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Theme :

AgriSense: Intelligent Disease Detection in Cereals Using RGB Imaging

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ملخص

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تواجه الزراعة الحديثة تحديات كبيرة، من بينها أمراض أوراق الحبوب، انخفاض غلّة المحاصيل، وتأثيرات التغيّر المناخي. لمواجهة هذه المشكلات، قمنا بتطوير AgriSense، وهو نظام مبتكر للكشف المبكر عن أمراض الحبوب باستخدام التعلم العميق ورؤية الحاسوب. يعتمد AgriSense على بنية معمارية متسلسلة من نوع "رئيس-مرؤوس"، حيث يحدد النموذج الأول ما إذا كانت النبتة سليمة أو مصابة، ثم يقوم النموذج اللاحق بتحديد المرض بدقة. يمكن للنظام اكتشاف 11 مرضًا خطيرًا يصيب القمح، الذرة، والأرز، بما في ذلك الصدأ البني، الصدأ الأصفر، التبقع السبتوري، والصدأ الورقي في القمح؛ الذبول، الصدأ الشائع، والتبقع الرمادي في الذرة؛ بالإضافة إلى اللفحة البكتيرية، التبقع البني، لفحة الأوراق، وتعفن الغمد في الأرز. من خلال تمكين التشخيص السريع والدقيق عبر واجهة سهلة الاستخدام، يساعد AgriSense المزارعين على اتخاذ إجراءات فورية، تقليل خسائر المحاصيل، وتعزيز ممارسات الزراعة المستدامة. يُبرز هذا العمل الإمكانات الكبيرة للتعلم العميق في إحداث ثورة في المجال الزراعي من خلال التصدي للتحديات الواقعية المرتبطة بأمراض أوراق الحبوب.

الكلمات المفتاحية:التعلم العميق، كشف أمراض الحبوب، المحاصيل الحقلية، التشخيص المبكر، الزراعة المستدامة.

ABSTRACT

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Modern agriculture faces major challenges, including cereal leaf diseases, reduced crop yields, and the impacts of climate change. To address these issues, we developed AgriSense, an innovative system for the early detection of cereal diseases using deep learning and computer vision. AgriSense is based on a sequential master-slave architecture, where the first model determines whether a cereal plant is healthy or infected, and subsequent models identify the specific disease. The system can detect 11 critical diseases affecting wheat, maize, and rice, including brown rust, yellow rust, septoria, and leaf rust in wheat ; wilting, common rust, and gray leaf spot in maize ; as well as bacterial leaf blight, brown spot, leaf blast, and sheath blight in rice. By enabling fast and accurate diagnosis through a user-friendly interface, AgriSense helps farmers take timely action, reduce crop losses, and promote sustainable agricultural practices. This work highlights the potential of deep learning to revolutionize agriculture by addressing real-world challenges related to cereal leaf diseases.

KeyWords : Deep Learning, Cereal Disease Detection, Cereal Crops, Early Diagnosis, Sustainable Agriculture.

RÉSUMÉ

RÉSUMÉ

L'agriculture moderne est confrontée à des défis majeurs, notamment les maladies des feuilles de céréales, la réduction des rendements et les impacts du changement climatique. Pour répondre à ces problèmes, nous avons développé AgriSense , un système innovant pour la détection précoce des maladies des céréales en utilisant l'apprentissage profond et la vision par ordinateur. AgriSense repose sur une architecture séquentielle maître-esclave, où le premier modèle détermine si une céréale est saine ou infectée, et les modèles suivants identifient la maladie spécifique. Le système peut détecter 11 maladies critiques affectant le blé, le maïs et le riz, y compris la rouille brune, la rouille jaune, la septoriose et la rouille foliaire du blé ; le flétrissement, la rouille commune et la tache grise du maïs ; ainsi que la brûlure bactérienne, la tache brune, le blast foliaire et la pourriture des gaines chez le riz . En permettant un diagnostic rapide et précis via une interface conviviale, AgriSense aide les agriculteurs à agir rapidement, à réduire les pertes de récolte et à promouvoir des pratiques agricoles durables. Ce travail met en évidence le potentiel de l'apprentissage profond pour révolutionner l'agriculture en répondant aux défis concrets liés aux maladies des feuilles de céréales

Mots Clés : Apprentissage Profond, Détection des Maladies des Céréales, Cultures Céréalières, Diagnostic Précoce, Agriculture Durable.

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Finally, my heartfelt thanks go to my family for their constant love and support. May Allah bless them with happiness, good health, and long lives.

DEDICATION

This work is dedicated to my beloved family, especially my parents, whose love, encouragement, and sacrifices have been my greatest source of strength. To my sisters Abir and Raouene and my brother Hatem, thank you.

I also dedicate this to my friends who encouraged me during these years of study—your friendship has been invaluable.

Finally, I dedicate this work to my promotion 2020-2025 Computer Science at the University of Guelma. Thank you for being part of this experience.

Summary

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GENERAL INTRODUCTION

Agriculture is the foundation of food security, providing the resources needed to feed the world's population. Among all crops, cereals like wheat, maize, and rice are the most important, as they form the basis of diets for billions of people. These crops supply essential nutrients and energy, making their successful cultivation critical for both human health and economic stability. However, modern agriculture faces many challenges that threaten its ability to produce enough food. These challenges include plant diseases, which can destroy entire fields, reduced crop yields due to environmental stress, and the growing impact of climate change.

Climate change is making farming even more difficult by causing unpredictable weather patterns, such as droughts, floods, and extreme temperatures. These changes weaken crops and make them more vulnerable to diseases. At the same time, plant diseases remain a major problem, spreading quickly and leading to significant losses if not detected early. Traditional methods of diagnosing diseases often require expert knowledge and laboratory tests, which can be time-consuming, expensive, and inaccessible to many farmers, especially in remote areas.

To address these challenges, we have developed **AgriSense** , an innovative solution designed to detect cereal diseases at an early stage. AgriSense uses deep learning and computer vision technologies to analyze images of plant leaves captured with a smartphone or uploaded through a simple, user-friendly interface. The system operates in two stages using a **sequential master-slave architecture** : the first model (DDN1), acting as the "master," determines whether the plant is healthy or infected. If a disease is detected, the second model (DDN2), acting as the "slave," identifies the specific type of disease. This sequential approach ensures efficient and accurate diagnosis, enabling farmers to take quick and effective action to protect their crops without requiring specialized expertise.

What makes AgriSense unique is its focus on 11 specific diseases that affect wheat, maize, and rice (four diseases for wheat, three for maize, and four for rice). To the best of our knowledge, there is no similar tool available in Algeria, making AgriSense a pioneering solution for local farmers. This absence of comparable solutions in the country underscores the importance of our project in addressing the specific needs of Algerian agriculture. By enabling early detection and timely intervention, AgriSense aims to reduce crop losses, improve yields, and promote sustainable farming practices.

Our thesis is organized into four chapters :

Chapter 1 : explains the importance of agriculture in ensuring food security, highlights the role of cereal crops in global nutrition, and discusses the challenges faced by modern farmers. It also introduces the motivation behind our project and provides an overview of the technologies used.

Chapter 2 : reviews existing research on plant disease detection, focusing on deep learning approaches and previous studies related to cereal crops.

Chapter 3 : describes the materials and methods used in this project, including how we prepared the dataset, designed the models, and trained them. Special attention is given to the sequential master-slave architecture that underpins the system's functionality.

Chapter 4 : presents the results of our experiments, evaluates the performance of AgriSense on wheat, maize, and rice diseases, and discusses its potential impact on agriculture.

Through AgriSense, we hope to empower farmers with a practical and accessible tool that helps them protect their crops and contribute to a more sustainable and resilient agricultural system.

CHAPTER I

CEREAL DISEASES

I.1 Introduction

Cereals are a major source of food around the world and they are a part of the daily diet for many people. The most important cereals are wheat, maize, rice, and barley. They are important not only because they are healthy, but also because they help the economy in many countries. In Algeria, these cereals are very important for farming and food security.

I.2 Global Health and Food Security

I.2.1 Definition of Food Security by the WHO

The World Health Organization (WHO) defines food security as a situation where all people have enough food that is both physically available and affordable. This food must be nutritious and safe, allowing people to stay healthy and lead an active life. This definition shows how important good nutrition is for public health. [W1]

I.2.2 WHO's Goals for Disease Prevention and Control

The WHO says that it is very important to protect crops from diseases to have enough food for everyone. Healthy crops give good food for people. If we stop plant diseases, farmers do not lose too much food, and there is always enough to eat. But if we do not stop diseases, there will be less food, and prices will go up. We must take care of crops to keep food safe for all. [W2]

I.2.3 Role of Organizations in Food Security

International organizations play a key role in food security by supporting agricultural development. They create projects that help farmers grow more food and use better farming methods. These projects focus on improving soil health, providing quality seeds, and training farmers in disease prevention. By reducing crop losses caused by plant diseases, they help ensure a steady food supply. Their efforts also support rural communities and make agriculture more sustainable. [W3]

I.3 Definition and Importance of Cereal Crops

I.3.1 Definition of Cereal Crops in the World

Cereal crops are plants grown primarily for their edible seeds, which serve as a staple in human and animal diets. These seeds, rich in carbohydrates, are a major source of energy in global diets. The most common cereals include wheat, corn, barley, rice, and oats. [W4]

I.3.2 Economic and Nutritional Importance of Cereal Crops

Cereals are very important for both food and the economy in many parts of the world. They provide food for billions of people and play a big role in national economies. Cereals give more than 60% of the calories people eat worldwide, with maize, wheat, and rice being the main sources of energy. In developing countries, cereals make up about 75% of total calorie intake and 67% of protein intake. Economically, cereals add billions of dollars to national incomes. For example, in Canada, they bring about $68.8 billion per year and create more than 370,000 jobs. Cereals are also important in many food industries, like making bread and beer. Because cereals can be eaten in different ways, such as whole grains, flour, or processed products, they help add variety to people's diets. Overall, cereals are essential for nutrition and farming in both rich and poor countries. [W5]

I.3.3 Economic and Nutritional Importance of Cereal Crops in Algeria

Cereal crops are very important for food security and the economy in Algeria. Wheat is the most consumed cereal, with each person eating about 220 kg per year. This means the country needs about 88 million quintals of wheat for its 44 million people. Even though the government has made efforts to increase local production, Algeria still imports about 70% of its cereals. This high dependence on imports makes the country vulnerable to global economic changes and food shortages. About 40% of Algeria's farmland is used to grow cereals, which are important for both human food and animal feed. Cereals provide over 60% of energy intake and 75-80% of protein intake in the Algerian diet. To reduce dependence on imports, the Algerian government has started programs to increase cereal production, improve food security, and keep prices stable for consumers. [W6]

Algeria

Cereal Production

	2019-2023 average	2023	2024 forecast	change 2024/2023
	000 tonnes			percent
Wheat	2 928	2 500	2 500	0.0
Barley	1 083	1 000	949	-5.1
Oats	74	76	74	-2.6
Others	9	8	10	25.0
Total	4 094	3 584	3 533	-1.4

FIGURE I.1 – Cereals Production in Algeria [W6]

I.4 Cereal Growth Stages

I.4.1 The Importance of Growth Stages in Cereal Crops

Understanding the growth stages of cereal crops is essential for effective crop management. These stages influence fertilization, irrigation, disease control, and overall yield optimization. The Zadoks scale provides a standardized system to track these stages and ensure timely agricultural interventions.[W7]

I.4.2 The Zadoks Scale

The Zadoks scale is a classification system used to describe the different growth stages of cereals. It divides the plant's development into 10 main phases, each further divided into 100 specific stages. This scale is widely used by farmers and researchers to track crop growth and optimize agricultural practices, such as applying fertilizers and fungicides at the right time.[W7]

Zadoks Stage	Description
GS00-GS09	Germination : Beginning of the cycle with seed germination.
GS10-GS19	Seedling growth : Emergence of the first leaves.
GS20-GS29	Tillering : Development of tillers (secondary shoots).
GS30-GS39	Stem elongation : Formation of nodes and key leaves.
GS40-GS49	Booting and spike development : Rapid growth phase.
GS50-GS69	Heading and flowering : Critical stage for plant reproduction.
GS70-GS99	Grain filling and maturation : Grain formation and drying.

Table I.1 – Cereal growth stages according to the Zadoks scale [W7]

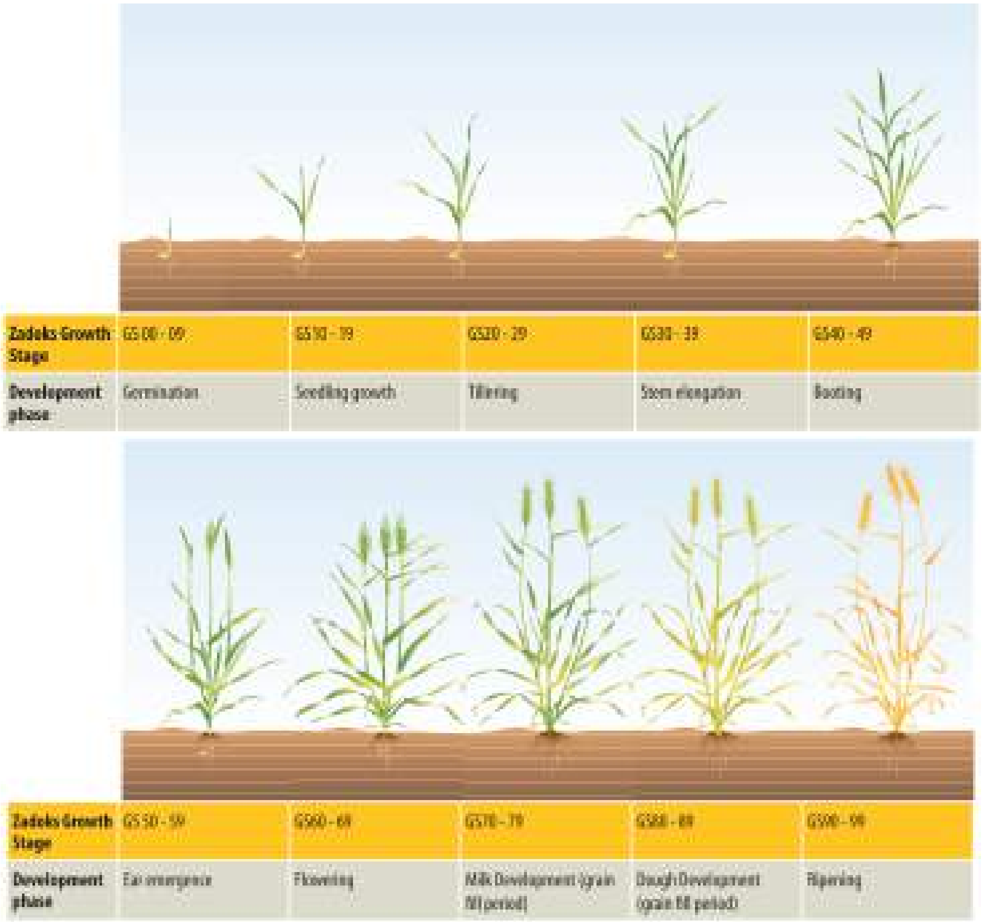


Figure I.2 – Cereal growth stages according to the Zadoks scale [W7]

I.4.3 Disease sensitive phases

Some growth stages are particularly sensitive to infections :

GS30-GS33 (Beginning of stem elongation) : At this stage, the plant starts growing vertically. This is the best time to apply the first fungicides to protect the new leaves.[W7]

FIGURE I.3 – Growth Stage 32 [W7]

GS37-GS39 (Flag leaf emergence) : The flag leaf is the most important for photosynthesis and grain filling. Protecting it from rust and septoria helps ensure a good yield. [W7]

FIGURE I.4 – Growth Stage 39 [W7]

GS50-GS59 (Heading) : The spike (ear) gradually emerges from the plant. It becomes highly vulnerable to fusarium, which can produce toxins dangerous for human and animal consumption.[W7]

Figure I.5 – Growth Stage 55 [W7]

GS60-GS69 (Flowering) : This is a critical period when diseases can prevent grain formation. An infection at this stage can cause major production losses.[W7]

Figure I.6 – Growth Stage 65 [W7]

By applying treatments at the right time, farmers can reduce the impact of diseases and protect their crop yield.

I.5 Challenges in Cereal Crop Cultivation

I.5.1 Impact of Climate Change

Climate change has a big impact on cereal production around the world. Changes in temperature, rainfall, and carbon dioxide levels affect the yields of crops like wheat, maize, and rice. In colder regions, higher CO2 levels can help increase wheat and maize yields. But in areas near the equator, these crops may produce less because of high temperatures and drought. Scientists predict that wheat yields could drop by 3 to 13% by the middle of the century and up to 17% by the end of the century due to rising temperatures. For rice, production may also decrease in many major growing countries because of water shortages made worse by climate change. To reduce these negative effects, farmers can change planting dates, improve water and fertilizer management, develop stronger crop varieties, and expand farming areas.yields.[FFA+23]

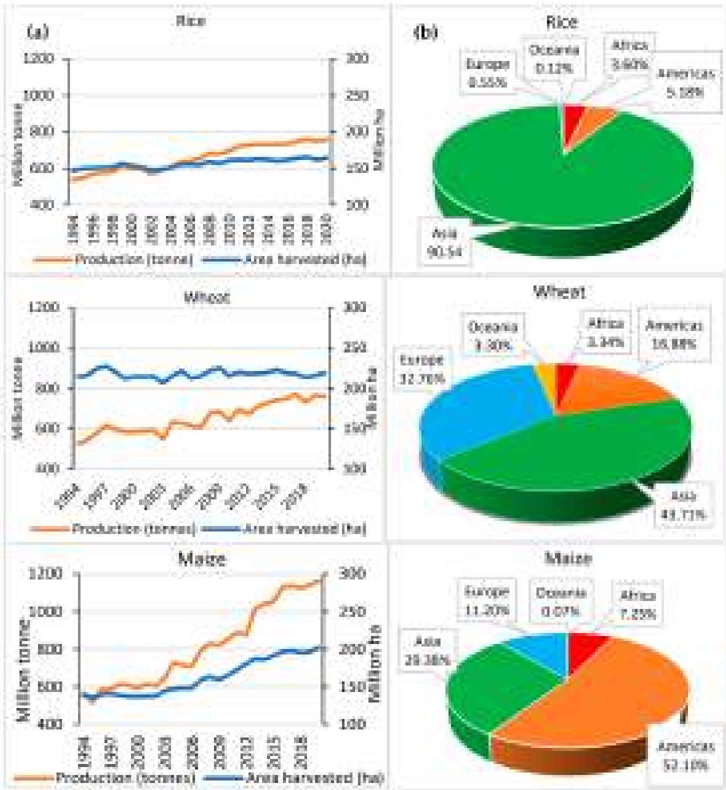


FIGURE I.7 – Worldwide (a) total production, harvested area, and (b) production share by region of wheat, rice, and maize 1994–2020[FFA+23]

I.5.2 Financial and Logistical Barriers

Money and organization problems make it harder to fight cereal diseases. Many farmers cannot afford modern technologies to prevent and treat these diseases, which makes it difficult to control them. To better protect crops, farmers need good seeds, efficient irrigation systems, and sustainable farming methods to better withstand climate changes.[W8]

I.5.3 Cereal disease

I.5.3.1 Wheat Diseases

Wheat is a crop that is vulnerable to many diseases caused by fungi, bacteria, and viruses. Some of the most common are rust diseases, such as :

a)yellow rust (Puccinia striiformis) [Figure I.8] and **brown rust (Puccinia recondita)** [Figure I.9], which create spots on the leaves and reduce photosynthesis. In severe cases, they can cause yield losses of up to 40%.[FHKS18]

FIGURE I.8 – Yellow Rust [W8]

FIGURE I.9 – Brown Rust [W10]

b)septoria (Zymoseptoria tritici) [Figure I.10] is another common disease which appears after winter and causes leaf spots. Without treatment, it can lead to yield losses of up to 50%.[FHKS18]

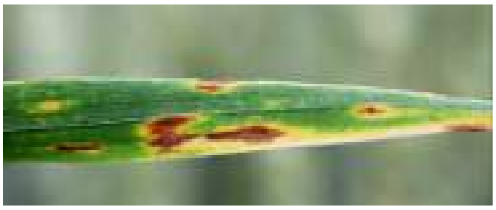


FIGURE I.10 – Septoria [W10]

c)Powdery mildew (Blumeria graminis) [Figure I.11], often seen in spring, creates white patches on leaves and stems, slowing wheat growth.[FHKS18]

FIGURE I.11 – Powdery Mildew [W12]

I.5.3.2 Corn Diseases

Corn can be affected by several fungal diseases that weaken its growth and reduce yields.

a)Common Rust (Puccinia sorghi) [Figure I.12] appears around flowering, especially in warm and humid conditions. It causes orange-brown pustules on the leaves, reducing leaf area and potentially lowering yields.[W14]

FIGURE I.12 – Common Rust [W15]

b)Gray Leaf Spot (Cercospora zeae-maydis) [Figure I.13] develops after flowering, when humidity is high. It causes gray spots on the leaves, reducing the plant's ability to absorb sunlight and produce energy, which can decrease yields.[W13]

Figure I.13 – Gray Leaf Spot [W16]

c)Anthracnose (Colletotrichum graminicola) [Figure I.14] mainly attacks the stem, causing black streaks and rot. This disease appears around flowering and can lead to significant losses in very humid conditions.[W14]

Figure I.14 – Anthracnose [W16]

d)Corn Leaf Blight (Exserohilum turcicum) [Figure I.15] affects corn from early growth to flowering, forming long spots on the leaves. This disease can cause serious yield losses, especially in warm and humid weather.[PP+87]

Figure I.15 – Corn Leaf Blight [W16]

I.5.3.3 Rice Diseases

Rice can get many diseases caused by fungi, bacteria, and viruses. These diseases can damage the plants and reduce rice production.

a)Rice Blast (Magnaporthe oryzae)[Figure I.16] Affects rice from early growth to flowering. It causes round spots on leaves and panicles, which can lower yields.[HZV+25]

Figure I.16 – Rice Blast [W18]

b)Bacterial Leaf Blight (Xanthomonas oryzae)[Figure I.17] Can happen at any time, but is most dangerous at the start of the season. It creates lines on leaves and can kill plants.[LCWY25]

Figure I.17 – Bacterial Leaf Blight [W19]

c)Tungro Disease (Rice tungro virus)[Figure I.18] Mostly affects rice after early growth. It makes the plants yellow and weak, and grains become smaller.[W17]

Figure I.18 – Tungro Disease [W20]

d)Sheath Blight (Rhizoctonia solani)[Figure I.19] Appears after early growth and makes brown patches on leaf sheaths, reducing the plant's strength.[W17]

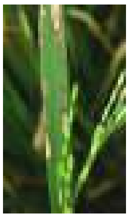


Figure I.19 – Sheath Blight [W21]

e)Brown Spot (Cochliobolus miyabeanus)[Figure I.20] Affects rice during active growth, creating brown spots on leaves, making photosynthesis harder.[W17]

Figure I.20 – Brown Spot [W22]

f)Leaf Scald (Rhynchosporium oryzae)[Figure I.21] Causes white or brown streaks on leaves, which reduces plant energy.[W17]

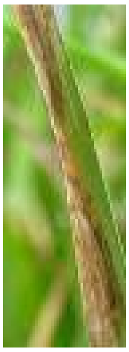


Figure I.21 – Leaf Scald [W23]

I.5.3.4 Barley Diseases

a)Net Blotch (Helminthosporium spp.)[Figure I.22]
Symptoms : Long brown lesions with yellow halos on leaves.
Favorable Conditions : Cool temperatures (around 15°C), rain, and wind.
Impact : Can cause yield losses of up to 50 q/ha, especially in winter barley. [W24]

Figure I.22 – Net Blotch [W24]

b)Leaf Scald (Rhynchosporium spp.)[Figure I.23] **Symptoms :** Brown or gray spots on leaves, often spreading in patches.
Favorable Conditions : High humidity.
Impact : Found in many regions and can cause significant losses.[W25]

Figure I.23 – Leaf Scald [W24]

c)Ramularia Leaf Spot (Ramularia spp.)[Figure I.24]
Symptoms : Small rectangular brown spots with yellow edges, similar to net blotch.
Favorable Conditions : Warm temperatures (20-28°C) and high humidity.
Impact : Appears late in the season and is often linked to non-parasitic stress.[W24]

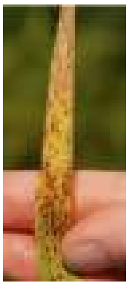


FIGURE I.24 – Ramularia Leaf Spot [W24]

d)Brown Rust (Puccinia hordei)[Figure I.25]
Symptoms : Small brown pustules on leaves that release spores.
Favorable Conditions : Moderate temperatures and high humidity.
Impact : Usually appears during stem elongation and can weaken plants.[W25]

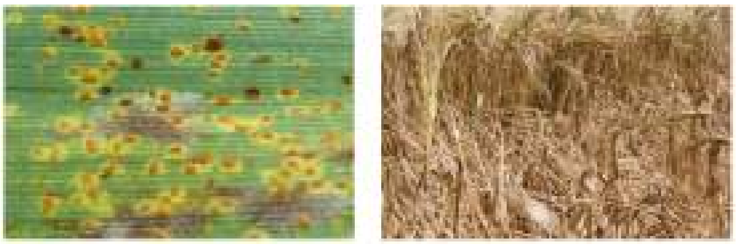


FIGURE I.25 – Brown Rust [W27]

e)Powdery Mildew (Blumeria graminis f. sp. hordei)[Figure I.26]
Symptoms : White powdery coating on leaves and stems.
Favorable Conditions : Light rain that prevents spores from spreading.
Impact : Can be limited by weather conditions but may affect plant health.[W26]

FIGURE I.26 – Powdery Mildew [W26]

I.6 Cereal Disease Management

Cereal diseases can cause big losses for farmers. To fight them, we use two types of methods : traditional methods and new technologies.

