato Disease Leaf Dataset (PLD)

This dataset contains high-resolution images of potato leaves affected by different diseases, as well as healthy leaves, making it ideal for training a machine learning model capable of distinguishing between categories. The source of the dataset is available at:

This dataset consists of 2,152 images distributed as follows:

- Early Blight: 1000 images
- Late Blight: 1000 images
- Healthy Leaves: 152 images

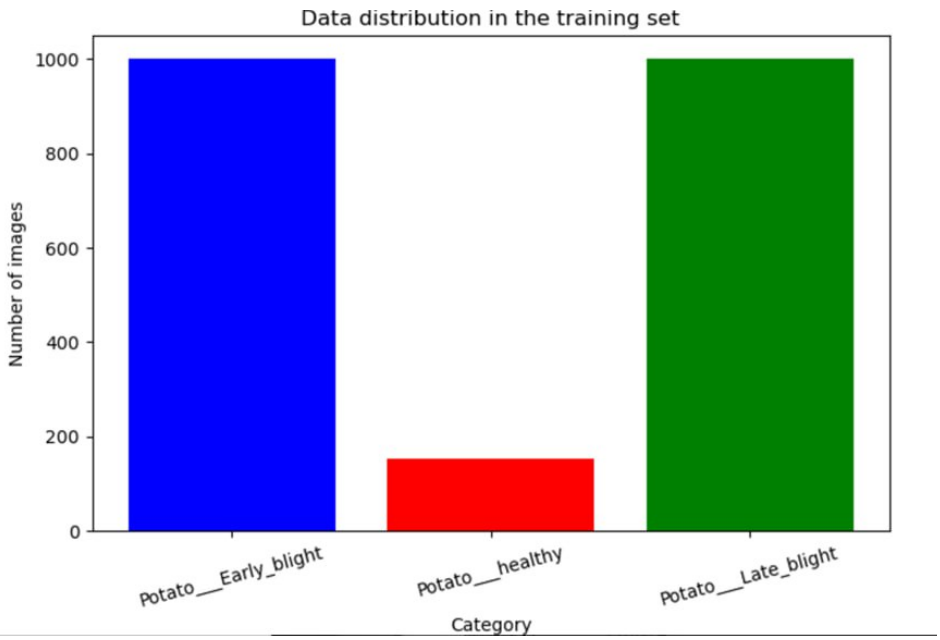


Figure 3.1: Information about the Potato Disease Leaf Dataset (PLD)

There is a significant imbalance in class distribution, as the number of healthy leaf images is much lower than that of diseased leaves. This imbalance could negatively impact model performance and may require data balancing techniques.

3.3 Preliminary Data Analysis

Before training the model, an exploratory analysis of the datasets was conducted to ensure their quality and assess their distribution. The key findings were:

- The Potato Disease Leaf Dataset suffers from significant class imbalance, with healthy leaf images being considerably fewer than diseased ones. This imbalance could lead to biased model predictions favoring the majority classes.
- The need for data augmentation techniques, particularly to generate more samples for the underrepresented class (healthy leaves), ensuring better generalization and reducing model bias.

3.4 Data Preparation and Processing

The data preparation and processing phase is a crucial step in the development of any machine learning model, as it significantly impacts the model's accuracy and generalization ability. In this project, a series of systematic steps were followed to ensure the quality and proper organization of the dataset before feeding it into the model.

3.4.1 Data Preparation

An initial visual inspection of the dataset was conducted by randomly displaying samples from each category to ensure that the images were clear, undamaged, and contained the necessary visual features for classification.

Regularization: It was observed that the images varied in dimensions, which could hinder the training process. To address this, all images were resized to a fixed dimension of 256×256 pixels.

Additionally, the dataset was organized into separate folders based on the disease categories (e.g., healthy leaves, early blight, and late blight), which facilitated efficient data handling during later stages.

3.4.2 Data Processing

Data Augmentation

Due to class imbalance—particularly the underrepresentation of healthy leaf images—data augmentation techniques were applied to balance the dataset and enhance model performance. This approach was necessary to prevent model bias toward overrepresented classes. By artificially generating new samples, the overall diversity of the dataset was enriched, improving the model's ability to learn robust patterns without requiring additional data collection.

The applied transformations included:

- Random rotation between -30° and +30° to account for different orientations of leaves.
- Horizontal and vertical flipping, generating mirrored versions of the images to enhance diversity.
- Brightness and contrast adjustments to simulate variations in lighting conditions.
- Random zooming, allowing the model to recognize disease patterns at different scales.

Data Splitting

The dataset was then systematically split into three subsets:

- 60% for training,

- 20% for validation during training,
- 20% for final testing.

The testing set was completely isolated during the training phase to ensure an unbiased and objective evaluation of the model's ability to generalize to unseen data. This splitting strategy is considered a standard practice in machine learning, as it allows for accurate performance assessment using a completely independent test set.

3.4.3 Model Selection

In this project, we chose to use a Convolutional Neural Network (CNN) as the main model for classifying potato diseases based on leaf images. The selection of CNN is justified by its outstanding performance in computer vision tasks such as image classification, object detection, and pattern recognition. Unlike traditional methods like SVM or KNN that require manual feature extraction, CNNs can automatically learn discriminative features from raw data through convolutional layers.

Moreover, several previous studies in digital agriculture have demonstrated the effectiveness of CNNs in detecting and classifying plant diseases, which further supports this choice. Therefore, CNN was considered the most suitable model for our problem due to its accuracy, robustness, and ability to handle complex visual variations present in potato leaves.

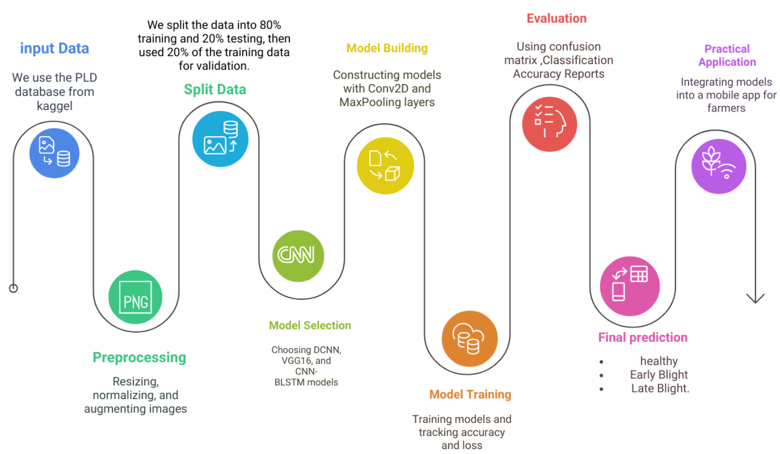


Figure 3.2: Overall pipeline of the proposed deep learning system for potato leaf disease classification, including preprocessing, data splitting, model training (CNN, DCNN, CNN-BLSTM), and final prediction.

Proposed Model

The model was built using the Keras library with TensorFlow as the backend. The model consists of the following architecture:

- Four convolutional layers (Conv2D), followed by pooling layers (MaxPooling2D) for dimensionality reduction.
- A Flatten layer to convert the resulting matrix to a vector.
- Three dense layers (Dense), and finally an output layer with a number of units equal to the number of data classes (3 classes) and a softmax activation function.
- Two dropout layers were used at 30% and 50% to prevent overfitting.
- The ReLU activation function was used in all convolutional and dense layers, and a softmax function was used in the final layer for multi-class classification.

