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Solution Intelligente pour Améliorer le Secteur Agriculture

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Intelligent Solution to Improve the Agricultural Sector

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DEDICATION

This thesis is dedicated to myself, for the countless hours of hard work, perseverance, and dedication, including the sleepless nights and moments of exhaustion that have brought this project to fruition.

May this work be a testament to my unwavering commitment to learning and personal growth.

ABSTRACT

In the agricultural sector, early detection and accurate diagnosis of crop diseases are critical for ensuring food security and maximizing yield. This thesis presents an intelligent solution aimed at improving the agricultural sector through the detection of wheat leaf diseases. By leveraging advanced deep learning techniques, specifically convolutional neural networks (CNN), InceptionV3, and YOLOv8 architectures, the study focuses on identifying and classifying common wheat leaf diseases such as septoria and stripe rust, as well as distinguishing healthy leaves. The complete workflow, from data collection and preprocessing to model training and evaluation, is highlighted. The results demonstrate significant improvements in disease detection accuracy, offering a promising tool for farmers and agronomists. This intelligent solution has the potential to revolutionize wheat farming by providing timely and precise disease management, ultimately leading to increased productivity and sustainability in the agricultural sector.

Keywords: Deep learning, Convolutional neural networks (CNN), InceptionV3, YOLOv8, crop disease, agricultural sector, wheat leaf

RÉSUMÉ

Dans le secteur agricole, la détection précoce et le diagnostic précis des maladies des cultures sont essentiels pour assurer la sécurité alimentaire et maximiser les rendements. Cette thèse présente une solution intelligente visant à améliorer le secteur agricole grâce à la détection des maladies des feuilles de blé. En tirant parti des techniques avancées d'apprentissage profond, notamment des réseaux de neurones convolutionnels (CNN), des architectures InceptionV3 et YOLOv8, l'étude se concentre sur l'identification et la classification des maladies courantes des feuilles de blé telles que la septoriose et la rouille jaune, ainsi que sur la distinction des feuilles saines. Le flux de travail complet, de la collecte des données et la prétraitement au l'entraînement et l'évaluation des modèles, est mis en évidence. Les résultats démontrent des améliorations significatives de la précision de la détection des maladies, offrant un outil prometteur pour les agriculteurs et les agronomes. Cette solution intelligente a le potentiel de révolutionner la culture du blé en fournissant une gestion des maladies précise et en temps opportun, menant finalement à une productivité et une durabilité accrues dans le secteur agricole.

Mots-clés : Apprentissage profond, Réseaux de neurones convolutionnels (CNN), InceptionV3, YOLOv8, maladie des cultures, secteur agricole, feuille de blé

مـــلخـــص

في القطاع الزراعي، يعد الكشف المبكر والتشخيص الدقيق لأمراض المحاصيل أمرًا حاسمًا لضمان الأمن الغذائي وتعظيم الإنتاجية. تقدم هذه الأطروحة حلاً ذكيًا يهدف إلى تحسين القطاع الزراعي من خلال اكتشاف أمراض أوراق القمح. من خلال الاستفادة من تقنيات التعلم العميق المتقدمة، تحديدًا الشبكات العصبية التلافيفية(CNN) ، وهياكل InceptionV3 وYOLOv8 ، تركز الدراسة على تحديد وتصنيف الأمراض الشائعة لأوراق القمح مثل التفحم والصدأ الأصفر، وكذلك التمييز بين الأوراق السليمة. يتم تسليط الضوء على سير العمل الكامل، من جمع البيانات ومعالجتها مسبقًا إلى تدريب النماذج وتقييمها. تُظهر النتائج تحسينات كبيرة في دقة اكتشاف الأمراض، مما يوفر أداة واعدة للمزارعين وعلماء الزراعة. هذه الحلول الذكية لديها القدرة على إحداث ثورة في زراعة القمح من خلال تقديم إدارة دقيقة وفي الوقت المناسب للأمراض، مما يؤدي في النهاية إلى زيادة الإنتاجية والاستدامة في القطاع الزراعي.

الكلمات المفتاحية: التعلم العميق، الشبكات العصبية التلافيفية(CNN) ، InceptionV3، YOLOv8، أمراض المحاصيل، القطاع الزراعي، أوراق القمح

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GENERAL INTRODUCTION

GENERAL INTRODUCTION

Agriculture, a cornerstone of human civilization, faces increasing pressure to enhance productivity and sustainability due to a growing global population. One significant challenge in modern agriculture is the detection and management of plant diseases, which can severely impact crop yields and food security. Intelligent solutions leveraging advanced technologies have emerged as essential tools to address these challenges.

This thesis, "Intelligent Solution to Improve the Agricultural Sector," focuses on applying artificial intelligence (AI) to detect wheat leaf diseases. Wheat, a staple crop worldwide, is crucial for food security, particularly in Algeria, where it plays a significant economic and sustenance role. However, wheat crops are vulnerable to various diseases, necessitating prompt detection and management.

The thesis content comes as follows:

Chapter 1: Introduction to Intelligent Solutions in Agriculture

This chapter provides a comprehensive overview of the agricultural sector, highlighting its significance in food security, economic development, and environmental sustainability. It addresses the key challenges faced by agriculture, such as climate change, insufficient farmland, a growing population, loss of biodiversity, and the use of agrochemicals. The chapter then explores the applications of intelligent solutions in agriculture, focusing on soil management, crop management, and disease management. The concept of smart farming is introduced, along with the challenges it faces, including the high cost of technology, unreachability of rural areas, lack of support from authorities, financial constraints, and knowledge gaps.

Chapter 2: AI in Detecting Plant Disease

This chapter delves into the use of AI techniques in plant disease detection, starting with an overview of machine learning (ML) and deep learning (DL) methods. It defines ML and DL, explains their types, and compares their effectiveness in plant disease detection. Convolutional neural networks (CNNs) are discussed in detail, covering their architecture, including convolutional layers, pooling layers, activation functions, fully connected layers, and loss functions. The chapter reviews existing research in this domain and presents a comparative study, synthesizing the findings to provide a clear understanding of the state-of-the-art in AI-based plant disease detection.

Chapter 3: Wheat Leaf Disease Detection: Model Design and Evaluation

This chapter is divided into two parts:

- Part One: Model Design & Architecture

It begins with an overview of wheat production in Algeria and the specific diseases affecting wheat leaves. The chapter describes the creation of models for wheat disease classification, detailing the processes of data collection, labeling, preprocessing, and augmentation. It then discusses the training of different models, including CNN, InceptionV3, and YOLOv8, and their evaluation.

- Part Two: Training & Results

This section outlines the development tools used and the implementation of the models. It covers the practical steps taken, such as uploading datasets to Kaggle, splitting the dataset, and creating and training the models. The evaluation metrics for CNN and InceptionV3, such as accuracy, loss, recall, precision, and confusion matrix, are presented. For YOLOv8, metrics like mAP, loss analysis, and precision and recall are discussed. The chapter concludes with a comparison of the results and insights into the models' predictions and testing, including the use of Roboflow workspace and web app for YOLOv8 predictions.

In conclusion, this thesis aims to contribute to the growing field of intelligent agriculture by developing effective AI-based solutions for detecting wheat leaf diseases. By addressing both theoretical and practical aspects, it seeks to enhance our understanding of how advanced technologies can be harnessed to improve agricultural practices and ensure food security. This work not only offers a solution to a specific agricultural problem but also underscores the broader potential of intelligent solutions in transforming the agricultural sector for the better..

CHAPTER 01 :

Introduction to intelligent solution in agriculture

Introduction:

The agricultural sector is important in global food security, economic development, and environmental sustainability. Experts expect the population to exceed 9 billion people by 2050, which will lead to a significant increase in demand for food, putting extreme pressure on agricultural systems to produce more with limited resources. At the same time, the agricultural sector faces numerous challenges, including climate change, resource depletion, the spread of pests and diseases, social and economic disparities among agricultural communities.

Addressing these challenges requires innovative approaches that take advantage of the latest technologies to improve agricultural practices, enhance productivity, and build resilience against changing environmental conditions. In recent years, there has been increasing interest and investment in developing and implementing smart solutions in agriculture, driven by advancements in artificial intelligence (AI), machine learning (ML), data analytics, and sensing technologies.

In this chapter, we provide an overview of the agricultural sector, highlighting the importance of agricultural innovation and the role of smart solutions in addressing key challenges. We outline the objectives and scope of the thesis, present the methodology and approach used in developing the smart solution, and provide a roadmap for the subsequent chapters. Through this research, we aim to contribute to the advancement of agricultural science and technology and promote sustainable and inclusive development in the agricultural sector.

1. Overview of the agricultural sector

Agriculture is the foundation of the sustainability of any economy. It plays a key role in long-term economic growth and structural transformation. Agriculture is considered the main source of food and wealth in most countries of the world and is the source of human existence. Agricultural production is essential to a country's economy because it provides its citizens with access to food, raw materials, job opportunities, and more. Recent observations show that crop production in the agricultural sector has not changed significantly, food prices are also rising rapidly due to insufficient crop production compared to consumer demand, and we mention farmers' use of traditional farming methods leads to low crop productivity, which is one of the factors contributing to low crop production, and soil properties for growing crops are generally not enough understood by farmers new to the agricultural industry[1].

2. Importance and role of agriculture

The importance of agriculture is evident in its role in food security, economic development, and environmental sustainability. It is essential to ensuring food security by producing a significant portion of the world's food supply. In addition, agriculture is a key factor of economic development, especially in rural areas, providing employment and supporting local economies. Furthermore, agriculture plays a crucial function in environmental sustainability, as sustainable agricultural practices can help conserve natural resources and mitigate climate change

2.1. Agriculture and food security:

Food security relies heavily on agriculture, which means having enough food for everyone to lead healthy and productive lives. When people have access to sufficient food, they are not only physically healthy but also economically secure. Food insecurity, on the other hand, often stems from poverty and has lasting effects on individuals and communities, it disrupts healthy growth and make people more vulnerable to illnesses. So sustainable and efficient agricultural practices are essential for coming against food insecurity and promoting overall well-being.[2].

2.2. Agriculture and economic development:

Agriculture supports economic growth by providing livelihood to farmers and contributing to the overall economy. When considering its contribution to economic development, we can assess the role and significance of agriculture, this contribution can be measured by its portion of the gross domestic production, its impact on job creation, exports, and other factors. Additionally, agriculture supports the industrial sector by providing raw materials and food for its workforce, and so generating demand for industrial products and more[3].

2.3. Agriculture and environmental sustainability:

Agriculture plays a crucial role in sustainable development by balancing the needs of producers with the conservation of natural resources. To be sustainable, an agricultural system must meet the needs of producers while also conserving natural resources for future generations, this requires achieving a balance between economic viability, social justice, and environmental sustainability. Sustainable agriculture not only ensures the long-term viability of agriculture, but also promotes economic prosperity by creating stable income, supporting rural communities, and promoting efficient use of resources[4].

The figure 1.1 illustrates the role of agriculture, highlighting its contributions to environmental sustainability, economic development, and food security.

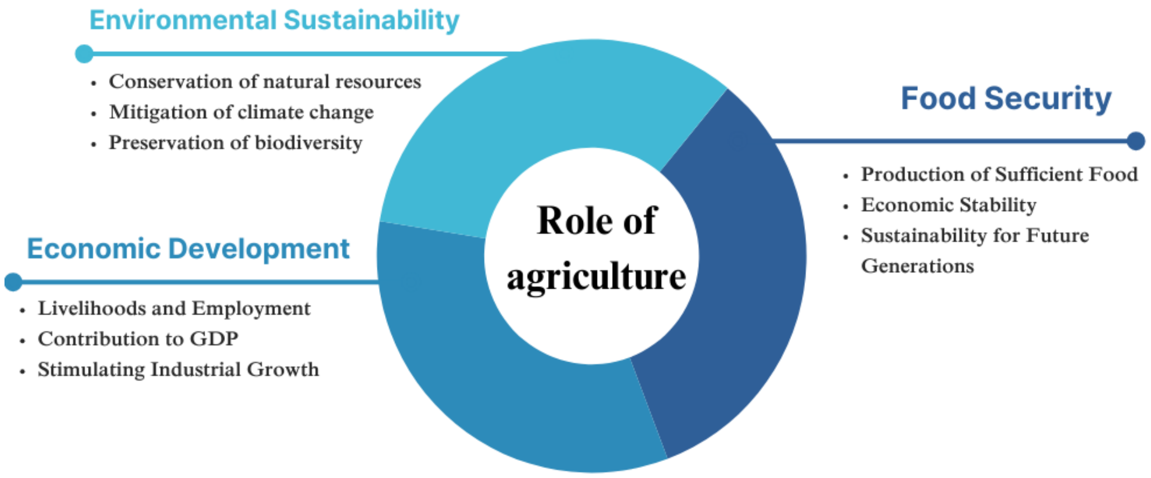

Figure 1.1 : Role of agriculture

3. Key challenges in agriculture

Agriculture faces many challenges, including climate change which poses a major threat, changing weather patterns and increasing the frequency of extreme events, secondly insufficient farmland leading to low yields and food insecurity, also growing populations necessitating sustainable agricultural practices, as well the loss of biodiversity weakening the resilience of agricultural systems, and also agrochemicals.

3.1. Climate change:

Changing weather patterns and extreme events driven by climate change are critical drivers of food insecurity, affecting the quality, availability, and access to food worldwide. Agriculture, highly dependent on climate, suffers from prolonged droughts or heavy rainfall, harming soil health. Global maize production could decline by 24% in 60 years, impacting countries reliant on it. Yet, despite agriculture's vulnerability to climate change, it also significantly contributes to global warming, highlighting the urgent need for sustainable practices to mitigate its impact[5].