I.6.1 Traditional Methods

These methods have been used for a long time to stop diseases from spreading.

I.6.1.1 Using resistant varieties

Some types of cereals are naturally stronger against diseases. For example, some wheat varieties resist brown rust (Puccinia triticina).[BDS25]

I.6.1.2 Crop rotation

Changing crops every year prevents diseases from staying in the soil. For example, switching between wheat and maize can reduce fungal infections.[Oil24]

I.6.1.3 Good farming practices

Plant cereals with enough space to reduce humidity, which can cause diseases.[W28]
Clean fields after harvest to remove infected plant remains.[W29]
Use fertilizers carefully because too much nitrogen can increase diseases.[RWG21]

I.6.1.4 Chemical treatments

Fungicides and insecticides help fight diseases, but they must be used carefully to avoid resistance and protect the environment.[PA14]

I.6.2 New Technologies

New technologies help detect and fight diseases faster and more effectively.

I.6.2.1 Early detection with images and sensors

Special cameras (hyperspectral and multispectral) : These can see disease symptoms before they are visible to the human eye.
Drones and field sensors : These monitor crops and warn farmers if there is a problem.

I.6.2.2 Artificial intelligence and agricultural data

Weather and soil-based alert systems : These predict disease risks and help farmers make better decisions.
Mobile apps : Farmers can take a picture of a plant, and the app will identify the disease and give advice.

I.6.3 A Combined Approach for Better Management

The best way to control diseases is to use multiple methods together :
-Follow good farming practices.
-Use new technologies to detect diseases early.
-Reduce pesticide use with natural solutions.
Good disease management helps protect crops, increase yields, and protect the environment.

I.7 Datasets Available

I.7.1 Wheat Datasets

I.7.1.1 Wheat Plant Diseases

This dataset [W32] includes a collection of high-resolution images(14,155 images) captured from real-world wheat fields, covering various wheat diseases and pests. It consists of : **-Pests :** Aphid, Mite, Stem Fly
-Rusts : Black Rust (Stem Rust), Brown Rust (Leaf Rust), Yellow Rust (Stripe Rust)
-Fungal Diseases :
Smut (Loose, Flag)
Common Root Rot
Helminthosporium Leaf Blight (Leaf Blight)
Wheat Blast
Fusarium Head Blight (Scab)
Septoria Leaf Blotch
Spot Blotch
Tan Spot
Powdery Mildew
Healthy

I.7.1.2 GWHD Dataset

This dataset consists only of healthy wheat growth, utilizing object detection. It includes 4,700 high-resolution RGB images and 190,000 labeled wheat heads, collected from various countries worldwide at different growth stages, covering a diverse range of genotypes.[DMST+20]

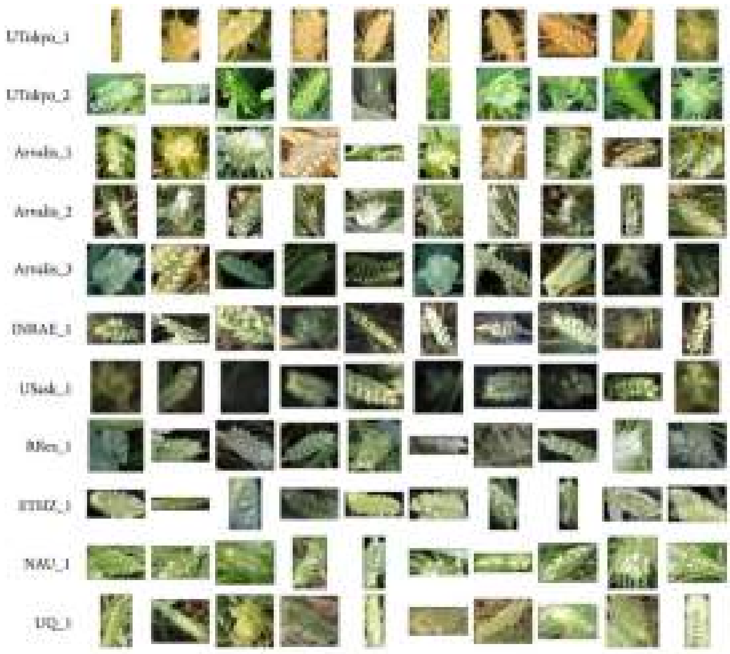


FIGURE I.27 – Dataset GWHD using bounding box [DMST+20]

I.7.2 Maize Datasets

I.7.2.1 Corn or Maize Leaf Disease Dataset

This dataset is designed for the classification of corn (maize) leaf diseases. It contains labeled images of maize leaves categorized into four classes : [W30]
-Common Rust : 1,306 images
-Gray Leaf Spot : 574 images
-Blight : 1,146 images
-Healthy : 1,162 images

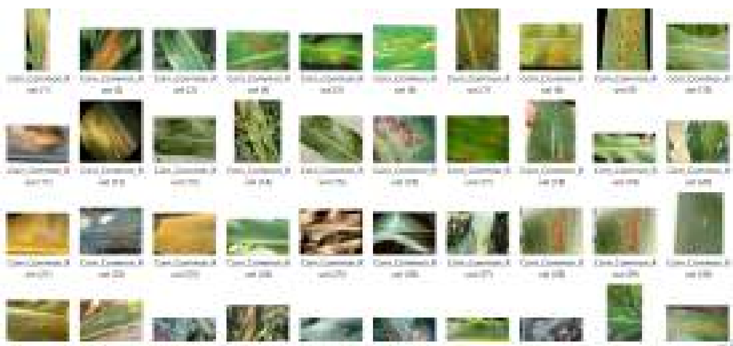


FIGURE I.28 – Common Rust [W30]

FIGURE I.29 – Gray Leaf Spot [W30]

FIGURE I.30 – Blight [W30]

FIGURE I.31 – Healthy [W30]

I.7.3 Rice Datasets

I.7.3.1 Rice Leaf Diseases Detection

This dataset contains annotated images for the classification of eight rice leaf diseases and healthy leaves. It includes over 11,000 images covering : [W31]
Bacterial Leaf Blight : 1,197 images
Brown Spot : 1,546 images
Healthy Rice Leaf : 1,085 images
Leaf Blast : 1,748 images
Leaf Scald : 1,332 images

Narrow Brown Leaf Spot : 954 images
Neck Blast : 1,000 images
Rice Hispa : 1,299 images
Sheath Blight : 1,629 images

I.8 Conclusion

Cereal crops like wheat, maize, rice, and barley are very important for food and the economy all over the world. But they can get sick because of fungi, bacteria, and viruses. These diseases can reduce the amount of food we have and make prices go up. To protect these crops, farmers use both old methods like crop rotation and new technology like sensors and smart cameras. These tools help find diseases early and stop them before they cause big problems. There are also many image datasets that help build smart systems to recognize plant diseases. This makes it easier for farmers to take care of their crops. The next chapter will talk about how Machine Learning in Agriculture is helping farmers grow better crops and control diseases more easily and making farming smarter and more efficient.

CHAPTER II

MACHINE LEARNING IN AGRICULTURE

II.1 Introduction

Cereal crops are essential for global food security, but they are often affected by various diseases that can seriously reduce yield and quality. As mentioned in Chapter 1, these diseases can spread quickly if not detected early. Early and accurate detection of cereal diseases is very important. It helps farmers take fast action and reduce crop loss. Traditional methods are often slow and depend on expert knowledge, which is not always available. To solve this problem, new technologies like artificial intelligence (AI) and machine learning (ML) are becoming popular. These smart systems can analyze images of leaves and help detect and identify diseases faster and more precisely.

II.2 Machine Learning

Machine learning is a field of computer science where systems can learn and improve automatically from experience without being manually programmed. Unlike traditional programming, where a developer writes specific instructions for each situation, machine learning allows computers to learn from data. By using algorithms, the machine studies large amounts of data to find patterns and make decisions. The more data it receives, the better it becomes at completing tasks or making predictions.[W43]

II.2.1 Types of Machine Learning

II.2.1.1 Supervised Learning

Supervised learning is a type of machine learning where the model is trained on labeled data. Each input comes with a known output, and the model learns to map inputs to the correct outputs.[W44]

II.2.1.2 Unsupervised Learning

Unsupervised learning deals with data that has no labels. The goal is to find patterns, structures, or groupings in the data.[W44]

II.2.1.3 Reinforcement Learning

Reinforcement learning involves an agent that learns by interacting with an environment. The agent receives rewards or penalties based on its actions and tries to learn the best strategy to maximize long-term rewards. [W44]

II.2.1.4 Semi-Supervised Learning

Semi-supervised learning uses a small amount of labeled data and a large amount of unlabeled data. This method is useful when labeling data is expensive or time-consuming. [W44]

Aspect	Supervised Learning	Unsupervised Learning	Semi-Supervised Learning	Reinforcement Learning
Data Requirement	Labeled data	Unlabeled data	Both labeled and unlabeled data	Interacts with an environment
Outcome	Predict specific outputs	Discover hidden patterns	Combines prediction and discovery	Optimizes sequential decisions
Use Case	Classificatio n, Regression	Clustering, Dimensionality Reduction	Complex problems with limited labels	Dynamic environments

FIGURE II.1 – Key Differences Between Machine Learning Types [W46]

II.3 Deep Learning

Deep learning is a type of machine learning that uses large neural networks with many layers to learn from data. These networks are designed to work like the human brain, with layers of connected units called neurons. Deep learning can automatically learn features and patterns from large and complex datasets, especially unstructured data like images, sounds, or text. Unlike basic machine learning, deep learning improves its performance through repetition and does not always need human help to correct mistakes.[W43]

II.4 Machine Learning vs Deep Learning

Artificial Intelligence (AI) is the ability of computers or robots to do tasks that usually need human thinking, such as learning, reasoning, or problem-solving. Machine learning and deep learning are two types of AI. Machine learning allows a computer to learn and improve from data with little help from humans. Deep learning is a more advanced type of machine learning. It uses artificial neural networks systems designed to work like the human brain—to learn complex patterns from large amounts of data.[W43]

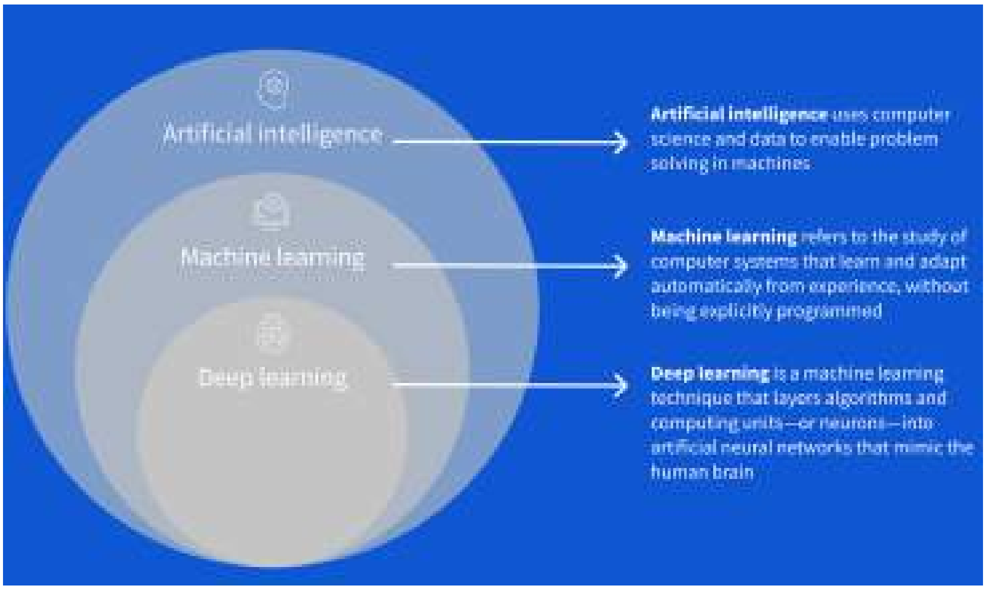


Figure II.2 – Machine Learning vs Deep Learning [W43]

II.5 Transfer learning

Transfer learning is a method in machine learning where a model developed for one task is reused as a starting point for a different but related task. This technique is especially helpful when the new task has limited labeled data. By using a model that has already learned general features from a large dataset, we can improve the learning process for the new task.[W45]

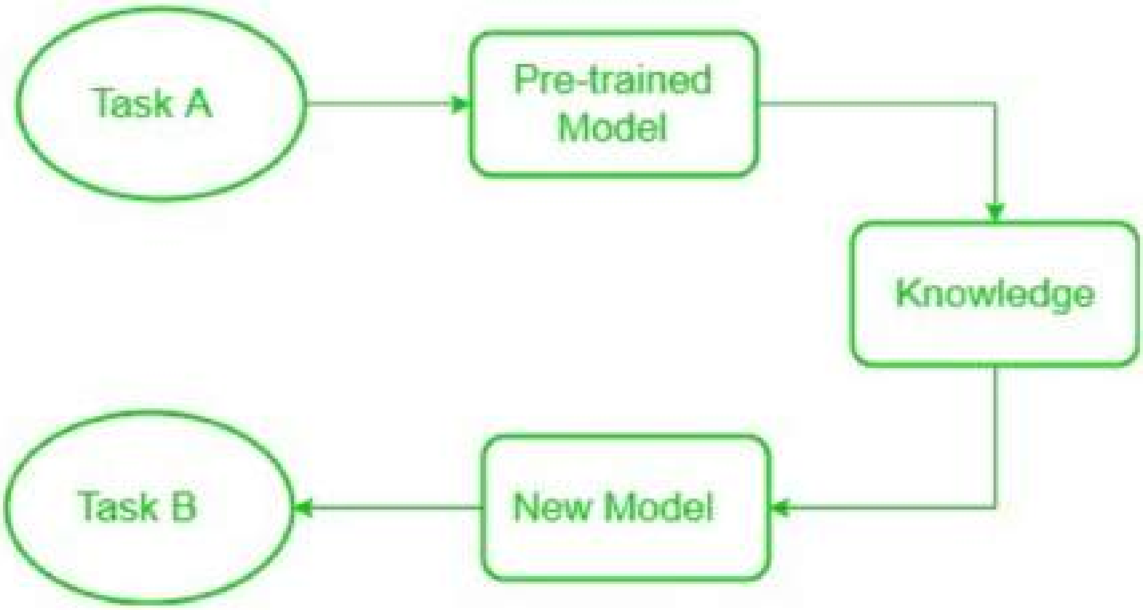


FIGURE II.3 – Transfer learning [W45]

II.6 Machine learning in agriculture

Machine learning is transforming agriculture by making farming smarter, faster, and more sustainable. With the power of data, farmers can now detect plant diseases before they spread, predict crop yields with high accuracy, and manage water and fertilizers more efficiently. Instead of treating the entire field the same way, they can apply the right solution at the right place and time. This reduces waste, protects the environment, and increases productivity. Machine learning also helps monitor animal health, detect pests early, and adapt to changing weather conditions. It acts like an intelligent assistant that learns from the land, supports decision-making, and empowers farmers to feed the world more effectively.[W47]

II.7 Performance Metrics

To check the performance of a deep learning classification model,it's important to calculate a set of fundamental metrics derived from the confusion matrix. These values allow us to quantify how well the model distinguishes between different classes. The key components are defined as follows :
True Positive (TP) : The number of instances where the model correctly predicted the positive class (For example : the model predicted YES, and the actual label was also YES).
True Negative (TN) : The number of instances where the model correctly predicted the negative class (For example : the model predicted NO, and the actual label was also NO).
False Positive (FP) : The number of instances where the model incorrectly predicted

the positive class (For example : the model predicted YES, but the actual label was NO). This is also known as a Type I error.
False Negative (FN) : The number of instances where the model incorrectly predicted the negative class (For example : the model predicted NO, but the actual label was YES).

II.7.1 Accuracy

Accuracy measures the overall correctness of the model by calculating the proportion of total correct predictions (both positive and negative) among all predictions.

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

II.7.2 Precision

Precision evaluates how many of the instances predicted as positive are actually positive. It reflects the model's ability to avoid false positives.

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

II.7.3 Recall

Recall indicates how many actual positive cases were correctly identified by the model. It reflects the model's ability to detect all relevant instances.

$$\text{Recall} = \frac{TP}{TP + FN}$$

II.7.4 F1-Score

The F1-score is the harmonic mean of precision and recall. It provides a single metric that balances both, especially useful when classes are imbalanced.

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{F1-score} = \frac{2TP}{2TP + FP + FN}$$

II.7.5 Confusion Matrix

The confusion matrix is a tabular representation that summarizes the number of correct and incorrect predictions. It allows visual inspection of classification performance across classes.

	Predicted : YES	Predicted : NO
Actual : YES	TP	FN
Actual : NO	FP	TN

Table II.1 – Confusion matrix for binary classification

II.8 Comparative Study of Research Articles on Cereal Diseases

Article 01 : Discrimination of Deoxynivalenol Levels of Barley Kernels Using Hyperspectral Imaging in Tandem with Optimized Convolutional Neural Network. [FLS20]
This article presents a model using a Convolutional Neural Network (CNN) for the analytical evaluation of hyperspectral imagery (382–1030 nm) and the classification of deoxynivalenol (DON) concentrations within barley grains. To augment precision, preprocessing methodologies such as wavelet transformations and max-min normalization are implemented, in conjunction with variable selection strategies including Competitive Adaptive Reweighted Sampling (CARS) and the Successive Projections Algorithm (SPA). The investigators conducted an analysis of 590 barley specimens sourced from Fusarium-infested agricultural fields, systematically categorizing them into three distinct classifications predicated on DON concentrations : Class I (0.19-1.25 mg/kg), Class II (1.25-5 mg/kg), and Class III (5-14 mg/kg). The refined CARS-SPA-CNN model attained an impressive accuracy rate of 89.41% in differentiating grains exhibiting low DON levels (¡5 mg/kg) from those with elevated concentrations, and 89.81% accuracy in distinguishing between Class I and Class II. These results underscore the considerable promise of hyperspectral imaging coupled with CNN technology for the rapid and non-destructive assessment of DON levels in barley grains.

Article 02 : Barley Disease Recognition Using Deep Neural Networks. [RGD+20]
This study developed a deep learning model to detect barley diseases using RGB images taken directly in the field. Since the dataset was small (312 images), the researchers used transfer learning and data augmentation—like rotating and flipping images—to improve the model's performance. The images, collected from infected fields, were sorted into four groups : healthy plants, scald, net form net blotch (NFNB), and spot form net blotch (SFNB). To make the most of the data, each image was split into 448 × 448 pixel sections, labeled by hand, and enhanced to create more training samples.The researchers tried out different deep learning models, including MobileNet, Xception, and InceptionV3, to see which one performed best. MobileNet turned out to be the best model because it's simple,

efficient, and works well with small datasets. It was able to tell whether a plant was healthy or diseased with 98.63% accuracy and correctly identified the specific disease 93.50% of the time. This means farmers could use deep learning to spot barley diseases early and take quick action to protect their crops.

Article 03 : Detection of Rice Leaf Diseases Using Image Processing. [PP20]

This article presents a method to detect diseases in rice leaves, focusing on bacterial leaf blight, leaf smut, and brown spot. The approach uses image processing techniques like Otsu's method for segmentation and feature extraction methods such as Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG). After that, they used a Support Vector Machine (SVM) to classify the diseases. The best results came from using HOG features with a polynomial SVM, which correctly identified diseases 94.6% of the time. The dataset had 120 images, with 40 for each disease, and came from the UC Irvine Machine Learning Repository. These results show that image processing and machine learning can help detect rice diseases early, giving farmers a useful tool to keep their crops healthy.

Article 04 : Disease Detection, Severity Prediction, and Crop Loss Estimation in Maize Crop Using Deep Learning. [KRD+22]

This study focuses on diseases like Turcicum Leaf Blight and Rust in maize, which reduce crop productivity. Manual detection takes time and needs experts, so the authors created a deep learning system called "Early Maize Disease Detector and Evaluator" (EMDDE). This system uses a real-life dataset labeled by plant experts and includes a custom model, MaizeNet, which achieves 98.50% accuracy. The study collected 2996 images of infected maize leaves, processed them using K-Means clustering to highlight disease areas, and used a nine-layer CNN model optimized for efficiency. The model was trained on 2460 images and evaluated with precision, recall, and F1 score. Results show that MaizeNet detects diseases, estimates severity, and predicts crop loss, with validation from experts. This system automates key agricultural tasks, making it faster and more accurate than traditional methods. It could also be improved by adding environmental and genetic factors.

Article 05 : Hyperspectral Imaging Combined With Deep Transfer Learning for Rice Disease Detection. [FWHZ21]

This study explores the use of hyperspectral imaging and deep transfer learning to detect rice diseases in different cultivars. Fast and accurate disease detection is important for better rice cultivation. Researchers collected hyperspectral data from healthy and diseased rice leaves, focusing on rice leaf blight, rice blast, and rice sheath blight. They tested three deep transfer learning methods : fine-tuning, deep CORrelation ALignment (CORAL), and deep domain confusion (DDC) to improve classification. Fine-tuning performed best, reaching over 88% accuracy, while deep CORAL was good at transferring knowledge between rice varieties. The study shows that hyperspectral imaging with deep learning can help detect rice diseases efficiently. Future research should include more samples and rice varieties for better results. These findings could improve disease management in agriculture.