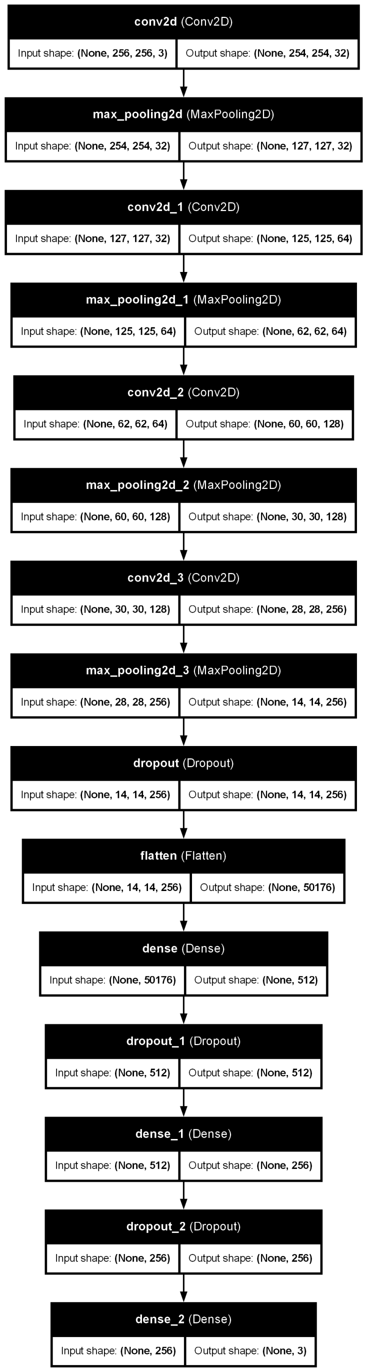


Figure 3.3: Architectur of the CNN used

3.4.4 Model Architecture Summary

The following table presents the detailed architecture of the CNN model used in this project.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_1 (Conv2D)	(None, 125, 125, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_2 (Conv2D)	(None, 60, 60, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 30, 30, 128)	0
conv2d_3 (Conv2D)	(None, 28, 28, 256)	295,168
max_pooling2d_3 (MaxPooling2D)	(None, 14, 14, 256)	0
dropout (Dropout)	(None, 14, 14, 256)	0
flatten (Flatten)	(None, 50176)	0
dense (Dense)	(None, 512)	25,690,624
dropout_1 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
dropout_2 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 3)	771

Table 3.1: The architecture of the used model for my test

3.4.5 Training and Validation Results

The image below shows the evolution of accuracy and loss during the training and validation of the convolutional neural network. The model was trained for 20 epochs. Both training and validation accuracy increased gradually, reaching values above 98%, with some fluctuations in validation. The training loss decreased rapidly in the first epochs and then stabilized at a very low level (below 0.1). The validation loss followed a similar trend, with slight variations towards the end of training.

Overall, the model learned well from the data without obvious signs of overfitting, as the loss and accuracy curves between training and validation are quite similar. These results indicate a good balance between learning and generalization.

Results obtained after the evaluation of our model

The classification report shows that the CNN model performed exceptionally well in identifying potato diseases, achieving an overall accuracy of 98.33%. It accurately distinguished between early blight, late blight, and healthy leaves with high precision and recall. These results confirm the model's effectiveness and reliability in handling agricultural image classification tasks.

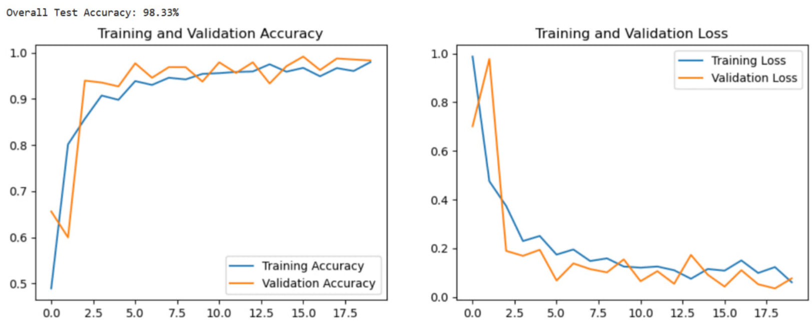


Figure 3.4: The Accuracy curve of our model used

CNN model evaluation: Model Performance Analysis

As shown in Table 1, which presents the training and validation accuracy and loss over 20 epochs, the model initially demonstrated modest performance. In the first epoch, the validation accuracy was 65.6% with a validation loss of 0.7013. However, the performance improved significantly by the third epoch, reaching a validation accuracy of 93.96%, reflecting the model's ability to quickly learn relevant visual features for distinguishing between different potato diseases.

The model achieved its best performance during epoch 16, where it recorded a validation accuracy of 99.17% and a very low validation loss of 0.0425. This improvement highlights the model's strong generalization capabilities and stability. Additionally, the consistently high validation accuracy in subsequent epochs indicates that the model successfully avoided overfitting.

The application of techniques such as model checkpointing (saving the model whenever validation accuracy improved) and early stopping played a crucial role in preventing overtraining and enhancing the model's reliability in real-world deployment scenarios.

Figure 3.5: Model Training and Validation Accuracy and Loss Over 20 Epochs

Classification Report:

	precision	recall	f1-score	support
Potato___Early_blight	0.97	1.00	0.99	200
Potato___Late_blight	0.99	0.95	0.97	200
Potato___healthy	0.99	0.99	0.99	200
accuracy			0.98	600
macro avg	0.98	0.98	0.98	600
weighted avg	0.98	0.98	0.98	600

Overall Test Accuracy: 98.33%

Figure 3.6: Result obtained after the evaluation of our model.

The Confusion Matrix

The confusion matrix provides a detailed evaluation of the model's performance in classifying the three categories. The model correctly identified all images of the Early Blight class without any misclassification. For the Late Blight and Healthy leaf classes, the model achieved very high accuracy, with only a few instances being misclassified. Most of the errors occurred between Late Blight and the other two categories. These results confirm the model's strong ability to distinguish between different potato leaf conditions and highlight its reliability for practical use in agricultural disease diagnosis.

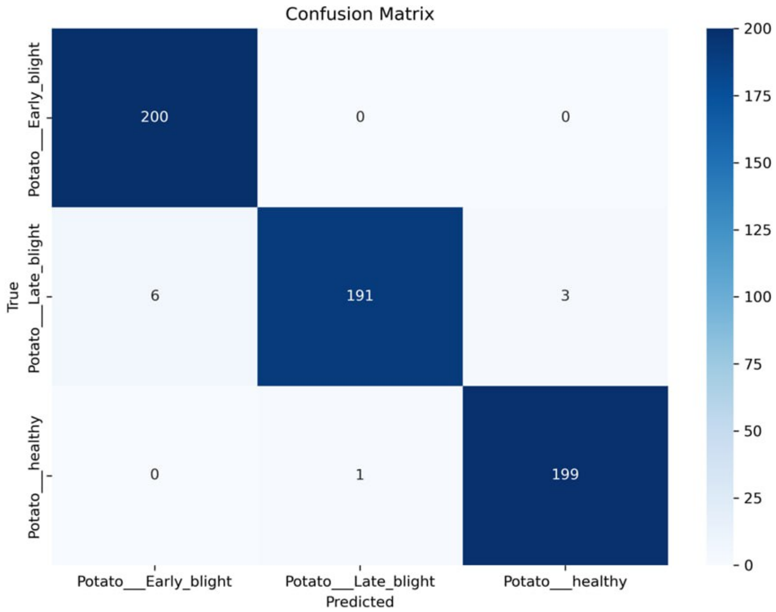


Figure 3.7: Confusion Matrix showing the classification performance

Error Rate Analysis per Potato Disease Class

The figure above (Figure 1) illustrates the error rate for each category in the potato disease classification task using the proposed model. It can be observed that the "late blight potato" class recorded the highest error rate at 13.5%, while both "early blight potato" and "healthy blight potato" classes showed 0.0% error rates. This discrepancy suggests that the model encounters some challenges in accurately distinguishing late blight cases, which may be due to visual similarities with other classes or variations in the quality of images within that category. This analysis highlights the importance of enhancing the model's performance or improving the dataset quality for the late blight class to achieve more robust classification results.

