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Smart Deep System to Detect and Diagnose Wheat Disease

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Thanking

بِسْمِ ٱللَّهِ ٱلرَّحْمَٰنِ ٱلرَّحِيمِ

First ,I want to thank “ALLAH” the God for His facilitation and ease in completing this work from its inception and throughout the months. He is the One who makes things easy, and I do not believe that all the pages of this document would suffice to express His blessings upon us and His favor on all creation. He is the One and the only ONE who blessed us with the gift of intellect and made this journey smooth for us.

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Finally, I thank all my family and may Allah bless them and lend their health and long life Inshallah

Dedication

I dedicate this work to

My family. A special feeling of gratitude to my dear parents who gave me everything without expecting anything in return and for supporting and encouraging me in my life. May ALLAH, our GOD, the Almighty, One and Merciful, bless you with good health and long life.

our unwavering support, endless love, and constant encouragement have been the foundation of my strength and success. I am eternally grateful for your presence in my life and for the countless sacrifices you have made. This dedication is a small token of my immense gratitude and deep appreciation for everything you have done for me. Thank you for being my guiding light and my greatest inspiration.

ABSTRACT

Wheat is the most important basic component of food security in addition to its impact on the agricultural and economic income of countries, although every year we notice significant losses in it, and one of the most important reasons for these losses is the diseases and fungi that infect it, including those who are difficult to distinguish or classify and how to deal with them.

The technological development that the world is witnessing in the field of industrial intelligence has become touching various fields, including agriculture, where we began to see today what is called “Smart agriculture”.

Our project involves the establishment of a smart system that verifies and classifies wheat diseases (brown rust, yellow rust, leaf rust, sptoria) using images processed by convolutional neural networks (CNNs). The first stage is dedicated to a neural network we called the “**Master**” or **DDN1** (**D**etection **D**isease **N**etwork), which determines whether the wheat is diseased or not. At the end of this stage, we will have one of two results: either the wheat is healthy, concluding the first stage, or the wheat is diseased and that need to call the second system that we called the “**Slave**” or **DDN2** (**D**iagnose **D**isease **N**etwork), prompting the second stage, where the specific wheat disease is classified.

Therefore, this program can be considered a foundation for the construction of the smart system, in addition to providing a strong basis for the future development of agricultural control systems, which will enhance production and surplus food security.

Keywords: Smart agriculture, wheat diseases, deep learning, deep neural network, Diagnose diseases.

ملخص

القمح هو أهم مكونات الأمن الغذائي الأساسية بالإضافة إلى تأثيره على الدخل الزراعي والاقتصادي للدول. ومع ذلك، نلاحظ كل عام خسائر كبيرة فيه، ومن أهم أسباب هذه الخسائر هي الأمراض والفطريات التي تصيبه، بما في ذلك تلك التي يصعب تمييزها أو تصنيفها وكيفية التعامل معها.

التطور التكنولوجي الذي يشهده العالم في مجال الذكاء الصناعي أصبح يمس مختلف المجالات، بما في ذلك الزراعة، حيث بدأنا نرى اليوم ما يسمى "الزراعة الذكية."

مشروعنا يتضمن إنشاء نظام ذكي يتحقق ويصنف أمراض القمح(التبقع البثوري ,الصدأ البني , الصدأ الأصفر ,التبقع السبتوري) باستخدام الصور المعالجة بواسطة الشبكات العصبية الالتفافية (CNN).

المرحلة الأولى مخصصة لشبكة عصبية نسميها(DDN1) "Master" ، والتي تحدد ما إذا كان القمح مريضًا أم لا. في نهاية هذه المرحلة، سنحصل على إحدى نتيجتين: إما أن يكون القمح سليمًا، مما ينهي المرحلة الأولى، أو يكون القمح مريضًا مما يستدعي استدعاء النظام الثاني الذي أسميناه(DDN2) "Slave" ، مما يستدعي المرحلة الثانية حيث يتم تصنيف مرض القمح المحدد.

لذلك، يمكن اعتبار هذا البرنامج أساسًا لبناء النظام الذكي، بالإضافة إلى توفير أساس قوي لتطوير أنظمة التحكم الزراعي في المستقبل، مما سيعزز الإنتاج والأمن الغذائي الفائض.

الكلمات المفتاحية: الزراعة الذكية، أمراض القمح، التعلم العميق، الشبكة العصبية العميقة، تشخيص الامراض

RÉSUMÉ

Le blé est le composant de base le plus important de la sécurité alimentaire, en plus de son impact sur les revenus agricoles et économiques des pays. Cependant, chaque année, nous constatons des pertes importantes, et l'une des principales raisons de ces pertes est due aux maladies et aux champignons qui l'infectent, dont certains sont difficiles à distinguer ou à classifier, et dont on ne sait pas toujours comment les traiter.

Le développement technologique que le monde connaît dans le domaine de l'intelligence artificielle touche désormais divers secteurs, y compris l'agriculture, où nous commençons à voir ce que l'on appelle "l'agriculture intelligente".

Notre projet consiste à établir un système intelligent qui vérifie et classifie les maladies du blé (brown rust, yellow rust, leaf rust, sptoria) en utilisant des images traitées par des réseaux neuronaux convolutifs (CNN). La première étape est dédiée à un réseau neuronal que nous appelons « **Master** » ou **DDN1** (**D**etection **D**isease **N**etwork), qui détermine si le blé est malade ou non. À la fin de cette étape, nous aurons l'un des deux résultats suivants : soit le blé est sain, concluant ainsi la première étape, soit le blé est malade et cela nécessite l'activation du second système que nous appelons « **Slave** » ou **DDN2** (**D**iagnose **D**isease **N**etwork), ce qui déclenche la deuxième étape, où la maladie spécifique du blé est classifiée.

Par conséquent, ce programme peut être considéré comme une base pour la construction du système intelligent, en plus de fournir une base solide pour le développement futur des systèmes de contrôle agricole, ce qui améliorera la production et la sécurité alimentaire excédentaire.

Mots-clés : Agriculture intelligente, maladies du blé, apprentissage profond, réseau de neurones profond, diagnostic des maladies

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General Introduction

In many developing countries, especially in Maghreb countries, cereals and their derivatives constitute the staple food for the populations. In Algeria, cereals occupy a large part of the total agricultural land spatially and extend over areas that represent up to 30% of cultivable land. However, despite the efforts made by the government and various agricultural sector organizations to increase cereal production, yields remain low. This yearly low yield can be attributed to various abiotic factors (thermal stress, water stress, deficiency or excess of soil elements, etc.) or biotic factors, including attacks by pests and parasites. Wheat is susceptible to various diseases, and cryptogamic diseases (rusts, powdery mildew, septoria, fusarium, etc.) caused by parasitic fungi pose a real threat to the yield of this crop. Recognizing the disease and identifying the causal agent is a crucial step in successful control, protecting the crop, and preserving yield

In this context, advancements in Artificial Intelligence (AI) and Deep Learning offer promising solutions. These technologies can transform agricultural practices by providing precise and timely disease detection. Our project, in collaboration with the Department of Biology, aims to harness the power of Deep Learning to develop an intelligent system for detecting and recognizing wheat diseases. This system will empower farmers with the ability to identify and manage diseases efficiently, thereby protecting their crops and improving yields.

We have chosen to structure our study around four main chapters.

- ✓ **Chapter 1**: **Wheat Diseases**: This chapter provides a general overview of wheat and their importance and the most diseases knowing. The last part of this chapter has been reserved for a state-of-the-art of recent research on detecting the diseases of wheat using various methods of deep network.

- ✓ **Chapter 2**: **Deep Network**: This chapter detailed the architecture of convolutional neural networks and mention the RNN, which is a fundamental part of deep networks, and the hyper parameters of CNN.

- ✓ **Chapter 3**: **Conception**: In this chapter, we present the basic architecture of our system as well as the development and operation of the different modules.

- ✓ **Chapter 4**: **Implementation**: We reserved this chapter for the overall implementation of our system and the training and testing of Model Master and slave. Then we present some experimental results obtained by our model.

We end our study with a general conclusion and prospectives for future work that may be developed by other student.

CHAPTER 1

Wheat Diseases

1. Introduction

Diseases affecting wheat represent a complex array of issues that can impact the health and productivity of wheat crops worldwide. These diseases can cause a variety of damage, ranging from mild to severe, leading to significant reductions in yields and grain quality.

Wheat diseases vary and encompass various symptoms, including spots, deformations, and necrosis, as well as diseases affecting stems, spikes, and other parts of the plant. Some diseases are particularly menacing as they can spread rapidly in fields, causing outbreaks that may result in substantial economic losses for farmers.

Effectively managing wheat diseases involves a combination of agronomic practices, integrated pest management techniques, and sometimes the use of disease-resistant or tolerant varieties. Key measures to minimize the impact of diseases on wheat crops include regular crop monitoring, crop rotation, weed control, and the appropriate use of pesticides.

2.World Health Organization and food security

2.1 WHO definition

The World Health Organization (WHO) is a United Nations agency dedicated to global public health. Founded on April 7, 1948, and based in Geneva, Switzerland, its mission is to achieve the highest health standards worldwide. The WHO leads international health efforts, establishes norms, provides technical guidance, and tracks health trends. [1]

2.2 WHO Objectives for Disease Prevention and Control

The World Health Organization (WHO) holds a pivotal position in global disease management and prevention. Their efforts can be broadly classified into three main areas, as outlined in the WHO's strategic documents:

2.2.1 Surveillance

The WHO diligently collects and analyzes data on global diseases, enabling early outbreak detection and monitoring disease spread. Additionally, they develop and distribute guidelines for effective disease surveillance. [2]

2.2.2 Prevention

The WHO advocates for various preventive measures aimed at mitigating disease burdens. These include vaccination campaigns, educational initiatives, and the innovation of new diagnostic technologies. [2]

2.2.3 Control

Through the development and implementation of treatment programs, alongside efforts to enhance sanitation and hygiene practices, the WHO endeavors to curb the proliferation of existing diseases. [2]

2.3 Food security organization (FSO)

Despite the existence of around 205 definitions of Food Security by Gentilini and approximately 200 by Smith, Pointing, and Maxwell, the most widely accepted definition comes from the 1996 World Food Summit. This definition states that food security is achieved when all individuals consistently have physical, social, and economic access to enough safe and nutritious food that meets their dietary needs and preferences for maintaining an active and healthy life. [3]

2.4 The relationship between wheat and FSO and WHO

The relationship between the trio that complements each other primarily revolves around the promotion of wheat as a staple food and the consideration of its nutritional value within global dietary guidelines.

2.4.1 Food Security

As mentioned earlier, wheat plays a crucial role in achieving food security globally. The WHO is involved in initiatives and programs aimed at ensuring access to an adequate and nutritious food supply for all populations, and wheat is a key component of this effort. [w1]

2.4.2 Health Considerations

While wheat is generally considered a healthy food, the WHO also acknowledges that some individuals may have allergies or intolerances to wheat, such as celiac disease or wheat sensitivity. In this context, the WHO provides guidance on managing these conditions while maintaining a nutritious diet. [4]

2.4.3 Dietary Guidelines

The WHO, along with other health organizations, develops dietary guidelines that emphasize the importance of consuming a variety of nutrient-rich foods, including grains like wheat, as part of a healthy eating pattern. These guidelines aim to promote overall

3. Definition and importance of wheat

3.1 Wheat definition

Wheat is any of several species of cereal grasses belonging to the genus Triticum (family Poaceae), along with their edible grains. It is one of the oldest and most important cereal crops. Among the thousands of varieties known, the most important ones include common wheat (Triticum aestivum), which is used for making bread; durum wheat (T. durum), used in making pasta (such as spaghetti and macaroni); and club wheat (T. compactum), a softer type used for cakes, crackers, cookies, pastries, and various types of flour. Additionally, some varieties of wheat are utilized by industries for producing starch, paste, malt, dextrose, gluten, alcohol, and other products. [w2]

3.2 Wheat importance

3.2.1 Nutritional importance

Wheat is a major component of many diets worldwide (table 1.1), providing essential nutrients such as carbohydrates, proteins, fiber, vitamins, and minerals. The WHO recognizes the nutritional significance of wheat and includes it as part of its recommendations for a balanced diet. [4]

The most significant advantage of wheat is its versatility. Starting from wheat, one can produce a variety of products ranging from bread and pastries to desserts.

Indeed, under suitable conditions, one can store wheat for extended periods without it spoiling. This is illustrated in the story of Prophet Yousuf (صلى الله عليه وسلم), where he successfully stored wheat for seven years by preserving it in its grain form, free from infestation or spoilage.

So, transitioning from its significance in nutrition to its importance in production, wheat can be sold either as a raw material or processed product.

Country	Exported (tons)
Russia	27.4 Millions
Australia	25.6 Millions
United states	24 Millions
Canada	21.5 Millions
Ukranie	19.4 Millions
France	16.1 Millions
Argentina	9.5 Millions
Germany	7.1 Millions
Rome	6.9 Millions
India	6.1 Millions

Table 1.1: Top 10 country exported (Tons) wheat in 2024 *[w3]*

3.2.2 Productivity importance

Food security: With wheat accounting for around 20% of global calories, it is the world's most significant food crop [4]. Increasing wheat output is necessary to feed the world's expanding population. There will be a greater need for wheat as the population grows. Malnutrition and food shortages may result if wheat productivity does not keep up.