Article 06 : Image recognition of four rice leaf diseases based on deep learning and support vector machine. [JLC+20]
This study focuses on identifying and classifying four rice leaf diseases using deep learning and SVM. Fast and accurate disease detection is essential for rice production and food security. Researchers used Convolutional Neural Networks (CNNs) to extract features from rice leaf images and then applied Support Vector Machine (SVM) for classification. The dataset included 8,911 images of healthy and diseased rice leaves. Using 10-fold cross-validation, the best SVM parameters were found, achieving 96.8% accuracy. The CNN-SVM combination performed better than traditional methods, making it a promising approach for rice disease diagnosis. The study suggests using larger datasets and improving deep learning models for even better accuracy in the future.
Article 07 : Identification of Maize Leaf Diseases based on Convolutional Neural Network. [Wu21]
This paper focuses on identifying maize leaf diseases using a Convolutional Neural Network (CNN). Accurate disease detection is important for better crop quality and productivity. Traditional methods rely on manual inspection, which can be slow and inaccurate due to human errors and environmental factors. In this study, researchers developed a two-channel CNN model combining features from VGG and ResNet architectures. The dataset included 4,205 images of healthy and diseased maize leaves (big spot, gray leaf spot, and rust). Data augmentation was used to fix class imbalance and improve model performance. The results showed that the two-channel CNN achieved 98.33% accuracy, better than the VGG model (93.33%). The study proves that combining different CNN models can improve disease classification. It highlights the potential of deep learning for automated disease detection in agriculture.
Article 08 : Disease Classification in Maize Crop using Bag of Features and Multiclass Support Vector Machine.[ARM+18]
This study focuses on classifying maize leaf diseases using bag of features and Support Vector Machines (SVMs). Researchers identified three diseases—Cercospora leaf spot, common rust, and leaf blight, along with healthy leaves—using 2,000 images from the PlantVillage database. They applied image processing techniques to extract features, achieving 83.7% accuracy with the bag of features method using SURF and K-means clustering. Other methods, like histogram-based and GLCM features, reached 81.3% accuracy with polynomial kernel SVMs. The results show that combining image processing and machine learning improves disease detection in maize crops. The study highlights the importance of these techniques for sustainable agriculture and suggests future research on larger datasets to improve accuracy.
Article 9 : Investigation on Data Fusion of Multisource Spectral Data for Rice Leaf Diseases Identification Using Machine Learning Methods. [FWZ+20]
This study explores the use of multisource spectral data to identify rice leaf diseases

using machine learning. It focuses on three diseases—leaf blight, rice blast, and sheath blight—and applies hyperspectral imaging (HSI), mid-infrared spectroscopy (MIR), and laser-induced breakdown spectroscopy (LIBS). The researchers used three levels of data fusion—raw data, feature fusion, and decision fusion—to improve classification accuracy. The results showed that HSI models performed best, reaching over 93% accuracy with PCA features. The study highlights that feature and decision fusion enhance disease identification, proving the effectiveness of combining different spectroscopic techniques for better rice disease detection. The findings suggest that advanced data fusion methods can make disease detection more accurate and efficient in agriculture.

Article 10 : Classification of Rice Leaf Diseases Based onMorphological Changes. [SPD12]

The study develops an automated system to classify rice leaf diseases, focusing on blast and brown spot. The authors used image processing techniques to analyze radial hue distribution from infected leaf images. After image acquisition and preprocessing, segmentation techniques were applied to isolate diseased areas. Extracted features, including hue distribution, were used for classification with Bayes' classifier and Support Vector Machine (SVM). The Bayes classifier achieved 79.5% accuracy, while SVM reached 68.1%. The results show that the proposed system provides an efficient method for diagnosing rice leaf diseases, helping to improve disease management and agricultural practices.

Article 11 : Wheat Disease Classification Using Continual Learning. [AKT23]

The article introduces a few-shot learning model using EfficientNet to classify 18 wheat diseases. The model was tested on three datasets, including a manually collected set of 40 images, achieving 93.19% accuracy. This method overcomes the limitations of traditional deep learning by requiring less data and adapting to new disease classes without retraining. It demonstrates great potential for efficient and practical agricultural disease detection.

Article 12 : Automatic detection of yellow rust in wheat using reflectance measurements and neural networks.[MBW+04]

This study proposes a low-cost optical device for remote disease detection in crops to help reduce pesticide use. The focus is on early detection of yellow rust in wheat plants using canopy reflectance. The researchers captured spectral images with a spectrograph placed at spray boom height and developed a normalization method to correct variations in reflectance and light intensity. They used neural networks (MLP) to create disease detection algorithms. The results showed that classification accuracy improved from 95% to over 99%, proving the device's effectiveness. This approach can help in early disease identification, leading to reduced pesticide use and sustainable agriculture.

Article 13 : A Neural Network-Based Approach to Multiple Wheat Disease Recognition. [APA+22]

This study explores computer vision techniques for detecting multiple wheat leaf diseases, including yellow spots, yellow rust, and brown rust. Using neural networks, the researchers achieved high accuracy between 95% and 99%, similar to expert assessments. A multi-label classification approach was introduced, allowing the detection of multiple diseases in a single image. The dataset included wheat leaf images, and preprocessing techniques like rotation, flipping, and normalization were applied to improve performance. The study used GoogleNet, a lightweight neural network, for efficient and accurate disease detection. Evaluation metrics such as accuracy, precision, recall, and F1-score showed excellent results. The model's lightweight design makes it suitable for mobile devices, enabling fast and automated detection in wheat fields. Overall, this method offers a practical solution for real-world agriculture, improving disease management with the potential for mobile applications.

Article 14 : Deep transfer learning model for disease identification in wheat crop. [NJM+23]

This study presents a deep transfer learning model for detecting wheat diseases using artificial intelligence (AI). The researchers used the WheatRust21 dataset, collected under field conditions, which includes cases of stripe rust, leaf rust, and stem rust. The study explored Convolutional Neural Networks (CNNs) and EfficientNet architectures for disease identification. A key feature of this model is its deployment on mobile devices, allowing real-time, on-site disease detection using images. The model achieved 99.35% accuracy, proving the effectiveness of AI-driven methods for identifying wheat diseases. The combination of CNN and EfficientNet further improved detection performance. This research highlights the potential of AI in agriculture, particularly for disease detection, and shows that these models can be practically implemented on mobile devices for field use.

Article 15 : Wheat leaf disease identification based on deep learning algorithms. [XCZ+23]

This study focuses on the Wheat Disease Challenge, highlighting the impact of wheat leaf diseases on agriculture and food security. The researchers developed a deep learning model called RFE-CNN, which integrates Residual Channel Attention Blocks (RCABs), Feature Boosters (FBs), and Embedding-based Metric Learning (EML). They used the LWDCD 2020 dataset and Convolutional Neural Networks (CNNs) for accurate wheat disease identification. The model combines parallel CNNs, RCABs, and FBs to extract important features and improve classification accuracy. It achieved an overall accuracy of 98.83%, with a maximum testing accuracy of 99.95% and an average accuracy of 99.50%. RFE-CNN outperforms traditional CNN models in accuracy, efficiency, and adaptability, proving its effectiveness in identifying wheat diseases. The study suggests future research on improving disease detection across different wheat varieties and ecological conditions using hyperspectral imaging.

Article 16 : Hybrid Deep Learning Model to Detect Uncertain Diseases in Wheat Leaves. [RP22]

The article discusses the serious threat of wheat rust pathogens to global wheat production, causing billions of dollars in losses each year. The study used VGG16 and Capsule Networks, achieving an accuracy of 93% in identifying rust diseases. Rust fungi depend on living host cells to grow and reproduce, making them difficult to control. A major challenge in disease management is the constant emergence of new rust races, which makes genetic resistance harder to maintain. Research has shown that race-specific genes in wheat produce NBS-LRR proteins, which play a key role in resistance to rust pathogens. To manage wheat diseases, farmers use fungicides, cultural practices, and optimized planting times to reduce the impact of rust and other diseases on wheat production.

Article 17 : Classification of wheat diseases using deep learning networks with field and glasshouse images. [LHMB23]

This article highlights the importance of identifying and controlling wheat diseases, such as yellow rust, Septoria tritici blotch, brown rust, and mildew, which greatly affect crop yield and quality. These diseases can look similar at certain growth stages, making them difficult to distinguish. To solve this problem, the study used deep learning, specifically convolutional neural networks (CNNs), to automatically detect and classify wheat diseases from images. Researchers collected over 19,000 images from fields and glasshouses in the UK and Ireland in 2019, covering five categories : Septoria, yellow rust, brown rust, mildew, and healthy wheat. They developed a CNN model called CerealConv, which has 13 convolutional layers with batch normalization, max pooling, and dropout to improve performance. CerealConv achieved an accuracy of over 97%, performing 2% better than the most accurate expert pathologist in manual classification. It also classified 999 images faster and more accurately than human experts. When critical parts of the images were masked, its accuracy dropped, proving that the model relies on relevant features for disease identification. This study confirms that deep learning models like CerealConv can effectively analyze real-world wheat disease images and perform as well as, or even better than, expert pathologists.

Article 18 : Computer Vision Framework for Wheat Disease Identification and Classification Using Jetson GPU Infrastructure. [ARSG21]

This article highlights the importance of wheat in Ethiopia, where it is the second most important grain crop, contributing 14% of the total calorie intake. Wheat is mainly grown by smallholder farmers for subsistence farming. Deep learning-based classification systems help in the early detection of wheat diseases, improving disease management. However, Ethiopian wheat farmers face challenges such as limited access to market information and weak market connections, which reduce their productivity and profits. The genetic diversity of wheat is essential for developing disease-resistant varieties, making genetic research and breeding programs important. The VGG19 model has shown high accuracy in classifying wheat diseases, proving its potential for automated disease detection. Automating wheat disease identification can help reduce crop losses, support Ethiopian farmers, and improve food security by increasing wheat productivity.

Article 19 : Leaf and spike wheat disease detection classification using an improved deep convolutional architecture. [**GSSS21**]
This paper highlights the importance of wheat as a widely consumed grain and the impact of diseases on crop loss. Automatic wheat disease classification using deep learning is presented as a way to improve crop yield by detecting and managing diseases efficiently. While deep learning classifiers are powerful, they can face challenges like overfitting and the need for large datasets and high computational power. To address this, transfer learning is used to enhance performance, especially when data and resources are limited, by using pre-trained models. The proposed model is based on VGG16 and achieves 97.88% accuracy in classifying 10 wheat diseases. This high accuracy demonstrates the model's effectiveness in identifying wheat diseases, which helps in early disease management and reducing crop losses. The success of VGG16 highlights its potential for real-world agricultural use, improving crop management and food security.
Article 20 : Identification of plant diseases using convolutional neural networks. [**JUP21**]
This paper explores the use of convolutional neural networks (CNNs) to classify soybean leaf diseases using pre-trained AlexNet and GoogleNet models. The dataset, collected from Kolhapur district, Maharashtra, India, includes 649 images for training AlexNet and 550 images for training GoogleNet, categorized into four classes : bacterial blight, brown spot, frogeye leaf spot, and healthy leaves. Both models achieved over 95% accuracy, demonstrating their effectiveness in accurately identifying soybean leaf diseases.
Article 21 : A generic approach for wheat disease classification and verification using expert opinion for knowledge-based decisions. [**NNRN+19**]
This study highlights how crop diseases reduce agricultural productivity due to outdated identification methods and limited knowledge sharing. While farmers have local expertise, the lack of platforms restricts regional information exchange. Research shows that diseases, cultivation methods, and insufficient knowledge contribute to declining crop yields. To improve disease identification and enable timely intervention, this study utilizes crowd-sourced data from agricultural stakeholders. Traditional machine learning models struggle with diverse agricultural regions due to their reliance on static data and lack of expert insights. To address this, high-quality images and symptom-based data were collected through crowdsourcing and augmented for training. A novel approach combining Decision Trees (DT) and deep learning models was proposed for wheat disease classification. Expert validation improved DT accuracy by 28.5% and CNN accuracy by 4.3%, achieving 97.2% accuracy and leading to decision rules for wheat disease classification in a knowledge-based system.
Article 22 : Classifying Wheat Hyperspectral Pixels of Healthy Heads and Fusarium Head Blight Disease Using a Deep Neural Network in the Wild Field. [**LHZ+17**]
This study focuses on classifying Fusarium Head Blight disease in wheat using deep neural

networks and hyperspectral imaging. The experiment took place from April 29 to May 15, 2017, in a wild field setting, considering factors like wind, humidity, and temperature that affect imaging. A total of 90 wheat ear samples were divided into 10 regions for hyperspectral imaging and a deep convolutional neural network (CNN) was used for analysis. The model's performance was evaluated using precision, recall, and F1 score. The results show that deep neural networks can effectively diagnose Fusarium Head Blight using hyperspectral imaging. The study highlights experimental conditions, sample division, and evaluation metrics, suggesting that hybrid neural networks could further improve disease diagnosis in wheat, leading to better agricultural disease management.

II.9 Comparison Of Articles

Title of Article	**Architecture**	**Dataset**	**Results**
Discrimination of Deoxynivalenol Levels of Barley Kernels Using Hyperspectral Imaging in Tandem with Optimized CNN	CNN with CARS-SPA optimization	590 barley samples (hyperspectral images 382–1030 nm)	89.41% accuracy for low vs. high DON levels, 89.81% for Class I vs. Class II
Barley Disease Recognition Using Deep Neural Networks	MobileNet, Xception, InceptionV3 (Transfer Learning)	312 RGB images (four classes : no disease, scald, NFNB, SFNB)	98.63% accuracy (binary), 93.50% (multiclass)
Detection of Rice Leaf Diseases Using Image Processing	SVM with HOG and LBP	120 rice leaf images (three diseases)	94.6% accuracy with polynomial kernel SVM + HOG
Disease Detection, Severity Prediction, and Crop Loss Estimation in Maize Crop Using Deep Learning	CNN (custom MaizeNet)	2996 maize leaf images	98.50% accuracy
Hyperspectral Imaging Combined With Deep Transfer Learning for Rice Disease Detection	Deep Transfer Learning (Fine-tuning, CORAL, DDC)	Hyperspectral data of rice leaves	88% accuracy (fine-tuning performed best)
Image Recognition of Four Rice Leaf Diseases Based on Deep Learning and SVM	CNN + SVM	8,911 rice leaf images	96.8% accuracy with CNN-SVM

Identification of Maize Leaf Diseases Based on CNN	Two-channel CNN (VGG + ResNet)	4,205 maize leaf images (big spot, gray leaf spot, rust)	98.33% accuracy (two-channel CNN), 93.33% (VGG alone)
Disease Classification in Maize Crop Using Bag of Features and Multiclass SVM	SVM with bag of features (SURF, K-Means)	2,000 maize images (PlantVillage)	83.7% accuracy (bag of features + SVM)
Investigation on Data Fusion of Multisource Spectral Data for Rice Leaf Diseases Identification	Machine Learning (PCA, Decision Fusion)	HSI, MIR, LIBS spectral data (rice diseases)	93% accuracy (HSI with PCA features)
Classification of Rice Leaf Diseases Based on Morphological Changes	Bayes Classifier, SVM	Radial hue distribution from infected rice leaves	79.5% (Bayes), 68.1% (SVM)
Wheat Disease Classification Using Continual Learning	Few-shot learning (EfficientNet)	Three datasets (including 40 manually collected images)	93.19% accuracy
Automatic Detection of Yellow Rust in Wheat Using Reflectance Measurements	Neural Network (MLP)	5137 leaf spectra	95–99% accuracy
A Neural Network-Based Approach to Multiple Wheat Disease Recognition	GoogleNet (Lightweight CNN)	Wheat leaf images	95–99% accuracy, multilabel classification
Deep Transfer Learning Model for Disease Identification in Wheat Crop	CNNs, EfficientNet	WheatRust21 dataset (stripe rust, leaf rust, stem rust)	– (results not fully detailed)
Wheat leaf disease identification based on deep learning algorithms	Two parallel CNNs (LWDCD 2020)	LWDCD 2020	99.95% accuracy
Hybrid Deep Learning Model to Detect Uncertain Diseases in Wheat Leaves	VGG-16 and a capsule network	No name mention	93% accuracy
Classification of wheat diseases using deep learning networks with field and glasshouse images	MobileNet, InceptionV3, VGG16	WheatleavesUK	91.43% accuracy

Computer Vision Framework for Wheat Disease Classification Using Jetson GPU Infrastructure	InceptionV3, ResNet50, and VGG16/19	Bishoftu dataset	99.38% accuracy
Leaf and spike wheat disease detection	classification using an improved deep convolutional Architecture	VGG16 (LWDCD2020)	97.88% accuracy
Identification of plant diseases using convolutional neural networks	AlexNet, GoogleNet	Soybean leaf	95% accuracy
A generic approach for wheat disease classification and verification using expert opinion for knowledge-based decisions	CNN	No name mention	97.5% accuracy
An in-field automatic wheat disease diagnosis system	GG-FCN-VD16 and VGG-FCN-S	Wheat Disease Database 2017 (WDD2017)	97.95% and 95.12% accuracies
Classifying Wheat Hyperspectral Pixels of Healthy Heads and Fusarium Head Blight Disease Using a Deep Neural Network in the Wild Field	Convolutional Neural Network (CNN)	Wild Field 2018	75% accuracy, 74.3% validation accuracy

Table II.2 – Comparison of Articles on Cereal Plants Disease Detection

After analyzing several research articles on cereal disease detection, it is clear that deep learning methods—particularly Convolutional Neural Networks (CNNs)—are the most effective for classifying plant images, whether based on RGB or hyperspectral imaging. These approaches enable fast, accurate, and automated disease detection. However, most studies propose "all-in-one" models that classify all disease types in a single step. Based on these observations, we decided to adopt a different approach, using a sequential master-slave architecture. In our method, a first model (DDN1) detects whether the plant is healthy or diseased, and if an infection is detected, a second model (DDN2) identifies the specific disease. This architecture is designed to improve the robustness, modularity, and accuracy of the diagnosis.

II.10 Conclusion

In this chapter, we explored the fundamental concepts of machine learning and its relevance in the field of agriculture. We began by introducing the main types of learning : supervised, unsupervised, reinforcement, and semi-supervised learning, followed by an overview of deep learning and its growing impact on image-based diagnosis. We then discussed the differences between machine learning and deep learning, highlighting their respective advantages in various agricultural tasks. Additionally, we introduced the concept of transfer learning, which allows models to benefit from previously learned knowledge, especially useful when data is limited. Finally, we presented a comparative study of several research works focused on cereal disease detection, providing insight into current trends, techniques, and performance outcomes. This analysis helps identify the most promising approaches and highlights areas that require further investigation.
The next chapter will focus on the design and conception of our proposed system, based on the knowledge and findings discussed here.

CHAPTER III

CONCEPTION

III.1 Introduction

Our chapter details the process that was followed to come up with a system that can make use of RGB images in the detection and classification of diseases in cereal leaves. The idea was to build an intelligent technology that is capable of, first, establishing the health state of a leaf and then finding out the disease type if it's not healthy.
A two-step process, more commonly referred to as a master-slave architecture, has been utilized in our system : Through DDN1, the first model detects whether the leaf is healthy or unhealthy.
If the leaf is sick, the second model, DDN2 is employed to confirm it and identify the disease it has precisely.
We have also extended our proposed method to the three categories of cereal crops like wheat, maize, and rice. Thus, six deep learning models are necessary with two models developed for each cereal (one model for detection and another for identification).
This chapter also details how the system was designed, the datasets as well as data preparation, and model building and training steps.

III.2 General architecture of the system

The system is structured in two sequential stages based on a master-slave architecture, Where the first stage (master) makes the initial decision, guiding the process, while the second stage (slave) performs a deeper analysis only if necessary. In the first stage, the system determines whether a cereal leaf (wheat, maize, or rice) is healthy or diseased. If the leaf is healthy, the process ends immediately. However, if the leaf is classified as diseased, the system moves to the second stage to identify the specific disease.
The first stage uses the DDN1 model, where each model is specialized by crop type :

DDN1_W for wheat, DDN1_M for maize, and DDN1_R for rice. Each model takes an image of a cereal leaf and performs a binary classification : healthy or diseased.
If the result is "diseased", the image is passed to the second stage, which uses the DDN2 model. Again, each model is crop-specific : DDN2_W for wheat, DDN2_M for maize, and DDN2_R for rice. These models perform multi-class classification to determine the exact disease affecting the plant. This two-stage design simplifies the classification task, improves model performance, and makes the system easier to maintain and update.

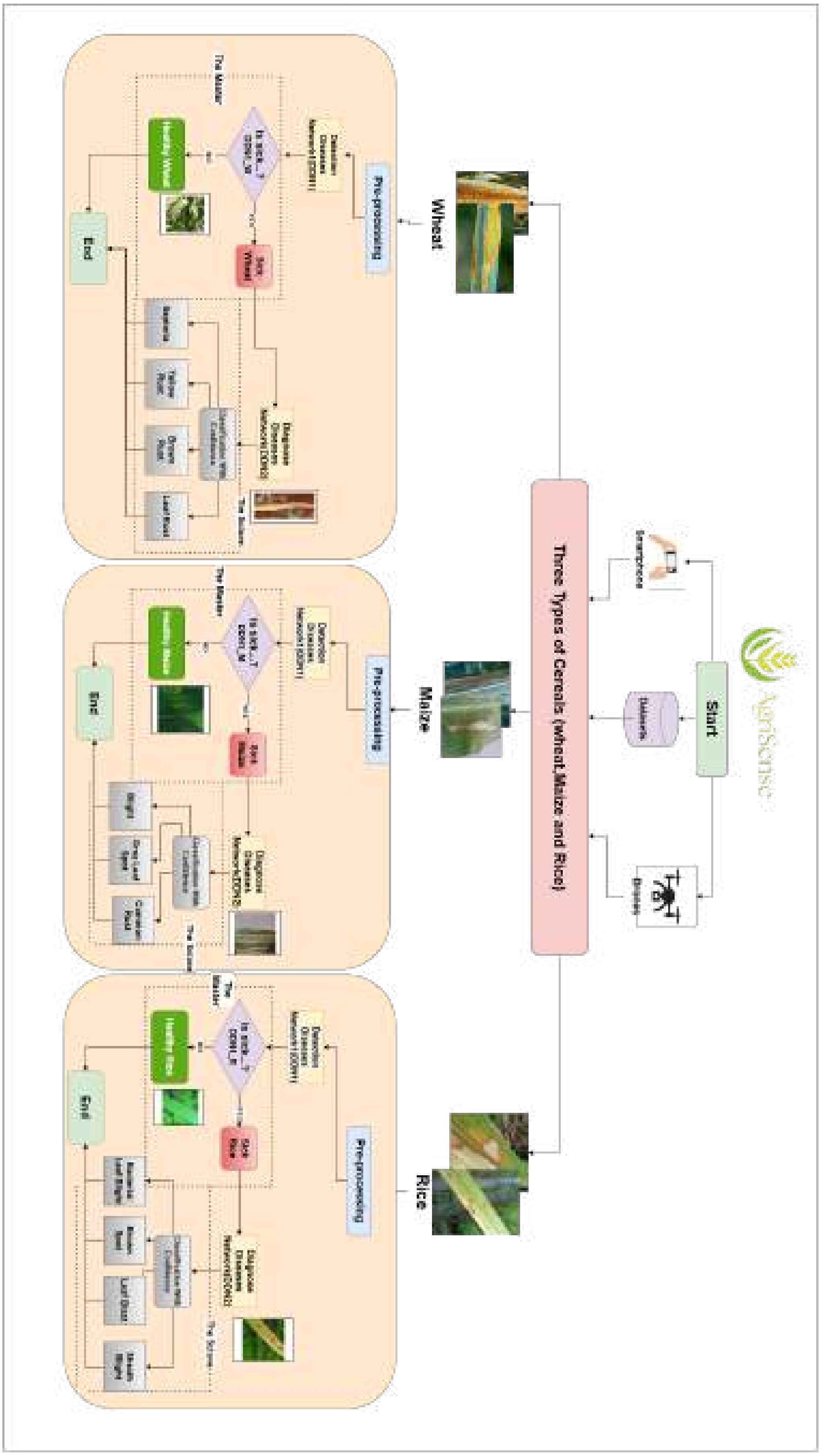


FIGURE III.1 – Architecture of Our System

III.3 Description of the Datasets

We use three different RGB image datasets in this study. Each one is about a specific cereal : wheat, maize, or rice. The images in these datasets show cereal leaves, and each image is labeled to say if the leaf is healthy or has a certain disease.