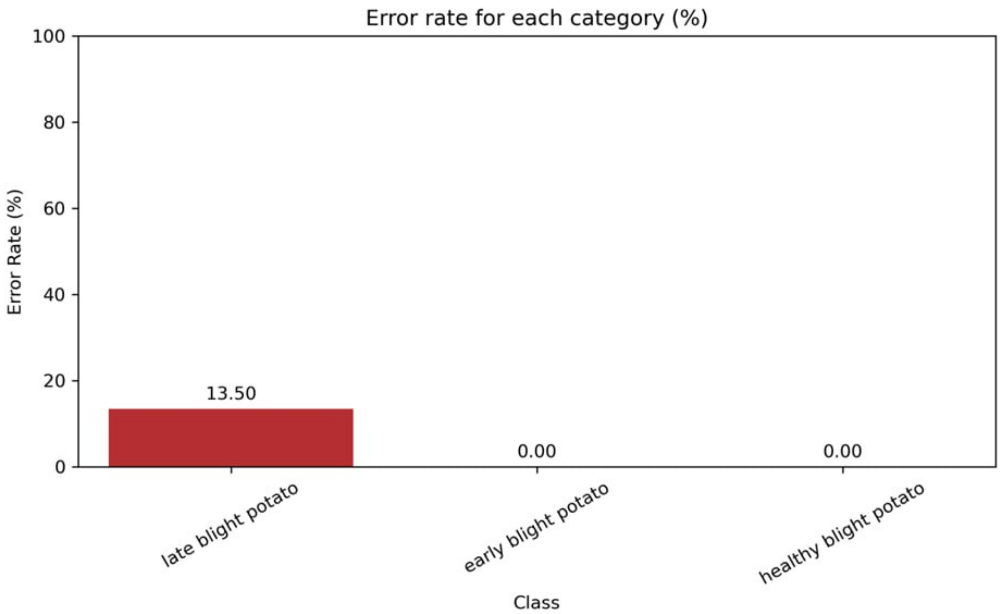


Figure 3.8: Error rate per class in percentage

Model 2: Using VGG16 for Potato Leaf Disease Classification

This model is based on the **VGG16** architecture, a deep convolutional neural network (CNN) developed by the Visual Geometry Group at the University of Oxford [55]. VGG16 is known for its simple yet effective design, consisting of repeated convolution and pooling layers, and has demonstrated strong performance in various image classification tasks.

The model was applied using the **Transfer Learning** approach, where a pre-trained network is adapted to a new task. In this case, VGG16 was loaded with weights pre-trained on the **ImageNet** dataset [56], a large-scale benchmark consisting of over 14 million labeled images across more than 1000 categories.

The original top layers of VGG16 were removed (`include_top=False`) and replaced with a custom classifier tailored to the potato disease classification task. The new head architecture included:

- A **Flatten** layer to convert 3D feature maps into a 1D vector.
- A **Dense** layer with 256 ReLU-activated units.
- A **Dropout** layer with a 50% rate to mitigate overfitting.
- A final **Dense** layer with three Softmax-activated units for multi-class prediction.

Additionally:

- All original layers of VGG16 were **frozen** (`base_vgg.trainable = False`) to retain their learned feature representations.
- Only the newly added layers were trained on the potato leaf dataset.

Training and Evaluation

The model was trained using the **Adam** optimizer for 20 epochs, with `categorical_crossentropy` as the loss function. To enhance generalization and prevent overfitting, the following techniques were applied:

- **EarlyStopping** to stop training once validation performance ceased improving.
- **ModelCheckpoint** to save the model with the best validation accuracy.

Evaluation on an independent test set (600 images) showed strong overall performance, achieving a classification accuracy of **96%**. Detailed class-wise metrics were as follows (Table 3.2):

The **macro average** and **weighted average** for all metrics (precision, recall, F1-score) were both 0.96, confirming the model's balanced and robust performance across all classes.

Class	Precision	Recall	F1-score	Support
Potato_Early_blight	0.99	0.96	0.97	200
Potato_Late_blight	0.92	0.97	0.94	200
Potato_healthy	0.98	0.95	0.97	200
Accuracy			**0.96**	600
Macro avg	0.96	0.96	0.96	600
Weighted avg	0.96	0.96	0.96	600

Table 3.2: Classification Report for VGG16 Model

Model Architecture Summary

The following table presents the detailed architecture of the VGG model used in this project. It includes the type of each layer, its output shape, and the number of parameters involved. The base model (VGG16) was used with frozen weights, and additional dense and dropout layers were added for classification.

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 8, 8, 512)	14,714,688
flatten (Flatten)	(None, 32768)	0
dense (Dense)	(None, 256)	8,388,864
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 3)	771
Total parameters		**39,883,595**
Trainable parameters		**8,389,635**
Non-trainable parameters		**14,714,688**

Table 3.3: Model Architecture Summary of the VGG16-based Model

3.5 Confusion Matrix Analysis

The confusion matrix provides a clear visualization of the VGG16-based model's performance on the classification task. It summarizes the number of correct and incorrect predictions for each class. As shown in (Figure 3.9), the model correctly identified 193 images of Potato Early blight, 198 of Potato Late blight, and 190 of Potato healthy. Only a few misclassifications occurred, mainly between Early and Late blight, which confirms the model's high precision in distinguishing between classes.

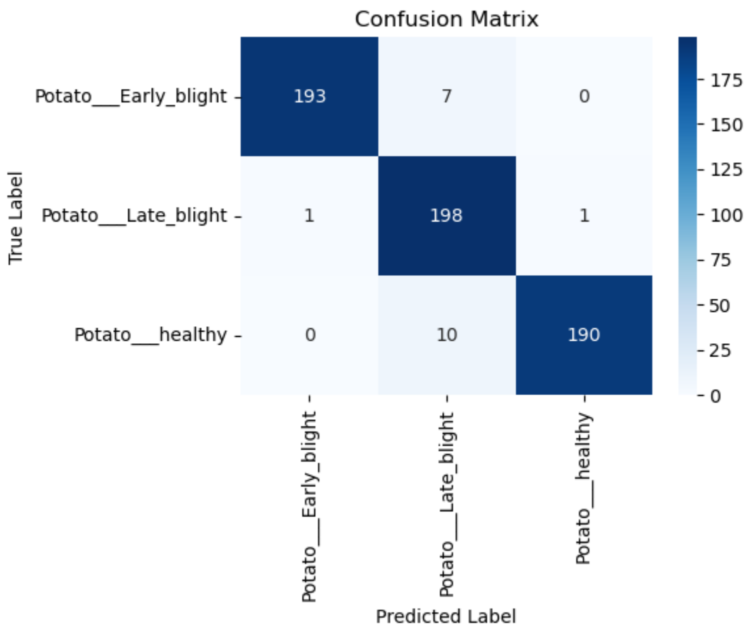


Figure 3.9: Confusion Matrix of VGG16 Classifier.