Economic development: Throughout the world, wheat is an important source of revenue for farmers. An increase in wheat productivity can contribute to farmers' and their families' standard of living. In rural places, it may also result in economic growth. [w4]

Over the era, maize output more than doubled, driven by both notable gains in yield and area. In a similar vein, increased yield and increased cultivated area were necessary for increases in rice output. The amount of land used for wheat cultivation worldwide has varied between 200 and 240 million hectares since 1961. The rise in worldwide wheat production, ascribed to steady yield increases, can be explained by the relative stability of wheat acreage, even though it has declined somewhat over the past 50 years. Global wheat production has nearly quadrupled during the past four decades, with yields rising gradually from an average of little over one ton per hectare in the early 1960s to the present 3.5 tons per hectare. Asia leads the world in wheat output (44%, TE2018), with the Americas (15%) and Europe (34%). Within the regions of each continent, there is a great deal of variability and notable variations in productivity. For example, productivity is higher in east/southeast Asia than in west/central Asia, leading to different regional shares. [5]

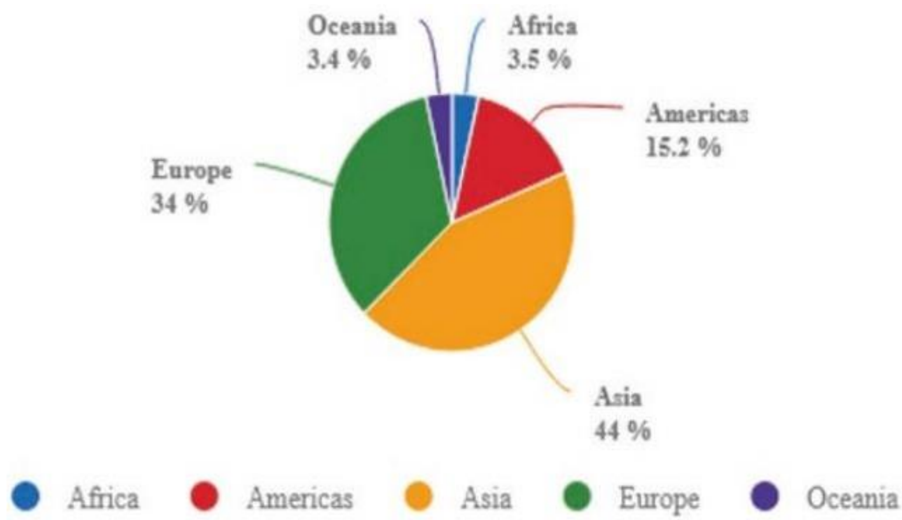


***Figure 1.1**: Production shares of wheat by region,.*

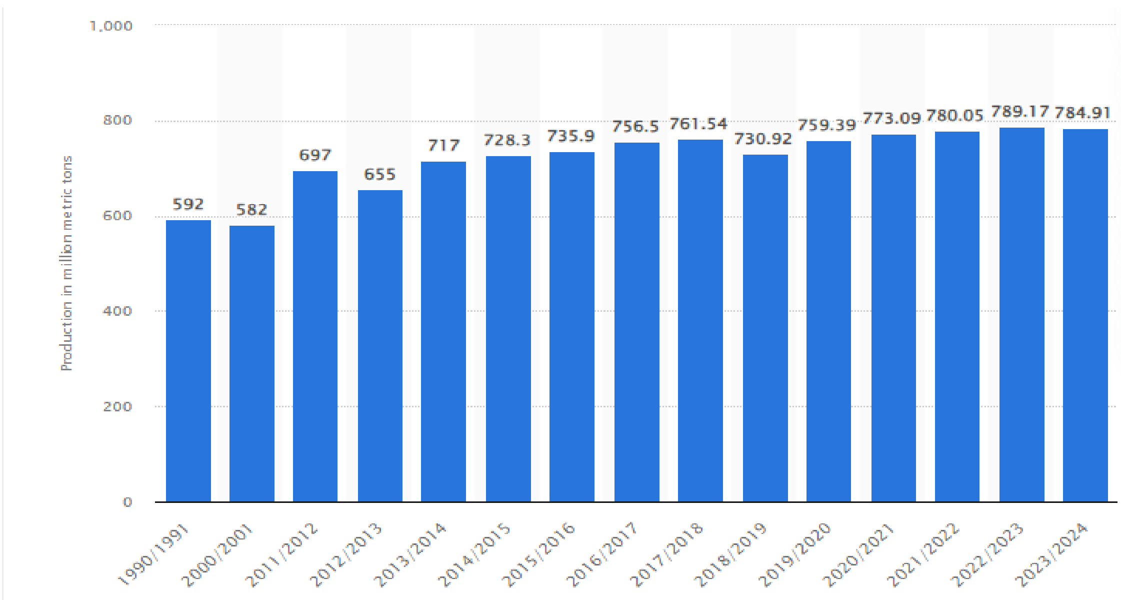


***Figure 1.2:** Production in million metric tons for wheat 1990-2024 [w1]*

4. Wheat growth

4.1 Blooming and Heading [6]

- **First Heading**: The head starts to protrude from the protective leaf sheath.
- **Quarter Emerged**: The head has emerged approximately 25% of the way.
- **About Half-Emerged**: The head has partially emerged.
- **Three-Quarters Emergence**: The head has emerged approximately three quarters of the way. **Completely Emerging**: The head has completely come out of the sheath. Beginning of Flowering: The base of the head is where flowering begins. Midway in the Bloom: The midpoint of the head is reached by the bloom (fig 1.3). Blooming at the Top: The crown of the head is covered in flowers. [6] Anthesis, or flowering, has reached its conclusion.

4.2 Filling with Grain [6]

- **Milk Step:** When crushed, the developing grain has a milky fluid.
- **Step of Soft Dough**: The grain starts to solidify but is still readily pulverized.
- **Hard Dough Stage**: The grain is beginning to turn yellow and is firmer and less easily mashed.(fig 1.3)

4.3 Physiological Maturity Ripening:

The grain is firm, fully formed, and ready to be harvested. The grains achieve their maximum dry weight (fig 1.3) and the plant turns golden brown. [w5]

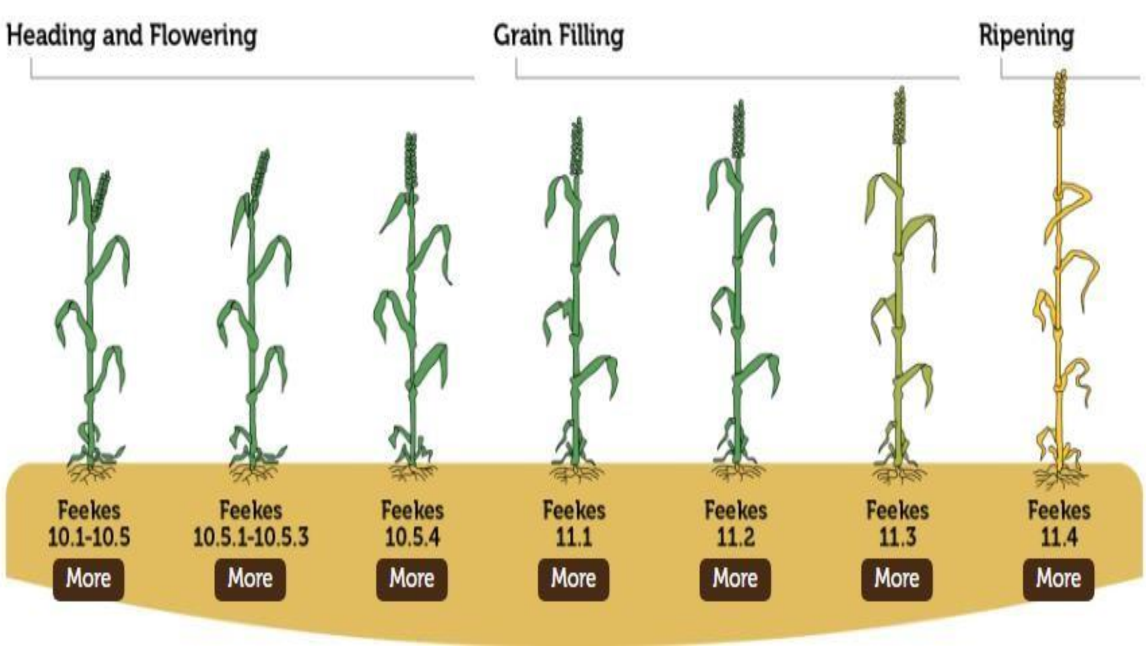


Figure 1.3: *Wheat growth from heading to ripening* [w5]

5. Wheat challenges

Twenty percent of the world's dietary energy comes from wheat, making it one of the most important crops for global food security. **[6]** Nonetheless, a number of obstacles confronting the wheat sector jeopardize its capacity to satisfy the needs of an expanding populace. These difficulties include everything from economic and logistical problems to pest outbreaks and climate change.

5.1 Impact of Climate Change

Climate alter is one of the biggest risks to wheat generation and in plant in common . Wheat yields are essentially affected by variables such as rising temperatures, moving precipitation designs, and a rise within the recurrence of extraordinary climate occasions like surges and dry seasons. Research indicates that there can be a 6% drop in wheat yields for each 1°C increment in temperature. making wheat sorts safe to warm and upgrading watering methods are vital for altering to these changes. **[6]**

5.2 Obstacles in Finance and Transportation

The financial aspects of wheat farming cannot be disregarded. Growing wheat can be dangerous since farmers often have to contend with unstable market prices. Furthermore, wheat availability and pricing stability are impacted by supply chain disruptions that are exacerbated by global pandemics and geopolitical upheaval. Investing in strong supply chains and making sure that trade is conducted fairly are necessary for stabilizing the wheat market. **[6]**

5.3 Wheat diseases

As we know diseases are the biggest influence on wheat growth and productivity, and here we address some of the most important diseases that face it.

5.3.1 Septoria

A) The symptoms of Septoria tritici blotch include:

-Little (small), chlorotic spots that extend and create into sporadic (fig 1.4), necrotic injuries. These injuries can have a yellowish or tan center with dim brown borders.

-Dark fruiting bodies called pycnidia create inside the injuries. These are symptomatic of the infection and contain conidia (spores).

-The injuries regularly coalesce, driving to a scourged appearance of the clears out, which can cause noteworthy diminishment in photosynthetic region and generally plant vigor . [7]

B) Most Affected Countries

- UK and Germany: Both countries have experienced significant issues with this disease, leading to extensive research and control measures.
- Morocco: There has been a notable prevalence shift towards S. tritici in Morocco, making it a major concern in this region. [7]

C) Diffusion Environment

-Rain-fed Conditions: The disease is commonly found in regions where wheat is grown under rain-fed conditions.

Short Crop Rotations: Short intervals between wheat crops can exacerbate the spread and impact of the disease.

-Airborne and Splash Dispersal: The pathogen spreads through both airborne spores and rain-splash from infected plant debris and within the crop. Effective management requires reducing infected debris and implementing both pre- and post-planting control measures.

These factors highlight the importance of environmental conditions and agricultural practices in managing the spread of Septoria tritici blotch. [7]

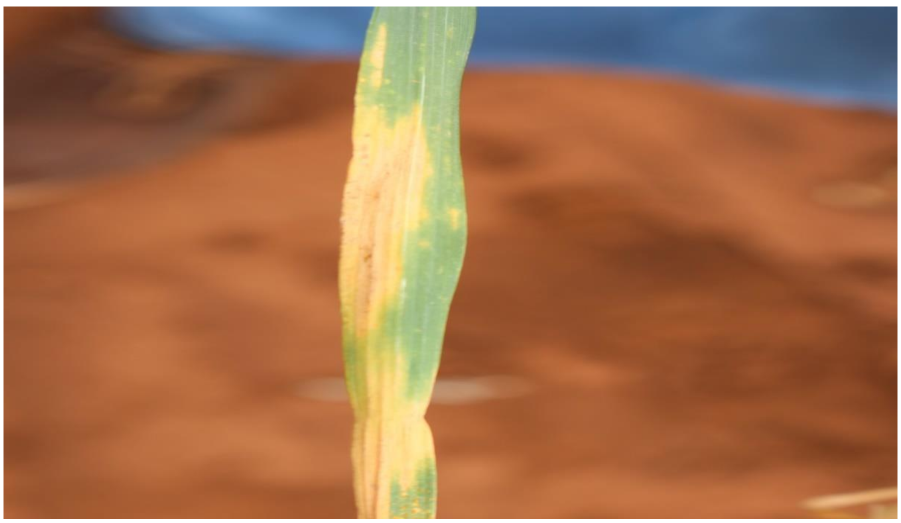


***Figure 1.4**: Disease Symptoms of septoria*

5.3.2 Wheat yellow mosaic virus

A) Symptoms:

- stunted growth of wheat plants without heading (fig 1.5).
- yield losse ranging from 20 to 70%, with severe losses occurring in some years. [8]

B) Most affected countries:

✓ China, particularly in provinces along the Yangtze and Yellow Rivers, including

- Sichuan, Henan, Hubei, Jiangsu, Sichuan, and Shaanxi.,and also Japan[8]

C) Diffusion environment:

Wheat yellow mosaic virus (WYMV) is prevalent in wheat (Triticum aestivum) fields in China.