III.3.1 Wheat Dataset

To better understand the structure of the Wheat Dataset, the following table [Figure III.2] displays the different classes, a representative image for each, and the corresponding image count.

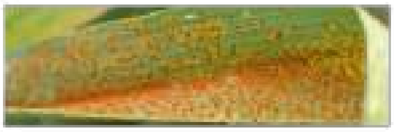
Wheat Dataset		
Classes	Example	Number of pictures
Healthy		735
Brown Rust		1128
Yellow Rust		1396
Septoria		208
Leaf Rust		36

Figure III.2 – Wheat Dataset Description

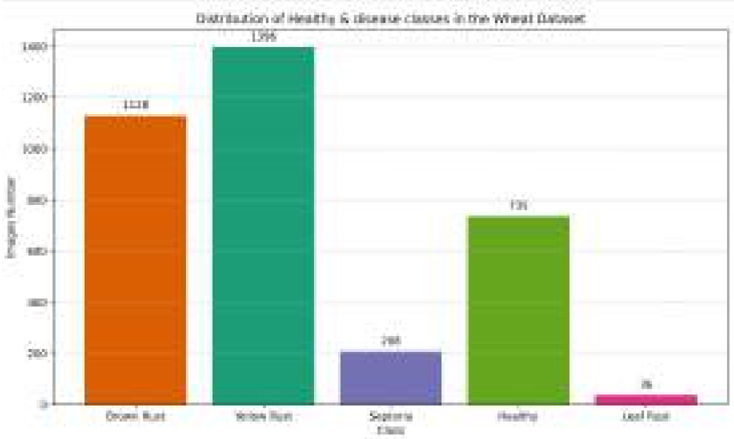


FIGURE III.3 – Distribution of Healthy and Disease Classes in the Wheat Dataset

III.3.2 Maize Dataset

The structure of the Maize Dataset is summarized in the table below[Figure III.4], showing each class name alongside a representative image and the total number of images.

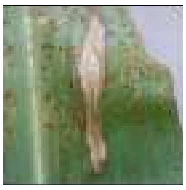
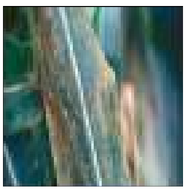
Maize Dataset		
Classes	**Example**	**Number of pictures**
Healthy		**1162**
Blight		**1146**
Common Rust		**1306**
Gray Leaf Spot		**574**

FIGURE III.4 – Maize Dataset Description

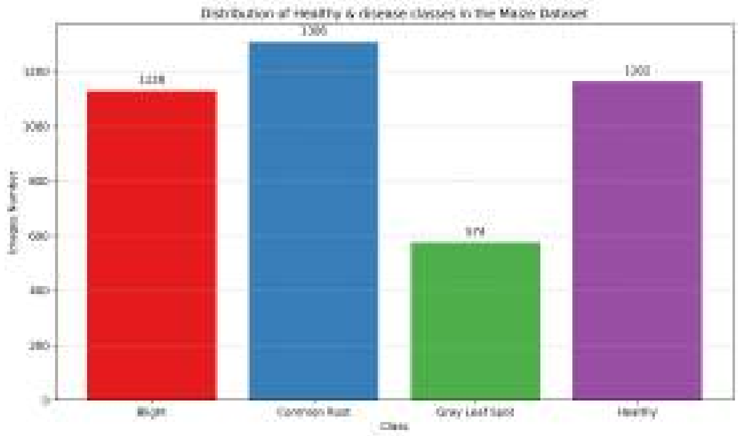


FIGURE III.5 – Distribution of Healthy and Disease Classes in the Maize Dataset

III.3.3 Rice Dataset

The table below presents an overview of the Rice Dataset, highlighting each class, an example image, and the number of images available per class

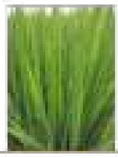
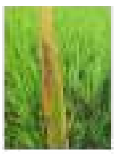
Rice Dataset		
Classes	**Example**	**Number of pictures**
Healthy		**1085**
Bacterial Leaf Blight		**1197**
Brown SPot		**1546**
Leaf Blast		**1748**
Sheath Blight		**1629**

FIGURE III.6 – Rice Dataset Description

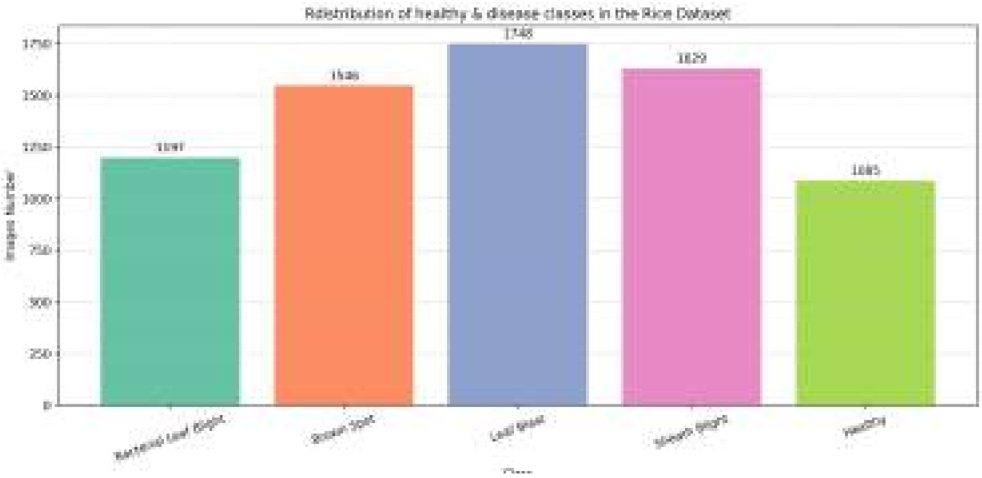


Figure III.7 – Distribution of Healthy and Disease Classes in the Rice Dataset

III.4 Data Preprocessing

To improve model performance and generalization, we applied several data preprocessing steps before training the deep learning models.

III.4.1 Data Augmentation

We resorted to data augmentation to enlarge the amount of training images and to alleviate class imbalance due to the dataset. Such a technique adds further images in each of which the original has been altered. The ultimate purpose is to make the model more resistant and the performance is more effective. We applied the following transformations :
rotation range = 30 : rotate the image randomly up to 30 degrees.
width shift range = 0.2 : move the image horizontally by 20%.
height shift range = 0.2 : move the image vertically by 20%.
zoom range = 0.2 : zoom in or out up to 20%.
horizontal flip = True : flip the image from left to right.
brightness range = [0.8, 1.2] : change the brightness between 80% and 120%.

Figure III.8 – Original vs Augmented Image

Wheat Dataset Before and After Data-Augmentation		
Class	Before	After
Healthy	735	1396
Brown Rust	1128	1396
Yellow Rust	1396	1396
Septoria	208	1396
Leaf Rust	36	1396

FIGURE III.9 – Wheat Dataset Before and After Data-Augmentation

Maize Dataset Before and After Data-Augmentation		
Class	Before	After
Healthy	1162	1306
Blight	1146	1306
Common Rust	1306	1306
Gray Leaf Spot	574	1306

FIGURE III.10 – Maize Dataset Before and After Data-Augmentationt

Rice Dataset Before and After Data-Augmentation		
Class	Before	After
Healthy	1085	1748
Bacterial Leaf Blight	1197	1748
Brown Spot	1546	1748
Leaf Blast	1748	1748
Sheath Blight	1629	1748

FIGURE III.11 – Rice Dataset Before and After Data-Augmentation

III.4.2 Image Resizing and Normalization

Before training, we resized all the images to fit the input size required by our models. Wheat leaf images were resized to 255×255 pixels, while maize and rice images were resized to 224×224 pixels. In all cases, we kept the three color channels (RGB) to preserve the color information important for identifying diseases.
After resizing, we normalized the pixel values of all images to a range between 0 and 1 by dividing each pixel value by 255. This step helps the models train more efficiently and improves convergence.

III.4.3 Dataset Splitting

Each dataset (Wheat, Maize, Rice) was split into three subsets :
The model was trained using 80% of the dataset.
A 10% portion was used for validation during training.
Another 10% was kept aside to test the model's performance.

III.5 Deep Learning Models for Disease Detection and diagnosis

This section presents the architecture and training of the DDN1 and DDN2 models for each cereal type. For each crop (wheat, maize, rice), DDN1 detects whether the leaf is healthy or diseased. If the leaf is diseased, DDN2 is then used to classify the specific disease.

III.5.1 Detection and Diagnosis of Wheat Diseases

III.5.1.1 DDN1 for Wheat : Healthy vs Diseased

The figure below [FigureIII.12] illustrates the training pipeline of the DDN1 model designed to detect whether a wheat leaf is healthy or diseased.

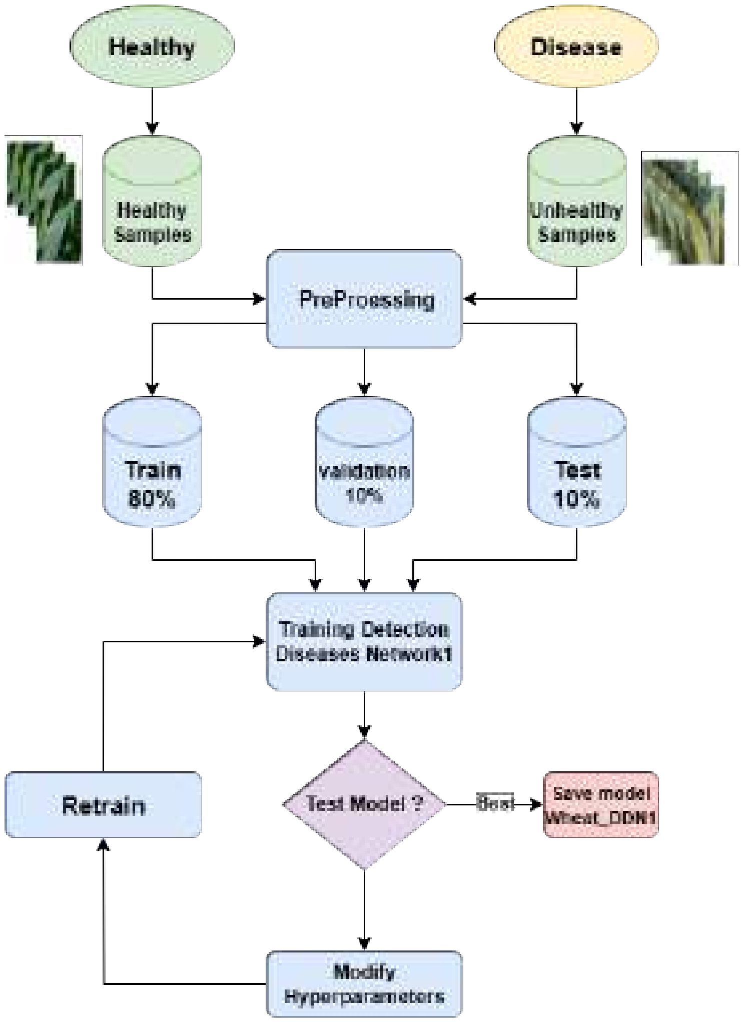


Figure III.12 – Wheat DDN1

III.5.1.2 Training of DDN1 for Wheat

The master network (DDN1) is responsible for determining whether wheat leaves are healthy or diseased. As shown in [Figure III.13], each image is first resized to 255×255 pixels and preprocessed through filtering operations. The image then passes through a sequence of three convolutional blocks (Conv2D + MaxPooling2D), where the number of filters increases progressively : 32, 64, and 128. These layers extract features which are then flattened and passed to a dense layer with a sigmoid activation function.
The model outputs 0 if the leaf is healthy and 1 if diseased. In case of a healthy result (0), no further analysis is needed. However, if the image is classified as diseased (1), the process continues with the slave network DDN2, which performs disease classification.
The detailed architecture of DDN1 is summarized in Table [Table III.1].

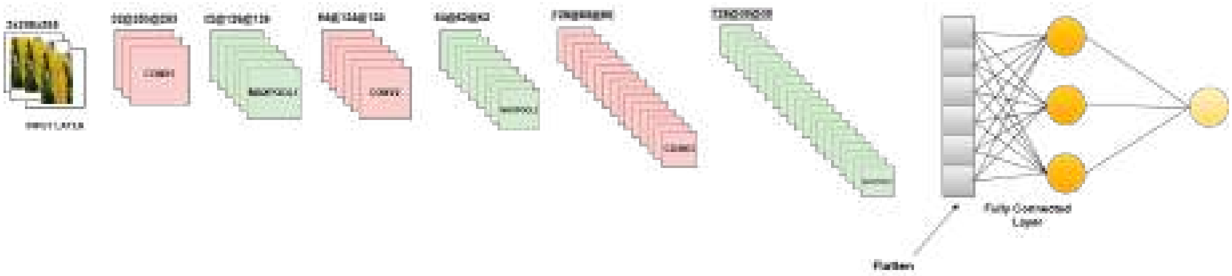


Figure III.13 – Wheat DDN1 Architecture

Layer	Feature Map Size	Kernel Size	Stride	Activation	Output Shape
Input	(255, 255, 3)	–	–	–	(255, 255, 3)
Conv2D	(253, 253, 32)	(3, 3)	(1, 1)	ReLU	(253, 253, 32)
MaxPooling2D	(126, 126, 32)	(2, 2)	(2, 2)	–	(126, 126, 32)
Dropout	–	–	–	–	(126, 126, 32)
Conv2D	(124, 124, 64)	(3, 3)	(1, 1)	ReLU	(124, 124, 64)
MaxPooling2D	(62, 62, 64)	(2, 2)	(2, 2)	–	(62, 62, 64)
Dropout	–	–	–	–	(62, 62, 64)
Conv2D	(60, 60, 128)	(3, 3)	(1, 1)	ReLU	(60, 60, 128)
MaxPooling2D	(30, 30, 128)	(2, 2)	(2, 2)	–	(30, 30, 128)
Dropout	–	–	–	–	(30, 30, 128)
Flatten	–	–	–	–	115200
Dense	128	–	–	ReLU	128
Dropout	–	–	–	–	128
Dense	1	–	–	Sigmoid	1

Table III.1 – Layers of Wheat DDN1

III.5.1.3 DDN2 for Wheat : Disease Classification

The training pipeline of the second network (DDN2), responsible for diagnosing specific wheat diseases, is illustrated in [Figure III.14].

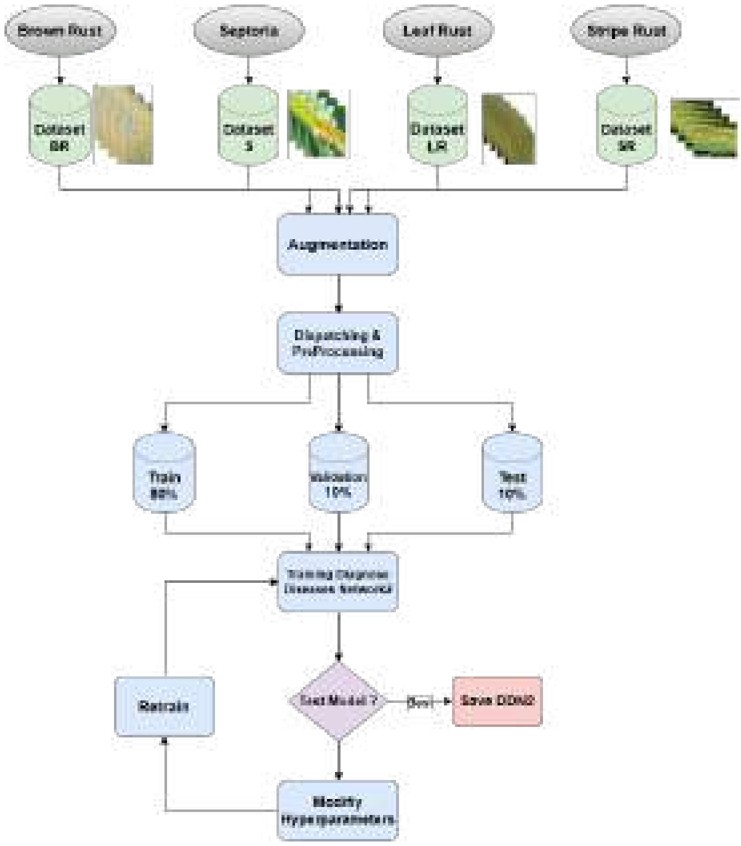


FIGURE III.14 – Wheat DDN2

III.5.1.4 Training of DDN2 for Wheat

This model is designed specifically to classify diseases into four different classes. It processes all images provided by the user by resizing them to 255×255 pixels and applying specific filters. The DDN2 model uses a Softmax activation function in the output layer. It performs similar operations as the first model, sharing the same input and initial layers, but differs in the number of classes it predicts. The full architecture of the first model (DDN1), used for detecting whether a wheat leaf is healthy or diseased, this architecture is detailed in [Figure III.14] and [Figure III.15].

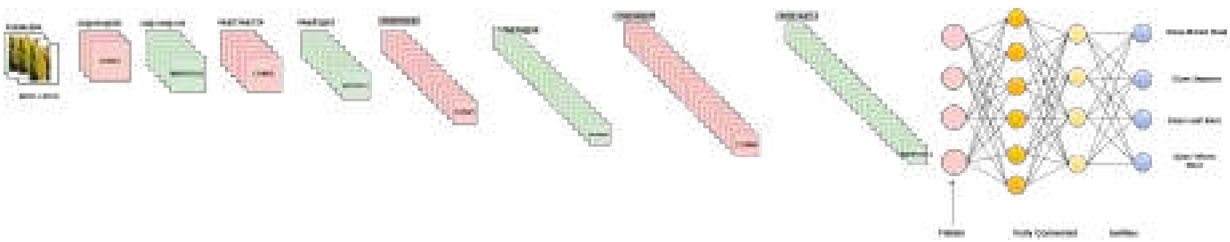


FIGURE III.15 – Wheat DDN2 Architecture

Layer	Feature Map Size	Kernel Size	Stride	Activation	Output Shape
Input	(255, 255, 3)	-	-	-	(255, 255, 3)
Conv2D	(253, 253, 32)	(3, 3)	(1, 1)	ReLU	(253, 253, 32)
MaxPooling2D	(126, 126, 32)	(2, 2)	(2, 2)	-	(126, 126, 32)
Conv2D	(124, 124, 64)	(3, 3)	(1, 1)	ReLU	(124, 124, 64)
MaxPooling2D	(62, 62, 64)	(2, 2)	(2, 2)	-	(62, 62, 64)
Conv2D	(60, 60, 128)	(3, 3)	(1, 1)	ReLU	(60, 60, 128)
MaxPooling2D	(30, 30, 128)	(2, 2)	(2, 2)	-	(30, 30, 128)
Conv2D	(28, 28, 128)	(3, 3)	(1, 1)	ReLU	(28, 28, 128)
MaxPooling2D	(14, 14, 128)	(2, 2)	(2, 2)	-	(14, 14, 128)
Flatten	-	-	-	-	25088
Dense	512	-	-	ReLU	512
Dropout	-	-	-	-	512
Dense	4	-	-	Softmax	4

Table III.2 – Layers of Wheat DDN2

III.5.2 Detection and Diagnosis of Maize Diseases

III.5.2.1 DDN1 for Maize : Healthy vs Diseased

The figure below [FigureIII.16] illustrates the training pipeline of the DDN1 model designed to detect whether a wheat leaf is healthy or diseased.

FIGURE III.16 – Maize DDN1

III.5.2.2 Training of DDN1 for Maize

The master network (DDN1) is responsible for detecting whether a maize leaf is healthy or diseased. Each image provided by the user is resized to 224×224 pixels and preprocessed using specific filters. It is then passed through a series of three convolutional blocks, each consisting of a Conv2D layer followed by a MaxPooling2D layer, with an increasing number of filters : 32, 64, and 128. After the final block, the extracted features are flattened and passed to a Dense layer with a sigmoid activation function, producing a binary output : 0 for a healthy leaf and 1 for a diseased leaf. If the output is 0, the process stops. However, if the output is 1, the system automatically activates the slave network (DDN2). This architecture is detailed in [Figure III.17] and [TABLE III.3].

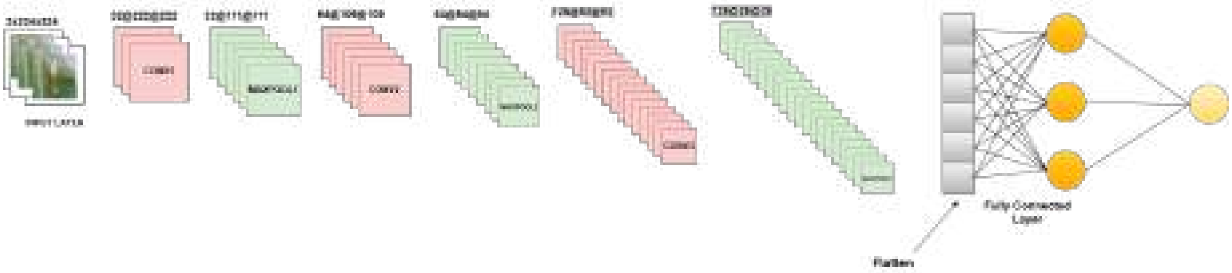


FIGURE III.17 – Maize DDN1 Architecture

Layer	Feature Map Size	Kernel Size	Stride	Activation	Output Shape
Input	(224, 224, 3)	-	-	-	(224, 224, 3)
Conv2D	(222, 222, 32)	(3, 3)	(1, 1)	ReLU	(222, 222, 32)
MaxPooling2D	(111, 111, 32)	(2, 2)	(2, 2)	-	(111, 111, 32)
Dropout	-	-	-	-	(111, 111, 32)
Conv2D	(109, 109, 64)	(3, 3)	(1, 1)	ReLU	(109, 109, 64)
MaxPooling2D	(54, 54, 64)	(2, 2)	(2, 2)	-	(54, 54, 64)
Dropout	-	-	-	-	(54, 54, 64)
Conv2D	(52, 52, 128)	(3, 3)	(1, 1)	ReLU	(52, 52, 128)
MaxPooling2D	(26, 26, 128)	(2, 2)	(2, 2)	-	(26, 26, 128)
Dropout	-	-	-	-	(26, 26, 128)
Flatten	-	-	-	-	86,528
Dense	128	-	-	ReLU	128
Dropout	-	-	-	-	128
Dense	-1	-	-	Sigmoid	1)

TABLE III.3 – Layers of Maize DDN1

III.5.2.3 DDN2 for Maize : Disease Classification

The training pipeline of the second network (DDN2), responsible for diagnosing specific maize diseases, is illustrated in [Figure III.18]

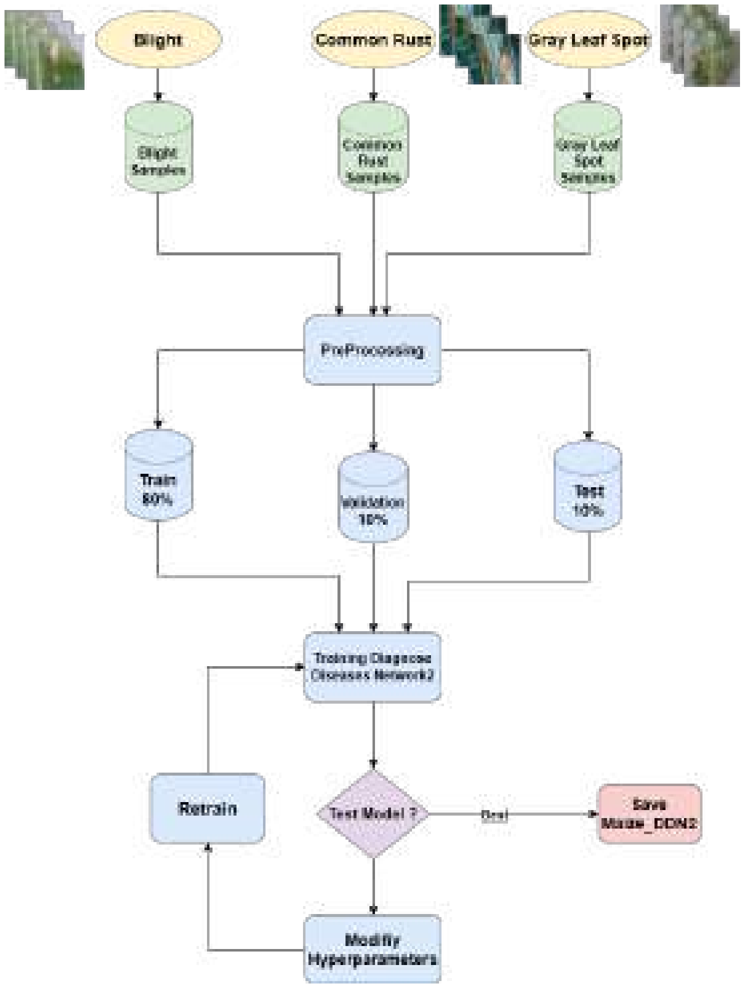


FIGURE III.18 – Maize DDN2

III.5.2.4 Training of DDN2 for Maize

This model is specifically designed to classify maize leaf diseases into three distinct classes. It processes all input images by resizing them to 224×224 pixels and normalizing their pixel values to ensure consistency during training and inference. The architecture is inspired by a traditional CNN design, with progressively deeper convolutional layers for hierarchical feature extraction. The model shares its input format and early convolutional structure with the first detection model (DDN1), but it differs in the final classification layer, where a Softmax activation is used to output probabilities across the three maize disease categories. This architecture is detailed in [Figure III.19] and [TABLE III.4].