VGG16 Model Accuracy and Loss Analysis

As shown in the figure below (Figure 3.10), the graph illustrates the progression of training and validation accuracy and loss during the training of the VGG16 model for potato disease classification. We observe that both training and validation accuracy increase rapidly and stabilize above 90%, indicating that the model is learning effectively and performing well on unseen data. Similarly, the training and validation loss decrease steadily over the epochs, with minimal difference between them, suggesting that the model is not overfitting. From this, we conclude that the model is well-trained and achieves a good balance between fitting the training data and generalizing to new samples.

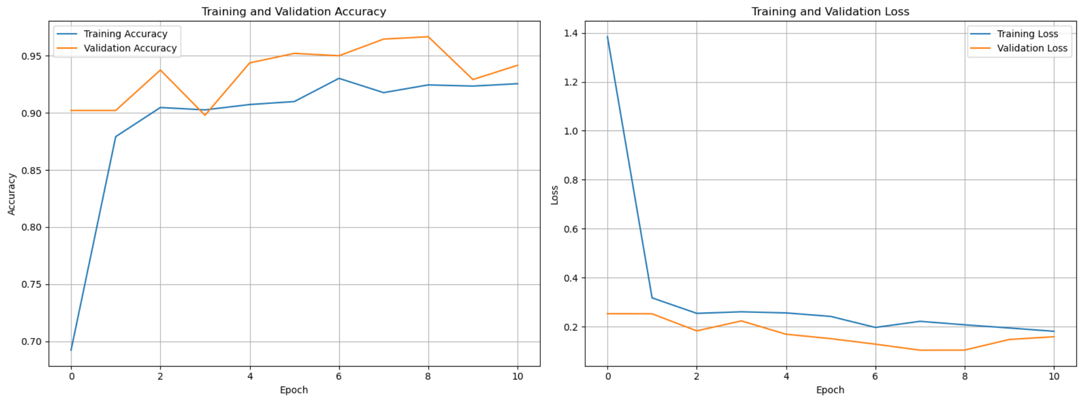


Figure 3.10: Training and validation accuracy and loss curves of the VGG16 model

Model 3: CNN-BLSTM Model for Potato Leaf Disease Classification

This model combines the strengths of **Convolutional Neural Networks (CNNs)** and **Bidirectional Long Short-Term Memory (BLSTM)** networks to classify potato leaf diseases based on image data. The hybrid architecture is designed to leverage CNNs' capability in spatial feature extraction and BLSTM's strength in modeling sequential dependencies, which together enhance classification performance.

The process starts by applying multiple convolutional and pooling layers to extract low- and high-level features from input images. These operations capture visual patterns and spatial hierarchies relevant to various leaf diseases.

Architecture of our model

The architecture consists of a hybrid structure combining CNN and BLSTM layers to capture both spatial and sequential patterns in the input data.

- **Two convolutional blocks**, each consisting of a `Conv2D` layer with ReLU activation followed by a `MaxPooling2D` layer for downsampling.
- **Dropout layers** after each block to reduce the risk of overfitting.

- A **Reshape layer** that transforms 3D feature maps (from CNN) into 2D sequences suitable for sequential analysis.
- A **Bidirectional LSTM layer**, which processes data in both forward and backward directions, capturing contextual relationships in the feature sequence.
- A **Dropout layer** (50%) to regularize the model.
- A **Dense layer** with Softmax activation for multi-class prediction of disease categories.

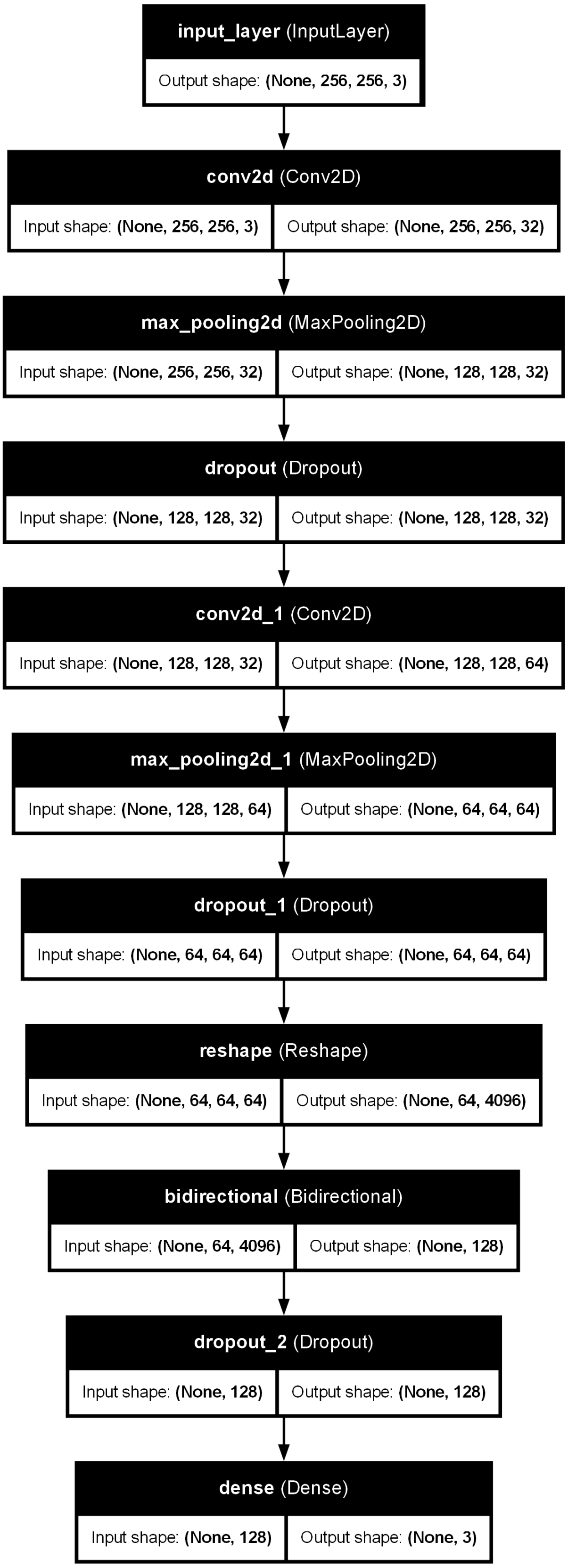


Figure 3.11: Architecture of the proposed CNN-BLSTM model

Unlike traditional CNNs or transfer learning models, this architecture explicitly exploits the sequential structure of CNN feature maps by feeding them into an LSTM layer, effectively combining spatial and temporal learning in a unified framework.

Training and Evaluation of the CNN-BLSTM Model

The CNN-BLSTM model was trained using the **Adam optimizer** over 20 epochs, with **categorical crossentropy** as the loss function. Several regularization and monitoring strategies were employed to ensure optimal performance and to prevent overfitting:

- **EarlyStopping** was used to halt training when the validation loss stopped improving.
- **ModelCheckpoint** saved the model with the highest validation accuracy.

After training, the model was evaluated on an independent **test set consisting of 656 images**, demonstrating **excellent performance**, with an overall **classification accuracy of 97%**.

Additionally, the model achieved:

- **Macro average**: Precision = **0.97**, Recall = **0.97**, F1-score = **0.97**
- **Weighted average**: Precision = **0.97**, Recall = **0.97**, F1-score = **0.97**

These results confirm the model's **strong generalization ability** and its **balanced performance** across all target classes.