WYMV has spread gradually into the middle and lower valleys of the Yangtze and Huai Rivers in China. [8]

It occurs in regions where semi-winter hardy wheat cultivars are grown under a similar climatic zone, with low temperatures ranging from 8 to 14°C in early spring (February to March).

The disease appears in areas with a winter temperature of about 0°C, where wheat plants grow throughout the winter.

The virus is transmitted by the Polymyxa graminis vector.

WYMV is the only bymovirus detected in wheat in China, contrary to previous reports mentioning Wheat spindle streak mosaic virus (WSSMV).

Pathogenic differences exist among WYMV isolates in China, with some isolates showing greater virulence than others. Variations in virulence may affect different wheat cultivars differently, leading to varying symptom severity and latent periods for symptom appearance after infection [8]

Figure 1.5*: symptom of wheat yellow mosaic virus [w6]*

5.3.3 Wheat stripe rust (yellow rust)

A) Symptoms:

On plant portions that are susceptible, long (fig 1.6), narrow stripes of yellow to orange emerge from pustules. [9]

B) Diffusion Environment:

- ✓ The warm, humid weather seen in temperate countries is ideal for the growth of this disease. [10]

C) Most impacted nations:

There have been reports of wheat stripe rust in more than 60 nations, including the US, Australia, China, Canada, India, Russia, the UK, France, Germany, Japan, Brazil, South Africa, and other nations.

***Figure 1.6**: Symptoms of wheat rust diseases*

5.3.4 Wheat Leaf rust

A) Symptoms:

On both leaf surfaces, wheat leaf rust causes tiny, round to elongated, yellow to orange-red pustules (fig 1.7) .

Masses of orange-yellow spores that readily rub off when touched are present in these pustules.

Severe infections may cause lower photosynthetic ability, early leaf senescence, and ultimately yield loss as a result of decreased kernel weight and grain counts per head. [11]

B) Environment and Diffusion:

- ✓ Wheat leaf rust grows best in places with moderate temperatures and lots of moisture. The pathogen's extensive dissemination can be attributed to its great degree of climatic adaptation. because it is airborne and spreads quickly across great areas, leaf rust is made possible by human activity and wind currents.

C) Most Affected Countries:

Wheat leaf rust affects a large number of wheat-growing regions worldwide.

-This disease often affects countries with significant wheat cultivation areas, such as the United States, Australia, Canada, India, China, and parts of Europe.

-Regions with favorable environmental conditions for the pathogen, including moderate temperatures and humidity, are particularly susceptible to outbreaks. [12]

***Figure 1.7**: Wheat plant infected by wheat leaf rust*

5.3.5 Wheat Stem Rust

A) Symptoms:

The symptoms of wheat stem rust, which is caused by Puccia graminis f. sp. tritici (Pgt), include reduced grain size and plant lodging as well as masses of red-brick urediniospores on the glumes (fig 1.8) , awns, leaf sheaths, and stems of sensitive plants. [12]

B) Diffusion Environment:

- ✓ Pgt is extensively spread, particularly in warm, humid areas.

C) Most Countries Affected:

Although less widespread than other wheat rusts, pgt is found all across the world. W. Since 1998 beginning in Uganda, it has spread globally, [12]

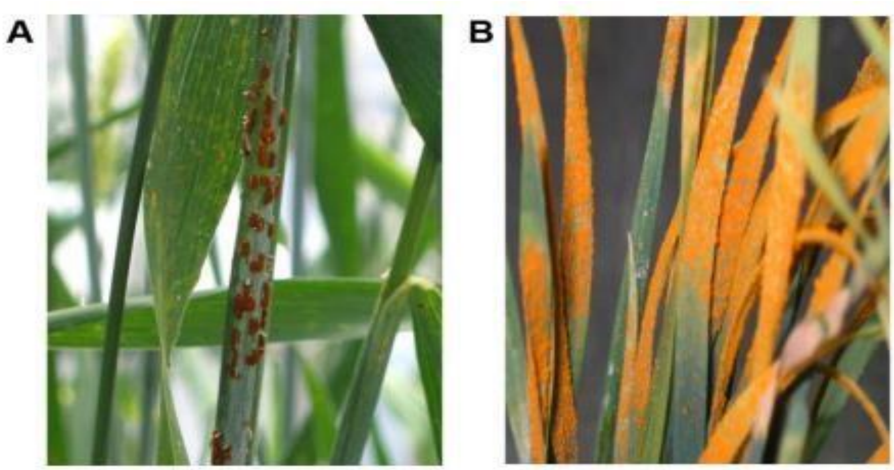


***Figure 1.8**: Symptoms of wheat rust (A), Puccinia striiformis f. sp. tritici (B) and Puccinia*

5.3.6 Wheat Brown rust

A) Symptoms:

-Severe infection of the flag leaf

-Orange-brown (fig 1.9) , distinct pustules that are more spherical and compact that are sporadically distributed

-Diminished region of green leaves

-Increased transpiration rate making people more vulnerable to drought

-Grain shrivel and particular weight losses [w7].

B) Environment of Diffusion:

- ✓ Conditions for optimal growth: 15–22°C
- ✓ Late nitrogen applications favor disease
- ✓ killed at 5°C and inhibited beyond 25°C in temperature
- ✓ primarily found in coastal areas that frequently experience mists, particularly in southern

counties. [w7]

C) Most affected countries:

Although no specific nations are mentioned, the disease is most common in coastal areas, particularly in southern counties, indicating areas with comparable climates, such as southern counties of the United Kingdom.

-Europe's coastal locations with comparable climates

Figure 1.9: *Wheat brown rust*

6. Improving the management of wheat diseases

6.1 Usual Instruments (classic)

6.1.1 Crop rotation

Crop rotation is the practice of planting various crops in succession on the same field.

-Decreases the accumulation of pest insects and diseases.

-A three- to four-year rotation of wheat that includes non-grass crops like corn and soybeans is advised.

6.1.2 Tillage:

- Discharging diseased crop waste into the ground.

-Reduces the ease of access for infections.

-Tilling at a suitable depth of 20 to 30 cm.

6.1.3 Healthy Seeds: Using seeds that have been verified as disease-free.

Selecting seeds that are suitable for the local climate.

6.2 Technological Tools

6.2.1 Data Analytics and Artificial Intelligence:

Using advanced data analytics and artificial intelligence techniques to predict disease risks and recommend preventive actions.

6.2.2 Drone Crop Monitoring:

Using drones equipped with sensors to monitor wheat fields, detect early signs of disease, and enable rapid intervention.

6.2.3 Decision Support Tools:

Helping farmers choose the best practices to control wheat diseases.

Consider various factors, such as climate, soil type, wheat variety, and cropping history.

6.2.4 Precision Agriculture:

Applying inputs (fungicides) at variable rates according to crop needs. Reduces the amount of input used and minimizes their environmental impact.

7. Dataset available wheat diseases

7.1 Dataset Wheat leaf

This dataset (fig 1.10 – fig 1.12) Contains several images taken as a sample on a field consisting of :

-97 pictures of septoria

-208 stripe rust

-102 healthy

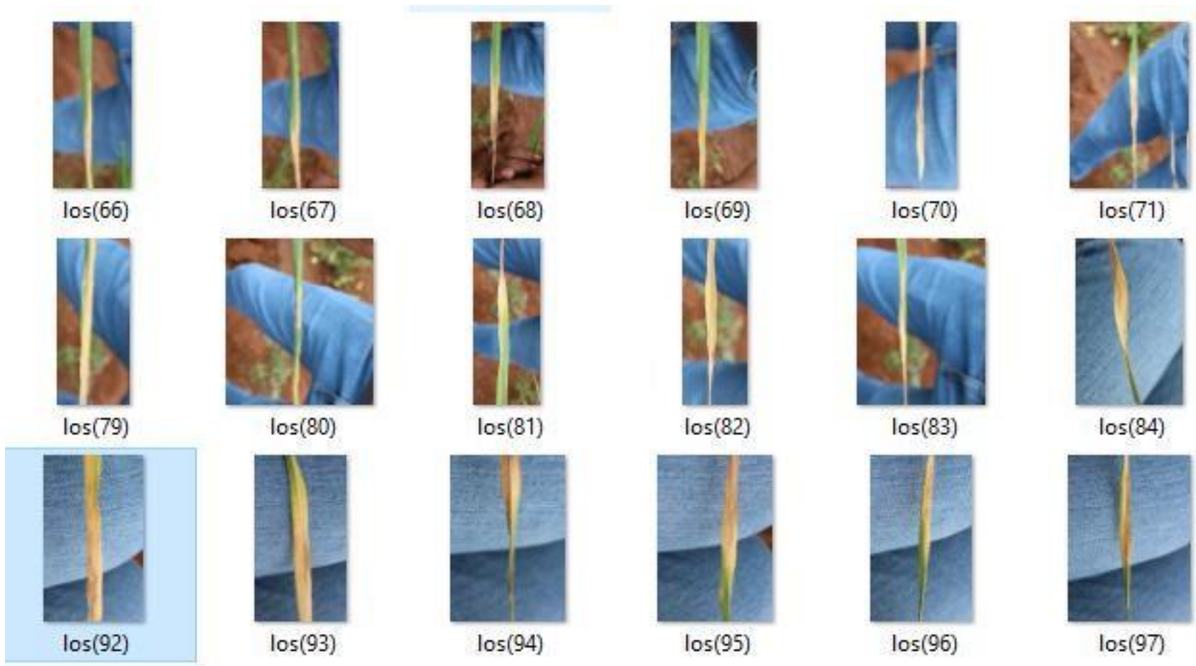


Figure 1.10: wheat-leaf dataset (septoria)

Figure1.11*: wheat-leaf dataset (stripe rust)*

Figure 1.12*: wheat-leaf dataset (healthy)*

7.2 Dataset Crop Disease Dataset

The same Principe like the first dataset but take another way in diseases and the nature of pictures taken (more exactly and details)

-here we have two division:

1. wheat leaf rust (fig 1.14)
2. Wheat loose smut (fig 1.15)

Figure 1.13: Crop DiseaseDataset

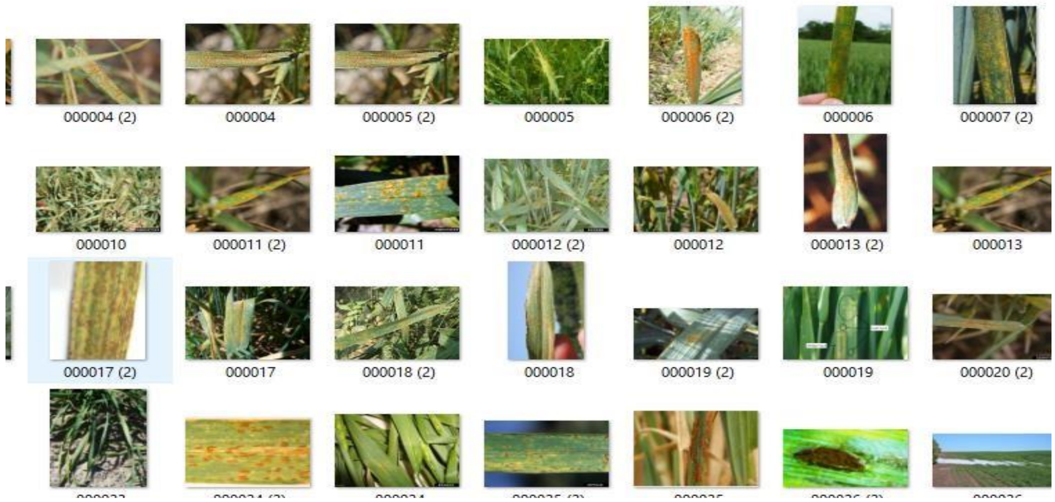


Figure 1.14*: Crop DiseaseDataset(wheat leaf rust)*

Figure 1.15*:Crop Disease Dataset(wheat loose smut)*

7.3 Wheat disease train and test dataset

This dataset (fig 1.16 – 1.18)is different than the others, it's contained two parts of pictures we needed

-Here we have the healthy wheat and wheat yellow rust and wheat brown rust

- 903 pictures represent wheat brown rust
- 1125 pictures represent wheat healthy
- 932 pictures reperesent wheat yellow rust

***Figure 1.16**: Wheat dis (wheat brown rust)*

***Figure 1.17** wheat healthy*

***Figure 1.18**: Wheat dis (wheat yellow rust)*

7.4 GWHD DATASET

This dataset contains only the healthy wheat growth using detection object with:

4700 high-resolution RGB (red green blue) images and 190000 labelled wheat heads collected from several countries around the world at different growth stages with a wide range of genotype. [13]