3.2. Insufficient farmland:

More than a third of the 1.38 billion hectares of arable land worldwide has been permanently damaged since 1961 due to wrong practices like monocropping and intensive tilling, leading to issues like soil erosion and desertification. The Food and Agriculture Organization (FAO) reported a 54 million-hectare decline in arable land across developed countries in 2011, with some regions already reaching their limit of farmable land. Currently, only 12% of the global land surface is used for crop production, and urbanization is unlikely to increase this number[5].

3.3. Growing population:

The world population reached 8 billion people in 2022, and it is possible that it will double over the next fifty years at the current growth rate, higher fertility rates and longer life expectancy due to advances in health and hygiene are driving this growth. However, this leads to increased demand for food, and with agriculture suffering, hunger has become a major problem. In 2021, 828 million people suffered from hunger, highlighting the urgent need for sustainable solutions as the global population is expected to surpass 9 billion in 2050, growing pressure on water resources and arable land[5].

3.4. Loss of biodiversity:

Agriculture has experienced significant genetic erosion lately, leading to the loss of entire species and reduced diversity within species. This loss of biodiversity is already impacting communities worldwide, forcing some to rely more on processed foods due to declining wild food sources, and threatening pollinator populations essential for crops like rice and fruits[5].

3.5. Agrochemicals:

Biocides, used as pesticides, can harm humans and animals consuming the treated food, potentially causing health issues like cancer or infertility. These pesticides also contribute to water pollution when washed into water bodies by rain but fertilisers and manures are actually essential for soil nutrients, supporting high crop yields. However, challenges like cost and access; limit their use in some regions, leading to reliance on animal waste .[6].

The figure 1.2 depicts the challenges in agriculture, including climate change, insufficient farmland, a growing population, agrochemicals, and loss of biodiversity.

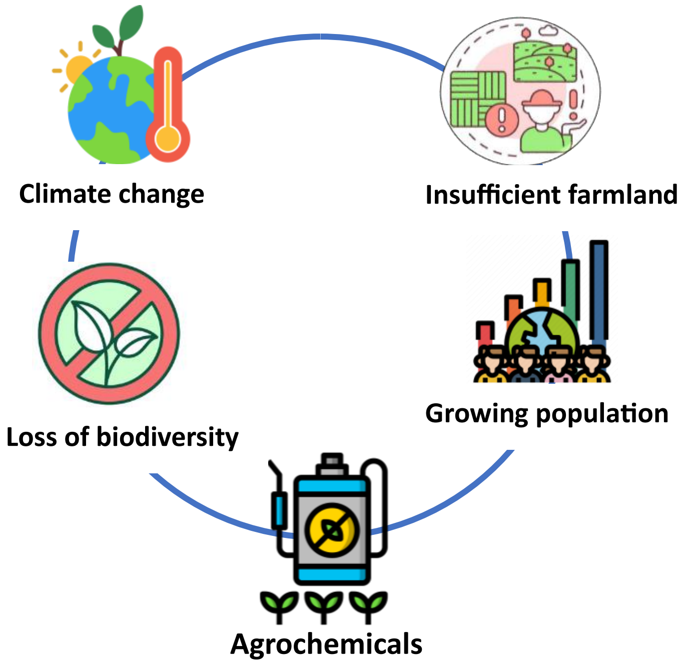

Figure 1.2: Challenges in agriculture

4. Applications of intelligent solutions in agriculture

Artificial intelligence has developed significantly in the last years, entering different aspects of our daily lives. It has also begun to address challenges in the agricultural sector and initiate various solutions.

4.1. Soil management:

Soil management is essential in agricultural activities, understanding different soil types and conditions will improve crop productivity and preserve soil resources, through the implementation of processes, practices, and treatments aimed to improve the performance of soils. Searchers found out that using Artificial Neural Network techniques can predict soil enzyme activity, and accurately predict and classify soil structure[7].

Figure 1.3 represents a diagram of a sensor-based irrigation system. It shows how soil sensors can be used to trigger an irrigation control kit to deliver water when the soil needs it.

Figure 1.3: Example of AI application in soil management "Sensor Based Irrigation" [8]

4.2. Crop management:

Crop management involves sowing, monitoring growth, harvesting, and crop storage and distribution, aimed at enhancing agricultural product growth and yield, and optimizing crop yields when choosing the suitable soil type for the crop. To address water deficits caused by soil, weather, or limited irrigation, farmers should employ diverse crop management strategies and prioritize flexible systems based on decision rules[7].

The figure 1.4 depicts a robotic system being used in agriculture, likely to manage crops.

Figure 1.4: Using robots for crop management [9]

4.3. Disease management:

Disease control is necessary for achieving optimal yields in agricultural harvests, particularly in large-scale farming. Researchers have developed various solutions for disease detection in different crops, they recommend that farmers adopt an integrated disease control and management model, incorporating physical, chemical, and biological measures, to effectively control diseases and minimize losses[7].

Figure 1.5 represents the use of deep neural networks to detect plant disease in real time.

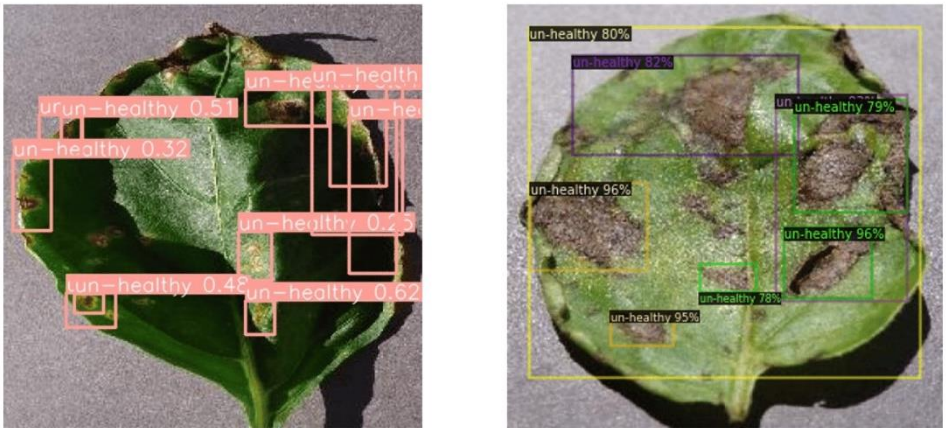

Figure 1.5: Plant disease detection using deep learning [10]

4.4. Weed management:

Weeds consistently reduce expected profits and yields, with fluctuations in losses influenced by crop exposure duration and weed spatial distribution. Weeds can have both positive and negative effects on ecosystems, such as aiding flooding or causing liver damage if consumed. they compete with crops for water, nutrients, and sunlight, with some species being poisonous and posing health risks[7]. [11]

Figure 1.6 represents an example of using deep learning model for weed detection

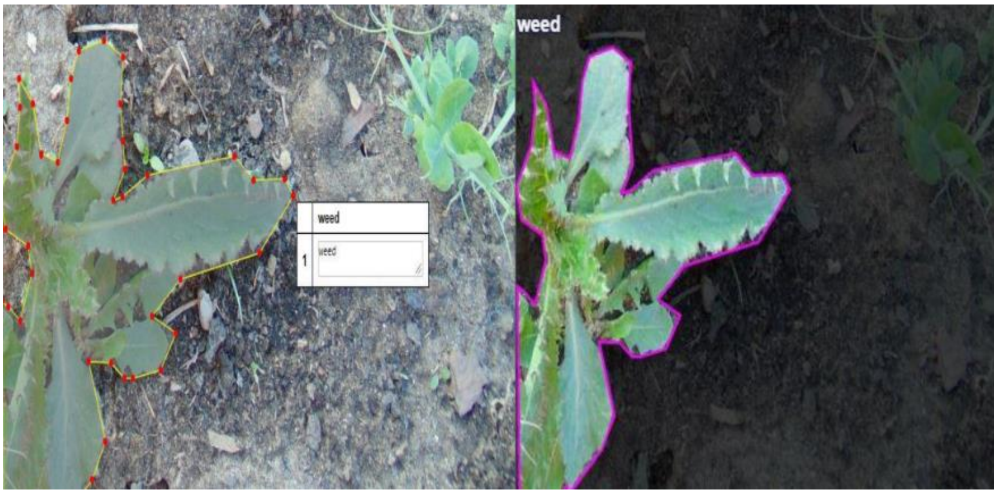

Figure 1.6: Weed detection using AI [8]

5. Smart Farming

The various solutions presented by AI to the agricultural sector have necessitated a shift from traditional farming to smart farming, this concept is emerging as the future of agriculture due to pressures from globalization and modernization. This shift emphasizes production efficiency, input intensity, and crop consistency, contrasting with traditional practices that prioritize localization and biodiversity. The transition to smart farming, reduces labor intensity and increases crop quality and quantity[12].

The next figure shows how smart farming has changed over time, focusing on how it reduces labor intensity.

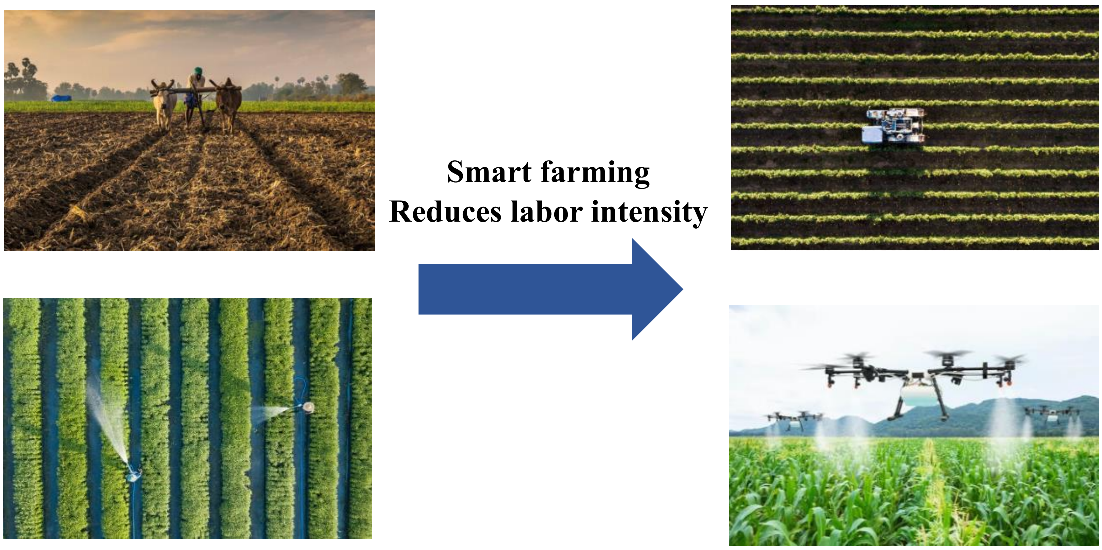

Figure 1.7: From traditional farming to smart farming

6. Challenges in smart farming

6.1. High cost of technology:

The recent advancements in technology (IOT & ML) are very promising for increased efficiency and accuracy, yet they come at a high cost. This introduces a significant challenge for farmers in developing countries, where affordability of these technologies remains a major concern, implementing them can be out of reach for many, especially those struggling to meet basic needs[13].

6.2. Unreachability of rural areas:

The very nature of farming, often taking place in remote and isolated areas, presents another hurdle. These locations often lack the necessary infrastructure, such as reliable electricity and internet connectivity, which are crucial for powering and connecting the devices and systems involved in smart farming[13].

6.3. Ignorance by the authorities:

The lack of support from authorities adds another layer of complexity for farmers in these rural regions. Often overlooked and denied crucial financial assistance, these individuals are left without the resources needed to invest in and adopt these new technologies, further hindering their potential benefits[13].

6.4. Lack of financial resources:

Financial constraints also play a significant role in this aspect, unpredictable factors like natural disasters, pests, and diseases can lead to loan defaults and decreased yields, creating a cycle of poverty and debt. This makes it difficult for farmers to invest in the additional costs associated with smart farming technologies[13].

6.5. Lack of knowledge:

A knowledge gap exists in many developing countries; farmers may lack the necessary education, skills, and even awareness about the potential and benefits of these new technologies. This lack of understanding can create a barrier to their adoption and integration into existing farming practices[13].

Conclusion:

This chapter explored the vital role of agriculture, its ongoing challenges, and the critical role agriculture plays in ensuring food security, economic development, and environmental sustainability. However, the sector faces significant challenges due to climate change, resource scarcity, and a growing population. Fortunately, intelligent solutions offer a ray of hope. Technologies like IoT and AI hold immense promise for revolutionizing agricultural practices. We explored potential applications in soil management, crop health monitoring, and disease control, all contributing to the concept of Smart Farming. While the developed technologies hold immense promise, yet overcoming obstacles like cost, infrastructure, and knowledge gaps remains crucial for widespread adoption. The following chapter, will delve into existing research on these intelligent solutions in agriculture.

The following chapter delves deeper into the existing research on these intelligent solutions in agriculture. We will explore specific examples of how Artificial Intelligence technologies are being harnessed to address the challenges faced by farmers today.

CHAPTER 02:

ARTIFICIAL INTELLIGENCE IN DETECTING PLANT DISEASE

Introduction:

Building a sustainable food system for a growing global population is a critical challenge in agriculture, one major hurdle is minimizing crop losses caused by plant diseases. Early detection is crucial to prevent significant yield reductions and ensure food security. Traditional methods for detecting plant diseases, while valuable, can be time-consuming, require expert knowledge, and are resource-intensive [14].To address these limitations, researchers are exploring the use of artificial intelligence (AI) with Internet of Things (IoT) sensors for automated leaf disease diagnosis and analysis [15].

In this chapter, we will explore various works applied in the field of crop management, with a specific focus on plant disease detection.

1. AI techniques used in Plant Disease Detection:

AI research aims to develop machines that can reason, learn, and solve problems like humans, these machines can analyze data, recognize patterns, and adapt to new situations, they're used in various applications, from speech recognition to complex problem-solving such as plant disease detection[16].
At present, machine vision-based plant diseases detection equipment has been initially applied in agriculture and has replaced the traditional naked eye identification to some extent.