Class	**Precision**	**Recall**	**F1-score**	**Support**
Potato__Early_blight	1.00	0.92	0.96	205
Potato__Late_blight	0.92	0.99	0.96	204
Potato__healthy	0.99	1.00	0.99	247
Accuracy			**0.97**	656
Macro avg	0.97	0.97	0.97	656
Weighted avg	0.97	0.97	0.97	656

Table 3.4: Classification Report for VGG16 Model

Model Architecture Summary

The following table presents the detailed architecture of the CNN-BLSTM model used in this project. It includes the type of each layer, its output shape, and the number of parameters involved. The architecture combines convolutional layers for spatial feature extraction with a bidirectional LSTM layer to capture temporal dependencies. Dropout layers were included to reduce overfitting, and a dense output layer was used for classification.

Layer (type)	**Output Shape**	**Param #**
InputLayer	(None, 256, 256, 3)	0
Conv2D	(None, 256, 256, 32)	896
MaxPooling2D	(None, 128, 128, 32)	0
Dropout	(None, 128, 128, 32)	0
Conv2D_1	(None, 128, 128, 64)	18,496
MaxPooling2D_1	(None, 64, 64, 64)	0
Dropout_1	(None, 64, 64, 64)	0
Reshape	(None, 64, 4096)	0
Bidirectional	(None, 128)	2,130,432
Dropout_2	(None, 128)	0
Dense	(None, 3)	387
Total Parameters		**2,150,211**
Trainable Parameters		**2,150,211**
Non-trainable Parameters		**0**

Table 3.5: Model Architecture Summary of the CNN-BLSTM Model

Confusion Matrix Analysis for CNN-BLSTM Model

The confusion matrix shown in Figure 3.12 illustrates the performance of the CNN-BLSTM model in classifying potato leaf diseases. The model correctly identified 189 samples of *Potato Early blight*, 202 of *Potato Late blight*, and 246 of *Potato healthy*. Misclassifications were minimal, with only a few *Early blight* images predicted as *Late blight*, and two *Late blight* images confused with *Healthy*. These results confirm the model's robustness and its effectiveness in distinguishing between visually similar classes.

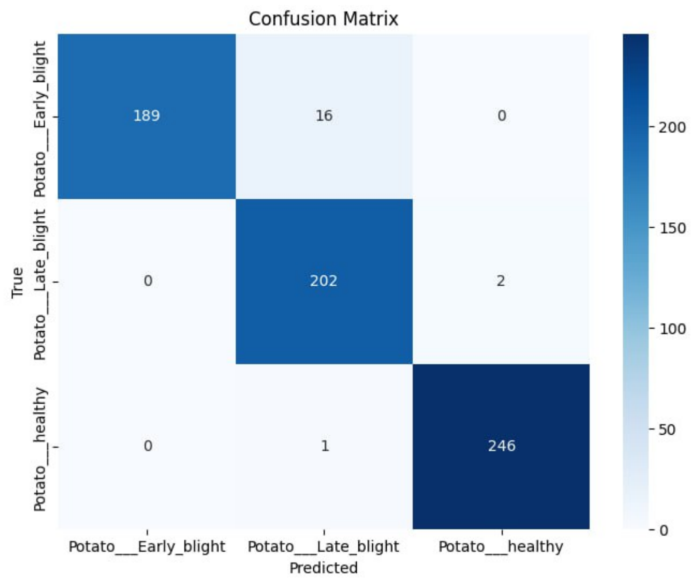


Figure 3.12: Confusion Matrix of the CNN-BLSTM Model on the Test Dataset

CNN-BLSTM Model Accuracy and Loss Analysis

Figure 3.13 presents the training and validation accuracy and loss curves for the CNN-BLSTM model across 20 epochs. The left plot demonstrates that both training and validation accuracy increased rapidly during the initial epochs, stabilizing around 97%–99%, indicating strong learning capability and generalization of the model. The right plot illustrates the training and validation loss, which decreased significantly in early epochs and remained low thereafter, showing convergence . The overall trend confirms that the CNN-BLSTM model effectively learned the task while maintaining stability throughout the training process.

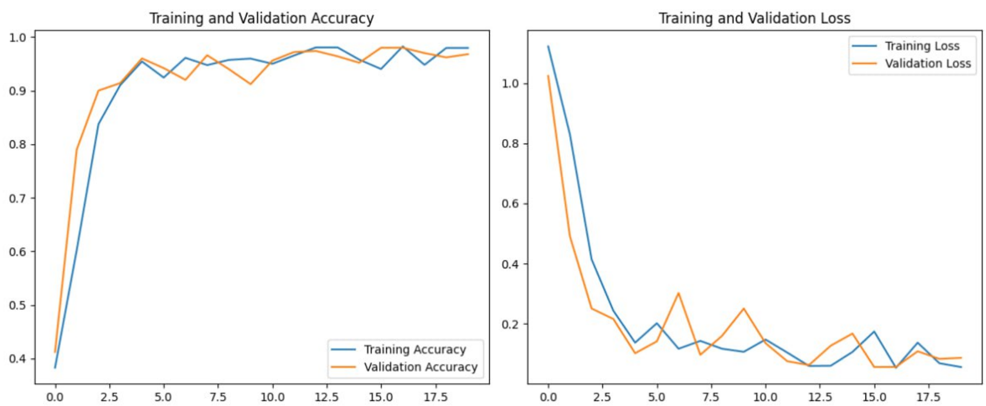


Figure 3.13: Training and Validation Accuracy and Loss Curves for the CNN-BLSTM Model

3.6 Comparative Summary of the Implemented Models

This section summarizes the key characteristics, architectural choices, and performance outcomes of the three deep learning models explored in this study: DCNN, VGG16, and CNN-BLSTM. Each model was trained and evaluated on the same potato leaf disease dataset, and their results are compared in terms of learning strategy, architecture, and classification accuracy.

Criterion	**DCNN**	**VGG16 (Transfer Learning)**	**CNN-BLSTM (Hybrid)**
Model Type	Proposed DCNN	Pretrained CNN	CNN + Bidirectional LSTM
Training Strategy	From scratch	Feature extraction (frozen base)	From scratch
Architecture Depth	4 Conv + 3 Dense layers	VGG16 + Dense head	2 Conv + BLSTM + Dense
Sequential Processing	No	No	Yes (via BLSTM)
Total Parameters	Medium	High	Medium
Accuracy (Test Set)	98.3%	96%	**97%**
Training Stability	Good	Very stable	Stable after reshaping
Complexity	Low to Medium	High (frozen layers)	High
Best Strength	Simplicity, fast training	Robust features via pretraining	Captures spatial + contextual patterns

Table 3.6: Comparative summary of the three implemented models.

Overall, the proposed **DCNN model** achieved the highest classification accuracy of **98.3%**, outperforming both the VGG16 transfer learning approach and the CNN-BLSTM hybrid model. This result demonstrates the strength of the custom-designed architecture, which was trained end-to-end specifically for this task. In addition to its superior accuracy, the DCNN exhibited fast training convergence and moderate computational complexity, making it a highly efficient and scalable solution for plant disease classification in real-world agricultural settings.

3.7 Development tools

3.7.1 Python:

Python is a modern and versatile programming language that combines simplicity with remarkable power. While its clear and intuitive syntax makes it accessible to beginners, Python is also widely adopted by experienced developers for building advanced systems across various domains. Its interpreted nature, dynamic typing, and extensive ecosystem of libraries enable rapid development and prototyping. Today, Python is a leading language in fields such as artificial intelligence, data science, automation, and web development, thanks to its ability to transform complex ideas into reliable and efficient solutions [57].