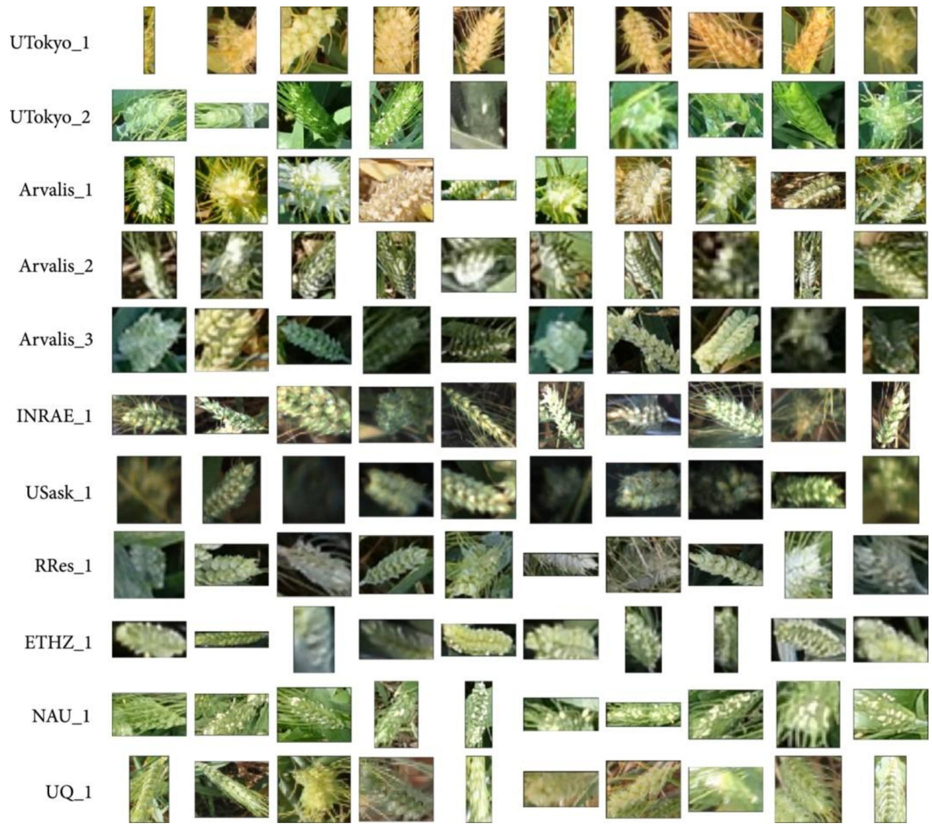


Figure 1.19: *Dataset GWHD using bounding box* [13]

8. Important Research Studies on Wheat Diseases

8.1 Article 1: Automatic detection of 'yellow rust' in wheat using reflectance measurements and neural networks [14]

The objective of this article is to address the imperative need to reduce pesticide usage in agriculture by proposing a cost-effective optical device for remote disease detection in crops based on canopy reflectance.

The authors conducted a study focusing on the early detection of "yellow rust" disease in wheat plants. They captured in-field spectral images using a spectrograph mounted at spray boom level and developed a normalization method to adjust for variations in reflectance and light intensity they called the dataset used "leaf spectra". The study utilized neural networks, particularly multilayer perceptrons (MLP), to develop disease detection algorithms.

According to the study's findings, the developed classification performance increased from 95% to more than 99%. These findings suggest the potential for a cost-effective optical device for early disease recognition in crops, which could significantly contribute to reducing pesticide usage in agriculture and enhancing agricultural sustainability

8.2 Article 2: A Neural Network-Based Approach to Multiple Wheat Disease Recognition [15]

The paper aims to propose modern computer vision methods for detecting multiple diseases in wheat leaves, including yellow spots, yellow rust, and brown rust.

The study utilized neural network architectures to achieve high accuracy rates, ranging from 0.95 to 0.99 for certain disease classes, comparable to expert phytopathologists. It introduced a novel approach for multilabel classification, where multiple diseases can be present in a single image. A dataset of wheat leaf images with various diseases was collected and used for model training, enabling the development of accurate disease detection models. Preprocessing techniques, such as rotation, flipping, and image normalization, were applied to enhance model performance. GoogleNet, a lightweight neural network architecture, was chosen for multilabel classification due to its efficiency and effectiveness. Evaluation metrics, including accuracy, precision, recall, and F1-score, were used to assess the model's performance, showing high accuracy rates for individual disease classes. The lightweight nature of the model allows for deployment on mobile devices, enabling rapid and automated disease detection in wheat crops. The proposed approach offers a practical solution for automated disease detection in real-world agricultural settings, with potential applications on mobile devices.

The study indicates that the models used achieved high accuracy rates in disease detection in wheat leaves, suggesting the effectiveness of the proposed approach for automated disease detection in agriculture.

8.3 Article 3: Deep transfer learning model for disease identification in wheat crop [16]

The paper aims to develop a deep transfer learning model for the identification of diseases in wheat crops using artificial intelligence (AI).

The study utilized the WheatRust21 dataset, which was collected under field conditions and includes instances of stripe, leaf, and stem rusts in wheat crops. Investigation was conducted on Convolutional Neural Networks (CNN) as well as EfficientNet architectures for the identification of wheat rust diseases. Additionally, the research focused on facilitating the deployment of the model on mobile devices, enabling on-site, image-based identification of wheat diseases.

The deep transfer learning model achieved an impressive accuracy rate of 99.35% in identifying diseases in wheat crops, demonstrating the effectiveness of AI-based approaches for this task. The utilization of CNN and EfficientNet architectures further enhanced the performance of disease identification. Moreover, the model's compatibility with mobile devices facilitates real-time, on-site identification, contributing to efficient disease management in wheat crops.

This research underscores the potential of AI-driven solutions for agricultural challenges, particularly in disease detection, and highlights the feasibility of deploying such models on mobile platforms for practical implementation in the field. (WheatRust21 dataset collected in field conditions for stripe, leaf, and stem rusts.)

8.4 Article 4: Wheat leaf disease identification based on deep learning algorithms [17]

The paper addresses the Wheat Disease Challenge, emphasizing the significant impact of wheat leaf diseases on agricultural productivity and food security.

The paper introduces a novel deep learning framework called RFE-CNN, which integrates Residual Channel Attention Blocks (RCABs), Feature Boosters (FBs), Embedding-based Metric Learning (EML), with using a dataset with name 'LWDCD 2020 'and Convolutional Neural Networks (CNN) for precise disease identification in wheat crops. The study utilizes parallel CNNs, RCABs, and FBs to extract features and enhance classification accuracy. he overall classification accuracy was 98.83%, and the maximum testing accuracy was 99.95%. We obtained an average accuracy score of 99.50

RFE-CNN outperforms established CNN models in terms of accuracy, efficiency, and adaptive capability, showcasing its superiority in disease identification tasks. The paper suggests future research directions, including improving disease recognition across different ecological locations and wheat varieties by leveraging hyperspectral imaging technology.

8.5 Article 5: Hybrid Deep Learning Model to Detect Uncertain Diseases in Wheat Leaves [18]

The article addresses the ongoing threat posed by wheat rust pathogens to global wheat production, highlighting the economic losses amounting to billions of dollars annually.

The vgg16 and capsule network are used ,The accuracy achieved equal a 93% Rust fungi rely on living host cells for their growth and reproduction, underscoring the challenge in combating their spreadThe continuous emergence of new rust races presents a formidable obstacle to achieving genetic resistance in wheat crops. The Studies have shown that race-specific genes in wheat encode NBS-LRR proteins, providing insights into the genetic mechanisms underlying resistance to rust pathogens.The strategies for managing wheat diseases include the use of fungicides, adoption of cultural practices, and optimization of planting times, aiming to mitigate the impact of rust pathogens and other diseases on wheat production.

8.6 Article 6: Classification of wheat diseases using deep learning networks with field and glasshouse images [19]

This article discusses the importance of identifying and controlling wheat diseases, particularly yellow rust, Septoria tritici blotch, brown rust, and mildew, which significantly affect crop yield and quality. The challenge arises from the similar appearance of these diseases during certain stages of their life cycles. To address this issue, the article explores the use of deep learning,

specifically convolutional neural networks (CNNs), for the automated detection and classification of wheat diseases using image data,

Images were collected from various locations across the UK and Ireland, capturing wheat leaves with visible symptoms of different diseases, along with healthy leaves, under realistic field and glasshouse conditions in 2019. The dataset comprised over 19,000 images, including five categories: Septoria, yellow rust, brown rust, mildew, and healthy.

The article developed and trained a CNN named CerealConv specifically for the identification and classification of wheat diseases. This CNN consisted of 13 convolutional layers with batch normalization, max pooling, and dropout.

CerealConv achieved a classification accuracy of over 97% on a test dataset containing the five predefined disease categories. When tested against manual classification by five expert pathologists, CerealConv outperformed them with an accuracy 2% higher than the most accurate pathologist. It classified the smaller dataset of 999 images faster and more accurately than the pathologists. To ensure CerealConv's reliance on relevant information for classification, masked images were used. When critical parts of the images were masked, CerealConv's classification accuracy dropped significantly, indicating its dependence on the correct information for classification.

Overall, the study suggests that deep learning methods, particularly the developed CNN model CerealConv, can effectively handle real field condition images of wheat diseases and perform at least as well as expert pathologists in disease identification and classification.

8.7 Article 7: Computer Vision Framework for Wheat Disease Identification and Classification Using Jetson GPU Infrastructure [20]

This article addresses the significance of wheat in Ethiopia, focusing on its status as the second most important grain crop and its contribution to 14% of the total calorie intake. Wheat production in Ethiopia primarily serves subsistence purposes, primarily cultivated by smallholder farmers.

Deep learning-based classification systems play a vital role in enhancing early identification of wheat diseases, thus aiding in effective disease management. Wheat farmers in Ethiopia encounter market constraints such as inadequate access to timely information and weak market linkages, which affect their productivity and profitability. The genetic variability within wheat species is crucial for developing resistance against diseases, highlighting the importance of genetic research and breeding programs,The VGG19 model has demonstrated promising results in accurately classifying wheat diseases, showcasing its potential in disease identification tasks, Automating wheat disease identification processes can mitigate yield loss and provide crucial support to the agricultural sector in Ethiopia, enhancing productivity and food security.

8.8 Article 8: Leaf and spike wheat disease detection & classification using an improved deep convolutional architecture [21]

The paper addresses the significance of wheat as a widely consumed grain and the impact of diseases on crop spoilage, Automatic wheat disease classification using deep learning is highlighted as a means to improve crop yield by effectively identifying and managing diseases, Deep learning classifiers, while powerful, may face limitations such as overfitting and the requirement for large datasets and computational resources.

Transfer learning is identified as a method to enhance classification performance, particularly

when dealing with limited data and resources, by leveraging pre-trained models.:

The proposed model utilizes the VGG16 architecture and achieves high accuracy in wheat disease classification, showcasing its potential in improving crop management practices.

The newly developed deep learning model showcased remarkable performance, achieving a testing accuracy of 97.88% in classifying 10 distinct wheat diseases. This high level of accuracy signifies the effectiveness of the model in accurately identifying and categorizing wheat diseases, which is crucial for implementing timely disease management strategies to mitigate crop yield losses. Additionally, the utilization of the VGG16 architecture further underlines the model's capability to achieve high accuracy in disease classification tasks, highlighting its potential for practical implementation in agricultural settings to enhance crop management practices and ensure food security.

8.9 Article 9: Identification of plant diseases using convolutional neural networks [22]

This paper focuses on the use of convolutional neural networks (CNNs) for classifying soybean leaf diseases using pre-trained AlexNet and GoogleNet models. The dataset used in this study consists of soybean leaf images collected from fields in Kolhapur district, Maharashtra, India. The dataset includes 649 images for training the AlexNet model and 550 images for training the GoogleNet model, categorized into four classes: bacterial blight, brown spot, frogeye leaf spot, and healthy leaves, The models achieved more than 95% accuracy

8.10 Article 10: A generic approach for wheat disease classification and verification using expert opinion for knowledge-based decisions [23]

This study focus on crop diseases significantly hamper agricultural productivity due to outdated identification methods. Despite farmers' local expertise, regional knowledge sharing is hindered by the absence of platforms. Research indicates declining crop yields due to diseases, cultivation methods, and inadequate local knowledge. This study leverages crowd-sourced data from agricultural stakeholders for disease identification, facilitating timely intervention. While existing Machine Learning (ML) algorithms offer disease management solutions, their reliance on static data leads to unreliable outcomes across diverse agricultural regions. Moreover, these algorithms overlook crucial insights from agricultural experts. To address the dynamic nature of wheat diseases, high-quality images and symptom-based data were collected through crowd-sourcing and augmented for training. A novel approach employing Decision Trees (DT) and various deep learning models is proposed for wheat disease identification and classification. Validation by domain experts enhanced DT accuracy by 28.5% and CNN accuracy by 4.3% (resulting in 97.2% accuracy), culminating in decision rules for wheat diseases in a knowledge-based system.

8.11 Article 11: **An in-field automatic wheat disease diagnosis system [24]**

The study aims to assess the impact of climate change on wheat production in Iran and evaluate the performance of the CERES-wheat model in simulating these effects. Additionally, the study collects a new in-field wheat disease dataset (WDD2017) to further analyze the impacts on crop health.