Figure 2.1 is a diagram showing the different types of artificial intelligence

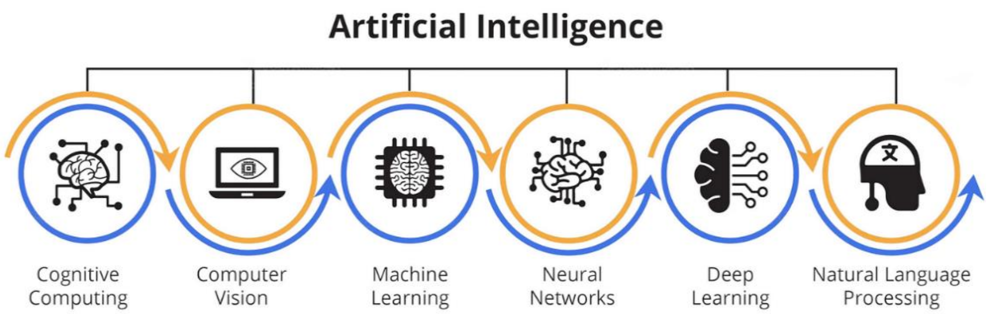

Figure 2.1 : Artificial Intelligence techniques [4]

1.1. Machine learning

1.1.1. Definition:

Machine learning (ML) lets computers learn from data without explicit instructions. By analyzing massive datasets, ML algorithms can identify patterns, make predictions, and even detect anomalies, this allows for tasks like understanding complex events, building predictive models, and proactively finding problems. [17].

1.1.2. Machine Learning Types

ML is categorized into three main learning styles: supervised learning, where the data is pre-labeled, unsupervised learning, where the data has no labels, and reinforcement learning, where the machine learns through trial and error with rewards and penalties.

- **Supervised Learning :**

Supervised learning train models using labeled data (inputs with desired outputs). It excels at tasks like classification (predicting categories) and regression (predicting continuous values). Even though classification seems separate, it can be seen as a type of regression predicting class likelihoods. Common supervised learning methods include SVMs and random forests for classification, and linear regression for numerical predictions[18].

- **Unsupervised Learning:**

Unsupervised learning, unlike supervised learning, doesn't require labeled data. It analyzes raw data to find hidden patterns. Common tasks include clustering (grouping similar data) and dimensionality reduction (simplifying complex data). K-means and KNN are popular clustering methods, while PCA and SVD tackle dimensionality reduction[18].

- **Reinforcement Learning :**

Reinforcement learning tackles problems through trial and error, unlike supervised learning. It's suited for scenarios where sequences and delayed feedback are important. The goal is to find the best course of action (policy) through exploration and reward signals. While control is the main objective, prediction of policy performance often comes first. Common RL methods include Monte Carlo for prediction and SARSA for control[18].

The figure 2.2 represents a diagram illustrating the different types of machine learning categorized as supervised and unsupervised learning. It also shows reinforcement learning.

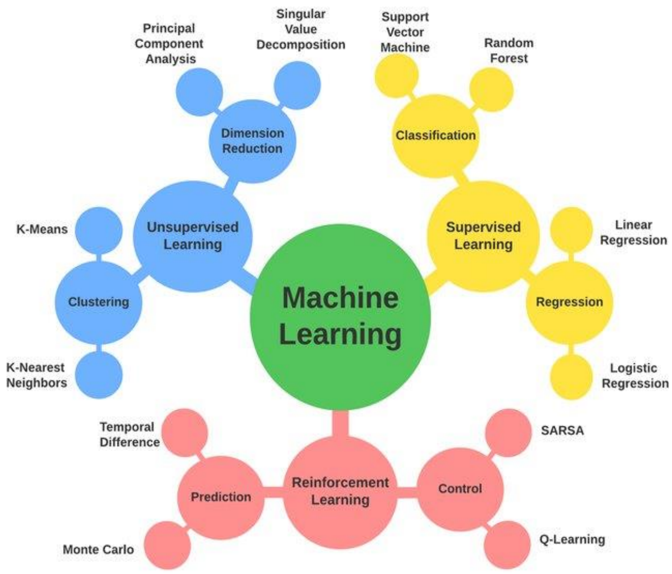

Figure 2.2 : Machine Learning techniques [6]

1.2. Deep learning

1.2.1. Definition

Deep learning (DL), a powerful subset of machine learning, utilizes complex neural networks to achieve groundbreaking results. Unlike traditional models, DL leverages multi-layered architectures inspired by the human brain, along with advanced transformations and graph technologies. This, along with vast data and powerful hardware, unlock breakthroughs in tasks like image recognition and natural language[19].

1.2.2. Types of DL networks

Deep learning neural networks (a.k.a artificial neural networks) attempt to mimic the human brain by creating a combination of data inputs, weights, and biases, these elements work together to accurately recognize, classify, and describe objects in the data. The most famous ones are discussed in this section.

- **Recursive Neural Networks (RvNN)**

RvNNs are inspired by auto-associative memory and excel at handling hierarchical data structures like trees or graphs, they process variable-sized inputs and generate fixed-sized outputs using a backpropagation learning system. They're particularly useful in natural language processing (NLP) for tasks like sentence classification and syntactic tree construction.

They iteratively merge units, calculate plausibility scores, and build compositional vectors to represent the entire structure[19].

Figure 2.3 showcases the architecture of RvNN tree

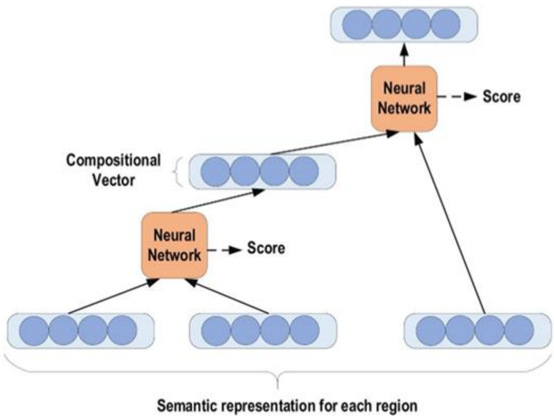

Figure 2.3 : An example of RvNN tree [7].

- **Recurrent Neural Networks (RNN)**

RNNs are popular deep learning algorithms for tasks like speech processing and natural language processing (NLP). Unlike traditional networks, RNNs handle sequential data, allowing them to capture context, and they can be seen as short-term memory units that process sequential information. However, they struggle with long-term dependencies due to vanishing or exploding gradients[19].

Figure 2.4 explains the architecture of RNN model

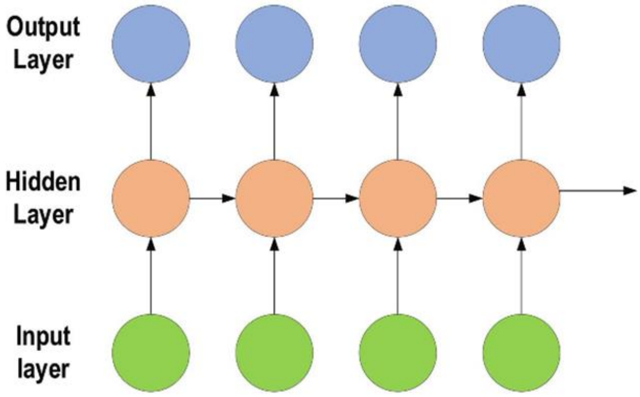

Figure 2.4 : Typical unfolded RNN Diagram [7]

- **Convolutional neural networks (CNN)**

Convolutional Neural Networks (CNNs) is one of the most known architectures of DL techniques. This technique is generally employed for image processing applications, yet it can also be used in speech processing, face recognition and video understanding [20]. It's also the go to model in most of leaf disease detection solutions.

2. Comparision between ML and DL

2.1 In theory

In the modern era, Machine Learning (ML) become necessary for enhancing machine intelligence. At its core, ML is a suite of algorithms that parse data, learn from them, and then apply what they've learned to make intelligent decisions.

Traditional ML algorithms, despite their complexity, are fundamentally systematic, they require domain experts, as they play a crucial role in data extraction by highlighting key features, thus simplifying the information so that algorithms can learn effectively and operate within their predefined boundaries [21].

In contrast, Deep Learning (DL), an advanced segment of ML, that achieves great power and flexibility by constructing a layered hierarchy of concepts, each concept is defined in relation to more fundamental ones, allowing for the derivation of abstract representations from less abstract ones. DL distinguishes itself with its ability to automatically learn the complex features directly from data, step-by-step, this eliminates the need of expert-driven feature selection, enhancing DL's adaptability and making it a more flexible tool.

The figure 2.5 is a diagram comparing machine learning and deep learning in terms of input, feature extraction, classification, and output.

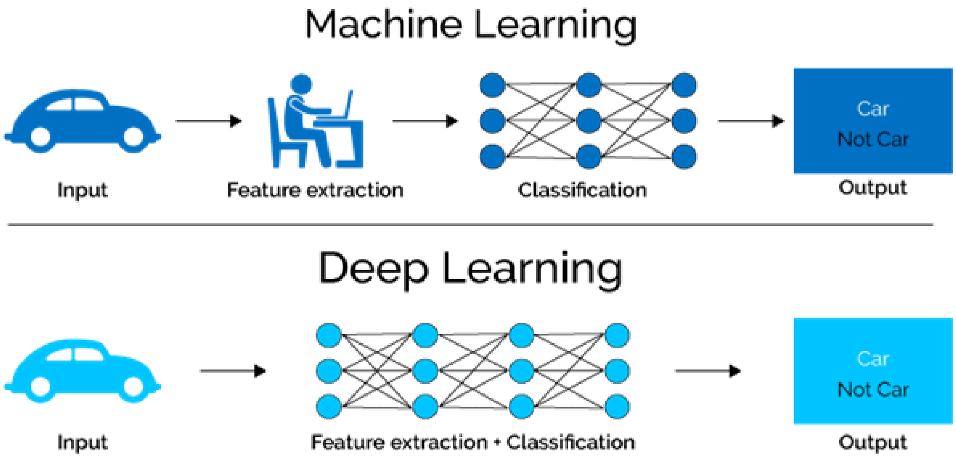

Figure 2.5 : Deep Learning vs Machine Learning [10].

2.2 In the field of plant disease detection

Traditional methods in leaf disease detection involve manually defining features like color variations, unusual edges, or specific shapes to identify signs of the illness. This requires expertise and can be fooled by changes in lighting or image quality.

Deep learning takes a different approach, by analyzing a large dataset showcasing both healthy and diseased leaves, it can automatically learn these features itself, and it becomes more robust to real-world conditions. This allows it to better identify diseases even in blurry or poorly lit images, making it a powerful tool for farmers and agricultural professionals.

Feature	***Machine Learning (ML)***	***Deep Learning (DL)***
Data Requirements	Smaller datasets	Large datasets
Feature Engineering	Required (expert knowledge needed)	Automatic
Model Complexity	Less complex	More complex
Interpretability	More interpretable	Less interpretable
Accuracy (general)	Can be high, depends on features	Potentially higher
Adaptability	Less adaptable	More adaptable
Lighting/Condition Sensitivity	May struggle with variations	More robust

Table 2.1: key point comparision between ML and DL

3 Convolutional neural networks

3.1. Definition

Convolutional Neural Networks (CNNs) are the go-to deep learning algorithm, especially for computer vision and understanding images. Unlike older models, CNNs automatically discover important features from data, without needing human supervision. Inspired by the brain's visual cortex, CNNs use shared weights and local connections to efficiently process 2D data like images, this reduces training complexity and speeds up the network, similar to how brain cells analyze visual information in smaller regions[19].

The figure 2.6 is an Example of CNN architecture used in plant disease detection [11]

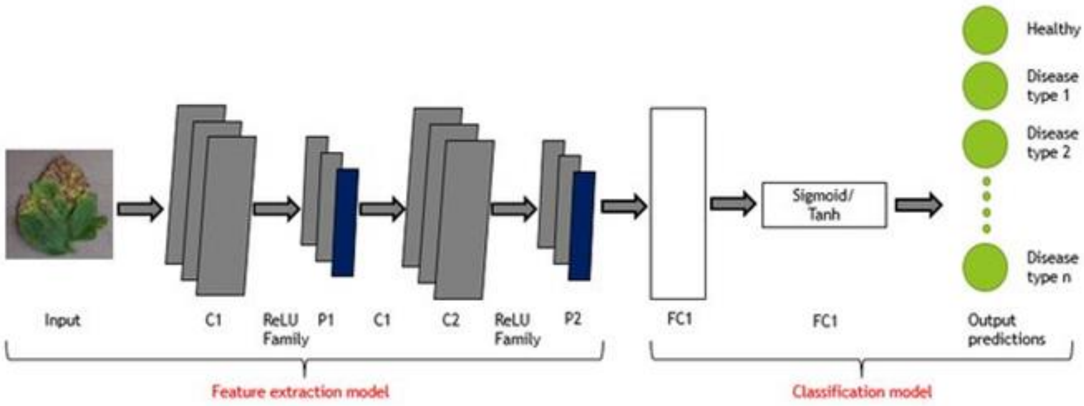

Figure 2.6 : Example of CNN architecture used in plant disease detection [11]

3.2. CNN layers

The architecture of Convolutional Neural Networks is a complex structure composed of multiple layers, each designed to perform a specific function, these layers work together to process input images and extract meaningful patterns that contribute to the network’s learning capabilities.

3.2.1. Convolutional Layer

The convolutional layer stands as the cornerstone of the CNN architecture, featuring a set of convolutional filters, also known as kernels. These kernels are essentially grids of weights that interact with the input image, which is represented as a multi-dimensional matrix, to produce what is known as the output feature map.