3.7.2 Anaconda:

Anaconda is a widely used open-source distribution designed to simplify the development and deployment of data science and machine learning applications. It includes a rich collection of pre-installed libraries and tools, making it ideal for handling complex data workflows. One of its most prominent features is the integration of Jupyter Notebook, an interactive environment that allows users to combine executable code, visualizations, and narrative text within a single document. This feature makes it particularly valuable in research and education, as it supports both experimentation and clear documentation. Anaconda also provides a powerful environment manager, Conda, which helps users create and manage isolated environments with specific library versions, reducing compatibility issues and improving project reproducibility. [58].

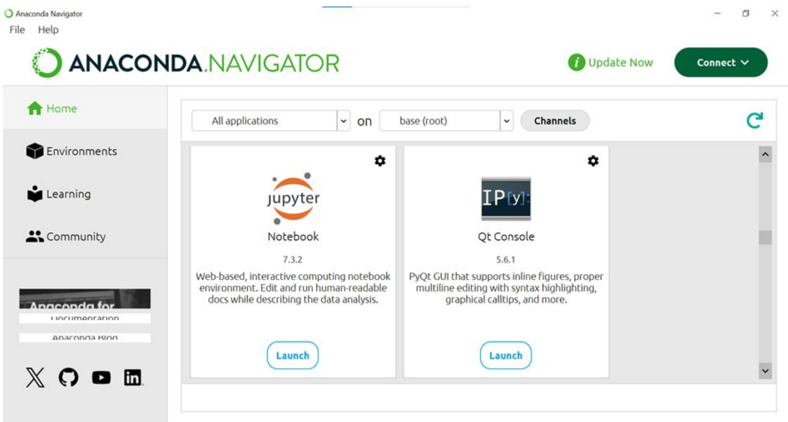


Figure 3.14: ANACONDA NAVIGATEUR

3.7.3 Jupyter Notebook:

Jupyter Notebook is an open-source, web-based interactive environment that allows users to create and share documents combining live code, narrative text, visualizations, and multimedia. It supports over 40 programming languages and provides an intuitive interface for exploratory data analysis, rapid prototyping, and reproducible research. In this project, Jupyter Notebook was employed to develop and evaluate the potato disease classification model, document experiments, and visualize results in a single, cohesive workflow.

3.7.4 PyCharm:

PyCharm is a Python IDE that combines an intuitive interface with advanced tools (contextual autocomplete, real-time code analysis, visual debugging, and environment management). It was used to structure code, organize modules, and automate testing, ensuring a more efficient and reliable development of our potato disease classification system.

3.8 Libraries Used

3.8.1 TensorFlow

TensorFlow is a comprehensive open-source platform for machine learning, offering a rich ecosystem of tools and libraries. It enables researchers to build advanced models and developers to deploy them easily. In this project, TensorFlow was used to design and train the potato disease classification model.

3.8.2 NumPy

NumPy is a fundamental library for scientific computing in Python. It provides efficient data structures, particularly powerful multidimensional arrays (ndarrays), along with a wide range of mathematical functions to operate on them. Known for its speed and simplicity, NumPy serves as the foundation for many other data analysis and machine learning libraries. In this project, NumPy was used for image data processing and manipulation, making it easier to prepare inputs for model training.[59]

3.8.3 Pandas

Pandas is a powerful Python library designed for data manipulation and analysis. It offers flexible and efficient data structures such as DataFrames and Series, making it easy to handle structured data, including numerical tables and time series. With its intuitive syntax and wide range of built-in functions, Pandas simplifies tasks like data cleaning, transformation, and exploration. In this project, Pandas was used to organize and preprocess image-related metadata, enabling a smooth workflow for data preparation and model training.[60]

3.8.4 Keras

Keras is an open-source library that provides a high-level Python interface for building and training artificial neural networks. Initially developed as an independent project, Keras was later integrated into TensorFlow as its official high-level API. It offers a simple and user-friendly syntax, allowing for quick model prototyping and experimentation. Keras supports various types of neural networks and simplifies tasks such as defining layers, compiling models, and managing training processes. In this project, Keras played a central role in designing and training the convolutional neural network used for classifying potato leaf diseases.[61]

3.8.5 OpenCV

OpenCV (Open Source Computer Vision Library) is an open-source library that provides a wide range of tools for computer vision tasks. It includes functionalities for image and video processing, object detection, feature extraction, and more. OpenCV is highly optimized for real-time applications and supports integration with multiple programming languages, including Python. In this project, OpenCV was used for preprocessing potato leaf images, such as resizing, normalization, and enhancing image quality, before feeding them into the classification model.

3.8.6 FastAPI

FastAPI is a modern, high-performance web framework for building APIs with Python. It is designed to be easy to use while delivering fast execution, thanks to its use of asynchronous programming and full support for type hints. FastAPI automatically generates interactive API documentation and ensures high code readability and maintainability. In this project, FastAPI was used to create an interface between the trained potato disease classification model and the mobile application, allowing users to send images and receive real-time diagnostic results efficiently.

3.8.7 Flutter

Flutter is an open-source UI toolkit developed by Google for building natively compiled applications for mobile, web, and desktop from a single codebase. It uses the Dart programming language and provides a wide range of pre-built widgets that allow for fast and expressive UI development. Flutter's performance is comparable to native apps, and it offers smooth animations, responsive design, and strong community support. In this project, Flutter was used to develop a cross-platform mobile application that interacts with the AI model through an API, allowing users to capture or upload images of potato leaves and receive instant diagnostic feedback.

3.9 User Interface and Features

In this section, we present the design and implementation of the user interface for the plant disease classification application developed as part of this thesis. Built using Flutter to ensure a consistent cross-platform experience, the interface allows users to easily upload plant leaf images through the camera or gallery, then displays the disease classification results after sending the image to the backend via API. The user experience is simplified with clear instructions and a visually intuitive layout for displaying the results.

Splash Screen

This splash screen represents the opening screen for the Potato AI app and is used to showcase the app's visual identity. It features a background containing a real-life image of a potato, with the app's official logo in the center, a green leaf icon inside a circle, followed by the app name, "Potato AI." This screen aims to reinforce the app's branding and present it to the user in a simple and professional manner, before transitioning to the main interface.

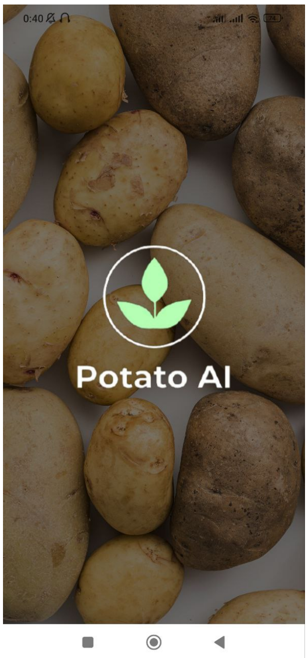


Figure 3.15: Splash Screen for Potato AI App

Welcome Screen

This screen provides a brief introduction to the "Potato AI" application. It welcomes the user and presents a simple overview of the app's main function — using artificial intelligence to detect and diagnose potato diseases accurately through plant images. The screen includes an engaging illustration, a friendly welcome message, and a "Start" button that guides the user to begin using the app. The purpose of this screen is to inform and prepare the user in a clear and visually appealing way.

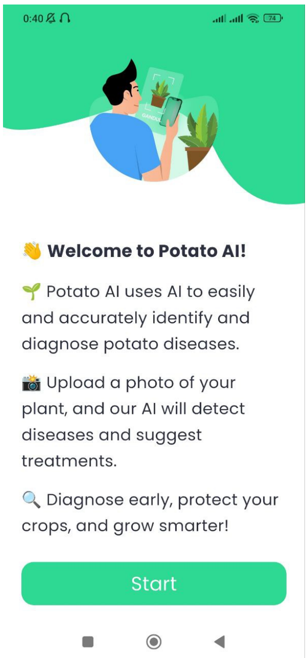


Figure 3.16: Welcome Page

Home Screen

The home screen of the Potato AI application serves as the main entry point. It welcomes the user with a friendly interface and provides quick access to core features such as scanning potato leaves, viewing disease information, and reading farming tips. The layout includes a search bar, navigation buttons, and educational sections such as farming videos.