Researchers conducted an evaluation of the CERES-wheat model's performance in predicting wheat yield, biomass, leaf area index, and growth stages under climate change scenarios. Furthermore, they collected the WDD2017 dataset to enhance disease recognition accuracy using the DMIL-WDDS model.Their system achieves the mean recognition accuracy of 97.95% and 95.12% respectively over 5-fold cross-validation

The study found a significant correlation between predicted and measured values, indicating the accuracy of the CERES-wheat model in simulating climate change impacts on wheat production. Additionally, the DMIL-WDDS model outperformed conventional CNN-based architectures in disease recognition accuracy. The results also highlighted the adverse effects of climate change on wheat production, including reductions in grain yield and biomass, particularly due to rising temperatures. These findings underscore the importance of predicting and understanding climate change effects for ensuring sustainable agriculture in arid regions like Ira

8.12 Article 12 : Classifying Wheat Hyperspectral Pixels of Healthy Heads and Fusarium Head Blight Disease Using a Deep Neural Network in the Wild Field [25]

The study aims to classify Fusarium Head Blight disease in wheat using deep neural networks applied to hyperspectral imaging data collected in a wild field setting. The experiment was conducted from April 29 to May 15, 2017, focusing on factors such as wind, humidity, and temperature that influence hyperspectral imaging. 90 wheat ear samples were divided into 10 regions for hyperspectral imaging, and a Deep Convolutional Neural Network (CNN) was employed for analysis. Evaluation metrics including precision, recall, and F1 score were used to assess the model's performance. The study demonstrates the successful use of deep neural networks for diagnosing Fusarium Head Blight disease in wheat through hyperspectral imaging. The analysis focused on the experimental factors, sample division, and model evaluation metrics, emphasizing precision, recall, and F1 score. Hybrid neural networks are suggested as a promising approach for disease diagnosis in wheat, offering potential advancements in agricultural disease management.

9. Comparison of articles

Title of article	Architecture	Dataset	Results
1. Automatic detection of 'yellow rust' in wheat using reflectance measurements and neural networks [14]	MLP	5137 leaf spectra	Accuarcy 99%
2. ANeural Network-Based Approach To Multiple Wheat Disease Recognition [15]	GoogleNet neural network architecture	A dataset of wheat leaf images with various diseases.	Accuarcy from 95% to 99%
3. Deep transfer learning model for disease identification in wheat crop [16]	Investigation of CNN & EfficientNet for Weat rust disease identification	WheatRust21	Aaccuracy 99.35%
4. Wheat leaf disease identification based on deep learning algorithms [17]	Two parallel CNNs	LWDCD 2020	Accuracy 99.95%

5. Hybrid Deep Learning Model to Detect Uncertain Diseases in Wheat Leaves [18]	VGG-16 and a capsule network	No name mention	Accuracy 93%
6.Classification of wheat diseases using deep learning networks with field and glasshouse images [19]	MobileNet InceptionV3, Vgg16	WheatleavesUK	Accuracy 91,43%,
7.Computer Vision Framework for Wheat Disease and Classification Using Jetson GPU Infrastructure[20]	Inceptionv3, Resnet50, and VGG16/19	Bishoftu dataset	Accuracy 99.38%
8. Leaf and spike wheatdisease detection & classification using an improved deep convolutional Architecture [21]	VGG16	LWDCD2020	Accuarcy 97.88%
9. Identification of plant diseases using convolutional neural networks [22]	AlexNet, GoogleNet	Soybean leaf	Accuarcy 95%
10. A generic approach for wheat disease classification and verification using expert opinion for knowledge-based decisions [23]	CNN	No name mention	97.5% accuracy
11. An in-field automatic wheat disease diagnosis system [24]	GG-FCN-VD16 and VGG-FCN-S	Wheat Disease Database 2017 (WDD2017)	Accuracies of 97.95% and 95.12%
12.Classifying Wheat Hyperspectral Pixels of Healthy Heads and Fusarium Head Blight Disease Using a Deep Neural Network in the Wild Field [25]	Convolutional Neural Network (CNN**)**	Wild Field2018	Accuracy: 75% validation accuracy 74,3%

Table 1.2 : *Comparison between important research Studies*

10. Conclusion

Wheat stands as a cornerstone of global food security, serving as a primary source of nutrition for billions of people worldwide. We cannot overstate its significance in providing sustenance, making it imperative to safeguard its production against various diseases and pathogens. Among these threats, wheat leaf diseases such as stripe rust and septoria pose significant challenges to crop yield and quality.

Stripe rust and septoria, alongside other crop diseases, not only diminish yields but also compromise the nutritional value of wheat, thereby exacerbating food insecurity. Traditional methods of disease detection relying on human observation are often insufficient, particularly given the scale of modern agricultural operations and the rapid spread of pathogens. Hence, there is a pressing need for more advanced and efficient disease detection techniques.

Deep learning, a subset of artificial intelligence, has emerged as a promising tool for combating wheat diseases. By leveraging neural networks to analyze vast amounts of image data, deep learning algorithms can identify subtle patterns indicative of disease presence with remarkable accuracy. This technology offers a more proactive approach to disease management, enabling timely interventions to mitigate crop losses and ensure food security.

Furthermore, the integration of deep learning with advanced imaging technologies facilitates real-time disease monitoring and decision-making, empowering farmers and plant pathologists to adopt more effective disease management strategies. The ability to detect diseases such as stripe rust and septoria early on enables targeted interventions, such as the precision application of fungicides, minimizing the need for blanket treatments and reducing environmental impact.

CHAPTER 2

Deep Neural Network

1. Introduction

Artificial intelligence represents the new generation in programming, marking a pivotal shift from previous programming approaches to the current era. This is evident in two main patterns that make the life of a human easy:

machine learning and deep learning. In machine learning, systems analyze data and learn patterns in order to make decisions and predict outcomes. On the other hand, deep learning utilizes artificial neural networks to represent and analyze data structurally, enabling a deeper understanding and complexity of information and situations.

2. Machine learning

Machine learning (ML) trains machines to handle data more efficiently. Sometimes, after viewing the data, we cannot interpret or extract information from the data. In that case, we apply machine learning. With the abundance of datasets available, the demand for machine learning is on the rise. Many industries apply machine learning to extract relevant data. The purpose of machine learning is to learn from the data. Researchers have conducted numerous studies on enabling machines to learn autonomously without explicit programming. Many mathematicians and programmers apply several approaches to find the solution to this problem, which has huge data sets. [27]

3. Machine Learning Approaches

To apply machine learning (fig 2.1) we need to apply their algorithms :

3.1 Supervised learning

is a fundamental machine learning task where the goal is to learn a function that maps input data to corresponding output labels based on example input-output pairs. In this approach. [27]

3.1.1 Decision Tree

This method represents choices and their consequences in the form of a tree graph. Each node in the graph represents an event or decision, while the edges represent the decision rules or conditions. Decision trees are constructed based on the principle of recursively partitioning the feature space. [27]

3.1.2 Naive Bayes

Naive Bayes is a classification technique based on Bayes' Theorem, assuming independence among predictors. It's commonly used in text classification tasks and calculates the conditional probability of each class given the input features. [27]

3.1.3 Support Vector Machine (SVM)

SVMs are powerful supervised learning models used for classification and regression tasks. [28]

3.2 Unsupervised learning

On the other hand, involves learning from unlabeled data without explicit supervision. Algorithms in this category are tasked with discovering hidden patterns or structures in the data without predefined labels.

3.3 Semi-supervised learning

Combines aspects of both supervised and unsupervised learning methods.

3.4 Reinforcement Learning

Is another paradigm where agents learn to take actions in an environment to maximize cumulative rewards. [28]

3.5 Neural Networks

Are a class of models inspired by the structure and function of the human brain. They consist of interconnected nodes organized in layers, and they can be trained using supervised, unsupervised, or reinforcement learning paradigms. [29]

3.6 Instance-Based Learning,

Represented by algorithms like K-Nearest Neighbors (KNN).

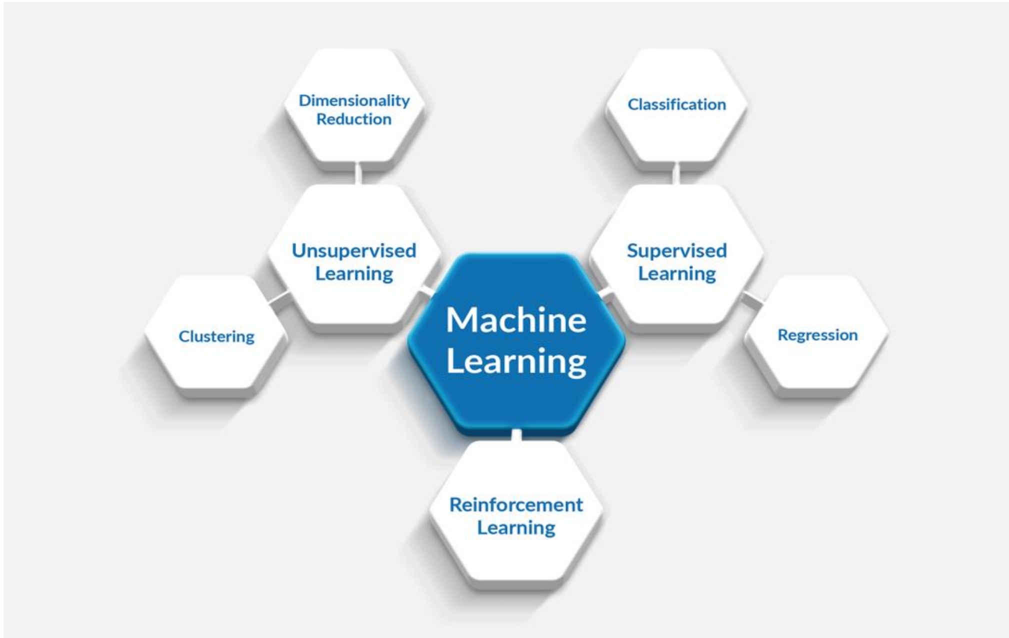


Figure 2.1 *: Machine learning algorithms [30]*

4. Deep learning

Deep learning is a sub-field of machine learning that deals with algorithms that are mostly based on specific types of artificial neural networks, sometimes with a high number of layers and nodes. It mirrors the function of human brains. Deep learning algorithms bear similarities to the structure of the nervous system (fig 2.2), where each neuron interconnects and transmits information. Deep learning models work in layers, and a typical model at least has three layers. Each layer accepts the information from the previous one and passes it on to the next one.

The difference between machine learning and deep learning models is in the feature extraction area. In machine learning, humans perform feature extraction, while deep learning models independently determine it.

Deep learning models perform well with large amounts of data, whereas old machine learning models stop improving after a saturation point. Thus, deep learning is a specific type of machine learning that is part of AI. [31]

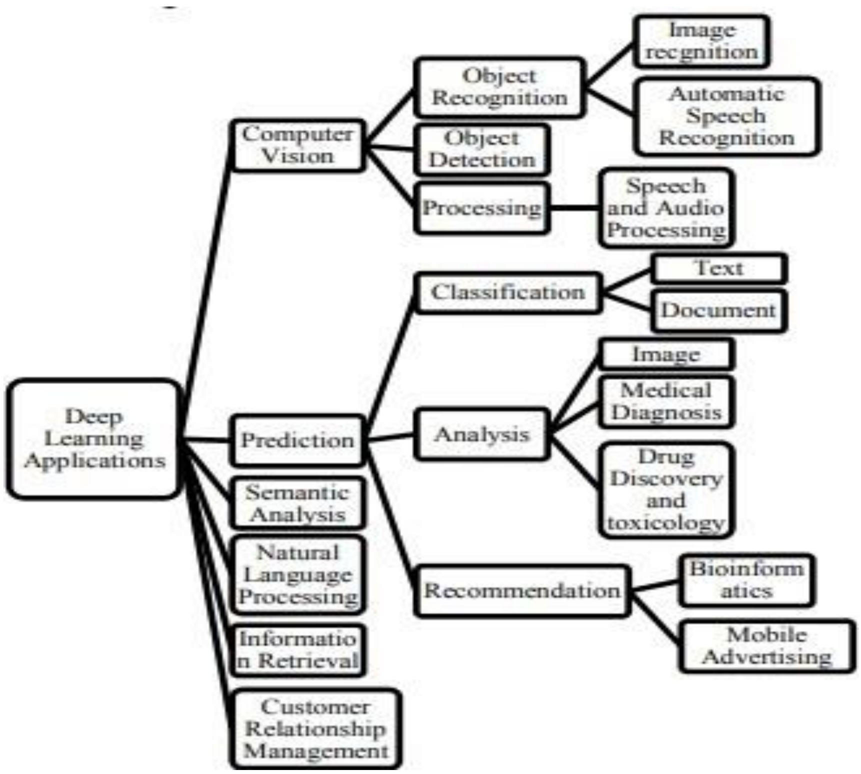


Figure 2.2: *Deep learning applications [32]*

4.1 The relation between machine learning (ML) and deep learning (DL)

While deep learning has shown remarkable success in certain domains, traditional machine learning algorithms still have their place, especially in scenarios with limited data, interpretable models, or specific constraints. The table 2.1 makes the difference between both of machine and deep learning.