Initially, these weights are assigned randomly and are refined throughout the training process, allowing the kernels to become adept at feature extraction. The convolutional operation involves sliding the kernel over the image, computing dot products to generate the feature map.

This process is influenced by factors such as padding and stride, which can alter the dimensions of the resulting feature map. The convolutional layer offers two primary benefits: sparse connectivity, which reduces the number of connections and memory usage, and weight sharing, which decreases the training time and computational costs by using a single set of weights across the entire input[19].

3.2.2. Pooling Layer

Following the convolutional operations, the pooling layer's main function is to perform sub-sampling on the feature maps, effectively reducing their size while retaining the most prominent features. This is achieved through various pooling methods, such as max, min, and global average pooling, which involve assigning sizes to both the stride and the kernel before executing the pooling operation. Despite its utility, the pooling layer has a notable drawback: it can obscure the precise location of features within the input image, potentially causing the CNN to overlook relevant information[19].

3.2.3. Activation Function

At the heart of neural networks lies the activation function, a critical component that maps input values to output values and determines whether a neuron should be activated based on the given input. This function introduces non-linearity into the network, enabling it to learn more complex patterns. Among the most commonly used activation functions in CNNs are: the sigmoid, which outputs values between zero and one; the tanh, which outputs values between negative one and one; and the ReLU, which is favored for its ability to convert all input values to positive numbers while maintaining a lower computational load. However, ReLU can sometimes lead to issues such as "Dying ReLU," where neurons cease to activate. To address this, variants like Leaky ReLU and Noisy ReLU have been developed, which ensure that negative inputs are not entirely disregarded and introduce noise to the function, respectively[19]..

3.2.4. Fully Connected Layer

The Fully Connected (FC) layer is typically found at the end of the CNN architecture. It operates on the principle of a multiple-layer perceptron neural network, where each neuron is interconnected with all neurons from the preceding layer. This layer acts as the classifier within the CNN, taking a vectorized form of the feature maps as input and producing the final output of the network[19].

3.2.5. Loss Functions

The output layer of the CNN, which is responsible for classification, employs various loss functions to compute the prediction error across training samples. This error, indicating the discrepancy between the actual and predicted outputs, is then optimized during the learning process. The loss function utilizes two parameters: the CNN's estimated output (prediction) and the actual output (label). Different types of loss functions are applied depending on the specific problem being addressed[19] [22]

The figure 2.7 depicts the Architecture and Classification of Handwritten Digits with a CNN model

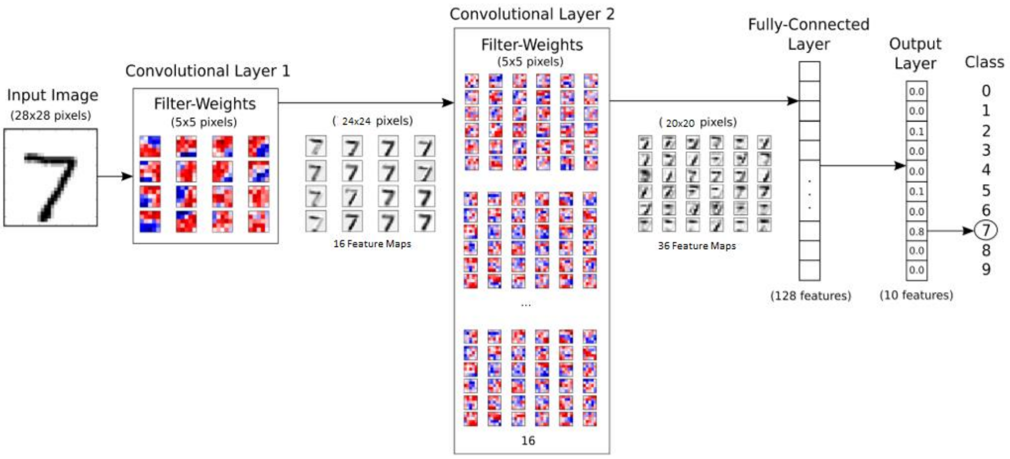

Figure 2.7 : Architecture and Classifying Handwritten Digits with a CNN [12]

4. Review of existing research:

Early and accurate detection of plant diseases is crucial for maintaining healthy crops and maximizing yield. To address this challenge, researchers have been developing a wide range of innovative systems for plant disease detection.

Ahmed & Reddy, 2021 [23] developed an ML-powered mobile based system to automate the plant leaf disease diagnosis process. The developed system uses Convolutional Neural networks (CNN) as an underlying deep learning engine for classifying 38 disease categories. Trained on a self-collected dataset of 96,206 healthy and infected plant leaf images, the CNN model achieves a commendable 94% classification accuracy.

Trivedi et al., 2021 [24] leverage Convolutional Neural Networks (CNNs) for classifying tomato diseases. Using Google Colab, they trained a CNN model on a dataset of 3,000 tomato leaf images (nine diseases and healthy leaves). The process involved preprocessing the images, segmenting the leaf regions, and fine-tuning the CNN hyperparameters. By analyzing features like color, texture, and edges, the CNN achieved an accuracy of 98.49% in disease classification.

Chowdhury et al., 2021 [25]proposed a two-stage deep learning method for tomato disease classification. Leveraging image segmentation (up to 98.66% accuracy), they achieve near-perfect disease classification (up to 99.95%) using EfficientNet models. This study highlights the potential of combining segmentation and deep learning for accurate disease detection in agriculture.

Md. A. Islam & Sikder, 2022 [26]explore potato disease classification using a convolutional neural network (CNN). They collected a dataset of 10,000 images containing three potato leaf classes (Early Blight, Late Blight, and healthy) from various sources including Kaggle and potato fields. The research process involved data acquisition, pre-processing, augmentation, and image classification for disease identification. The study reports the highest accuracy (100%) with 40 epochs, with other trials at 30 and 50 epochs achieving 99.97% and 99.98% accuracy, respectively.

Altalak et al., 2022 [27]proposed a hybrid deep learning approach for detecting and classifying tomato plant leaf diseases early. The hybrid system is a combination of a convolutional neural network (CNN), convolutional attention module (CBAM), and support vector machines (SVM). The model is trained on the PlantVillage dataset, encompassing images of tomato leaves with nine different diseases. The authors report an impressive accuracy of up to 97.2%.

J. et al., 2022 [28]explored the efficiency of pre-trained convolutional neural networks (CNNs) for plant disease identification. They focused on fine-tuning hyperparameters of popular models like DenseNet-121, ResNet-50, VGG-16, and Inception V4. Using the PlantVillage dataset containing 54,305 images across 38 disease classes, the authors evaluated model performance through metrics like classification accuracy, sensitivity, specificity, and F1 score. Notably, DenseNet-121 achieved an impressive 99.81% classification accuracy, surpassing other models.

Pande, 2022 [29]investigates the use of Convolutional Neural Networks (CNNs) for diagnosing potato diseases using leaf images. Their research proposes an automated system for potato leaf disease detection and classification through image processing and machine learning. Leveraging image processing techniques, Pande divided a dataset of over 2,000 healthy and unhealthy potato leaf images (collected from Kaggle) and employed pre-trained models to identify and classify these diseases. The study reports an accuracy of 91.41% on a test dataset representing 30% of the total images.

Md. M. Islam et al., 2023 [30]investigated the effectiveness of convolutional neural networks (CNNs) for crop disease detection. They compared the performance of various models, including CNN, VGG-16, VGG-19, and ResNet-50, on the PlantVillage dataset containing 10,000 images. Notably, ResNet-50 achieved the highest accuracy of 98.98%, outperforming other models (CNN: 98.60%, VGG-16: 92.39%, VGG-19: 96.15%). Leveraging this finding, the authors developed a web application powered by the ResNet-50 transfer learning model.

Jung et al., 2023 [31]present a multi-step disease detection system for plants. The system leverages a Convolutional Neural Network (CNN) comprised of five pre-trained models and utilizes images of both healthy and diseased plant pairs for training. This innovative approach employs a three-step classification process: first, identifying the crop type, then detecting the presence of disease, and finally classifying the specific disease. To enhance generalizability, the model incorporates an "unknown" category. Notably, the system achieved a high accuracy of 97.09% in crop and disease classification during validation testing.

Joseph et al., 2024 [32]address the challenge of limited disease detection datasets for rice, wheat, and maize. They created new datasets specifically targeting common bacterial and fungal diseases affecting these crops. The datasets were then used to train and evaluate eight fine-tuned deep learning models. Notably, Xception and MobileNet achieved the highest testing accuracy (0.9580 and 0.9464 respectively) for maize leaf disease recognition, while MobileNetV2 and MobileNet (0.9632 and 0.9628 respectively) excelled for wheat. For rice, Xception and Inception V3 led with 0.9728 and 0.9620 accuracy. The authors propose a novel CNN model trained from scratch on the combined dataset. This new model achieved impressive performance across all three crops, with testing accuracy reaching 0.9704, 0.9706, and 0.9808 for maize, rice, and wheat, respectively.

5. Comparative study:

This table summarizes the key findings from the reviewed articles. It allows for a comparison of methodologies (image-based, mobile app), disease coverage, achieved accuracy, and potential advantages and limitations of each approach.

Study	Methodology	Disease Types	Accuracy	Advantages	Limitations
Ahmed & Reddy (2021)	Mobile app with CNN	38 plant diseases	94%	User-friendly, mobile-based	Limited disease coverage, custom dataset
Trivedi et al. (2021)	CNN with hyperparameter tuning	Tomato (9 diseases)	98.49%	Leverages Google Colab for training	Limited dataset size, specific diseases
Chowdhury et al. (2021)	Two-stage: Segmentation (U-net) + EfficientNet	Tomato (healthy/unhealthy, 6 & 10 class)	99.12-99.95%	High accuracy with segmentation	Requires labelled training data
Islam & Sikder (2022)	CNN (reported 100% accuracy)	Potato (Early/Late Blight, healthy)	100%	Questionable high accuracy	Limited disease classes, potential overfitting
Altalak et al. (2022)	CNN + CBAM + SVM	Tomato (9 diseases)	97.2%	Hybrid approach, leverages SVM	Requires specific dataset (PlantVillage)

J. et al. (2022)	VGG16, InceptionV4, RestNet50, DenseNet-121	38 plant diseases	97.59%(Inception4), 92.75%(VGG16), 98.73%(RestNet50), 99.81% (DenseNet)	High accuracy with pre-trained models	Relies on pre-existing datasets
Pande (2022)	Pre-trained CNNs	Potato (healthy/unhealthy)	91.41%	Automated system	Lower accuracy, limited dataset details
Md. M. Islam et al. (2023)	CNN,VGG16, VGG19, RestNet50	PlantVillage (various)	98.60%(CNN), 92.39%(VGG-16), 96.15%(VGG19), 98.98% (ResNet-50)	High accuracy, web application	Limited disease coverage (PlantVillage)
Jung et al. (2023)	GoogleNet,VGG19	Multi-class (crop, disease type)	97.09%	Multi-step classification, "unknown" category	Requires diverse training data
Joseph et al. (2024)	MobileNet, Xception, InceptionV3, MRW-CNN	Rice, Wheat, Maize (bacterial/fungal)	94.64%(MobilNet), 95.80%(Xception), 96.20%(Inception3), 98.08% (MRW-CNN)	New disease-specific datasets, high accuracy	Requires large datasets for training

Table 2.2: comparative study of 10 articles about plant disease detection

6. Synthesis

Deep learning, particularly Convolutional Neural Networks (CNNs), is revolutionizing plant disease detection, researchers are achieving impressive accuracy in identifying various plant diseases, with studies reporting success rates between 91.41% and 99.98%.

The approaches used are diverse, some studies leverage pre-trained CNN models, while others fine-tune hyperparameters or even explore novel architectures that combine CNNs with techniques like SVM or CBAM. Notably, all the reviewed research focuses on image-based disease detection using leaf images.

Disease coverage varies, while some studies target specific crops and their associated diseases (tomato, rice, etc.), others aim for broader classification using diverse datasets like PlantVillage. Emerging trends include multi-step classification that considers crop type, disease presence, and specific disease type. Additionally, combining deep learning models with image segmentation shows promise for improved accuracy.

Challenges remain, limited disease coverage in some studies restricts real-world applicability. Models trained on specific datasets might not perform well on unseen data, highlighting the importance of generalizability. High-quality labelled datasets are crucial for effective training, and studies with limited datasets or questionable high accuracy require further investigation to ensure generalizability.

Future directions include developing models that identify a wider range of plant diseases, exploring sensor-based detection methods alongside image-based approaches, and integrating disease detection systems with mobile applications and agricultural tools for real-time monitoring. Research on improving data collection and labeling techniques is also essential to enhance model generalizability.

By addressing these challenges and continuing to explore new techniques, deep learning-based plant disease detection systems have the potential to become invaluable tools for farmers and agricultural professionals.

Conclusion:

In conclusion, this chapter explored the state-of-the-art applications of Artificial Intelligence (AI) in detecting plant diseases in agriculture. We discussed fundamental AI techniques, focusing on machine learning (ML) and deep learning (DL), and their application in image-based disease detection. Convolutional neural networks (CNNs) were highlighted for their effectiveness, and we provided a detailed look at their architecture and components. Our comparative analysis emphasized the superior accuracy of DL over ML in handling complex image data. A review of existing research illustrated the advancements and ongoing challenges in using AI for plant disease detection.

Overall, this chapter underscores the transformative potential of AI in agriculture. The reviewed studies demonstrate significant improvements in accuracy and efficiency over traditional methods, highlighting the ability of AI to automate and enhance disease detection processes. However, challenges such as model robustness and data quality remain. By leveraging advanced DL models, the agricultural industry can improve disease management, leading to healthier crops and higher yields. This chapter sets the stage for exploring practical implementations of these technologies in the next chapters.