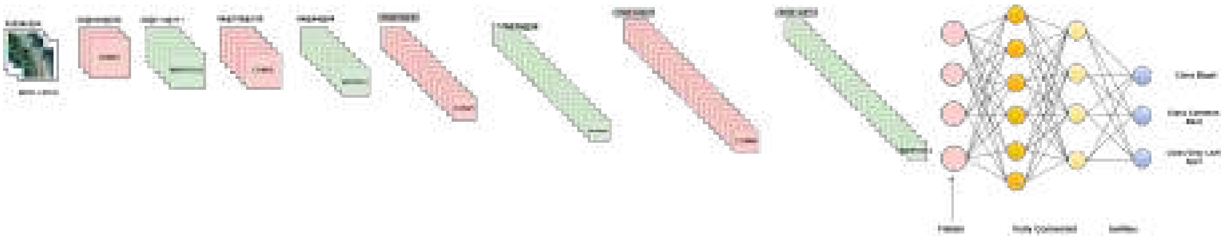


Figure III.19 – Maize DDN2 Architecture

Layer	Feature Map Size	Kernel Size	Stride	Activation	Output Shape
Input	(224, 224, 3)	-	-	-	(224, 224, 3)
Conv2D	(222, 222, 32)	(3, 3)	(1, 1)	ReLU	(222, 222, 32)
MaxPooling2D	(111, 111, 32)	(2, 2)	(2, 2)	-	(111, 111, 32)
Conv2D	(109, 109, 64)	(3, 3)	(1, 1)	ReLU	(109, 109, 64)
MaxPooling2D	(54, 54, 64)	(2, 2)	(2, 2)	-	(54, 54, 64)
Conv2D	(52, 52, 128)	(3, 3)	(1, 1)	ReLU	(52, 52, 128)
MaxPooling2D	(26, 26, 128)	(2, 2)	(2, 2)	-	(26, 26, 128)
Conv2D	(24, 24, 128)	(3, 3)	(1, 1)	ReLU	(24, 24, 128)
MaxPooling2D	(12, 12, 128)	(2, 2)	(2, 2)	-	(12, 12, 128)
Flatten	-	-	-	-	18,432
Dense	512	-	-	ReLU	512
Dropout	-	-	-	-	512
Dense	3	-	-	Softmax	3 (disease classes)

Table III.4 – Layers of Maize DDN2

III.5.3 Detection and Diagnosis of Rice Diseases

III.5.3.1 DDN1 for Rice : Healthy vs Diseased

The figure below [FigureIII.20] illustrates the training pipeline of the DDN1 model designed to detect whether a rice leaf is healthy or diseased.

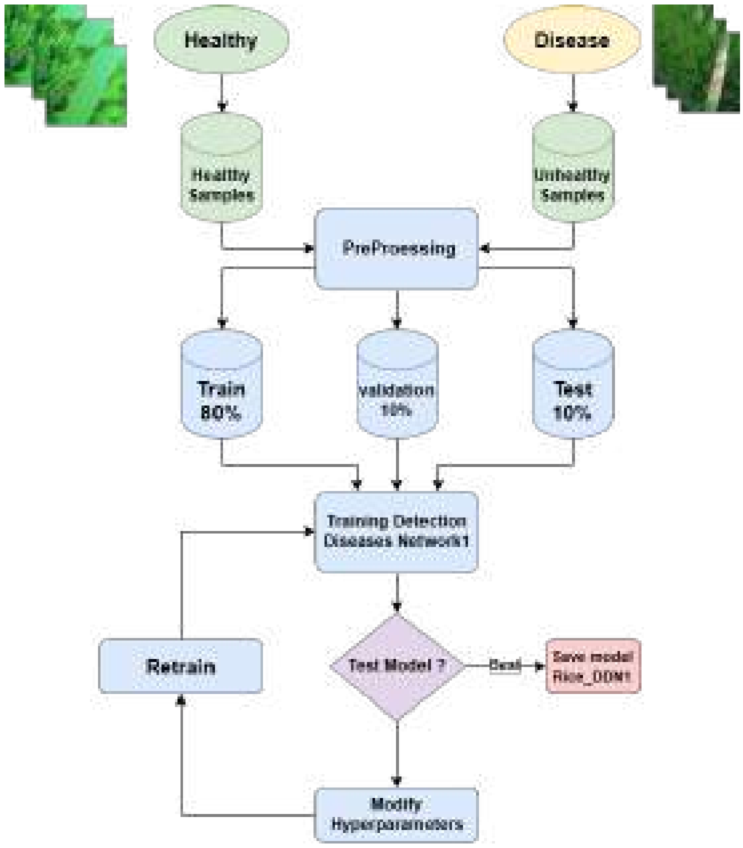


FIGURE III.20 – Rice DDN1

III.5.3.2 Training of DDN1 for Rice

The master network (DDN1) is responsible for detecting whether a rice leaf is healthy or diseased. Each image provided by the user is resized to 224×224 pixels and preprocessed using specific filters. It is then passed through a series of three convolutional blocks, each consisting of a Conv2D layer followed by a MaxPooling2D layer, with an increasing number of filters : 32, 64, and 128. After the final block, the extracted features are flattened and passed to a Dense layer with a sigmoid activation function, producing a binary output : 0 for a healthy leaf and 1 for a diseased leaf. If the output is 0, the process stops. However, if the output is 1, the system automatically activates the slave network (DDN2). This architecture is detailed in [Figure III.21] and [TABLE III.5].

FIGURE III.21 – Rice DDN1 Architecture

Layer	Feature Map Size	Kernel Size	Stride	Activation	Output Shape
Input	(224, 224, 3)	-	-	-	(224, 224, 3)
Conv2D	(222, 222, 32)	(3, 3)	(1, 1)	ReLU	(222, 222, 32)
MaxPooling2D	(111, 111, 32)	(2, 2)	(2, 2)	-	(111, 111, 32)
Dropout	-	-	-	-	(111, 111, 32)
Conv2D	(109, 109, 64)	(3, 3)	(1, 1)	ReLU	(109, 109, 64)
MaxPooling2D	(54, 54, 64)	(2, 2)	(2, 2)	-	(54, 54, 64)
Dropout	-	-	-	-	(54, 54, 64)
Conv2D	(52, 52, 128)	(3, 3)	(1, 1)	ReLU	(52, 52, 128)
MaxPooling2D	(26, 26, 128)	(2, 2)	(2, 2)	-	(26, 26, 128)
Dropout	-	-	-	-	(26, 26, 128)
Flatten	-	-	-	-	86,528
Dense	128	-	-	ReLU	128
Dropout	-	-	-	-	128
Dense	- 1	-	-	Sigmoid	1

TABLE III.5 – Layers of Rice DDN1

III.5.3.3 DDN2 for Rice : Disease Classification

The training pipeline of the second network (DDN2), responsible for diagnosing specific rice diseases, is illustrated in [Figure III.22].

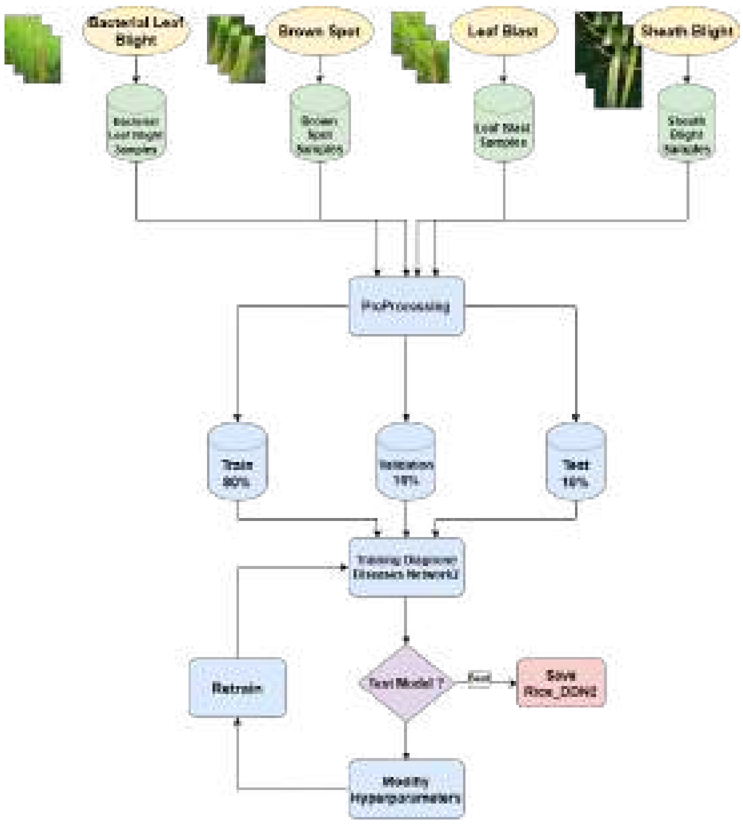


FIGURE III.22 – Rice DDN2

III.5.3.4 Training of DDN2 for Rice

This model is designed to classify rice leaf diseases into four different classes. Each input image is resized to 224 × 224 pixels and normalized to ensure consistent results. The model uses a simple CNN structure with several Conv2D and MaxPooling2D layers to extract features from the image. It shares the same input size and early layers as the first model (DDN1), but the final layer is different. It uses a Softmax activation function to give the probabilities of the four rice disease classes. This architecture is detailed in [Figure III.23] and [TABLE III.6].

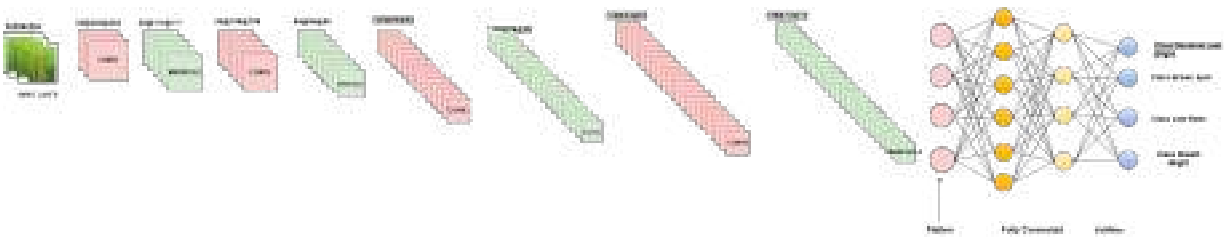


FIGURE III.23 – Rice DDN2 Architecture

Layer	**Feature Map Size**	**Kernel Size**	**Stride**	**Activation**	**Output Shape**
Input	(224, 224, 3)	-	-	-	(224, 224, 3)
Conv2D	(222, 222, 32)	(3, 3)	(1, 1)	ReLU	(222, 222, 32)
MaxPooling2D	(111, 111, 32)	(2, 2)	(2, 2)	-	(111, 111, 32)
Conv2D	(109, 109, 64)	(3, 3)	(1, 1)	ReLU	(109, 109, 64)
MaxPooling2D	(54, 54, 64)	(2, 2)	(2, 2)	-	(54, 54, 64)
Conv2D	(52, 52, 128)	(3, 3)	(1, 1)	ReLU	(52, 52, 128)
MaxPooling2D	(26, 26, 128)	(2, 2)	(2, 2)	-	(26, 26, 128)
Conv2D	(24, 24, 128)	(3, 3)	(1, 1)	ReLU	(24, 24, 128)
MaxPooling2D	(12, 12, 128)	(2, 2)	(2, 2)	-	(12, 12, 128)
Flatten	-	-	-	-	18432
Dense	512	-	-	ReLU	512
Dropout	-	-	-	-	512
Dense	4	-	-	Softmax	4

Table III.6 – Layers of Rice DDN2

III.6 Conclusion

This chapter was centred on the description of our innovative system that automates the task of identifying and diagnosing leaf diseases that affect different kinds of cereals. The system is composed of mainly two stages : a first model which can be called the master (the DDN1 in our case), responsible for recognizing the health or disease status of the leaf, and the second model (The slave or DDN2) which can easily communicate with the DDN1 and then is used to identify the exact disease if the leaf is sick. In addition, we spoke about the datasets that were unfolded in the domains of wheat, maize, and rice, and the handling steps that varied from one to another like resizing, normalizing, and augmenting the images to improve the training set. The following chapter will be the platform where we not only evaluate the models but also present the results with an in-depth analysis.

CHAPTER IV
IMPLEMENTATION, TESTS AND RESULTS

IV.1 Introduction

In this chapter, we show the important parts of our work. Before, we prepared the data and trained the models DDN1 and DDN2 for each cereal : wheat, maize, and rice. Now, we will present the tools we used, the results for each model, and compare our models with others. We will also explain how we made the web application and share screenshots of its interface. At the end, we discuss the results, the strengths and weaknesses of our approach, and ideas for future work.

IV.2 Hardware and Software Tools

IV.2.1 Hardware Tools

IV.2.1.1 Computing Station

At the University 8 Mai 1945, in the LAIG laboratory, our primary work was carried out on a dedicated computer. The configuration of this machine included 32 GB of RAM, an Intel i7 7th generation CPU, an NVIDIA GeForce GT 1050ti GPU with 2 GB of memory, and the Windows 10 Pro operating system.[?]

IV.2.1.2 Personal Hardware

To control the Computing Station remotely and save backups, we used a personal computer with :8 GB RAM, 512 GB SSD, Intel i7 8th generation CPU and Windows 11.

IV.2.2 Software Tools

IV.2.2.1 PyCharm CE

is a software tool that helps developers write and manage Python code. It is an IDE (Integrated Development Environment), which means it offers many features in one place. These features include code checking, a visual debugger to find and fix errors, tools to test programs, and support for version control systems like Git. PyCharm also allows the development of web applications, especially with Django. It is created by JetBrains, a company based in the Czech Republic.[?]

IV.2.2.2 Python

Python is a high-level programming language that is easy to understand and use. It is popular among many developers because it is simple to learn and works well for many types of projects. Python is also free to use and can run on different operating systems. In our project, we used Python version 3.9, which works well with the libraries we needed.[?]

IV.2.3 Library Used

IV.2.3.1 TensorFlow

TensorFlow is a free and open-source tool created by Google. It is used to build and run machine learning and deep learning models. It helps developers, data scientists, and researchers create smart systems more easily, even for complex tasks like predictions and data analysis.[?]
In our project, TensorFlow was used as the main framework to implement and train the deep learning models DDN1 and DDN2.

IV.2.3.2 Keras

Keras is a free Python library used to build deep learning models. It was first a separate tool but is now part of TensorFlow. Keras makes it easier to create neural networks by using simple code. It lets you build models using layers like Dense and Dropout, and organize them with Sequential models. Starting from TensorFlow version 2.16, a new version called Keras 3 will be used by default, but the older version (Keras 2) can still be used.[?]
In our project, Keras was used to design and structure the CNN architectures of both DDN1 and DDN2.

IV.2.3.3 OS module

OS is a built-in Python module that helps you work with the computer's operating system. It allows your Python program to create, delete, and manage folders and files.

With the "os" and "os.path" modules, you can check what is inside a folder, find or change the current folder, and do many other file-related tasks.[?]
In our project, the OS module was used to manage image directories and handle file paths during preprocessing and model evaluation.

IV.2.3.4 OpenCV

OpenCV (Open Source Computer Vision Library) is a free tool used for computer vision and machine learning. It was first made by Intel and is now managed by the OpenCV community. OpenCV helps programmers work with images and videos — for example, to detect objects, faces, or handwriting. It works with many programming languages like Python, C++, and Java. OpenCV is often used with NumPy, which is good at doing fast math with numbers and arrays. Together, they make it easier to process and understand images.[?]
In our project, OpenCV was used to read, resize, and manipulate RGB images before feeding them into the deep learning models.

IV.2.3.5 NumPy

NumPy is a basic and important Python library for scientific computing. It gives you special tools to work with large sets of numbers, called arrays. NumPy also has many fast functions to do math, logic, change shapes of arrays, sort data, select parts of arrays, read and write files, and more. It can also do things like linear algebra, statistics, and random simulations.[?]
In our project, NumPy was used for numerical operations on image data, including array manipulation and normalization.

IV.2.3.6 Matplotlib

Matplotlib is a Python library used to create graphs and charts. It helps to show data visually. You can use it together with other Python libraries like NumPy and SciPy for scientific computing. Matplotlib also lets you add graphs into applications with different tools like Tkinter, wxPython, Qt, or GTK.[?]
In our project, Matplotlib was used to visualize training history (loss and accuracy curves) and display sample predictions.

IV.2.3.7 Flask

Flask is a lightweight web framework for Python. It helps you build web applications quickly and easily. With Flask, you can create web pages, handle user requests, and connect your Python programs to the internet. It is simple to use and good for small to medium projects.[?]

In our project, Flask was used as a backend service to deploy the trained models and handle image upload, prediction, and response delivery to the user interface.

IV.2.3.8 HTML, CSS, and JavaScript

HTML, CSS, and JavaScript were used to create the front end of the web app. -HTML builds the structure of the pages.
-CSS makes the pages look nice (colors, fonts, layout).
-JavaScript adds interactivity, like buttons that work or images that change.

IV.3 Results

IV.3.1 Wheat Results

IV.3.1.1 Wheat DDN1

After testing and updating the Detection Diseases Network model for wheat, we got the following results [Figure IV.1],[Figure IV.2] and [Figure IV.3] using these configurations :
-Optimizer : Adam
-Batch size : 32
-Epochs : 30
-Relu For all convolutional layers function except the output layer use Sigmoid.

We observe that the training accuracy [Figure IV.1] increases step by step with each epoch and reaches around 98% at the end. This means the model is learning the training data very well. The validation accuracy [Figure IV.1] also increases at first, but after about 5 epochs, it starts to go up and down. These small changes are normal and temporary. Although it does not improve as smoothly as the training accuracy, it still shows good learning. In the end, the validation accuracy reaches 90%, which is a good result. It shows that the model can generalize well to new data.

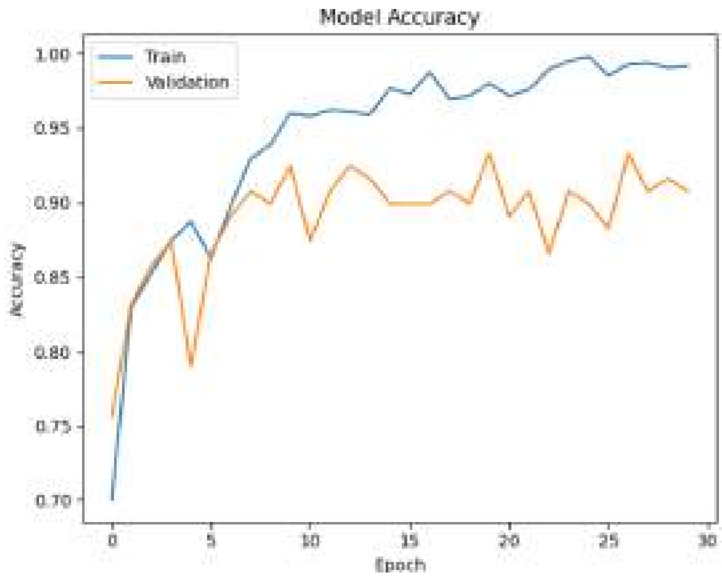


FIGURE IV.1 – Training and Validation Accuracy Curves for Wheat DDN1

The training loss [Figure IV.2] goes down step by step from a high value to almost zero, which means the model is learning the training data well. The validation loss [Figure IV.2] also goes down at first, but after a few epochs, it starts to change up and down. Even though it stays higher than the training loss, it stays mostly stable, with a small increase at the end.

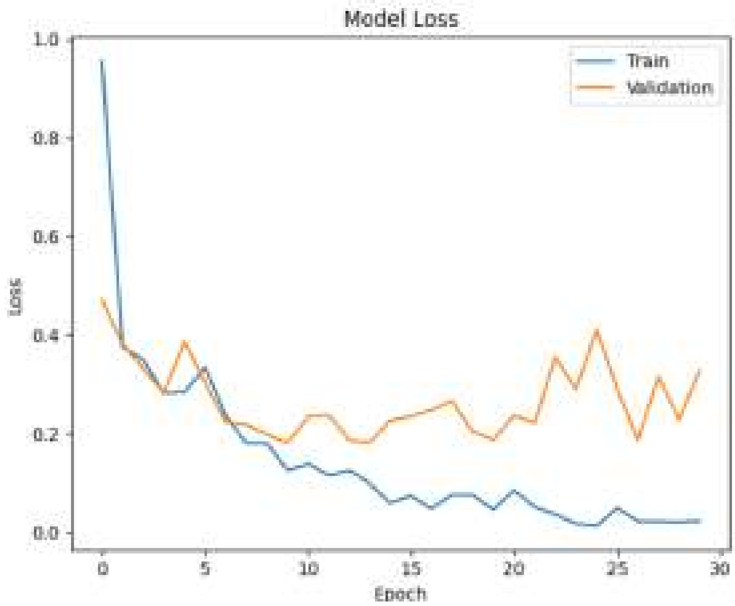


FIGURE IV.2 – Training and Validation Loss Curves for Wheat DDN1

The model demonstrates strong performance in classifying healthy and not healthy categories [Figure IV.3], with high accuracy observed for both. Furthermore, the low number of false positives and false negatives indicates that the model achieves good precision and recall across both classes.