Aspect	Deep Learning	Machine Learning
Relationship	Deep learning is a subset of machine learning.	Machine learning is a broader field encompassing deep learning.
Model Complexity	Typically uses simpler models with fewer parameters.	Employs complex models with many layers and parameters (artificial neural networks).
Feature Engineering	Automatically learns hierarchical features from raw data.	Often relies on manual feature engineering to extract relevant features from data.
Model Interpretability	Deep models can be complex and difficult to interpret.	Models are often more interpretable, making it easier to understand how decisions are made.
Data Requirements	Often requires large amounts of data for effective training.	Can functionwith smaller datasets.
Applications	Wide range of applications including regression, classification, clustering, etc…	Particularly suited for complex tasks like image recognition, natural language processing, and self-driving cars.

Table 2.1: Comparison Machine learning vs Deep learning [w8]-[w10]

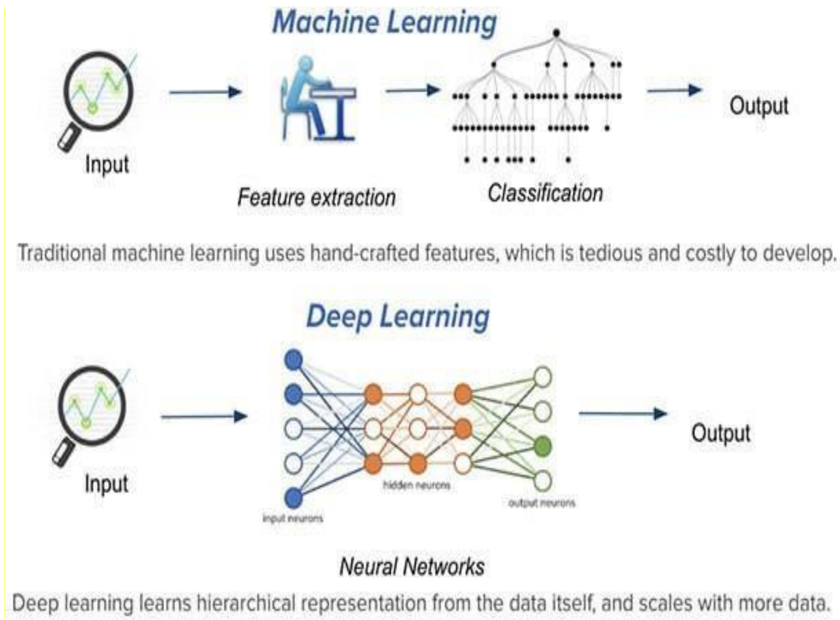


Figure 2.3: Machine learning Vs deep learning

4.2 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs, or ConvNets) are specialized neural architectures (fig 2.5) primarily employed for various computer vision assignments, including image classification and object recognition. These neural networks leverage linear algebra, particularly convolutional operations, to discern patterns within images. [33]

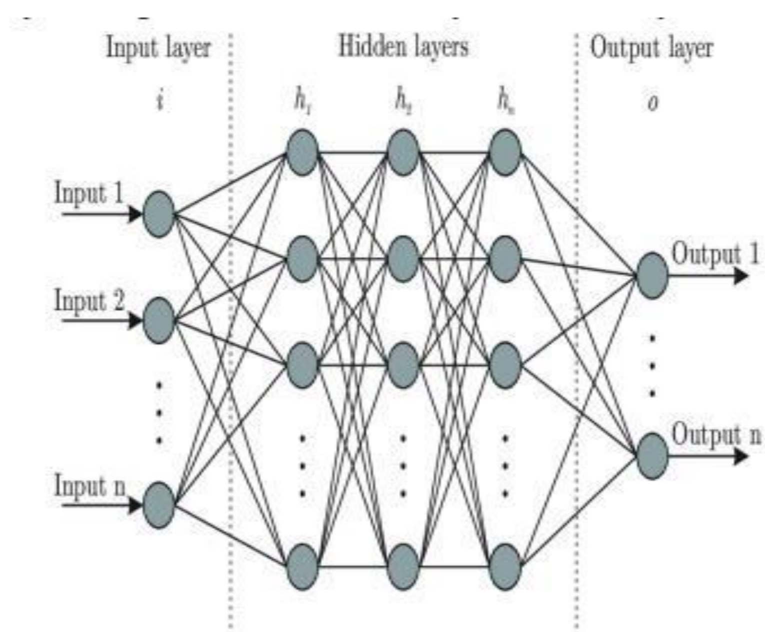


Figure 2.4*: Neural network [34]*

Imagine you have a bunch of puzzle pieces, and you want to put them together to see the whole picture. CNN works in a similar way. They break down a picture into small parts and analyze each part to understand what's in the picture.

4.3 Convolution layer

This layer is the heart of the convolutional neural network, with its parameters consisting of a collection of filters. Although these filters are small in size, they span the entire depth of the input volume. The primary function of the convolutional layer is to extract high-level features. The initial layer, illustrated in (fig 2.5) , extracts low-level features such as color and edges. Subsequent convolutional layers further extract high-level features, ultimately resulting in a comprehensive understanding of the image. [35]

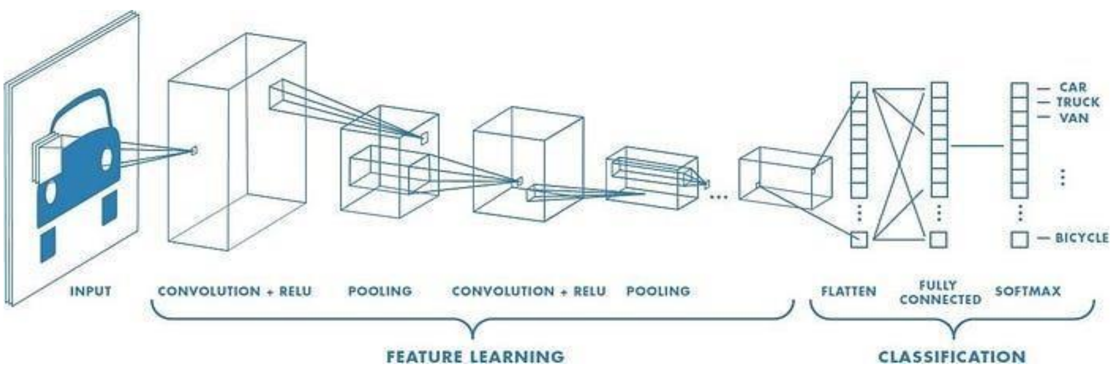


Figure 2.5*: Neural network with many layers [36]*

4.3.1 Pooling Layer

Pooling layers reduce the size of feature maps, which in turn reduces the number of parameters to learn and the computational burden on the network. These layers group features together in certain areas of convolution-generated feature maps. This lets operations be done on summed-up features instead of precisely located ones. This increases the model's robustness against feature position variations within the input image. [38]

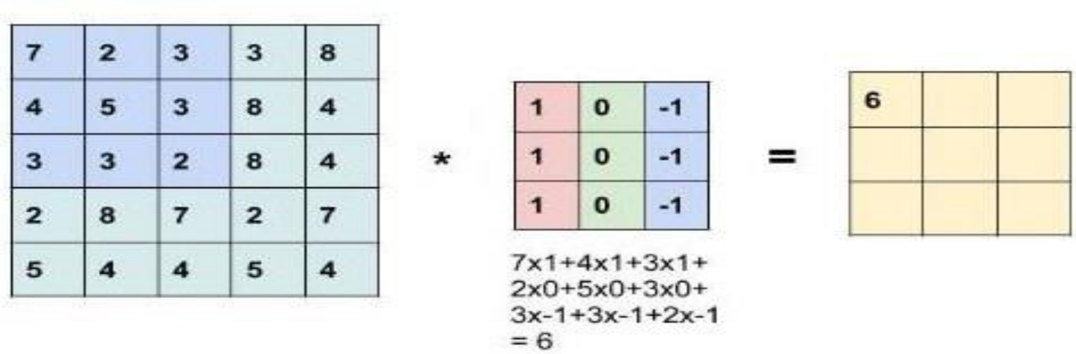


Figure 2.6 *Filter matrix in convolution layer. [37]*

A) Max pooling layer

Max pooling is the process of selecting the maximum element within the filter-covered region of the feature map (fig 2.7). As a result, the output from the max-pooling layer consists of a feature map that highlights the most prominent features from the preceding layer.

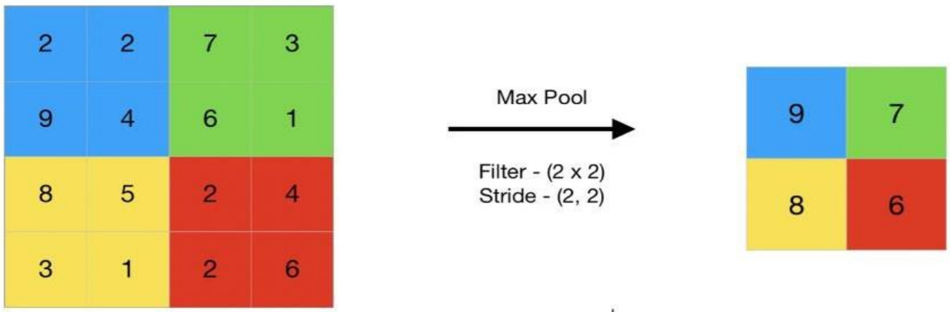


Figure 2.7 *:Max pooling matrix* [38]

B) Average Pooling

Average pooling calculates the average value of the elements within the filter-covered region of the feature map (fig 2.8). Unlike max pooling, which emphasizes the most prominent feature within a patch of the feature map, average pooling provides the average value of features present in that patch.

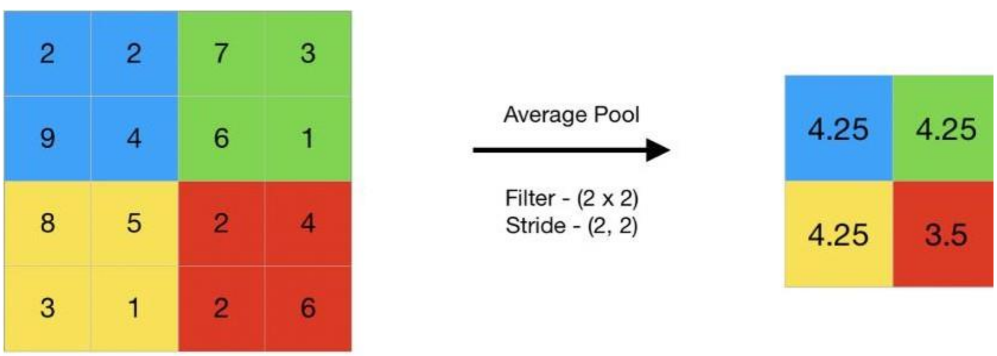


Figure 2.8*: Average pooling matrix [38]*

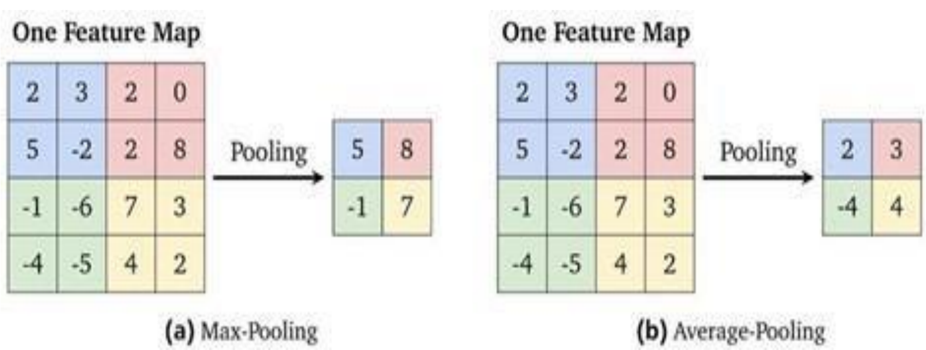


Figure 2.9*: The Pooling layer example*

4.4 Fully Connected Neural Networks

Fully Connected Neural Networks are often identified by their multilayer perceptrons. It consists of fully connected layers that link every neuron in one layer to every neuron in the other layer. Fully connected networks significantly benefit from their "structure- agnostic" nature, which eliminates the need for specific input assumptions. While being structure agnostic makes fully connected networks very broadly applicable, such networks tend to have weaker performance than special-purpose networks tuned to the structure of a problem space. [39]

Works best in

-Any table dataset which has rows and columns formatted in Csv.

- Classification and regression issues with the input of real values.