CHAPTER 03:

Wheat Leaf Disease Detection: Model Design and Evaluation

Introduction:

In the preceding chapter, we delved into the realm of image processing techniques, particularly their application in precision agriculture. Recent years have witnessed a surge in the adoption of deep learning-based detection techniques, fueled by advancements in artificial vision. Despite the remarkable progress achieved thus far, the challenge of leaf disease detection remains a persistent issue in precision agriculture. In this chapter, we present our novel contributions to this ongoing endeavor, focusing on the design and evaluation of Convolutional Neural Networks (CNNs), InceptionV3, and YOLOv8 models. Our approach leverages the power of these models to effectively identify and classify diseases in wheat leaves.

We begin by discussing the importance of wheat production in Algeria and the impact of leaf diseases on crop yield and quality. This sets the stage for our exploration of advanced machine learning models tailored for disease detection. The first part of this chapter delves into the design and architecture of the models, covering data collection, preprocessing, augmentation, and model training. The second part focuses on the training process, evaluation metrics, and the results obtained from each model. Through this comprehensive approach, we aim to contribute significantly to the field of precision agriculture by enhancing the accuracy and efficiency of wheat leaf disease detection.

1. Wheat production in Algeria

The importance of wheat leaf work stems from Algeria's significant wheat production, which reached 7 million tonnes for the 2022/2023 season, positioning it as Africa's second largest wheat producer. This level of production underlines the crucial role of wheat in Algeria's agricultural sector and food security. With annual wheat consumption at 11.4 million tonnes in 2023, yet Algeria imports about 7.7 to 9 million tons of wheat annually, making it the fourth largest importer of the material in the world. [33]

2. Wheat leaf diseases

Wheat leaf diseases pose a significant threat to crop yield and quality. Among the most common diseases affecting wheat leaves are yellow rust and septoria leaf blotch. Yellow rust is characterized by yellowish-orange lesions on leaves, which can rapidly spread and lead to substantial yield losses if not managed effectively. Septoria leaf blotch, on the other hand, appears as small, dark spots with yellow halos, eventually coalescing into larger necrotic areas. Both diseases can severely impact wheat productivity if not promptly identified and controlled.

PART ONE: Model Design & Architecture

1. Model creation for wheat disease leaf classification

In this section, we outline the conceptual framework for a deep learning model aimed at detecting wheat leaf diseases. The project is designed to assist farmers and agricultural professionals in identifying and managing diseases that affect wheat crops. It comprises several backend machine learning models, including CNN, InceptionV3, YOLOv8. These models are trained on a dataset of labeled images of wheat leaves with various diseases, such as septoria and stripe rust, as well as healthy leaves. The objective of the models is to accurately classify input images into one of these categories, enabling early detection and intervention to prevent crop yield loss.

The figure 3.1 illustrates the steps we followed for our model design

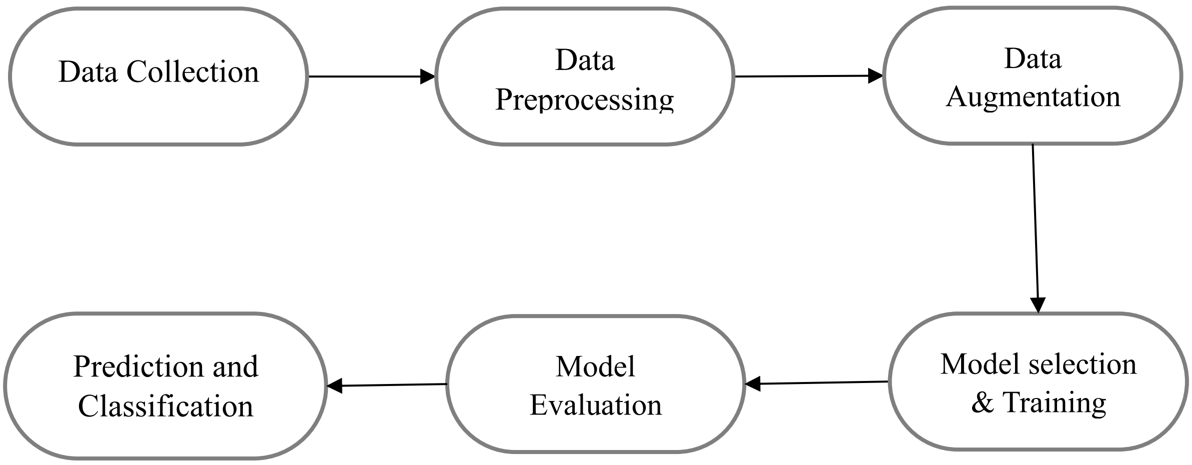

Figure 3.1: Overview of the model design

2. Data Collection and Labeling

Acquiring high-quality images for training and testing machine learning models can be a time-consuming and resource-intensive process. This research benefitted from the utilization of a pre-existing dataset: the Wheat leaf dataset available on Kaggle. This publicly accessible collection contains 102 healthy, 208 stripe rust, and 97 septoria detected wheat leaf. By employing this established dataset, we ensured a robust foundation for training and evaluating our three modelss, while optimizing the efficiency of our research.

The figure 3.2 depicts a portion of our dataset

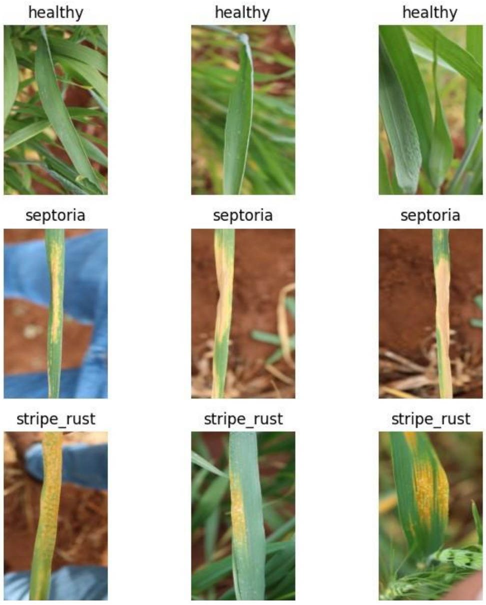

Figure 3.2: Overview of the dataset

3. Data preprocessing:

During the data preprocessing stage, the dataset was meticulously prepared for further analysis. Initially, bad or duplicate images were removed to maintain data accuracy. Subsequently, all images were resized to a standard 700x700 pixels to ensure consistency and ease of handling. Additionally, annotations were created for the dataset to facilitate precise labeling. Moreover, the dataset was split into training (70%), validation (20%), and test (10%) sets, a crucial step in preparing the data for model training and evaluation. These preprocessing steps collectively refined and optimized the dataset for subsequent analysis and model development.

4. Data augmentation:

In the data augmentation process, the training set was expanded using a data generator. Three images were generated for each of the 'Healthy' and 'Septoria' classes, while one image was generated for the 'Stripe Rust' class. As a result, the training set now comprises 388 files for 'Healthy', 384 files for 'Septoria', and 410 files for 'Stripe Rust'. This augmentation strategy aims to increase the diversity and robustness of the training data, potentially improving the model's performance and generalization ability.

Figure 3.3 showcases an example of an image from the dataset and how it was augmented.

Figure 3.3: Example of an augmented image from the dataset

5. Model import and training:

In the "Model import and training" stage, convolutional neural network (CNN) , YOLOv8 and InceptionV3 models were imported and trained on the preprocessed dataset, both models were evaluated based on their performance metrics to determine which one yielded better result. The comparison aimed to identify the model that achieved higher accuracy and efficiency in classifying wheat leaf diseases.

5.1. CNN:

The CNN model architecture used in this study consists of multiple layers designed to extract features from the input images. The model begins with a convolutional layer with 32 filters of size 3x3, followed by a ReLU activation function to introduce non-linearity. This is followed by a max pooling layer with a 2x2 pool size to reduce the spatial dimensions of the output. Subsequently, two additional convolutional layers with 64 and 128 filters respectively, each followed by a max pooling layer, further extract and abstract features from the images. The output from the convolutional layers is flattened into a 1D array and passed through two fully connected dense layers with 128 units each and ReLU activation. Finally, the output layer consists of a dense layer with a softmax activation function, which outputs the predicted probabilities for each class. This architecture is designed to learn and classify images of wheat leaves into the respective classes.

The figure represents the CNN model architecture in details

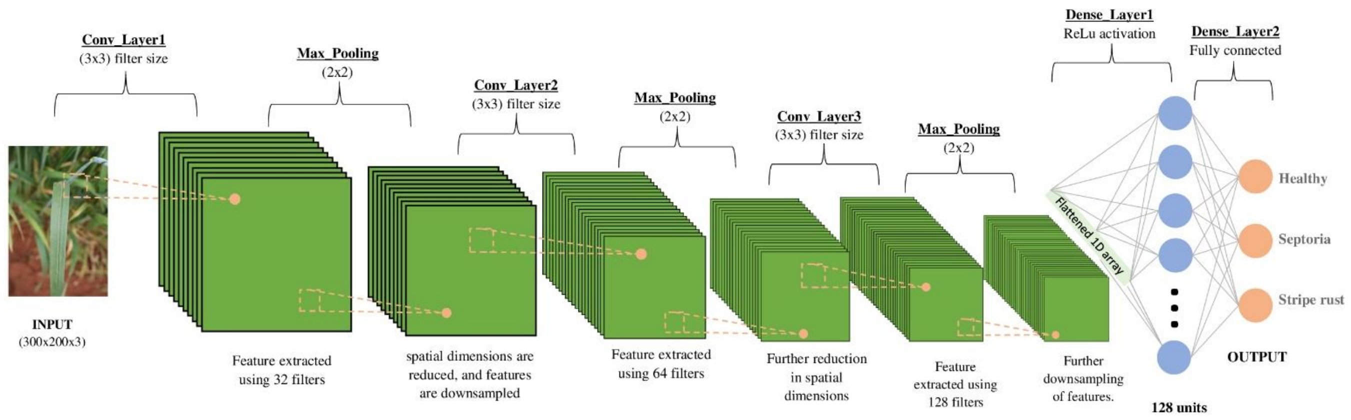

Figure 3.4: CNN model Architecture

5.2. InceptionV3:

In this section, we employ the InceptionV3 architecture, a state-of-the-art convolutional neural network (CNN) known for its efficiency and effectiveness in image classification tasks. Here's a breakdown of the architecture:

- **Load the InceptionV3 model:**

The pre-trained InceptionV3 model is loaded with weights from ImageNet. The include_top=False argument excludes the top (fully connected) layers of the model, leaving only the convolutional base.

- **A global spatial average pooling layer:**

A GlobalAveragePooling2D layer is added on top of the InceptionV3 base. This layer reduces the spatial dimensions of the input and extracts the average value of each feature map, creating a fixed-length vector for each channel.

- **A fully connected layer:**

A Dense layer with 1024 units and ReLU activation is added. This layer serves as a feature extractor, learning higher-level features from the pooled features.

- **A logistic layer (output layer):**

A dense layer with 3 units, and a softmax activation is added as the output layer, this layer computes the propabilities for each class based on the features extracted by the previous layers.

Figure 3.5 is an illustration of inceptionV3 architecture, showcasing the different layers .

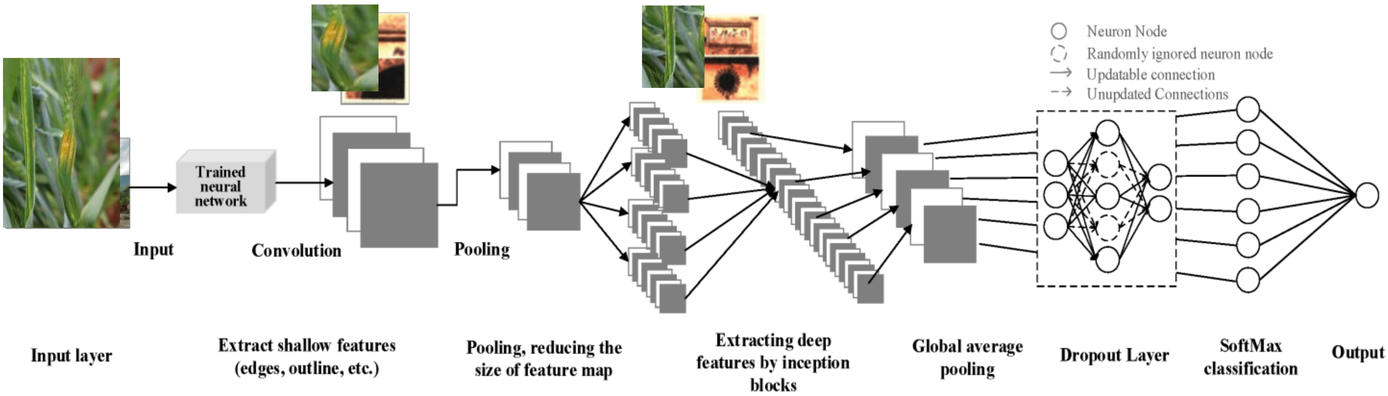

Figure 3.5 : InceptionV3 model architecture

5.3. YOLOv8:

YOLOv8 (You Only Look Once version 8) is a state-of-the-art deep learning architecture renowned for its speed and accuracy in image classification. It processes the entire image using a single neural network, which allows for efficient and real-time classification. By dividing the image into regions and predicting probabilities for each, YOLOv8 delivers precise and rapid classification results, making it highly effective.

Figure 3.6 represents the YOLOv8 model architecture we used in our work.