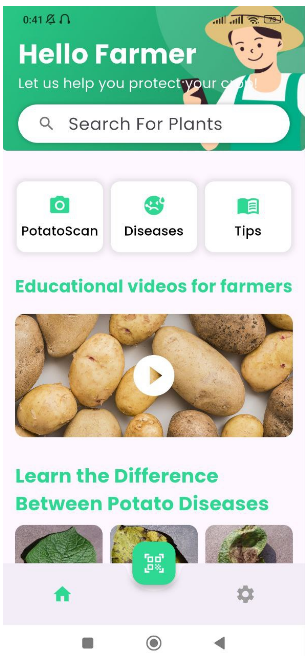


Figure 3.17: Home Screen

The lower section of the home screen provides an interactive comparison between healthy leaves and those affected by common diseases. When the user taps on a photo, a brief description appears to help distinguish between healthy, early blight, and late blight cases.

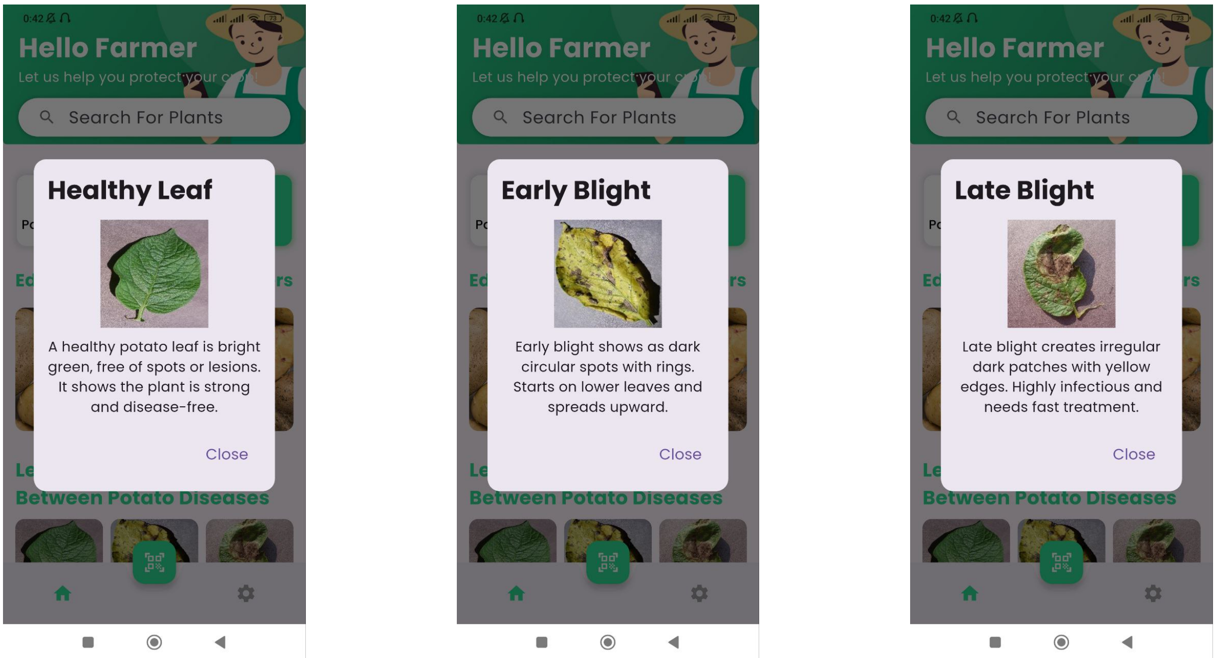


Figure 3.18: Interactive visual comparison of potato leaf conditions.

Farmer Tips Screen

This screen provides essential agricultural tips to help farmers prevent crop diseases and improve farming practices. It displays a list of simple, practical recommendations—such as avoiding overhead irrigation, using certified seeds, rotating crops, and ensuring proper drainage. The tips are shown in a clean and user-friendly layout, with icons to enhance readability and engagement.

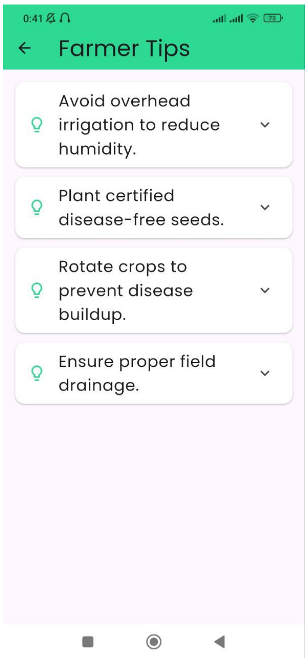


Figure 3.19: Farmer Tips Screen

Scanning and Model Selection

This section illustrates the process of scanning potato leaves and selecting the AI model for disease diagnosis. The user starts by clicking the “Take a picture” button, which triggers a pop-up allowing the selection of a machine learning model from options such as DCNN, VGG16, or CNN-BiLSTM. After choosing a model, the camera interface opens, guiding the user to align a single leaf within the frame for accurate analysis. The user can either capture a photo using the device’s camera or select an existing image from the phone’s gallery.

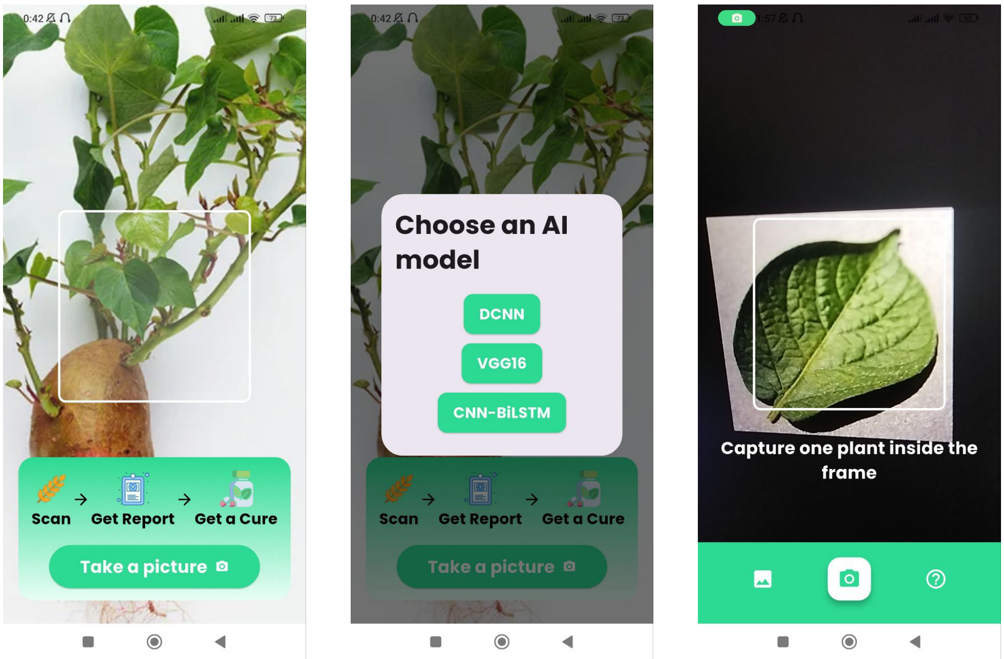


Figure 3.20: Scanning and model selection process for leaf classification.