-Any model with the highest flexibility, like that of ANNS

PS: CSV (comma separated values) is one of the form of dataset used used to store tabular data

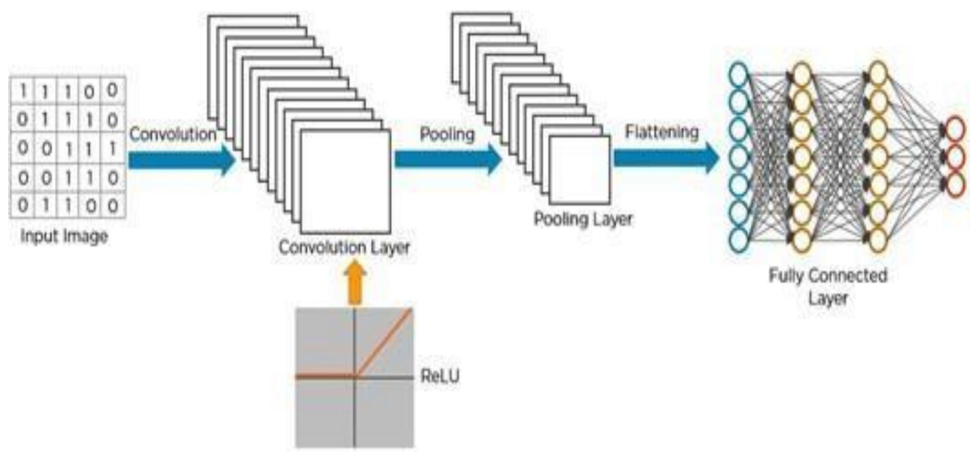


***Figure 2.10**: Convolution neural network process*

5. Recurrent neural network (RNN)

A Recurrent Neural Network (RNN) represents another advancement in artificial neural networks, specifically designed to learn from sequential data. Like conventional neural networks (fig 2.11), an RNN consists of multiple layers, each with its own weights and biases. However, in an RNN, connections between nodes form a directed cycle graph, allowing information to flow in sequential order. One notable advantage of RNNs is their ability to capture temporal dynamics. Unlike feedforward networks (FFN), RNNs incorporate internal memory to retain sequence information from previous inputs, making them well-suited for tasks such as natural language processing and speech recognition. By introducing recurrent hidden states, RNNs effectively capture dependencies across different time scales, enabling them to handle temporal sequences efficiently. [40]

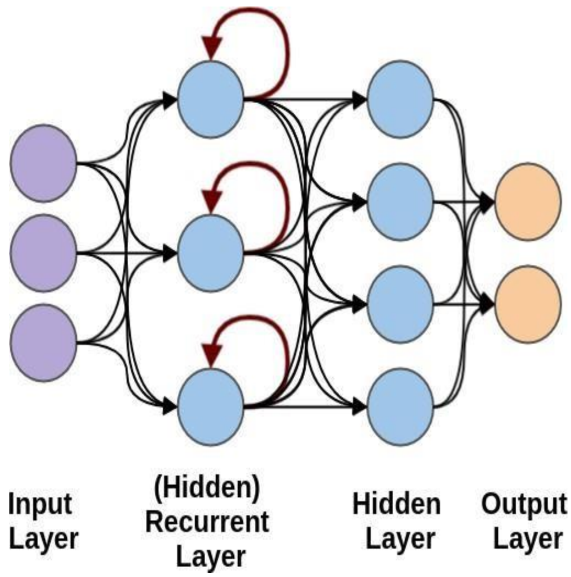


Figure 2.11*: Recurrent Neural Networks architecture*

5.1 Long Short-Term Memory (LSTM) [40]

Artificial recurrent neural networks (RNNs) specifically design LSTM (Long Short- Term Memory) to address long-term dependencies. Unlike traditional RNNs, LSTM incorporates feedback connections to process entire sequences of data. Its typical architecture comprises three main components: the input gate, the forget gate, and the output gate.

The input gate chooses the pertinent data to integrate into the cell state. In the meantime, the forget gate employs a sigmoid function, which outputs values between 0 and 1, to determine which information to discard. Lastly, the output gate determines which information from the current time step to retain for the next step.

LSTM's (fig 2.12) cell state serves as long-term memory, retaining valuable information from previous time intervals. This feature enables LSTM to effectively capture and retain crucial patterns over extended periods, making it suitable for various applications involving time-series data, such as classification, processing, and prediction tasks. [40]

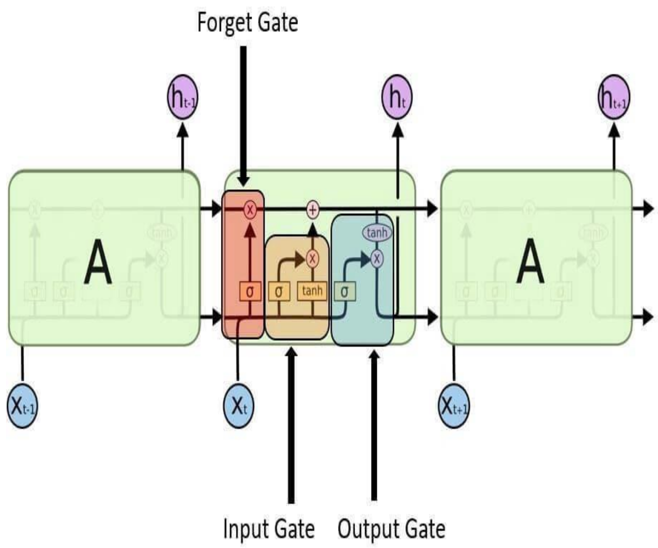


Figure 2.12: *Long Short-Term Memory architecture.*

6. Hyperparameters of the model

Hyperparameters are parameters whose value is defined before the start of the Learning process. For deep neural networks, we can distinguish three types of Hyperparameters: [w11]

6.1 Layer hyperparameters

kernel size, dropout, activation method for hidden layers and for the final layers, etc…

6.2 Model compilation hyperparameters

optimizer, loss, learning rate, etc.

6.2.1 Optimizer

Optimizers are algorithms used to modify attributes of the neural network such as weights

and learning rates to reduce losses, The most commonly used otpimizers in deep learning

include: [w12]

6.2.2 Stochastic gardien descent (SGD)

This is the simplest and most commontly used optimize.It adjusts the model's weights using the opposite direction of the cost function gradient with respect to the

parameters, the stochastic version calculates the gradient on a random sample of the traning data at each step.

6.2.3 Adam optimizer

It combines SGD with adaptive estimation of fardient moments to adjust learning rates for each model parameter.

6.2.4 RMSprop Optimizer

It uses adaptive estimation of gradient by using an exponential moving average of the squares of gardients to adjust learning rates for each parameter.

6.2.5 Adagrad Optimize

It adapts learning rates for each parameter based on the frequency of occurrence of each parameter in the training data.

There are many other optimizers available, and the choice of optimize depends on various factors such as the size of the training data, the complexity of the model, and the avuabke traninig time.

6.2.6 Regularization

Regularization is a technique used to prevent overfitting and improve the generalization performance of a model. The goal of regularization is to reduce the complexity of the model and prevent the weights of model parameters from becoming too large. There are several regularization techniques such as dropout regularization, which involves randomly removing neurons from the model during training to reduce neuron co-adaptation. [w13] (fig 2.13) represent the difference without Regularization and with it

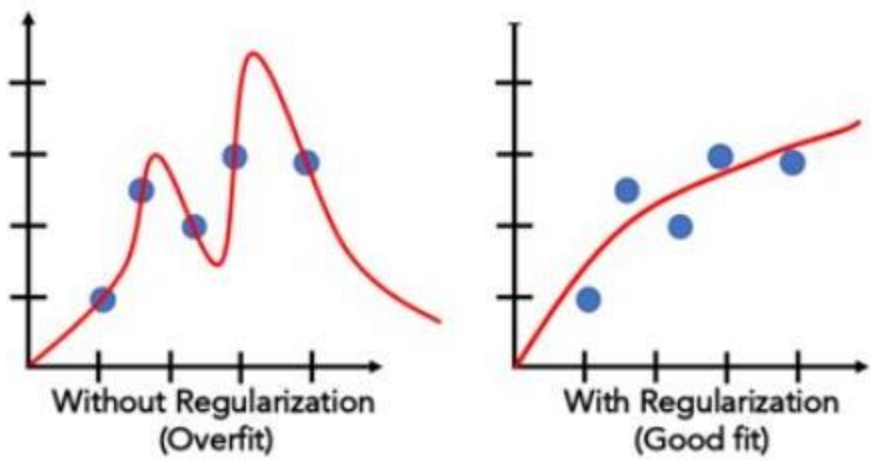


Figure 2.13: *With and without regularization*

6.3 Model execution hyperparameters

batch size, number of epochs.

6.3.1 Epoch

An epoch is a complete iteration of the learning algorithm over the entire training dataset. An epoch occurs when the learning algorithm has performed computations on all the training data once. The number of epochs can reach several thousands, as the procedure repeats indefinitely until the model's error rate is sufficiently reduced. Generally, the higher the number of epochs, the more likely the learning algorithm is to converge to a model that generalizes well and can be used to make accurate predictions on new data. [w14]

6.3.2 Batch size

Training data is divided into several small batches. The purpose is to avoid problems related to lack of storage space. Batches can be easily used to feed the machine learning model for training. This process of data decomposition is called "batching". [w14]

7. Activation Functions

The most commonly used activation functions are: [w15]

7.1 ReLU Function (Rectified Linear Unit)

The ReLU function takes an input value x and returns either that value if it is positive, or zero if it is negative. Thus, the ReLU function is linear for positive values and nonlinear for negative values. The ReLU function is often used as the activation function in neural networks because it is simple and effective. It is also faster to compute than other nonlinear activation functions such as the sigmoid function or the hyperbolic tangent function

f(x) = max (0, x)

7.2 Sigmoid Function

It transforms an input value into a value between 0 and 1. It is often used in neural networks with a single hidden layer.

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

7.3 Hyperbolic Tangent Function

The hyperbolic tangent (or tanh function) is a mathematical function, where x is the input to the function and tanh(x) is the output. The tanh function is similar to the sigmoid function, but it is centered around zero and has a wider output range, ranging from -1 to 1. Therefore, it is better suited for tasks where the data has zero mean and high variance. It is defined as follows:

$$f(x) = \tanh(x) \frac{e^{x} + e^{-x}}{e^{x} + e -^{x}}$$

7.4 Softmax Function

It takes an input vector of real numbers and returns a vector of normalized probabilities, whose sum is equal to 1. Each element of the output vector represents the probability that the input belongs to a particular class. Mathematically, the softmax function is defined as follows:

$$softmax(xi) = \frac{e^{xi}}{\sum_{j=1}^{n} e^{xj}}$$

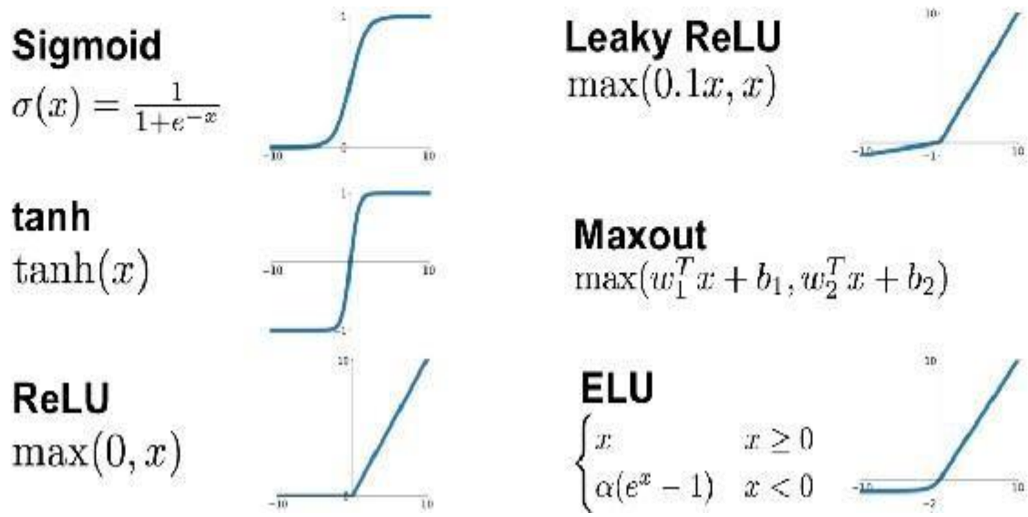


Figure 2.14: *Activation functions graphe*

8. Transfer learning

In deep learning, the model gains model weight and bias by training on a sizable amount of data. Other network models receive these weights for testing. Pre-trained weights can be the starting point for the new network model (fig 2.15). [41]

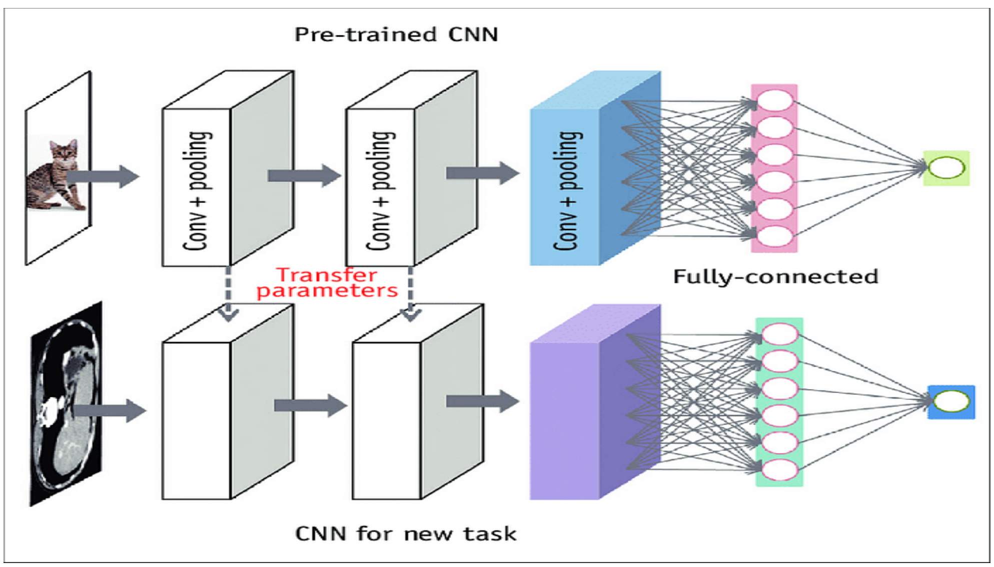


Figure 2.15 : *Transfer learning layers (CNN Pre-trained)* [42]

8.1 The pre trained model

These domains have already been used to train a pre-trained model. Many pre-trained architectures are accessible; the following are the justifications for utilizing pre-trained models: First, in order to train the massive models on vast datasets, additional processing power is needed.