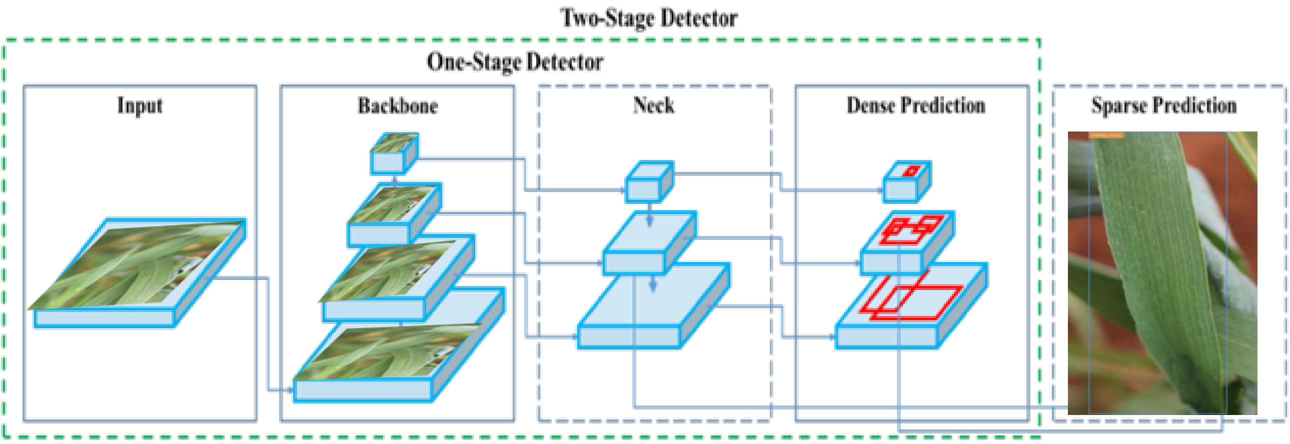

Figure 3.6 : YOLOv8 model architecture

6. Model evaluation

To evaluate the performance of CNN, InceptionV3 and YOLOv8 models, we'll use a comprehensive set of metrics including accuracy, recall, precision and confusion matrix. While traditional metrics like accuracy provide an overall measure of correct classifications, and the trade-off between precision and recall, offers a more nuanced view of model performance.

Accuracy: Measures the proportion of correctly predicted pixels out of all pixels. Formula:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FN+TN+FP}}$$

Recall (IoU): Measures the overlap between predicted and ground truth masks. Formula:

$$\text{Accuracy} = \frac{\text{TP}}{\text{TP} + \text{FN} + \text{FP}}$$

Precision: Measures the proportion of correctly predicted positive pixels out of all pixels predicted as positive. Formula:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Confusion matrix : A confusion matrix is a table used to evaluate the performance of a classification model by displaying the actual versus predicted classifications, including true positives, true negatives, false positives, and false negatives. It is calculated as follows:

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

6.1. Evaluating the CNN model:

For illustrating the performance of our CNN model over time during training, we generated the following graphs:

- A graph of training accuracy and validation accuracy
- A graph of training loss and validation loss

The figure 3.7 illustrates the loss and accuracy graphs for the training and validation of CNN model

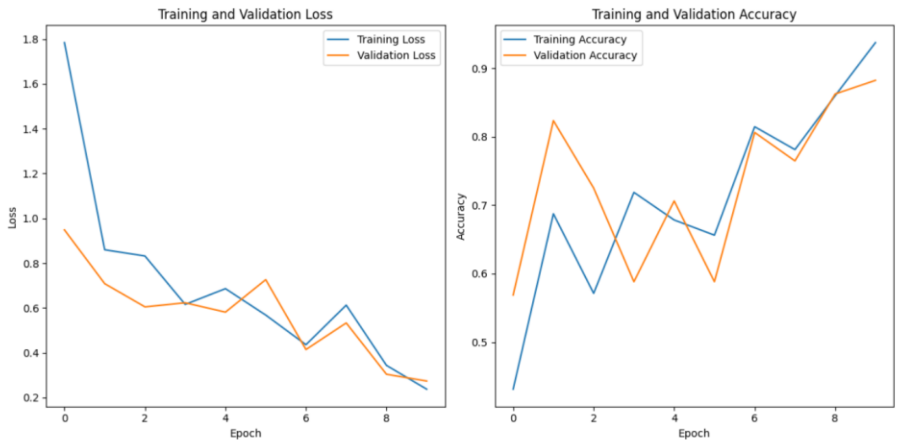

Figure 3.7: Accuracy and loss graphs for CNN

6.2. Evaluating the InceptionV3 model:

For illustrating the performance of our InceptionV3 model over time during training, we generated the following graphs:

- A graph of training accuracy and validation accuracy
- A graph of training loss and validation loss

The figure 3.8 illustrates the loss and accuracy graphs for the training and validation of Inceptionv3 model

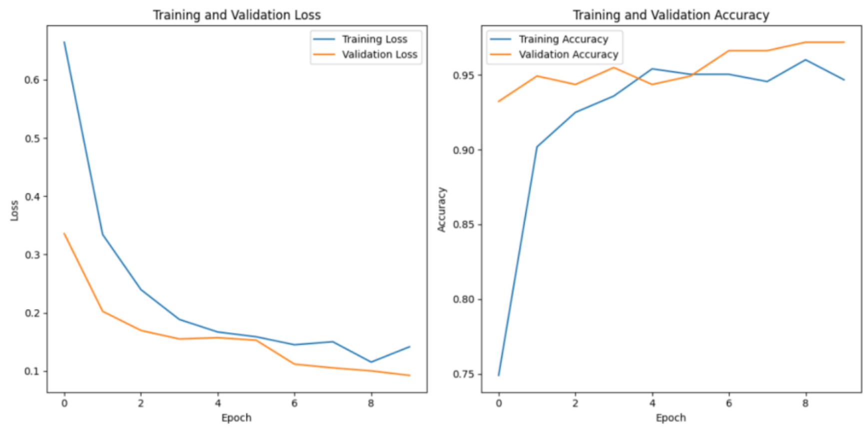

Figure 3.8: Accuracy and loss graphs for InceptionV3

6.3. Prediction and classification

In the next part, we will explore the prediction of the validation dataset and the testing of new images. This step is crucial for evaluating the performance of our model on data it has never seen before, allowing us to measure its ability to generalize and handle unknown cases. We will use the new images to test our model's ability to recognize the different classes of wheat leaves and diagnose diseases correctly. By analyzing the results of these tests, we can assess the robustness of our model and identify any areas for improvement.

PART TWO: Training & Results

1. The development tools

In this section, we will first introduce the Python programming language used for model implementation, along with the software tools and libraries such as Keras, TensorFlow, Matplotlib, NumPy, scikit-learn, TensorBoard, OpenCV, and others. Additionally, we will discuss the hardware employed to implement our model.

Figure 3.9 illustrates the different tools we used to train our models and conclude the results.

Figure 3.9: Programming language and softwares used

2. Models implementation

In this part we presented the tasks necessary for the implementation of our models.

2.1. Upload dataset to Kaggle:

Before uploading to Kaggle, it is essential to ensure that our dataset is well-organized and properly formatted. Our dataset comprises images of wheat leaves, categorized into three classes: Healthy, Septoria, and Stripe Rust. The images have been preprocessed to a uniform size of 500x300 pixels, and all pixel values have been normalized.

To create a new dataset on Kaggle, we start by logging into our account and navigating to the 'Datasets' section. Here, we click on the 'New Dataset' button to begin the upload process. We provide a suitable title and description for our dataset, such as "Wheat Leaf Disease Classification Dataset," and add relevant tags to improve discoverability.

2.2. Dataset split

For our wheat leaf disease detection dataset, we decided on the following split:

- Training Set: 70% of the data
- Validation Set: 20% of the data
- Test Set: 10% of the data

This ratio ensures a substantial amount of data for training while retaining enough examples for meaningful validation and testing.

The figures 3.10 and 3.11 depicts how we split the dataset for each of the three models

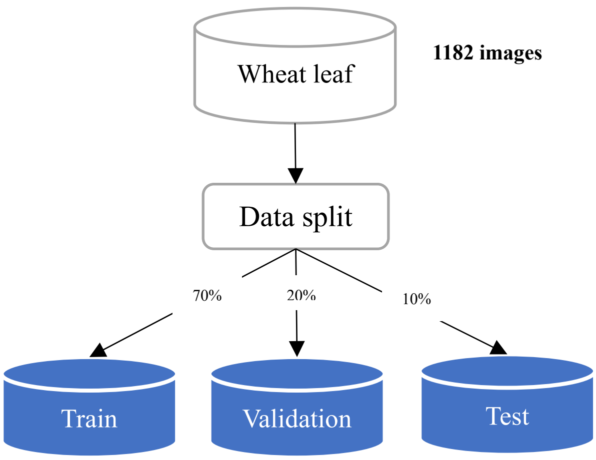

Figure 3.10: Data split for CNN+InceptionV3

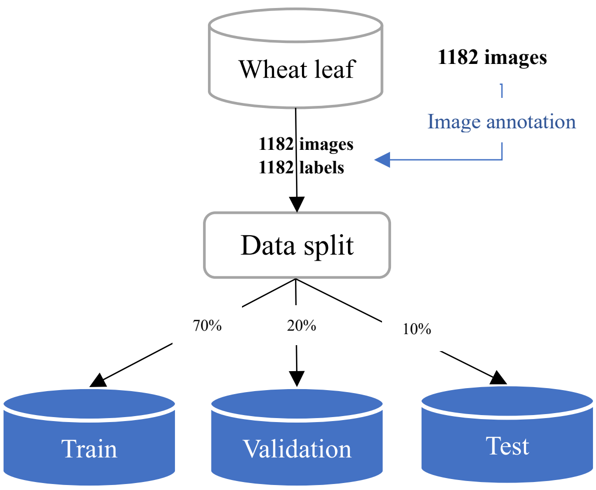

Figure 3.11: Data split for YOLOv8

2.3. Model loading and creation

2.3.1. CNN

To define our CNN model for wheat leaf disease detection, we construct a Sequential model starting with a Conv2D layer of 32 filters, ReLU activation, and an input shape of 299x299x3, followed by a MaxPooling2D layer. Next, we add Conv2D layers with 64 and 128 filters, each followed by MaxPooling2D layers. The model is then flattened, followed by a Dense layer with 128 neurons and ReLU activation. Finally, we add a Dense output layer with softmax activation for the three classes (Healthy, Septoria, Stripe Rust). We compile the model using the Adam optimizer, with categorical crossentropy loss and accuracy as the evaluation metric.

```
# Define the CNN model
model_cnn = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(299, 299, 3)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(128, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(3, activation='softmax')
])

# Compile the model
model_cnn.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])
```

2.3.2. InceptionV3

To leverage the powerful InceptionV3 architecture for our wheat leaf disease classification task, we start by loading the pre-trained InceptionV3 model with the top layers excluded. We then add a global average pooling layer to reduce spatial dimensions, followed by a fully connected layer with 1024 neurons and ReLU activation to capture complex patterns. Next, we add a softmax output layer for our three classes (Healthy, Septoria, Stripe Rust). We combine the base and top layers, freeze the base model layers to retain pre-trained weights, and compile the model using the Adam optimizer with categorical crossentropy loss and accuracy as the evaluation metric. This setup effectively blends pre-trained knowledge with new learning specific to our dataset.

```python
# Load the InceptionV3 model
base_model = InceptionV3(weights='imagenet', include_top=False)

# Add a global spatial average pooling layer
x = base_model.output
x = GlobalAveragePooling2D()(x)

# Add a fully connected layer
x = Dense(1024, activation='relu')(x)

# Add a logistic layer (output layer for 3 classes)
predictions = Dense(3, activation='softmax')(x)

# Combine the base model and top layers
model_inception = Model(inputs=base_model.input, outputs=predictions)

# Freeze the base model layers
for layer in base_model.layers:
    layer.trainable = False

# Compile the model
model_inception.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

2.4. Model Training

We train the models using the training data generator for 10 epochs, setting steps per epoch based on the training samples and batch size. The model is validated at each epoch using the validation data generator, with validation steps calculated similarly.

2.4.1. CNN

```python
# Train the model
history_cnn = model_cnn.fit(train_generator,steps_per_epoch=train_generator.samples // train_generator.batch_size,
    epochs=10,validation_data=validation_generator,validation_steps=validation_generator.samples // validation_generator.batch_size)
```

2.4.2. InceptionV3