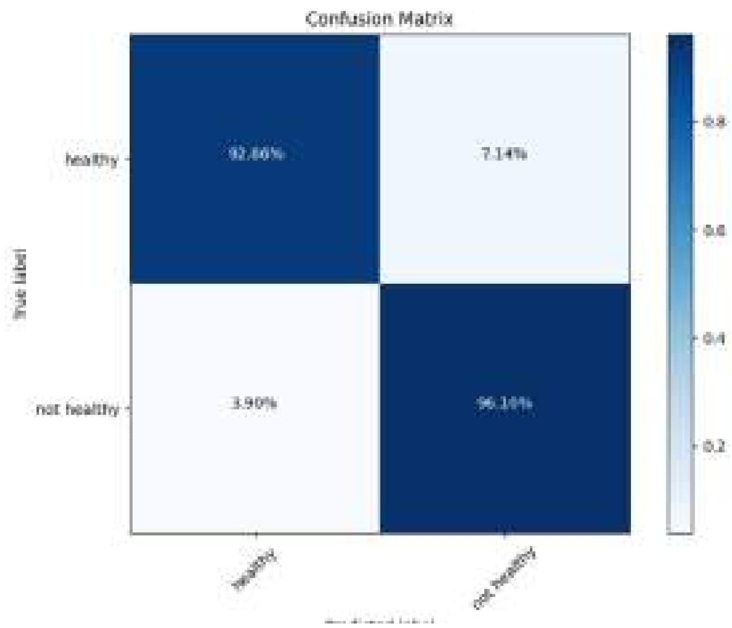


FIGURE IV.3 – Confusion Matrix for Wheat DDN1

IV.3.1.2 Wheat DDN2

After testing and updating the Diagnose Diseases Network model for wheat, we got the following results [Figure IV.4],[Figure IV.5] and [Figure IV.6] using these configurations :
-Optimizer : Adam
-Batch size : 32
-Epochs : 50
-Relu For all convolutional layers function except the output layer use Softmax.

Both training and validation accuracy [Figure IV.4] begin at about 50% in the first epoch. As training continues, both accuracies increase steadily with each epoch, eventually reaching nearly 91%.

FIGURE IV.4 – Training and Validation Accuracy Curves for Wheat DDN2

This graph [Figure IV.5] shows the model loss for both training and validation datasets over 50 epochs. The training and validation loss drop significantly during the first 60% of the epochs, then stabilize at low values, indicating effective learning and good performance with minimal overfitting (around 0.08).

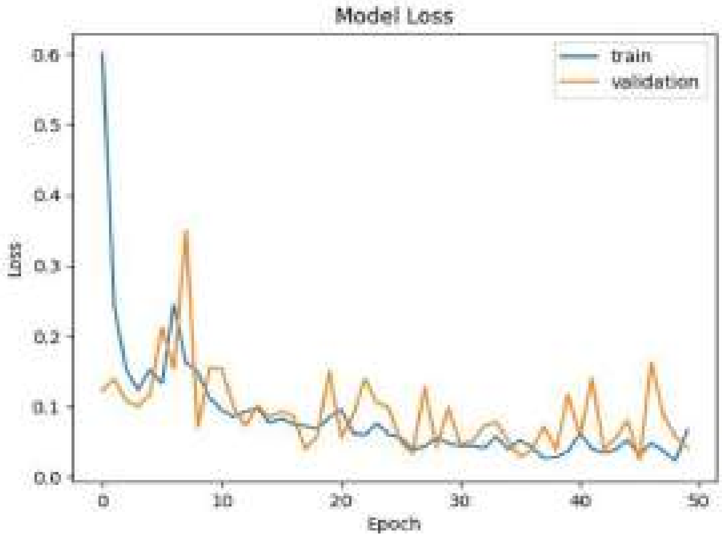


FIGURE IV.5 – Training and Validation Loss Curves for Wheat DDN2

The model shows high accuracy for all disease categories [Figure IV.6], with very few misclassifications. The best accuracy is for Brown Rust at 99.39%, while Wheat Leaf Rust has the lowest accuracy at 85.19%. Some Wheat Leaf Rust samples (7.41%) are incorrectly classified as Brown Rust, and another 7.41% are mistaken for Septoria, likely because these diseases look similar visually.

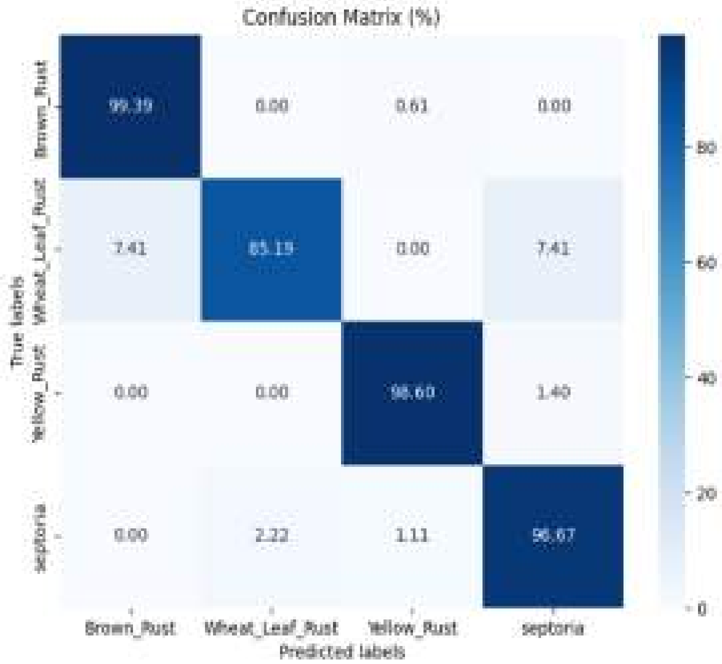


FIGURE IV.6 – Confusion Matrix for Wheat DDN2

IV.3.2 Maize Results

IV.3.2.1 Maize DDN1

After testing and updating the Detection Diseases Network model for maize, we got the following results [Figure IV.7],[Figure IV.8] and [Figure IV.9] using these configurations :
-Optimizer : Adam
-Batch size : 32
-Epochs : 30
-Relu For all convolutional layers function except the output layer use Sigmoid.

The training accuracy [Figure IV.7] increases rapidly and converges to 100%, while the validation accuracy [Figure IV.7] remains stable around 0.99%. There is no obvious sign of overfitting. Therefore, the model learns the training data well and generalizes correctly to unseen data, with only a slight divergence between the two curves.

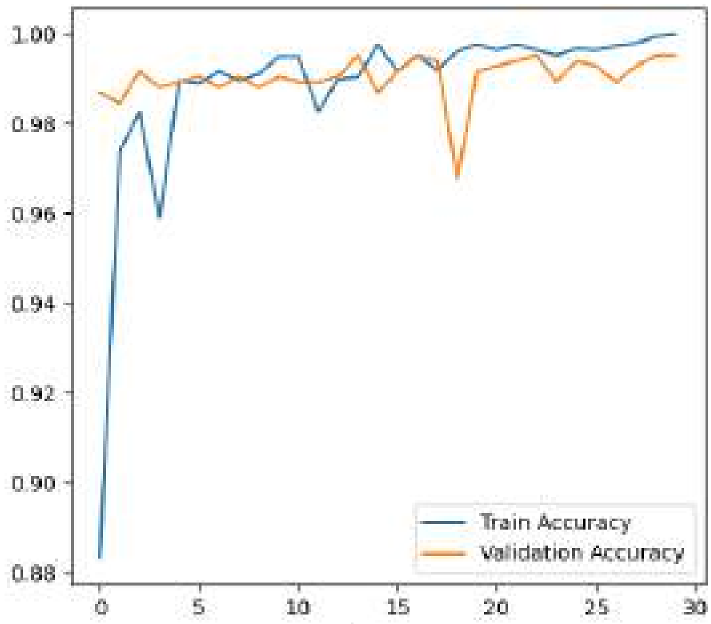


FIGURE IV.7 – Training and Validation Accuracy Curves for maize DDN1

The training loss [Figure IV.8] drops quickly to 0%, while the validation loss [Figure IV.8] remains stable around 0.05%. The two curves remain close without any sign of overfitting. Therefore, the model converges quickly with low loss, indicating good learning and generalization.

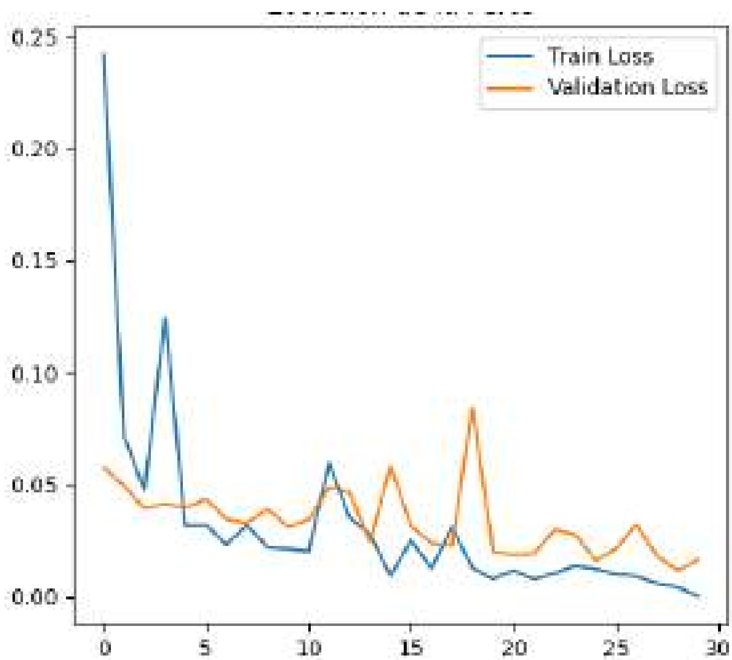


FIGURE IV.8 – Training and Validation Loss Curves for Maize DDN1

For the "Healthy" class, the model achieves perfect precision (100.00%). For the "Not Healthy" class, it reaches a precision of 99.35%, with only 0.65% error rate. Therefore, the model is well performant, with very low overall error and excellent ability to distinguish between the two classes.

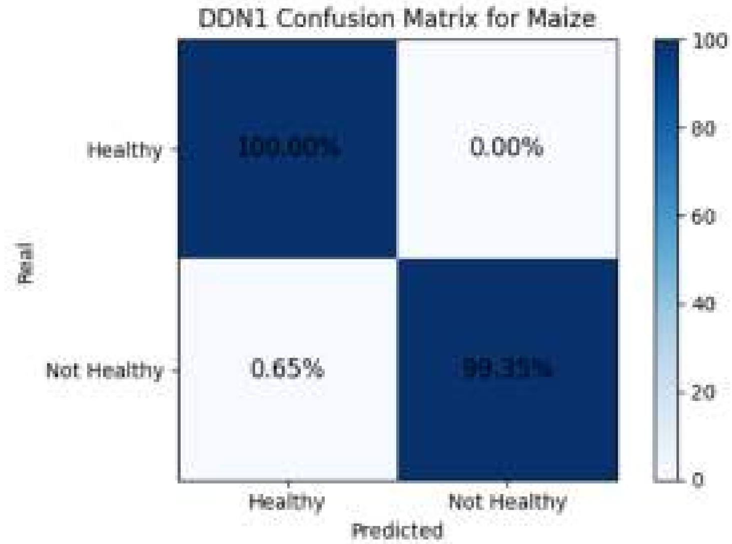


FIGURE IV.9 – Confusion Matrix for Maize DDN1

IV.3.2.2 Maize DDN2

After testing and updating the Diagnose Diseases Network model for maize, we got the following results [Figure IV.10],[Figure IV.11] and [Figure IV.12] using these configurations :
-Optimizer : Adam
-Batch size : 32
-Epochs : 50
-Relu For all convolutional layers function except the output layer use Softmax.

The training accuracy [Figure IV.10] increases steadily and converges around 90%, while the validation accuracy [Figure IV.10] shows fluctuations but also stabilizes near 90%. There is a slight divergence between the two curves, but no significant overfitting is observed.Therefore,the model learns effectively from the training data and generalizes reasonably well to unseen data, with consistent performance across epochs.

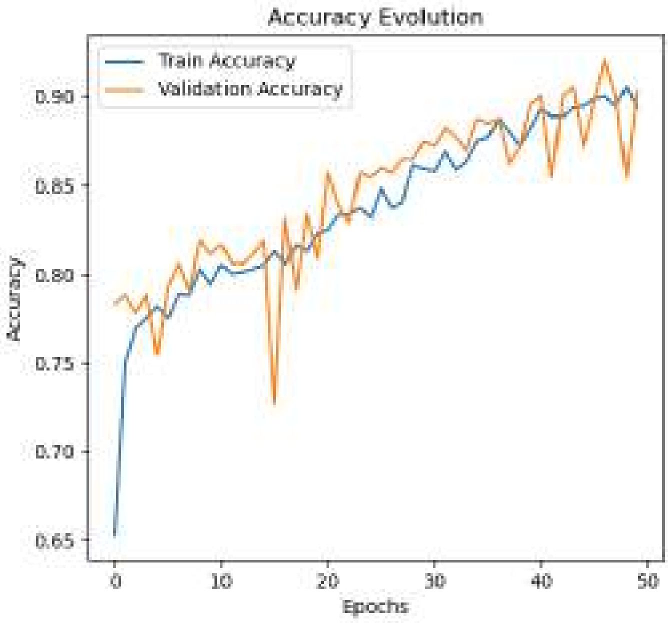


FIGURE IV.10 – Training and Validation Accuracy Curves for Maize DDN2

The training loss [Figure IV.11] decreases rapidly at first and then plateaus around 0.30, while the validation loss [Figure IV.11] follows a similar trend but remains slightly higher. Both curves show some noise but maintain a stable pattern without signs of overfitting.Therefore,the model converges quickly with low loss, indicating good learning dynamics and effective generalization to validation data.

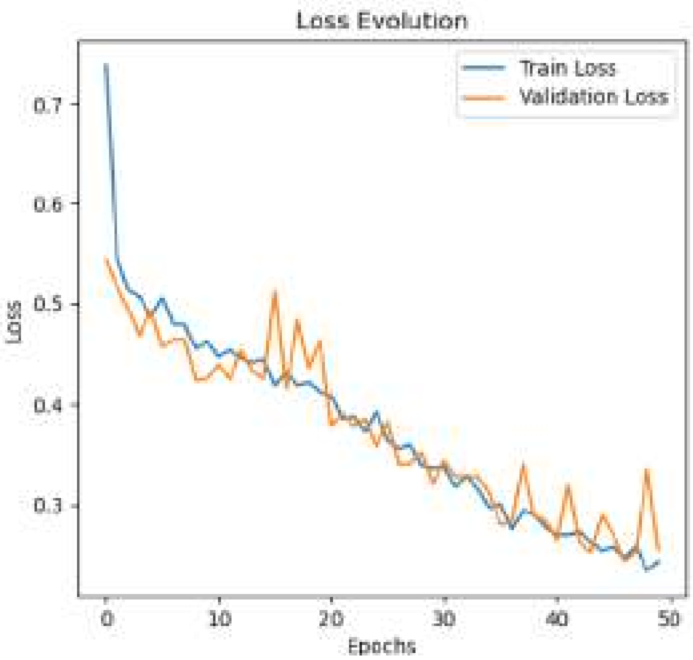


FIGURE IV.11 – Training and Validation Loss Curves for Maize DDN2

The model performs well overall[Figure IV.12], with high precision for each class, though there are some notable misclassifications between "Blight" and "Gray Leaf Spot.

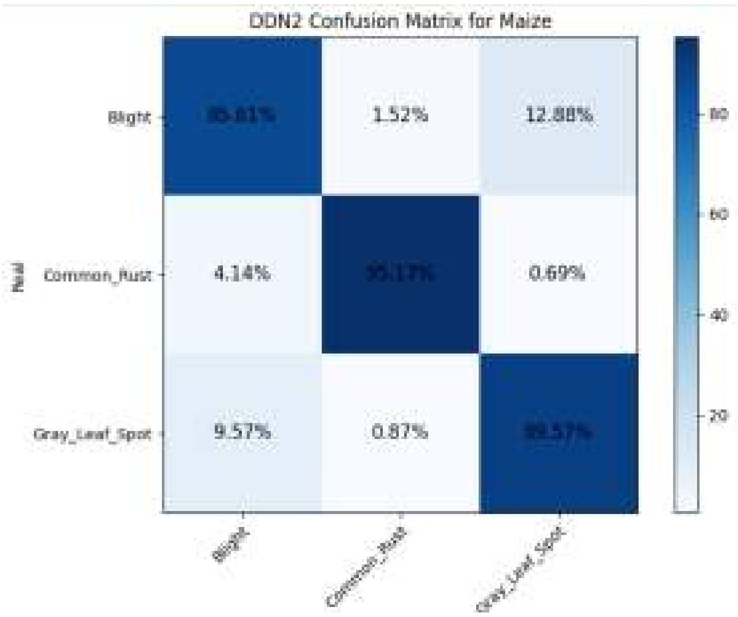


FIGURE IV.12 – Confusion Matrix for Maize DDN2

IV.3.3 Rice Results

IV.3.3.1 Rice DDN1

After testing and updating the Detection Diseases Network model for Rice, we got the following results [Figure IV.13],[Figure IV.14] and [Figure IV.15] using these configurations :
-Optimizer : Adam
-Batch size : 32
-Epochs : 30
-Relu For all convolutional layers function except the output layer use Sigmoid.

The training accuracy [Figure IV.13] increases steadily and converges around 98%, while the validation accuracy [Figure IV.13] shows fluctuations but also stabilizes near 98%. There is a slight divergence between the two curves, but no significant overfitting is observed. Therefore, the model learns effectively from the training data and generalizes reasonably well to unseen data, with consistent performance across epochs.

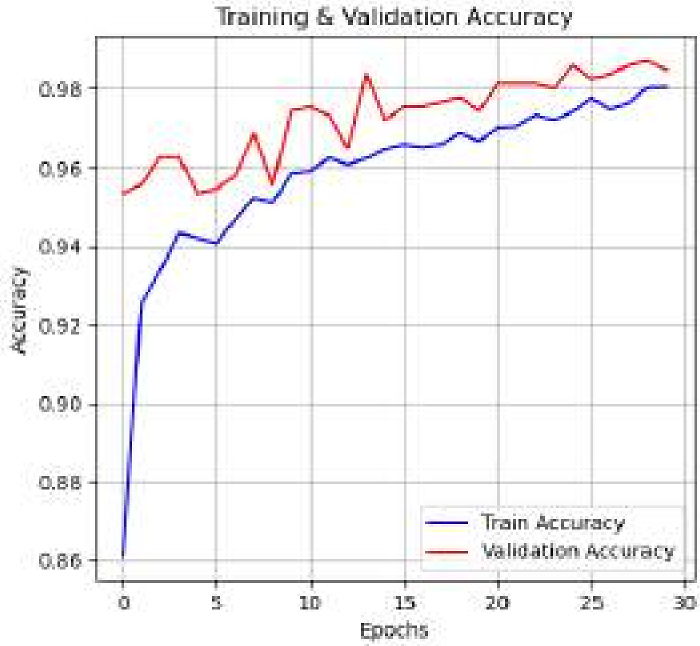


FIGURE IV.13 – Training and Validation Accuracy Curves for Rice DDN1

The training loss [Figure IV.14] decreases rapidly at first and then plateaus around 0.07, while the validation loss [Figure IV.14] follows a similar trend but remains slightly higher. Both curves show some noise but maintain a stable pattern without signs of overfitting. Therefore, the model converges quickly with low loss, indicating good learning dynamics and effective generalization to validation data.

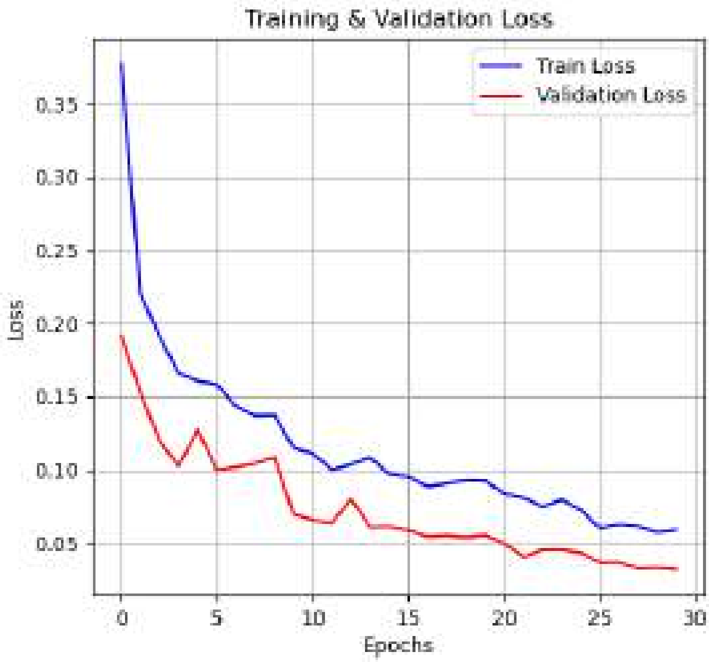


FIGURE IV.14 – Training and Validation Loss Curves for Rice DDN1

The model performs well [Figure IV.15], with high precision for both classes, indicating strong classification capabilities.

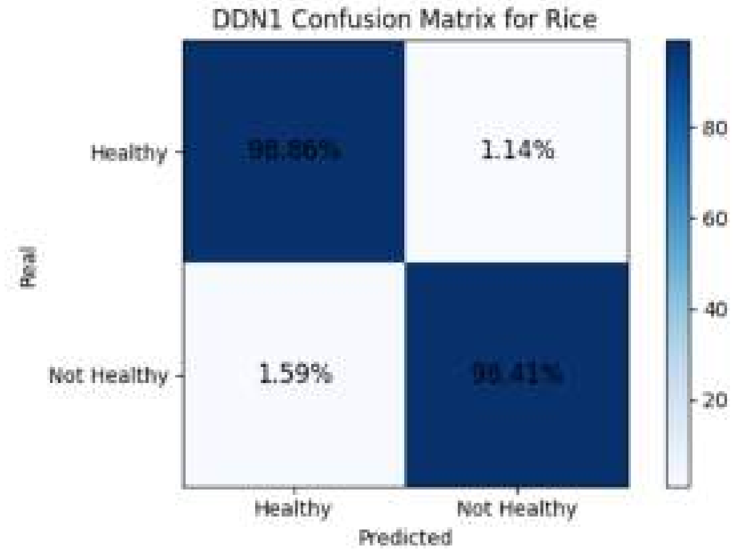


FIGURE IV.15 – Confusion Matrix for Rice DDN1

IV.3.3.2 Rice DDN2

After testing and updating the Diagnose Diseases Network model for Rice, we got the following results [Figure IV.16],[Figure IV.17] and [Figure IV.18] using these configurations :

-Optimizer : Adam

-Batch size : 32

-Epochs : 50

-Relu For all convolutional layers function except the output layer use Softmax.

The training accuracy [Figure IV.16] increases steadily from 0.5 to around 0.9, while the validation accuracy [Figure IV.16] shows fluctuations but stabilizes near 90%.