Results Screen (AI Classification Output)

Once the user captures an image of a potato leaf or selects one from the phone gallery, the system processes the image using a machine learning classification model. Upon completion, the user is automatically redirected to the **Results Screen (AI Classificatio**.

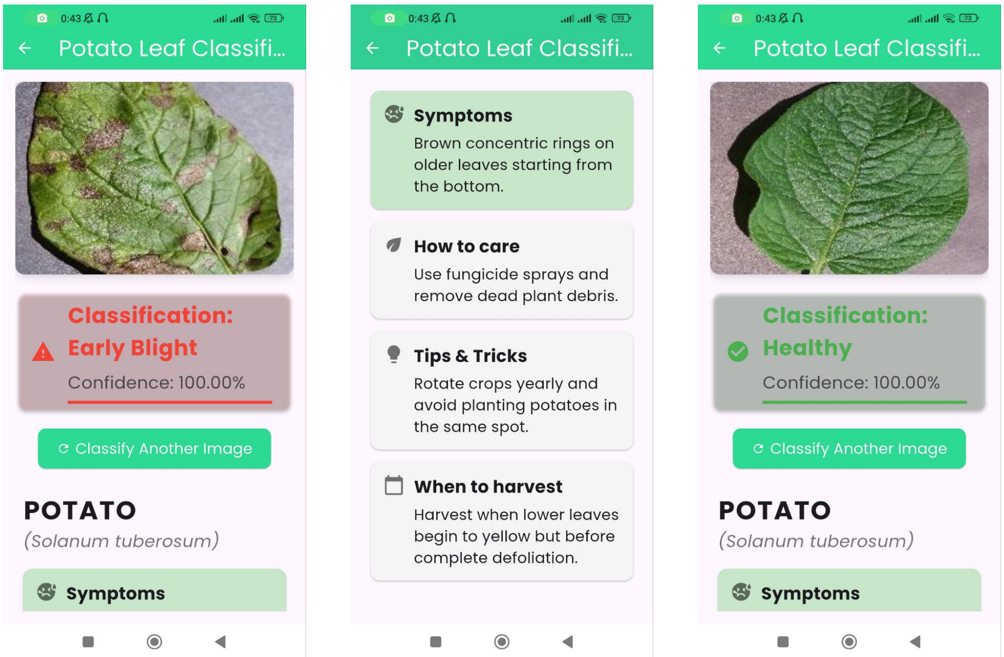
This screen provides a concise and informative summary of the classification output:

- **Classification Result:** Clearly displayed at the top, with a confidence score (e.g., 100%). The classification label (e.g., "Early Blight", "Late Blight", or "Healthy") is color-coded—green for healthy cases, red or orange for disease cases—to enhance readability and quick interpretation.
- **Plant Name:** The scientific name of the classified plant is shown beneath the result (e.g., *Solanum tuberosum*).
- **Information Cards:** The screen contains four collapsible cards providing detailed insights:
  - **Symptoms:** Describes visible signs of the diagnosed condition on the plant leaves.
  - **How to Care:** Recommends treatment actions such as fungicide application or removal of infected plant debris.
  - **Tips & Tricks:** Offers preventive strategies like crop rotation and site selection.

  - **When to Harvest:** Advises the optimal time to harvest based on leaf color and condition.

- **Reclassification Option:** A dedicated button allows the user to classify another image, returning them to the image input interface.

The result screen thus serves as a decision-support tool, offering both the diagnostic outcome and actionable agricultural guidance in a user-friendly format.



Early Blight Early Blight Healthy

Figure 3.21: Sample Results from Leaf Disease Classification.

App Settings Screen

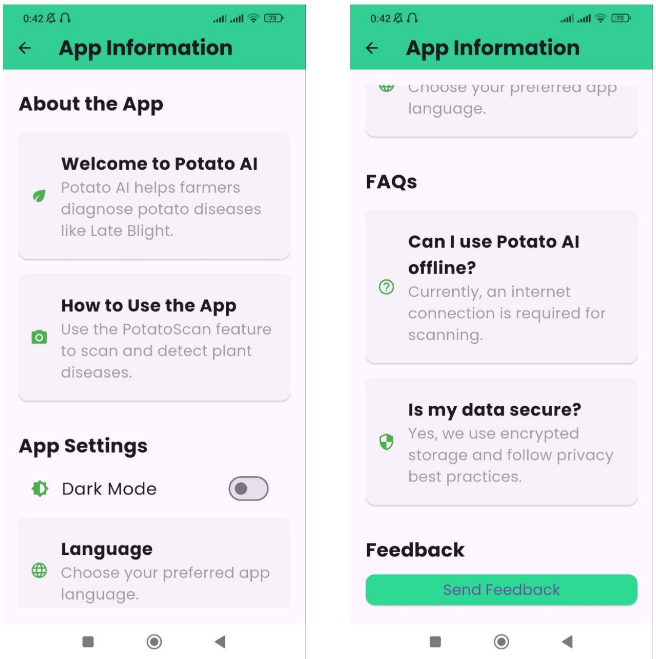
Figure 3.22 shows the settings screen of the Potato AI application, which allows users to customize their experience. This screen includes several important sections:

- **Dark Mode:** A switch to enable or disable the dark theme, improving readability in different lighting environments.

- **Language:** An option to select the preferred language of the app interface.

- **FAQs:** Frequently asked questions addressing offline usage and data security concerns.

- **Feedback:** A dedicated button for users to provide feedback, enabling developers to improve the app.



(a) Settings Overview (b)setting

Figure 3.22: App Settings screen of Potato AI.

Conclusion

In this chapter, we presented the overall methodology used to develop a potato leaf disease classification system based on machine learning. The process included data acquisition, preprocessing steps such as resizing and augmentation, and the selection of relevant models. We also discussed the optimization techniques applied to improve model performance.

This methodological framework ensures a structured approach for training and evaluating different deep learning models. It sets the stage for the next chapter, where we detail the implementation of these models and analyze their experimental results.

General Conclusion

General Conclusion

This graduation project focused on solving a major issue in modern agriculture: the early and accurate detection of potato leaf diseases. These diseases significantly reduce crop yields and pose a threat to food security, especially in developing regions. Traditional diagnostic methods rely heavily on human expertise, which is not always available, and are often time-consuming and error-prone.

To address this problem, we proposed an AI-based approach using deep learning, particularly Convolutional Neural Networks (CNNs), to automatically classify potato diseases from leaf images. Our objective was not only to apply existing CNN models but also to explore whether a custom-designed architecture could outperform well-known predefined ones.

To achieve this, we adopted a comparative methodology involving three models:

- Two widely used predefined CNN architectures served as benchmarks.
- A third, **custom CNN architecture** was designed and trained specifically for the characteristics of our dataset.

Our proposed model integrated several optimizations in terms of depth, filter size, and regularization, enabling it to learn more discriminative features related to disease symptoms. The evaluation, based on accuracy and other performance metrics, clearly showed that **our proposed architecture outperformed the two predefined models**, achieving higher classification accuracy and better generalization on unseen data.

This result validates the effectiveness of tailoring deep learning models to specific tasks and datasets. Furthermore, our work demonstrates the potential of AI to revolutionize disease diagnosis in agriculture by offering scalable, fast, and accessible solutions.

In conclusion, the approach we developed contributes not only to the academic exploration of CNN architectures in plant disease detection but also to practical, real-world applications that can assist farmers, improve yield management, and promote precision agriculture.

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