```python
# Train the model
history_inception = model_inception.fit(train_generator,steps_per_epoch=train_generator.samples // train_generator.batch_size,
    epochs=10,validation_data=validation_generator,validation_steps=validation_generator.samples // validation_generator.batch_size)
```

2.4.3. YOLOv8

The dataset was trained on YOLOv8 in Roboflow for 300 epochs, with a focus on optimizing object detection. The dataset was meticulously organized, annotated, and augmented using Roboflow's platform to enhance its diversity and robustness. The 300 epochs of training allowed the model to iteratively improve its ability to detect and classify wheat leaf diseases accurately and efficiently.

2.5. Model evaluation for CNN and InceptionV3

2.5.1. Accuracy and Loss

For illustrating the performance of our CNN and InceptionV3 model over time during training and validation, we generated the following graphs:

- A graph of training accuracy and validation accuracy
- A graph of training loss and validation loss

The figure 3.12 and 3.13 illustrates the loss and accuracy graphs for CNN and InceptionV3 models accordignly

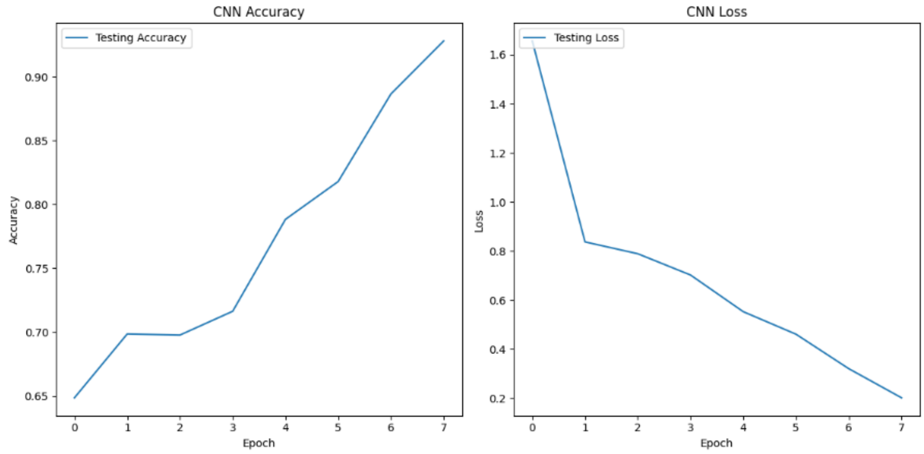

Figure 3.12: Accuracy and loss graphs for CNN

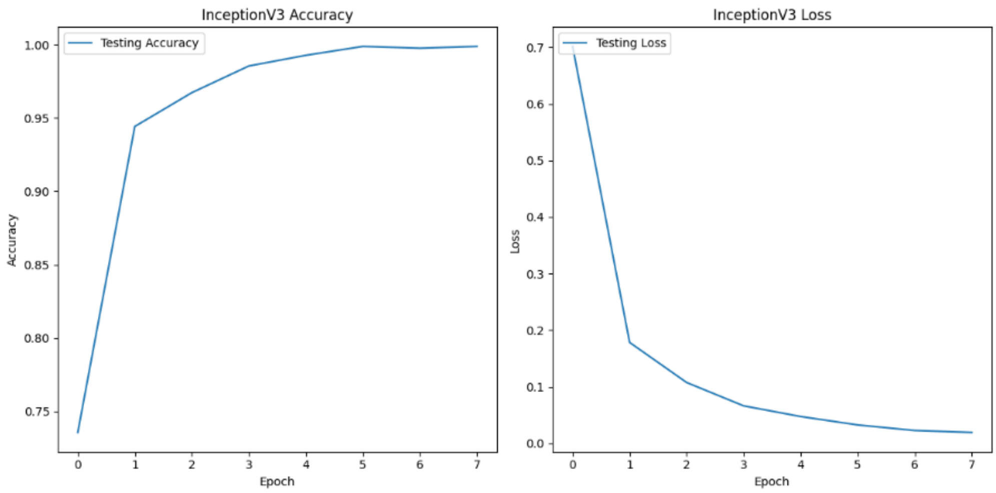

Figure 3.13: Accuracy and loss graphs for InceptionV3

2.5.2. Recall:

In our comparison of CNN and InceptionV3 models for wheat leaf disease detection, the recall graph illustrates the performance of each model across different classes (healthy, stripe_rust, septoria). A higher bar in this graph signifies that the model is more effective at identifying positive cases, thereby reducing the number of false negatives.

The figure 3.14 represents Recall results for CNN and InceptionV3 models

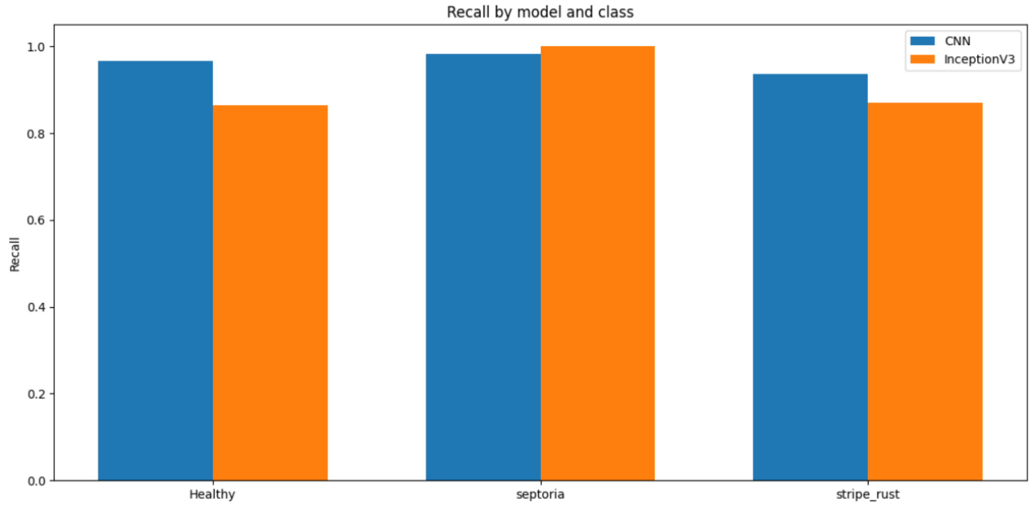

Figure 3.14: Recall results for CNN and InceptionV3

2.5.3. Precision:

In the precision graph comparing CNN and InceptionV3 models, we observe how each model performs in correctly predicting the different classes of wheat leaf conditions. A higher precision value means the model is more reliable in its positive predictions, ensuring that the identified diseased leaves are truly diseased with minimal false alarms.

The next figure is the precision results for CNN and InceptionV3

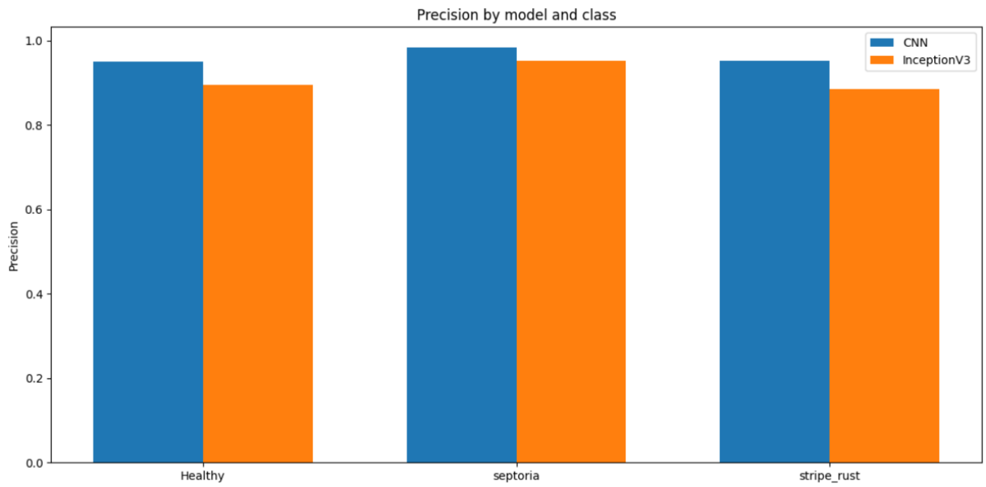

Figure 3.15: Precision results for CNN and InceptionV3

2.5.4. Confusion Matrix

The confusion matrices for CNN and InceptionV3 present a clear visualization of how each model predicts across the different classes. By analyzing these matrices, we can identify specific areas where each model excels or needs improvement, such as distinguishing between healthy and diseased leaves. This detailed breakdown helps in understanding the model's behavior and guiding further improvements.

Figure 3.16 depicts the confusion matrix results for CNN and InceptionV3, showcasing the prediction across the 3 classes.

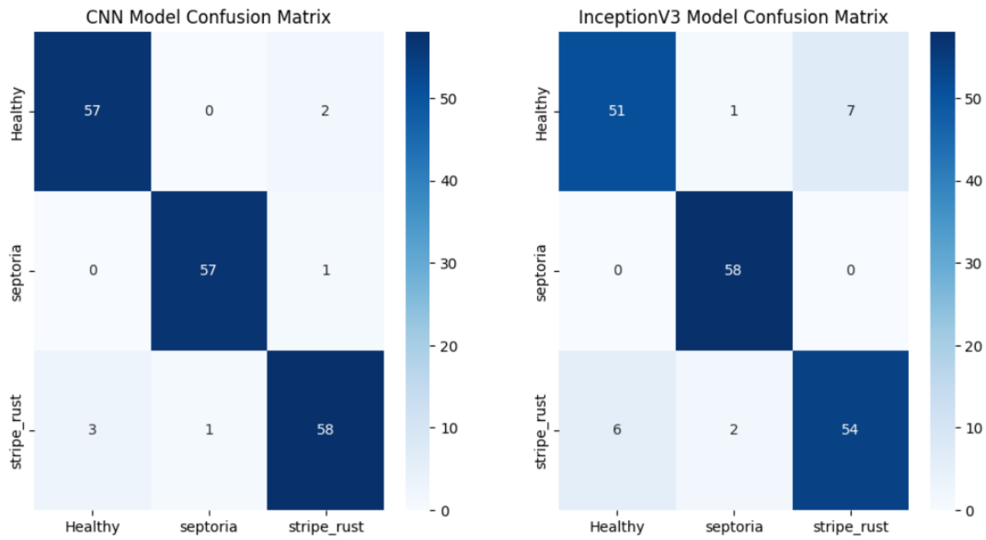

Figure 3.16: Confusion Matrix results for CNN and InceptionV3

2.6. Model evaluation for YOLO

Roboflow comprehensively evaluated the model on mean Average Precision (mAP), box/class/object loss, precision, and recall, offering a detailed assessment of its performance in object detection and classification.

2.6.1. mAP :

The mean Average Precision (mAP) graph obtained from training YOLOv8 in Roboflow provides a visual representation of the model's performance in detecting objects across different classes. The model obtained a mean Average Precision of 97.4%, offering insights into the model's accuracy and robustness in object localization and recognition tasks.

The figure 3.17 is a graph showing the increase in mAP results for YOLOv8 model

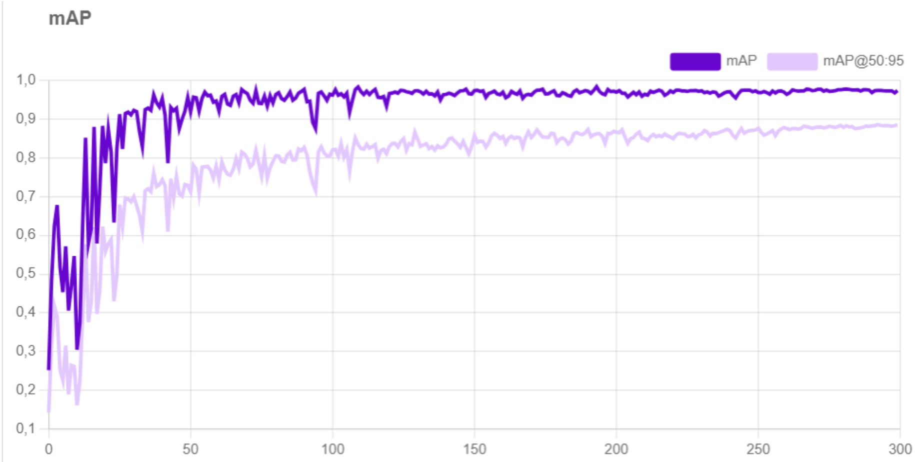

Figure 3.17: mAP results for YOLOv8

2.6.2. Loss analysis

The loss analysis presents a graphical overview of the box loss, class loss, and object loss during the training of a YOLOv8 model. These graphs illustrate the model's learning process, showing how well it is able to predict bounding boxes, classify objects, and detect their presence in the input images.

The next figure are 3 different graphs of the loss analysis, including box, class and object loss.

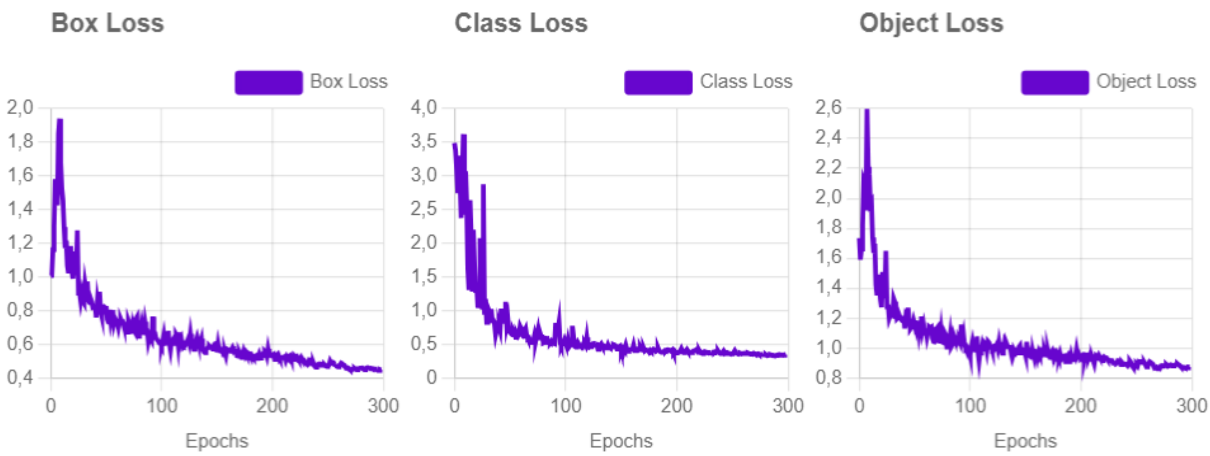

Figure 3.18: Loss analysis graphs for YOLOv8

2.6.3. Precision and Recall

The model achieved a precision of 97.9% and a recall of 95.2%. These metrics highlight the model's ability to accurately identify diseased wheat leaves (precision) and its effectiveness in capturing most instances of diseased leaves in the dataset (recall). This performance demonstrates the model's capability in detecting wheat leaf diseases with high precision while maintaining a high recall rate.

Figure 3.19 illustrates the recall and precision results for YOLOv8 in graphs

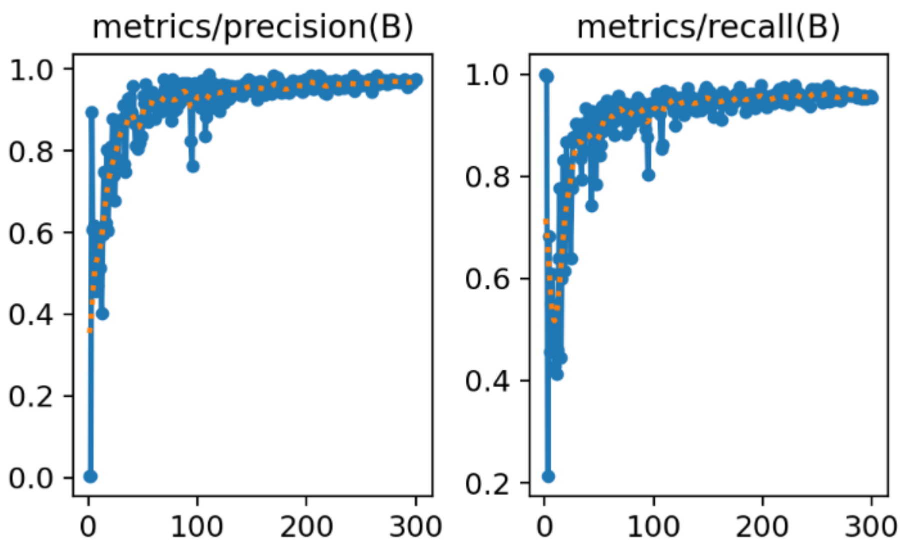

Figure 3.19: Recall and precision graphs for YOLOv8

3. Comparing the results

In comparing the three models, YOLOv8 demonstrates the highest accuracy at 98%, showcasing its ability to effectively classify wheat leaf diseases. It also achieves an impressive precision of 97.9%, indicating a low rate of false positives. YOLOv8's recall of 95.2% highlights its capacity to correctly identify most positive instances. The CNN model achieves an accuracy of 93.29% and matches its precision and recall, making it a robust performer in disease classification. InceptionV3 follows closely with an accuracy of 90.5%, demonstrating balanced precision and recall at 91% and 90.67%, respectively. Overall, YOLOv8 stands out for its high accuracy and recall, while the CNN model showcases strong precision and recall balance.

	Accuracy	Precision	Recall
CNN	93.29%	93.33%	93.33%
InceptionV3	90.5%	91%	90.67%
YOLOv8	98%	97.9%	95.2%

Table 3.1: result comparision between the 3 models

4. Prediction and testing

we evaluate the performance of our implemented models on the test dataset. The testing procedures for CNN, InceptionV3, and YOLOv8 models are thoroughly examined to determine their effectiveness in detecting wheat leaf diseases.

4.1. CNN and InceptionV3 prediction

To evaluate the performance of our CNN and InceptionV3 models, we use a set of test images from the wheat leaf dataset. The following code loads the best models, preprocesses the test images, makes predictions, and displays the results with the predicted class and confidence level.