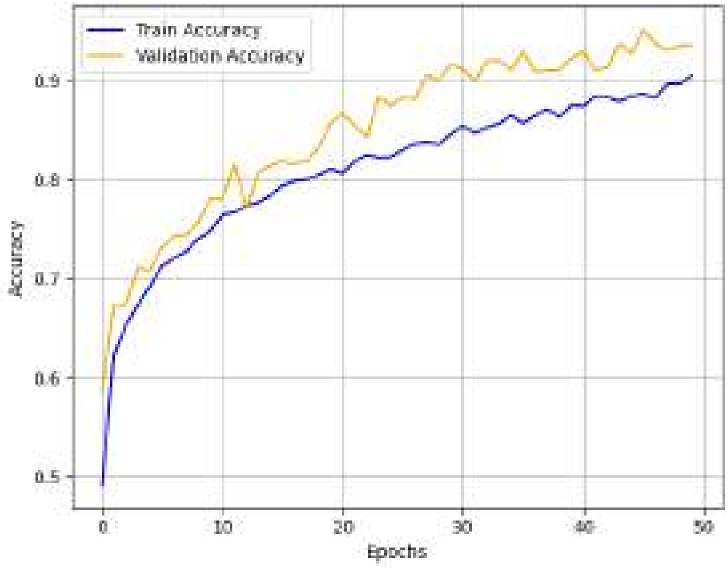


FIGURE IV.16 – Training and Validation Accuracy Curves for Rice DDN2

The training loss [Figure IV.17] decreases rapidly from 1.2 to around 0.3, while the validation loss [Figure IV.17] also decreases but remains slightly higher. Both curves show a general downward trend, indicating effective learning and convergence.

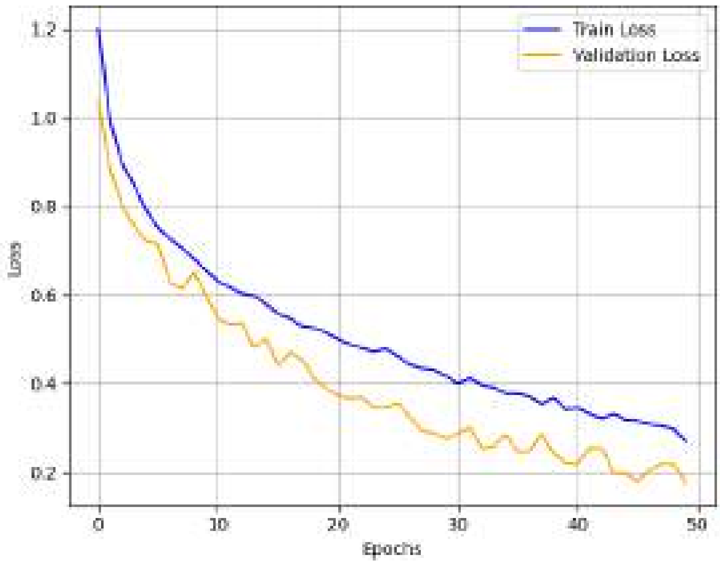


FIGURE IV.17 – Training and Validation Loss Curves for Rice DDN2

The model achieves high precision for most classes [Figure IV.18], with strong diagonal values indicating correct predictions. For example, "Leaf Blast" has 97.71% accuracy, and "Sheath Blight" has 95.43%. However, there are some misclassifications, such as "Bacterial Leaf Blight" being confused with "Brown Spot" (1.14%) and vice versa.Therefore,the model performs well overall, with high accuracy for the majority of classes, but there is room for improvement in distinguishing between similar diseases like "Bacterial Leaf Blight" and "Brown Spot."

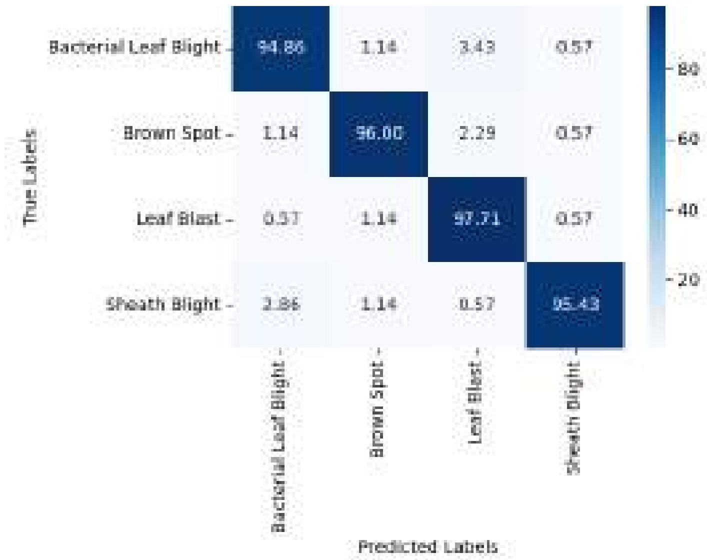


FIGURE IV.18 – Confusion Matrix for Rice DDN2

IV.4 Comparison of Pretrained Models on Maize DDN2

All models were fine-tuned on a plant disease dataset after being pretrained on ImageNet.

Model	Accuracy	Precision (avg)	Recall (avg)	F1-Score (avg)	Best Class Performance	Worst Class Performance
MobileNetV2	91%	0.91	0.91	0.91	Common Rust (97% F1)	Blight (87% F1)
InceptionV3	88%	0.88	0.88	0.88	Common Rust (96% F1)	Gray Leaf Spot (83% F1)
ResNet50	79%	0.80	0.79	0.78	Common Rust (94% F1)	Blight (69% F1)
VGG16	89%	0.89	0.89	0.89	Common Rust (96% F1)	Blight (85% F1)
VGG19	88%	0.87	0.87	0.87	Common Rust (94% F1)	Blight (82% F1)
DDN2_M	90%	0.85	0.90	0.87	Common Rust (97% F1)	Gray Leaf Spot (73% F1)

TABLE IV.1 – Comparison of Pretrained Models on Maize DDN2

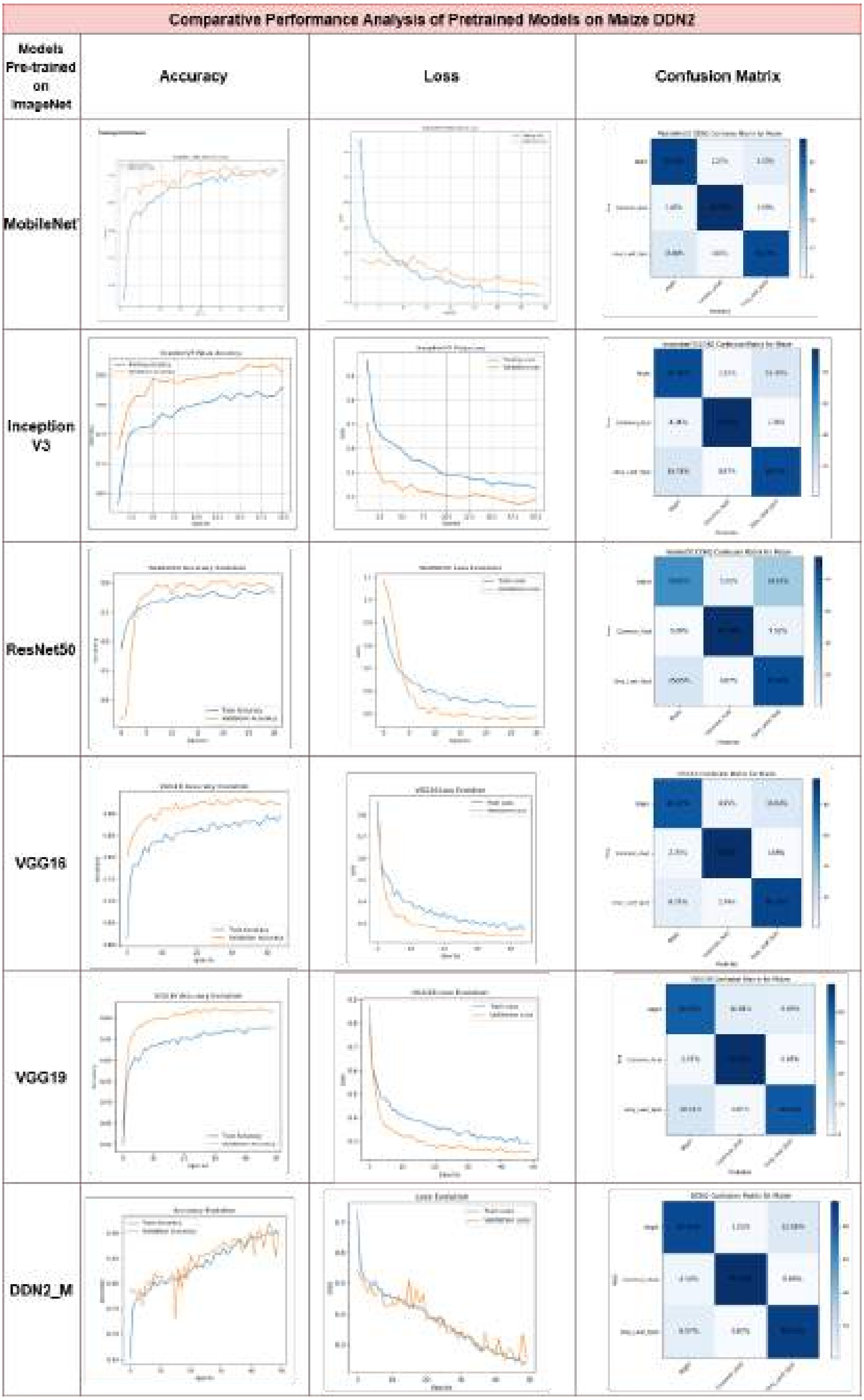


FIGURE IV.19 – Comparative Performance Analysis of Pretrained Models on Maize DDN2

IV.5 Comparison of Pretrained Models on Rice DDN2

Model	Accuracy	Precision (avg)	Recall (avg)	F1-Score (avg)	Best Class Performance	Worst Class Performance
MobileNetV2	93%	0.93	0.92	0.92	Brown Spot (96% F1)	Bacterial Leaf Blight (85% F1)
InceptionV3	90%	0.90	0.89	0.89	Rice Blast (94% F1)	Sheath Blight (82% F1)
ResNet50	83%	0.84	0.83	0.83	Rice Blast (88% F1)	False Smut (71% F1)
VGG16	91%	0.91	0.90	0.90	Rice Blast (95% F1)	Bacterial Leaf Blight (84% F1)
VGG19	90%	0.89	0.89	0.89	Brown Spot (93% F1)	False Smut (80% F1)
DDN2_R	96%	0.96	0.96	0.96	Sheath Blight (97% F1)	Bacterial Leaf Blight (95% F1)

Table IV.2 – Comparison of Pretrained Models on Rice DDN2

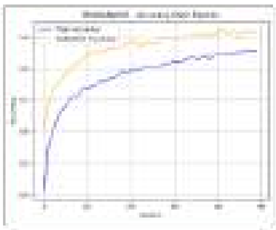
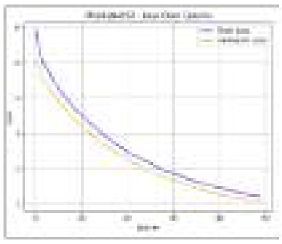
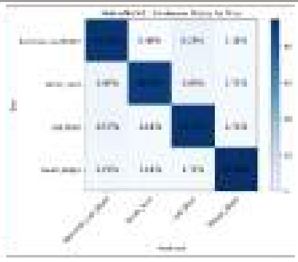
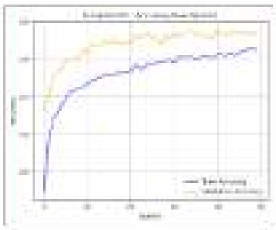
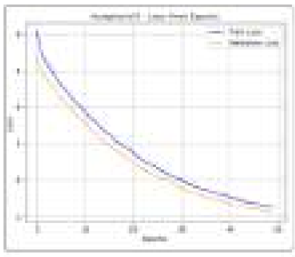
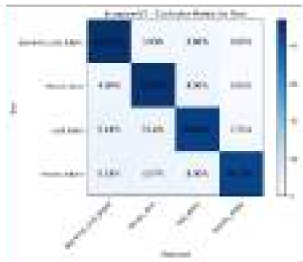
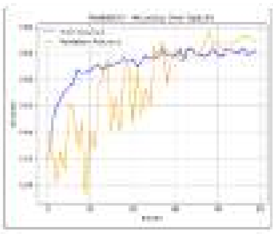
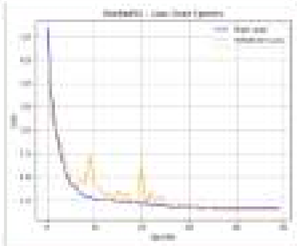
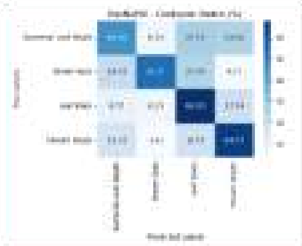
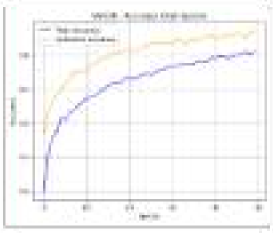
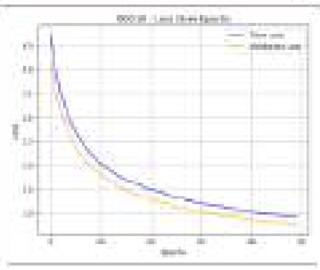
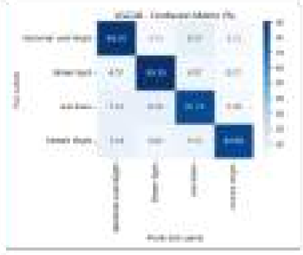
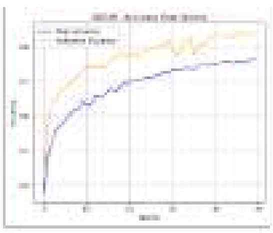
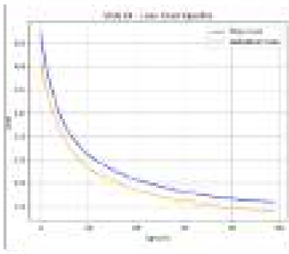
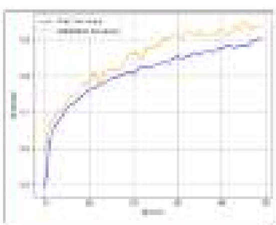
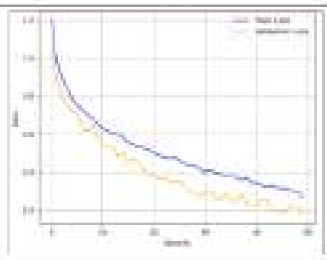
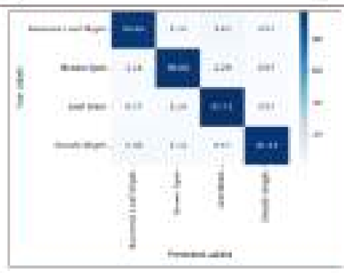
Comparative Performance Analysis of Pretrained Models on Rice DDN2			
Models Pre-trained on ImageNet	Accuracy	Loss	Confusion Matrix
MobileNet			
Inception V3			
ResNet50			
VGG16			
VGG19			
DDN2_R			

Figure IV.20 – Comparative Performance Analysis of Pretrained Models on Rice DDN2

IV.6 Web Application of our System and Tests

IV.6.1 Web Application

FIGURE IV.21 – Home Page

Home Page : Welcome screen featuring cereal images, the "AgriSense" logo, and a "Get Started" button to launch the app.

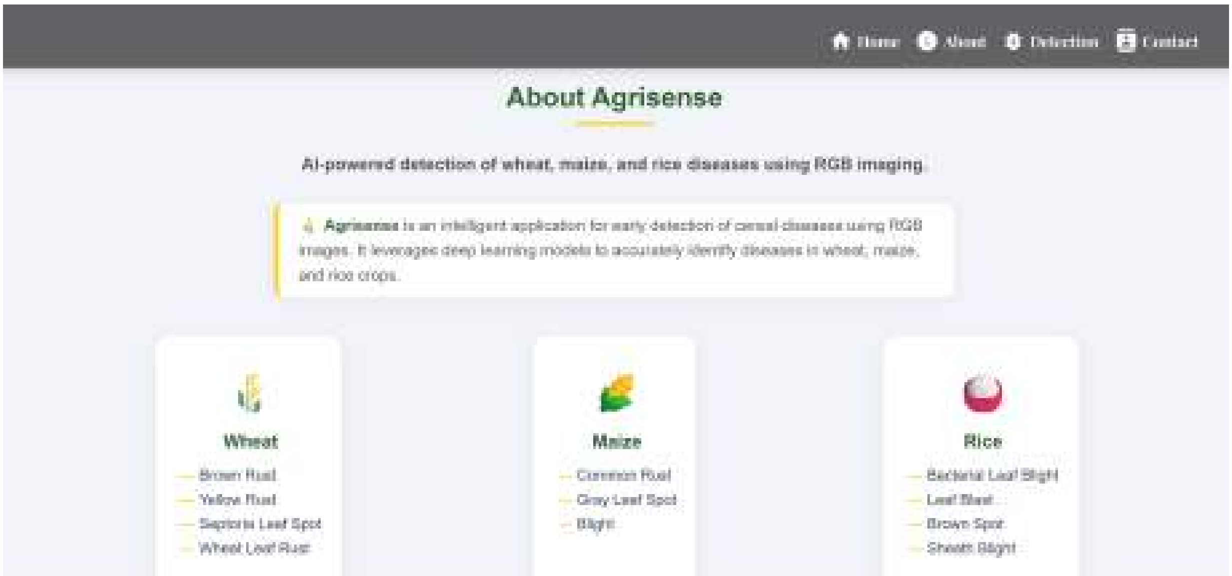


FIGURE IV.22 – About Page

About Page : Introduces AgriSense, its purpose, supported crops, and diseases, with icons for clear visual representation.

FIGURE IV.23 – Detection Page

Detection Page : Allows users to choose a cereal (wheat, maize, rice) and start disease detection with images and action buttons.

FIGURE IV.24 – Contact Page

Contact Page : Provides location, email, and social media links, with acknowledgments of contributors and institutional affiliations.

IV.6.2 Tests

FIGURE IV.25 – Cereal Disease Detection

FIGURE IV.26 – Wheat Disease Detection – Upload Image

Wheat Disease Detection – Upload Image : Users upload a wheat image using the file input, "Upload and Analyze" button starts the detection.

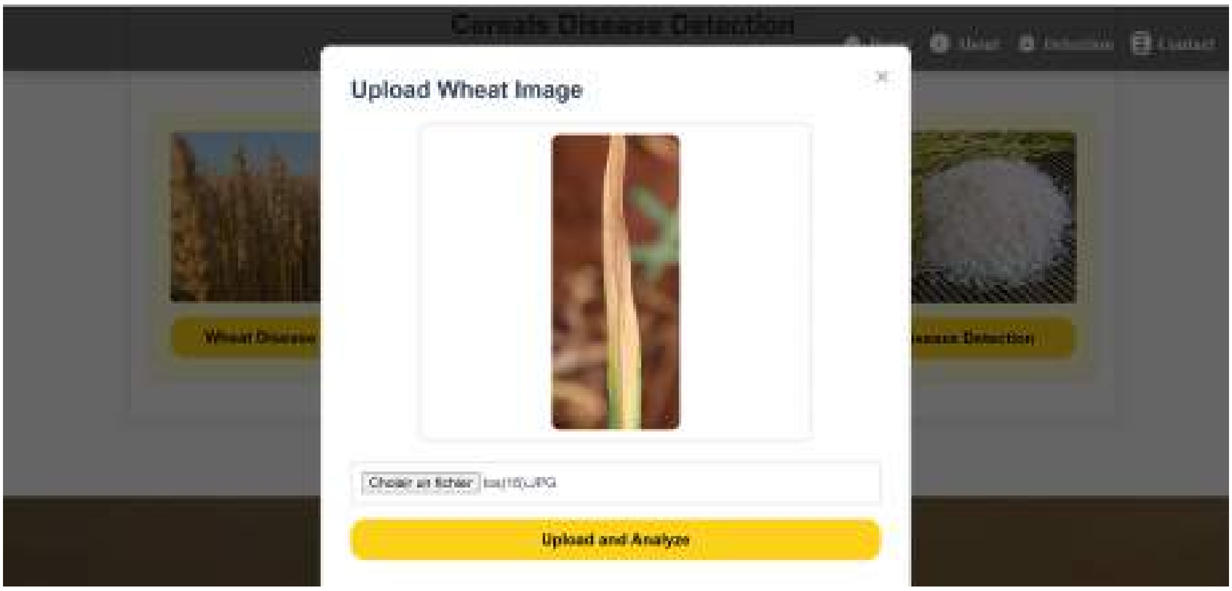


FIGURE IV.27 – Wheat Disease Detection – Image Uploaded

Wheat Disease Detection – Image Uploaded : The selected wheat image and filename are displayed ; users can proceed by clicking "Upload and Analyze."

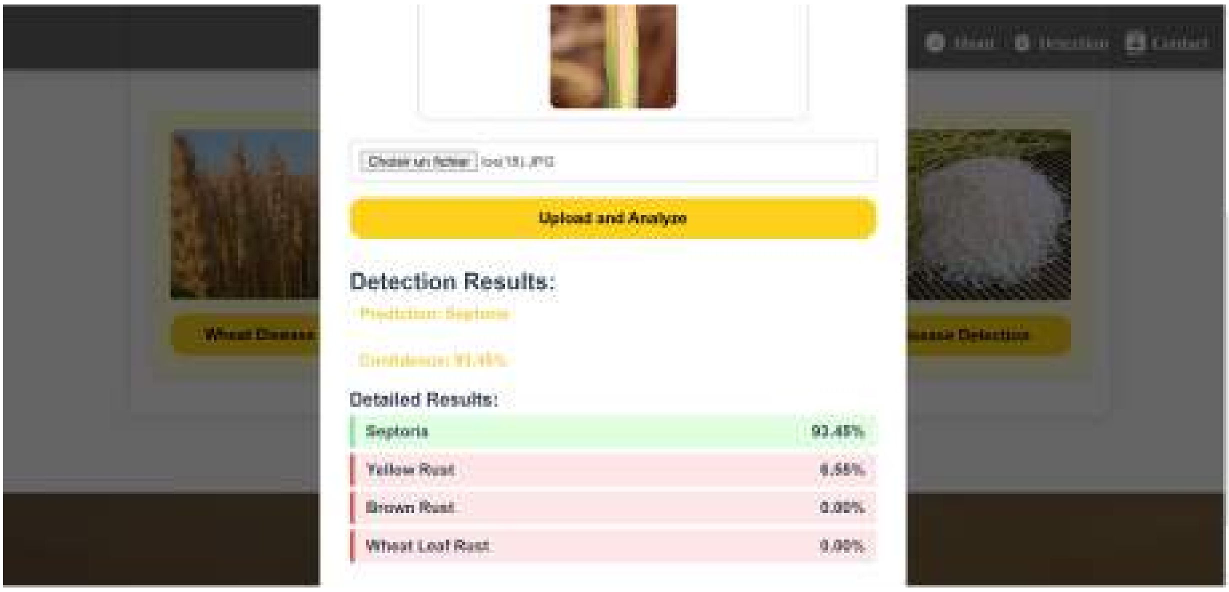


FIGURE IV.28 – Wheat Disease Detection – Results

Wheat Disease Detection – Results : The app predicts Septoria with 93.45% confidence, showing other diseases with lower scores in a results table.

FIGURE IV.29 – Maize Disease Detection – Results

After uploading, the app identifies the maize as Healthy with a high confidence of 99.90%.

FIGURE IV.30 – Rice Disease Detection – Upload Image

Rice Disease Detection – Upload Image : Users select and upload a rice image using the file input, then click "Upload and Analyze" to detect diseases.