```python
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from tensorflow.keras.models import load_model

# Load the best models
cnn_model = load_model('cnn_best_model.keras')
inception_model = load_model('inception_best_model.keras')
# Define the class names (assuming the classes are 'healthy', 'stripe_rust', and 'septoria')
class_names = ['healthy', 'stripe_rust', 'septoria']
# Function to preprocess an image
def preprocess_image(image_path, target_size):
    img = load_img(image_path, target_size=target_size)
    img_array = img_to_array(img) / 255.0
    img_array = np.expand_dims(img_array, axis=0)
    return img_array

# Test images paths
image_paths = ['/kaggle/input/wheatleaf/THE_DATASET/test/sample1.JPG',
               '/kaggle/input/wheatleaf/THE_DATASET/test/septoria2.JPG']
# Function to predict and display the image with its predicted class and confidence
def predict_and_display(model, image_path, model_name, target_size, ax):
    img_array = preprocess_image(image_path, target_size)
    prediction = model.predict(img_array)
    predicted_class_index = np.argmax(prediction)
    predicted_class = class_names[predicted_class_index]
    confidence = np.max(prediction)

    # Load the image for display in original size
    img = load_img(image_path)
    # Display the image with its predicted class and confidence
    ax.imshow(img)
    ax.set_title(f'{model_name} Prediction: {predicted_class}\nConfidence: {confidence:.2f}')
    ax.axis('off')

# Create a subplot for each model and each image
fig, axes = plt.subplots(2, len(image_paths), figsize=(15, 10))
# Predict and display results for CNN model
for i, image_path in enumerate(image_paths):
    predict_and_display(cnn_model, image_path, 'CNN', cnn_target_size, axes[0, i])
# Predict and display results for InceptionV3 model
for i, image_path in enumerate(image_paths):
    predict_and_display(inception_model, image_path, 'InceptionV3', inception_target_size, axes[1, i])

# Display the plot
plt.tight_layout()
plt.show()
```

After running this code, the result was as follows in figure 3.20 and 3.21 which illustrates the prediction of images using the 2 models alongside their confidence:

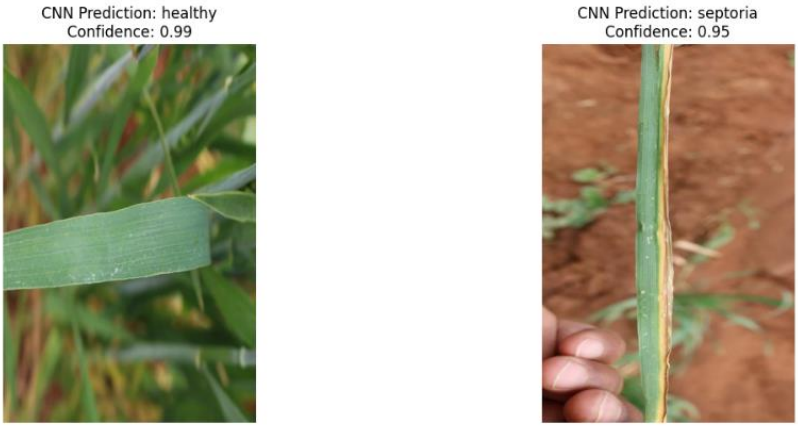

Figure 3.20 : Prediction results for CNN

Figure 3.21 : Prediction results for InceptionV3

4.2. YOLOv8 prediction

To evaluate the performance of the YOLOv8 model, we utilize the Roboflow workspace, which provides an integrated environment for training, testing, and deploying computer vision models. Below, we discuss how to test the YOLOv8 model in Roboflow and the two types of results it generates: visualized images with bounding boxes and confidence scores, and JSON files with detailed prediction information.

4.2.1. Roboflow workspace

We use the 'Deploy' tab to access the testing interface. Upload the test images or select them from your dataset in the workspace.

The Figure 3.22 represents the YOLOv8 predicition results after using the Roboflow workspace

Figure 3.22: YOLOv8 predicition results on Roboflow workspace

4.2.2. Roboflow Web App

We first upload the image, fix the parameters we want as an output and we run the inference. Figure 3.23 illustrates the interface generated by Roboflow workspace for YOLOv8 model

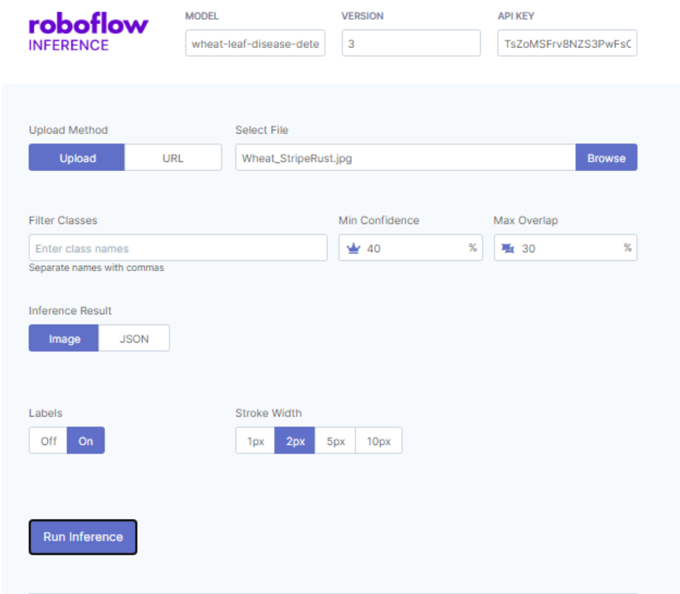

Figure 3.23 : Roboflow web app interface

Figure 3.24 represents the results received after using the interface generated by Roboflow workspace

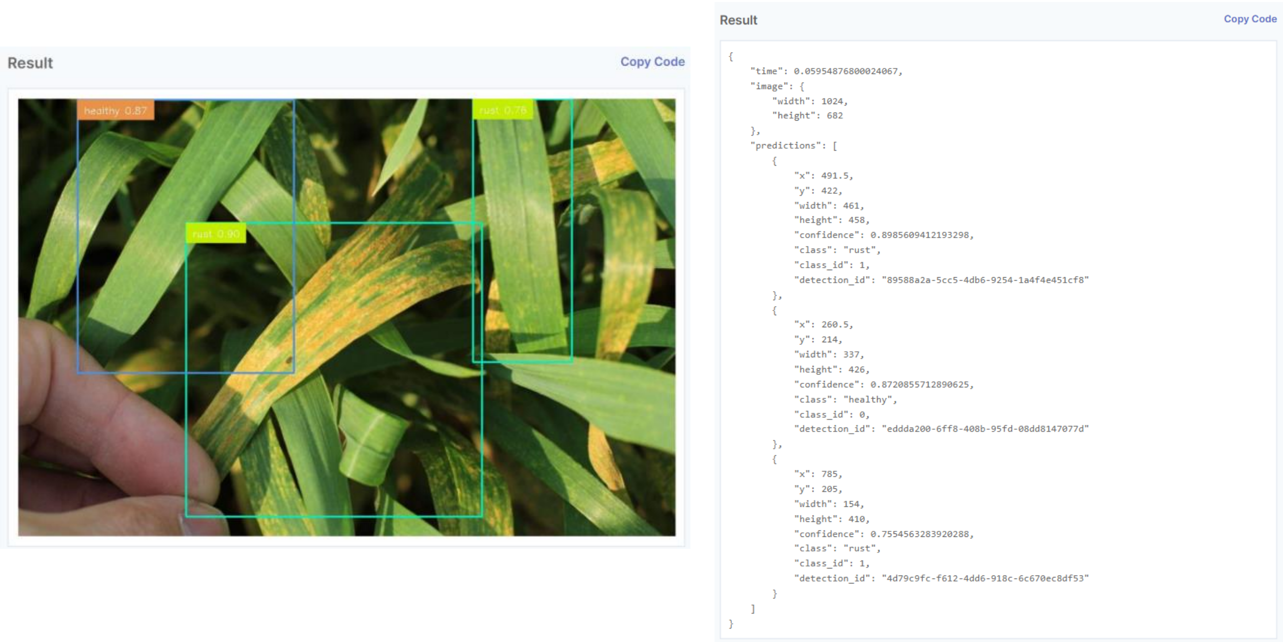

Figure 3.24: YOLOv8 prediction result using roboflow web app

Conclusion

This chapter focused on both the design and practical implementation of our system for detecting wheat leaf diseases. We began by presenting the dataset, which includes labeled images of wheat leaves affected by various diseases such as septoria and stripe rust, as well as healthy leaves.

Next, we outlined the architectures of the convolutional neural network (CNN), InceptionV3, and YOLOv8 models. The CNN architecture was chosen for its robustness in image classification tasks, InceptionV3 for its advanced capability in handling complex patterns, and YOLOv8 for its speed and accuracy in real-time image classification. We detailed the creation and training of these models, describing the process of uploading our dataset to Kaggle and splitting it into training, validation, and test sets to ensure diverse and comprehensive model training. Through careful selection of hyperparameters and the use of data augmentation techniques, we improved the models' performance and robustness. Evaluation metrics such as accuracy, error rate, F1 score, recall, and precision were used to assess the models' effectiveness.

Overall, this chapter lays a solid foundation by detailing the architecture and training processes of our models, setting the stage for further refinement and exploration of their real-world applications in subsequent chapters.

GENERAL CONCLUSION AND PRESPECTIVE

GENERAL CONCLUSION

In conclusion, this thesis has explored the application of intelligent solutions, specifically deep learning models, in the detection of wheat leaf diseases. Through the development and evaluation of models such as CNN, InceptionV3,and YOLOv8 we have demonstrated the potential of these technologies to significantly impact the agricultural sector. By accurately identifying diseases such as septoria, stripe rust, and overall health status, these models can assist farmers in making informed decisions, leading to improved crop management practices and increased yields.

The research has also highlighted the importance of data preprocessing, augmentation, and model selection in developing effective disease detection systems. Furthermore, the implementation of these models in a user-friendly web interface showcases their practicality and accessibility for end-users, ensuring that the benefits of this technology can be widely distributed and utilized.

Looking ahead, there is immense potential for further advancements in this field, including the integration of real-time monitoring systems and the expansion of the model to detect a wider range of agricultural diseases next to wheat crops. By continuing to innovate and refine these technologies, we can contribute to a more sustainable and productive agricultural sector, ultimately benefiting farmers and communities worldwide.

PRESPECTIVES

Future research in intelligent solutions for agricultural enhancement, particularly in wheat leaf disease detection, could focus on several key areas.

- Refining existing architectures and exploring ensemble techniques could enhance the accuracy and speed of disease detection models.
- Real-time monitoring systems utilizing drones or IoT devices could offer farmers timely insights for proactive disease management.
- Expanding the model's repertoire to include a wider array of diseases and pests would empower farmers to tackle multiple challenges simultaneously.
- Collaboration with agricultural institutions to gather and share data could lead to more robust and universally applicable models.
- Integrating the disease detection model into mobile applications would facilitate easy access and utilization for farmers.
- Incorporating climate data into the model could elevate disease prediction and management strategies, considering the influence of changing environmental conditions.

Research on interpretable machine learning models could provide explanations for model predictions, fostering trust and usability among farmers and stakeholders. Also, engaging with local communities and farmers would ensure that the developed solutions are practical, accessible, and beneficial in real-world scenarios. These perspectives pave the way for further advancements in the field, contributing to sustainable and efficient crop management practices..

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