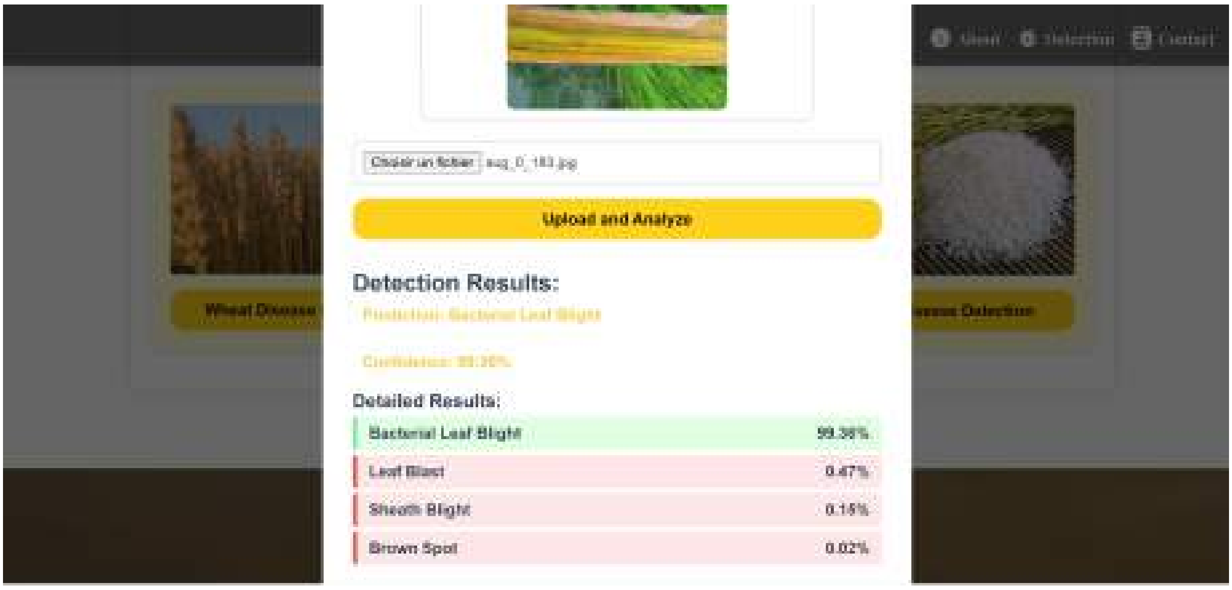


FIGURE IV.31 – Rice Disease Detection – Results

Rice Disease Detection – Results : The app detects Bacterial Leaf Blight with 99.36% confidence, highlighting it and listing other diseases with low scores.

IV.7 Conclusion

The proposed cereal disease detection system, AgriSense, demonstrates high accuracy and practicality, making it well-suited for early diagnosis in precision agriculture. However, real-time deployment remains a challenge due to image variability and potential hardware limitations. Future work should focus on optimizing model performance across diverse field conditions, improving inference speed on mobile devices, and expanding the dataset to include more varieties and disease stages. Overcoming these limitations will be essential to develop a robust, scalable, and field-ready solution for intelligent crop disease management.

GENERAL CONCLUSION

In this work, we presented AgriSense, an innovative system designed to address one of the most pressing challenges in modern agriculture : the early detection of plant diseases. Our system is built on a unique architecture that combines three sequential deep learning models in a master-slave configuration. The first model acts as the "master" determining whether a leaf is healthy or infected. If an infection is detected, the second model, acting as the "slave" identifies the specific disease affecting the leaf. This sequential approach ensures both efficiency and accuracy, making AgriSense a reliable tool for farmers to quickly diagnose and respond to crop health issues.

The system is capable of recognizing 11 critical diseases that affect wheat, maize, and rice three of the world's most important cereal crops. For wheat, AgriSense can detect brown rust, yellow rust, septoria, and leaf rust. For maize, it identifies blight, common rust, and gray leaf spot. Finally, for rice, the system recognizes bacterial leaf blight, brown spot, leaf blast, and sheath blight. By focusing on these diseases, which are among the most destructive for cereal crops, AgriSense provides a comprehensive solution tailored to the needs of farmers growing these staples.

Overall, this work demonstrates how deep learning can be effectively applied to support agriculture and mitigate the impact of leaf diseases on cereal production. Early detection of diseases not only helps reduce crop losses but also promotes sustainable farming practices by minimizing the overuse of pesticides and other chemical treatments. Furthermore, the accessibility of AgriSense through a user-friendly interface makes it a practical tool for farmers, particularly in regions like Algeria where no similar solutions currently exist.

In future work, we plan to extend AgriSense to other cereal crops such as barley and sorghum, incorporate additional disease types, and combine RGB with hyperspectral imaging to enhance diagnostic precision and robustness.

By combining advanced technology with a focus on real-world agricultural challenges, AgriSense has the potential to empower farmers, improve food security, and contribute to a more resilient agricultural system. This project underscores the transformative role of artificial intelligence in addressing global challenges and highlights the importance of continued innovation in the field of precision agriculture.

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PAPER TITLE	*Harnessing AI for Precision Agriculture: Advanced Techniques in Wheat Disease Detection and Diagnosis*
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ICSAR

All Sciences Academy

Annex

1 Project presentation

1.1 Project idea

AgriSense is a smart agriculture project that combines artificial intelligence and mobile technology to help detect diseases in cereal crops.
The core of the project is a mobile application designed to assist farmers. With just a photo taken from a smartphone, the app can tell if the plant is healthy or sick. If a disease is detected, the app identifies the exact type of disease (such as brown rust, yellow rust, leaf spot, etc.) using a deep learning model trained on a large number of plant images.
The idea came from real challenges faced by farmers:
difficulties in diagnosing crop diseases, delays in treatment, reduced yields, and overuse of chemicals. AgriSense offers a quick, easy-to-use, and reliable solution that works directly in the field — no technical skills required. The app uses two AI models:
The first model (DDN1) checks if the plant is healthy or infected.
The second model (DDN2) identifies the specific disease when an infection is found.
The user simply chooses the type of cereal (wheat, rice, or maize), takes or uploads a photo, and the app shows a diagnosis with a confidence score.
While the app is mainly made for smartphones, the AI model can also be used on drones. This could allow automatic image collection and analysis over large farming areas, offering future possibilities for wide-scale crop monitoring from the air.

1.2 Value Proposition

1.2.1 Innovation

AgriSense brings a new and smart solution to modern agriculture. By combining artificial intelligence with mobile technology, it changes how cereal crop diseases are detected. Farmers can get a diagnosis directly in the field just by taking a photo. The system is light and can be used both in a mobile app or installed on a drone, making precision farming easy and accessible.

1.2.2 High Accuracy

AgriSense uses RGB images and deep learning models to detect crop diseases early and with high accuracy. It works in two steps: first, it checks if the plant is healthy or sick, then it identifies the exact disease. This two-level process helps improve treatments and reduces crop loss.

1.2.3 Reduced Crop Loss

By finding diseases at an early stage, AgriSense helps farmers avoid large yield losses. Quick and targeted actions can protect the crops and stop the spread of infections.

1.2.4 Eco-Friendly Treatments

Because AgriSense shows exactly where the disease is, farmers can apply treatments only where needed. This avoids overusing chemicals and supports more eco-friendly, sustainable farming that is safer for people and nature.

1.2.5 Easy to Use

One of the main strengths of AgriSense is that it's simple to use — no technical skills are needed. The app works on any smartphone and only requires the user to take or upload a photo of the plant. It's also usable in rural areas where other tools might not be available.

1.2.6 Lower Costs

By reducing the need for lab tests and helping apply the right treatment at the right place, AgriSense helps lower farming costs while still keeping crop quality high.

1.2.7 Reduced Risk

AgriSense lowers health and environmental risks by limiting the use of chemicals. Only the affected areas are treated, which protects farmers, crops, and the environment.

1.3 Team Members

Hala Hamouchi: In charge of developing the AgriSense mobile application and implementing the AI models (DDN1 and DDN2) used to detect and identify cereal crop diseases from images.
Prof. Chemess Ennehar Benchereit: Project supervisor. She guides the scientific work, supports the technical development, and ensures the project follows its research goals and quality standards.

1.4 Project Objective

In the next five years, our goal is to be a top solution in smart farming by giving farmers a simple and trusted tool that uses AI to detect cereal diseases early.

1.5 Project Timeline

Phase	**1st m**	**2nd m**	**3rd m**	**4th m**	**5th m**	**6th m**	**7th m**	**8th m**
Preliminary research	✓	✓						
AI model development (DDN1 & DDN2)		✓	✓					
Mobile app development			✓	✓				
Integration and field testing				✓				
Pilot phase					✓	✓		
Deployment						✓	✓	
Marketing and promotion							✓	✓

Table 1: AgriSense project implementation schedule

2 Innovative Aspects

AgriSense brings a big change to farming by using artificial intelligence in a mobile app to detect cereal crop diseases. Unlike traditional methods, which often depend on expert knowledge or general chemical treatments, AgriSense offers a fast and accurate diagnosis directly from a simple photo taken on-site.

This solution creates a new space in precision agriculture by making smart technology easy to use, even in remote rural areas, without expensive tools or special skills.

Another key innovation is the system's flexible design. The two AI models (DDN1 and DDN2) can work inside a mobile app or be installed in a drone to scan large fields and capture images automatically.

AgriSense is also built to improve over time. The system gets better with updates based on user feedback and new technology. This helps it stay effective, adjust to new diseases, and give reliable results in the long term.

3 Strategic market analysis

3.1 Market Overview

In Algeria, agriculture ranks as the third most important sector in the national economy. It contributes around 12.4% to the country's Gross Domestic Product (GDP), with an

annual value estimated at 25 billion dollars. Over the past decade, the sector has maintained an average growth rate of 2.7%, meeting 73% of Algeria's food requirements.
Smart agriculture is rapidly expanding, driven by the growing demand for innovative and efficient technologies that boost productivity, reduce crop losses, and optimize resource use. Among these technologies, artificial intelligence (AI) systems for plant disease detection have become essential. They provide farmers with quick, reliable, and user-friendly diagnoses, helping them respond early and protect their crops more effectively.

3.1.1 Market Characteristics

a)Fast growth:
The smart agriculture market is growing quickly, especially because of the spread of smartphones and the rise of AI technologies in rural areas.
b)Growing need for effective solutions:
Farmers are looking for tools that can quickly detect plant diseases, reduce unnecessary treatments, and help them plan better actions.
c)Emerging technologies:
The combination of mobile apps, drones, and AI models is becoming a key part of modern farming practices.

3.1.2 Key Market Segments

a)Small farmers:
They are interested in simple, low-cost, and easy-to-use solutions that work on smartphones without needing constant internet access.
b)Medium-sized farms:
They prefer technologies that can work with different types of cereal crops and offer detailed health reports.
c)Large farms and agricultural cooperatives:
They look for full systems that combine mobile disease diagnosis, drone-based monitoring, and large-scale treatment options.

3.2 Measuring Market Competition Intensity

The market for cereal disease detection using mobile AI tools is growing, with moderate to high competition. Several companies and research groups are offering or developing similar solutions.

3.2.1 Main Competitors

a)Manual or expert diagnosis:
Farmers often rely on visual inspection or advice from local experts. These methods are low-cost but can be slow and not always reliable.
b)Ground-based sensors:
Some systems use in-field sensors to monitor crops. While useful, they can be expensive, complex to install, and less practical for small or medium farms.
c)Other AI-based mobile apps:
A few existing apps use artificial intelligence to detect plant diseases, but many focus on specific crops or require complex user input. Some may also lack user-friendly interfaces or precision.

3.2.2 Competitive Forces Analysis

a)Barriers to entry:
Developing an accurate and lightweight AI model that works well on mobile devices requires advanced knowledge in deep learning and agriculture, along with real-world testing. This limits easy entry for new competitors.
b)Customer expectations:
Farmers and agricultural organizations expect tools that are reliable, simple to use, and cost-effective. They prefer solutions that provide clear results quickly and can be used directly in the field.
c)Existing market rivalry:
Competitors are constantly improving their products by adding features, supporting more crops, or increasing accuracy. To stay competitive, a solution like AgriSense must deliver real value and practical benefits to users.

3.3 Marketing Strategy

To grow our user base and reach more farmers, AgriSense will offer different subscription plans. Each plan is made for a specific type of user: small, medium, or large farms. Users can choose between seasonal or yearly subscriptions.

3.3.1 Our Subscription Plans

a)Free Plan:
Price: 0 DZD per month
Crops: 1 crop
Limit: 5 images per month

For: People who want to test the app or learn how it works

b)Single Plan:
Price: 700 DZD per month
Crops: 1 crop
Limit: Unlimited images for that crop
For: Small farmers who grow only one type of cereal

c)Standard Plan:
Price: 1,500 DZD per month
Crops: 2 crops
Limit: Unlimited images for each crop
For: Medium-sized farms

d)Premium Plan:
Price: 2,500 DZD per month
Crops: All crops
Limit: Unlimited images for all crops
For: Big farms, cooperatives, or agricultural institutions

If you choose a yearly subscription, you get 2 months free.

3.3.2 Communication Strategy

We want to make AgriSense known to more people. To do that, we will use simple and effective ways to talk to farmers and partners.
a)Online Marketing:
-Create a clear and easy website with all information about the app, plans, and success stories.
-Use Google search tools to help people find our website.
-Post on social media like Facebook and Instagram to show how the app works and share offers.
b)Agriculture Events:
-Go to agriculture fairs and exhibitions to meet farmers and show the app.
-Do live demos to explain how AgriSense can help them detect diseases early.
c)Partnerships:
-Work with agriculture cooperatives and equipment sellers to spread our app.
-Give discounts or rewards to those who bring new users to AgriSense.

3.3.3 Sales Strategies

We will use simple and smart ways to sell our solution to more users.

a)Promotional Offers:

-Give free trials or low-price tests to help users try the app.

-Offer discounts for long-term plans or group subscriptions (like cooperatives or farmer groups).

b)Distribution Network:

-Work with local sellers and agriculture stores to promote and sell AgriSense.

-Build strong partnerships with trusted distributors.

c)After-Sales Service and Technical Support:

-Share online guides and training videos to help users understand and use the app. -Use feedback surveys to ask users what they think and how we can improve the service.

3.3.4 Customer Analysis

Our potential customers include:

a)Individual farmers:

They want easy tools to check the condition of their crops, reduce losses, and improve production.

b)Agricultural cooperatives:

They aim to give their members simple and useful solutions to spot crop problems and take quick action, especially for different cereal types.

c)Agricultural service companies:

These companies use modern tools like AgriSense to provide accurate and professional crop support for farmers.

d)Public institutions and NGOs:

They support sustainable farming and can use AgriSense to train farmers, monitor crop health, and improve food security.

4 Production and Organization Plan

4.1 Production Process

The production of our AgriSense solution, based on a mobile application for visual crop health check, includes the following steps:

4.1.1 Software Development

a)Interface Design: We will create a simple, multilingual, and user-friendly interface so that farmers can easily use the application.
b)Application Development: We will integrate trained artificial intelligence models into the application to recognize signs of diseases on cereal crop images.
c)Compatibility Testing: We will make sure the application works well on different Android smartphones, even without an internet connection.

4.1.2 AI Model Training

a)Image Collection and Labeling: We will use a dataset of images of cereal crops (rice, wheat, maize) showing different types of diseases.
b)Model Training: We will develop lightweight CNN models and convert them into .tflite format so they can run offline in the application.

4.1.3 Testing and Validation

a)Laboratory Testing: We will check the accuracy and speed of the application in a controlled environment.
b)Field Testing: Farmers will use the application in real agricultural conditions to make sure it works well in the field.

4.1.4 Launch and User Support

a)Application Release: We will publish the application on Android platforms and distribute it through local partners.
b)Training and Help Materials: We will prepare online guides, video tutorials, and local training sessions to help new users use the application effectively.

4.2 Required Resources and Materials

4.2.1 Hardware

-Android smartphones for testing.
-Servers for training the AI models.

4.2.2 Software Components

-AI Models: Lightweight models (.tflite) built into the application.
-Mobile System: Android application with a simple and multilingual interface.
-Local Database: Secure offline storage of results and history, no internet needed.

4.3 Human Resources

4.3.1 Development Team

-AI Developers: Design and training of artificial intelligence models.
-Mobile Developers: Build the Android application that works without internet.
-UX/UI Designers: Create a simple, user-friendly interface.

4.3.2 Testing and Validation Team

-Field Technicians: Test the application directly in farms and real situations.
-Quality Assurance Specialists: Check performance and help fix problems.

4.3.3 Support and Training Team

-Agricultural Trainers: Help farmers, cooperatives, and institutions learn how to use the application.
-Technical Support Staff: Provide assistance remotely and through local partners.

4.3.4 Coordination Team

-Project Manager: Manages the full development cycle and partnerships.
-Logistics Manager: Organizes field tests, equipment, and training sessions.

5 Financial Study

5.1 Estimated Capital

Expense Item	Estimated Cost (USD)	Estimated Cost (DZD) (1 USD = 130 DZD)
AI Model Development		
Data collection and labeling	5,000 USD	700,000 DZD
Model training and testing	7,000 USD	980,000 DZD
Conversion to mobile format (.tflite)	3,000 USD	420,000 DZD
Mobile Application Development		
Android application design and coding	10,000 USD	1,400,000 DZD
Multilingual interface	2,000 USD	280,000 DZD
Field Testing and Equipment		
Test smartphones	4,000 USD	560,000 DZD
Field validation and technician fees	5,000 USD	700,000 DZD
Infrastructure and Tools		
Cloud servers (training phase)	6,000 USD	840,000 DZD
Local database and storage system	2,000 USD	280,000 DZD
Training and User Support		
User guides, videos, and workshops	3,000 USD	420,000 DZD
Technical support setup	2,000 USD	280,000 DZD
Marketing and Launch		
Launch campaign	5,000 USD	700,000 DZD
Ads and promotions (online & offline)	4,000 USD	560,000 DZD
Miscellaneous and Operations		
Admin, logistics, and legal	4,000 USD	560,000 DZD
Office tools and small equipment	2,000 USD	280,000 DZD
Total Estimated Capital	**70,000 USD**	**9,800,000 DZD**

Table 2: Estimated capital required for the AgriSense project

5.2 Monthly Operating Costs

Expense Item	Monthly Cost (USD)	Monthly Cost (DZD)
Human Resources		
AI and mobile developers	6,000 USD	840,000 DZD
Technical support staff	2,000 USD	280,000 DZD
Training and community support	1,000 USD	140,000 DZD
Infrastructure and Tools		
Server and cloud infrastructure	1,500 USD	210,000 DZD
Device maintenance and testing	800 USD	112,000 DZD
Marketing and Communication		
Online campaigns and ads	1,000 USD	140,000 DZD
Community outreach and printing	500 USD	70,000 DZD
General and Administrative		
Office rental	1,000 USD	140,000 DZD
Utilities and supplies	700 USD	98,000 DZD
Total Monthly Operating Cost	**14,500 USD**	**2,030,000 DZD**

Table 3: Monthly operating costs for the AgriSense project

5.3 Three-Year Financial Projections

Year	Revenue (USD)	Revenue (DZD)	Costs (USD)	Costs (DZD)	Net Profit (USD)	Net Profit (DZD)
1st Year	250,000	35,000,000	174,000	24,360,000	76,000	10,640,000
2nd Year	350,000	49,000,000	174,000	24,360,000	176,000	24,640,000
3rd Year	450,000	63,000,000	174,000	24,360,000	276,000	38,640,000
Total	**1,050,000**	**147,000,000**	**522,000**	**73,080,000**	**528,000**	**73,920,000**

Table 4: Three-year financial projections for the AgriSense project

5.4 Financial Analysis

Aspect	Details
Initial Investment	Estimated at 70,000 USD / 9,800,000 DZD based on development, training, equipment, marketing, and support needs.
Revenue and Profitability	Revenues increase steadily each year. Thanks to optimized operating costs, the project becomes profitable from the first year, generating net profit of 76,000 USD (10.6 million DZD) in Year 1.
Cost Optimization	Operating expenses have been minimized through the use of lightweight mobile models, local databases, and affordable infrastructure. This optimization contributes significantly to early profitability.
Market Potential	High potential in smart agriculture: strong demand for AI-based crop disease detection tools, especially in rural and remote areas. The multilingual offline mobile application allows wide adoption. Gradual market expansion and subscription-based services can improve financial performance over time.

Table 5: Financial analysis of the AgriSense project

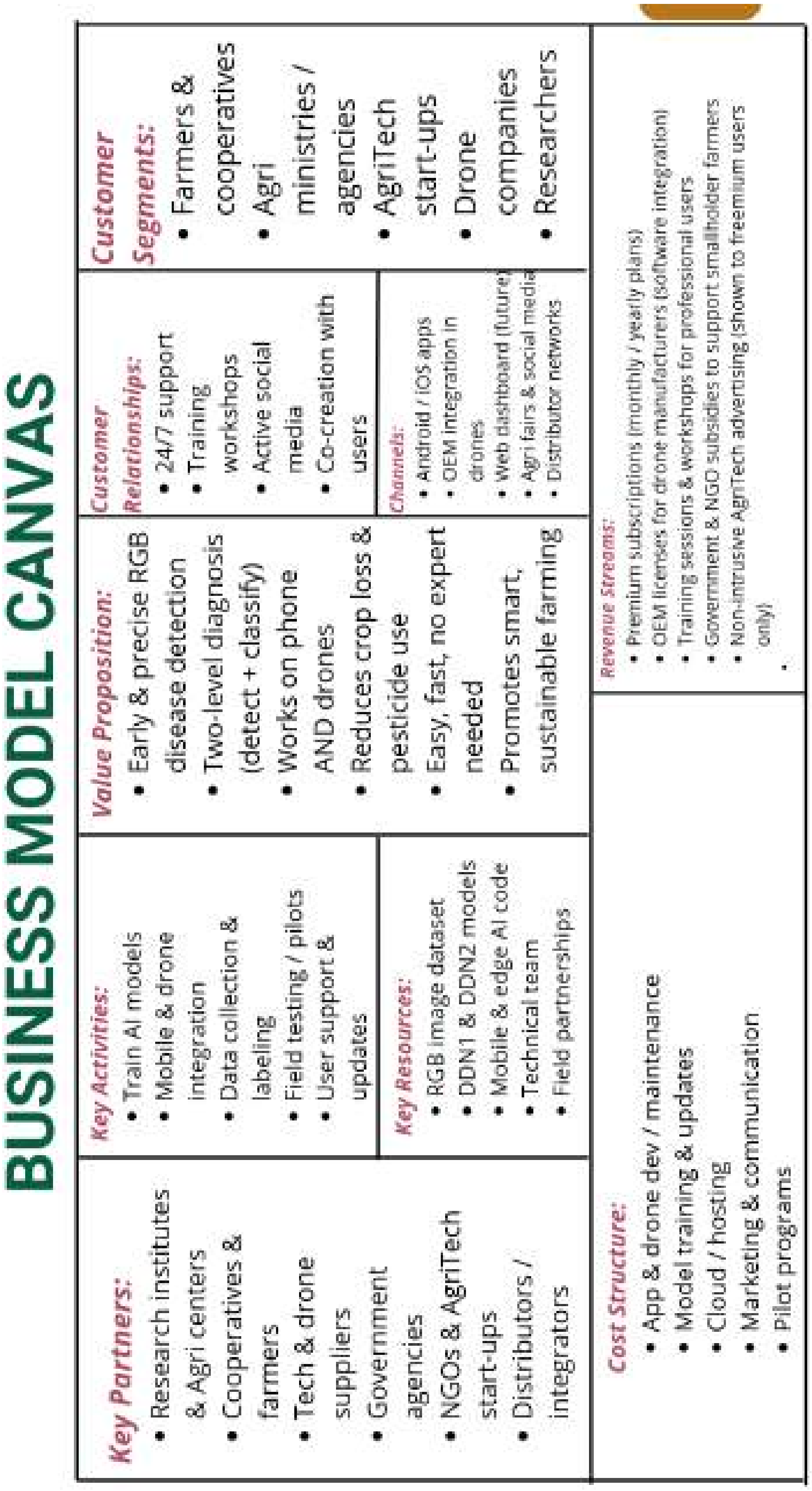

Figure 1: BUSINESS MODEL CANVAS