Secondly, it takes an excessive amount of time—up to several weeks—to train the network. Using pre-trained weights to train the new network helps expedite the learning process.

8.1.1 LeNet

LeNet is initial Convolutional architecture, which consist of two convolutional layers with ReLu and average pooling layers, followed by another convolutional layer, which is used for flattening, then two-fully-connected layers and eventually one softmax-layer. [43]

8.1.2 AlexNet

Compared to LeNet, AlexNet has a far deeper neural network. Rectified Linear Units, or ReLUs, are employed in this network to introduce non-linearity and accelerate it. This network has six2.3 million parameters in addition to five convolutional layers, three fully connected layers, and an output layer. [44]

8.1.3 Vgg

VGG: Visual Geometry Group is the full name of VGG .
VGG16 and VGG19 are typically present in the VGG network. Because this network replaces the big size kernels with many 3x3 filters, we are able to extract complicated features at a minimal cost. [45]

8.1.4GoogleNet

GoogleNet achieves good accuracyBecause of its high calculation order, GoogleNet[46] produces good accuracy but necessitates substantial processing resources. Instead of fully-connected layers at the final point, GoogleNet was substituted with average pooling after the last convolutional layer, which will result in fewer parameters. [47]

9. CNN for wheat diseases

Convolutional Neural Networks (CNNs) are proving to be highly effective in detecting and classifying wheat diseases, which is crucial for optimizing pesticide use, improving yield, and ensuring quality. Traditional methods for detecting wheat diseases, such as manual inspection, are often subjective, inefficient, and inaccurate. Modern approaches use CNNs to overcome these issues by leveraging their ability to process complex images and identify subtle differences in disease symptoms.

One notable approach is a lightweight multiscale CNN model that combines residual modules and inception modules, enhancing the model's ability to focus on relevant disease features while minimizing background noise. This model integrates CBAM and ECA modules within its residual blocks to further improve disease recognition accuracy, achieving a remarkable 98.7% accuracy on test datasets. This performance surpasses other well-known CNN architectures like AlexNet, VGG16, and InceptionResNetV2, as well as lightweight models like MobileNetV3 and EfficientNetB0. [48]

In addition to high accuracy, these CNN models are designed to be efficient enough for deployment on mobile devices, allowing for quick and accurate disease detection in the field. This makes them particularly valuable for modern precision agriculture, where rapid and reliable disease detection is essential for timely intervention and management.

Overall, CNN-based models represent a significant advancement in the fight against wheat diseases, offering a powerful tool for farmers and agronomists to safeguard crops and ensure food security. [48]

10. Performance Metrics

To evaluate a network, (tab 2.2), it is necessary to calculate a certain number of parameters such as:

True Positive (TP): The cases predicted YES and the actual output was also YES.

True Negative (TN): The cases predicted NO and the actual output was NO

False Positive (FP): The cases predicted YES and the actual output was NO.

False Negative (FN): The cases predicted NO and the actual output was YES

10.1 Confusion Matrix

Confusion matrix is a measure used while solving classification problems. It can beapplied to binary classification as well as for multiclass classification problems

		Predicted classes	
		class = Positive	class = Negative
Actual classes	class = positive	TP	FN
	class = Negative	FP	TN

Table 2.2: Confusion Matrix.

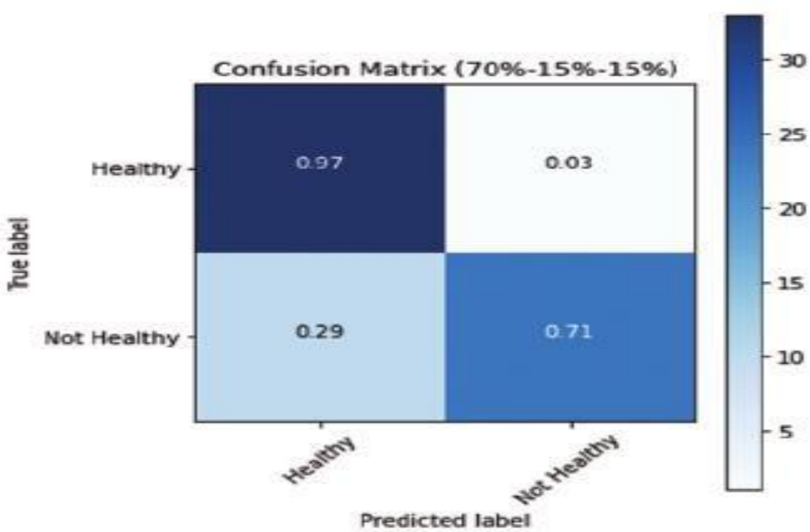


***Figure 2.16**: Example of confusion matrix for dataset split [49]*

10.1 F-Mesure

$$\textbf{F1-Mesure} = 2x\ \frac{Precision*recall}{Precision+recall}$$

10.2 Accuracy

Accuracy can be calculated as follows=

$$accuarcy = \frac{TP}{TP + FP}$$

10.3 True Positive Rate/ Recall/ Sensitivity

A Recall is essentially the ratio of true positives to all the positives in ground truth

$$.\textbf{Recall} = \frac{TP}{TP+FN}$$

10.4 True Negative Rate

Probability of a negative prediction in a negative case.

$$\textit{True Negative Rate} = 1 - \frac{TN}{TN+FP}$$

10.6 False Positive Rate

$$\textit{False Positive Rate} = 1 - \frac{TN}{TN+FP}$$

11. Conclusion

Using convolution neural networks researchers have successfully developed efficient systems for detecting wheat diseases using digital images. Despite challenges such as the need for large datasets and complexities in disease classification, employing CNNs represents a significant step towards improving agricultural practices and crop management.

CHAPTER 3

Conception

1. Introduction

The rapid advancement of deep learning technologies has revolutionized many fields, including agriculture. The analysis and classification of wheat images to distinguish between healthy and diseased plants have greatly benefited from these technological advancements. Deep learning, with its deep neural networks, enables unprecedented precision in detecting and identifying plant diseases.

Our project focuses on the application of deep learning for the classification of healthy and diseased wheat images. By utilizing convolutional neural networks (CNNs), we aim to develop a model capable of accurately detecting signs of diseases in wheat crops. This technology holds immense potential for improving crop management by enabling early and targeted interventions, thereby reducing agricultural losses and contributing to more sustainable food production.

2. System Architecture

Our system is based on sequential architecture also called Master-slave architecture mainly composed of three modules :

Module 1: Preprocessing data (fig 3.1)

Module 2 :The Master (Detection Diseases Network) represent in fig 3.2

Module 3: The Slave (Diagnose Diseases Network) represent in fig 3.3

2.1 Preprocessing

The system started with insert or taken a picture for the wheat to go to the next step that made the PreProcessing (fig 3.1) and to made it we need to resize.

2.1.1 Image resizing

Is the process of altering the dimensions of an image (255x255) , Can adjustment Image quality and resolution

A) Detection Diseases

While the preprocessing done and all the image inserted are resized The preprocessing dispatch To Detection Diseases Network

B) Diagnose Diseases Network

To verify the detection label "healthy or sick" when we have healthy wheat then we done ,else the picture is sick (fig 3.1) then we need Diagnose Diseases Network while the preprocessing done and all the image inserted are resized The preprocessing dispatch to classification of the diseases

2.1.2 Diagnose Diseases Network

This network is only for the Sick wheat , It's the final step to classification to 4 classes diseases (fig 3.1) using feature map. After the prediction the network put the output of the classification with confidence .

The architecture detailed in the figure below (fig 3.1)

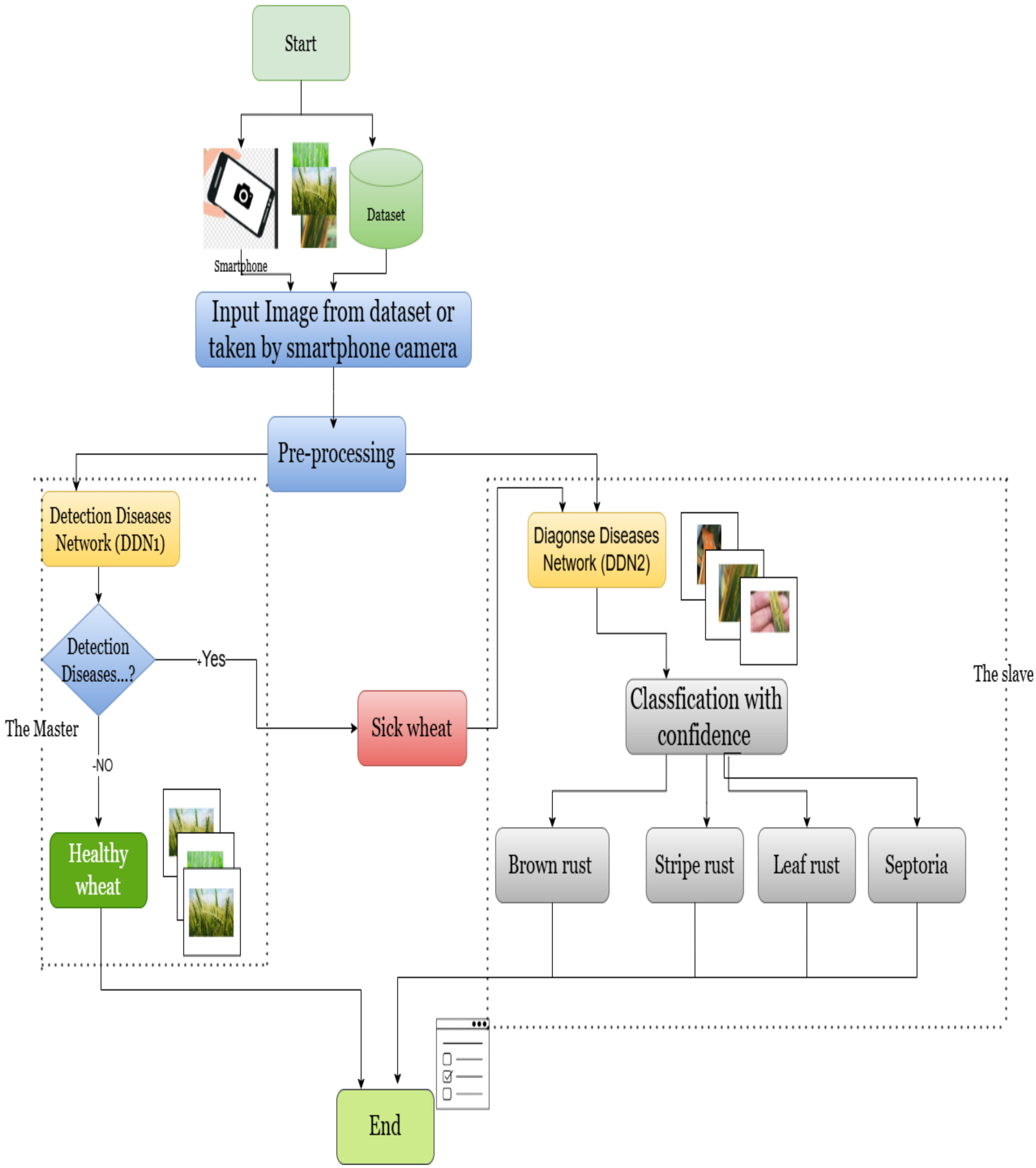


Figure 3.1 *Architecture of our system*

2.2 The Master Network (DDN1)

Starting with put the dataset of the healthy wheat and the diseases wheat For dispatching and Preprocessing to the split data (fig 3.2) Our data split to 80% train ,10% validation and 10% for the test

2.2.1 Training data

Train the model means that we already put the hyper parameter and split our data. Therefore the results will be Strong or Weak (fig 3.2)

Strong : the strong (accuracy more than 80 % and loss less than 1.0) mean we done and save the Model DNN1

Weak : the weak (accuracy > 80% and loss about 2.0 to 5 or more)we need to modify the hyperparamater (fig 3.2) that mean search what is not compatible with the network and replace it (Probably Epoch , Batch size or at level of the pictures of dataset)

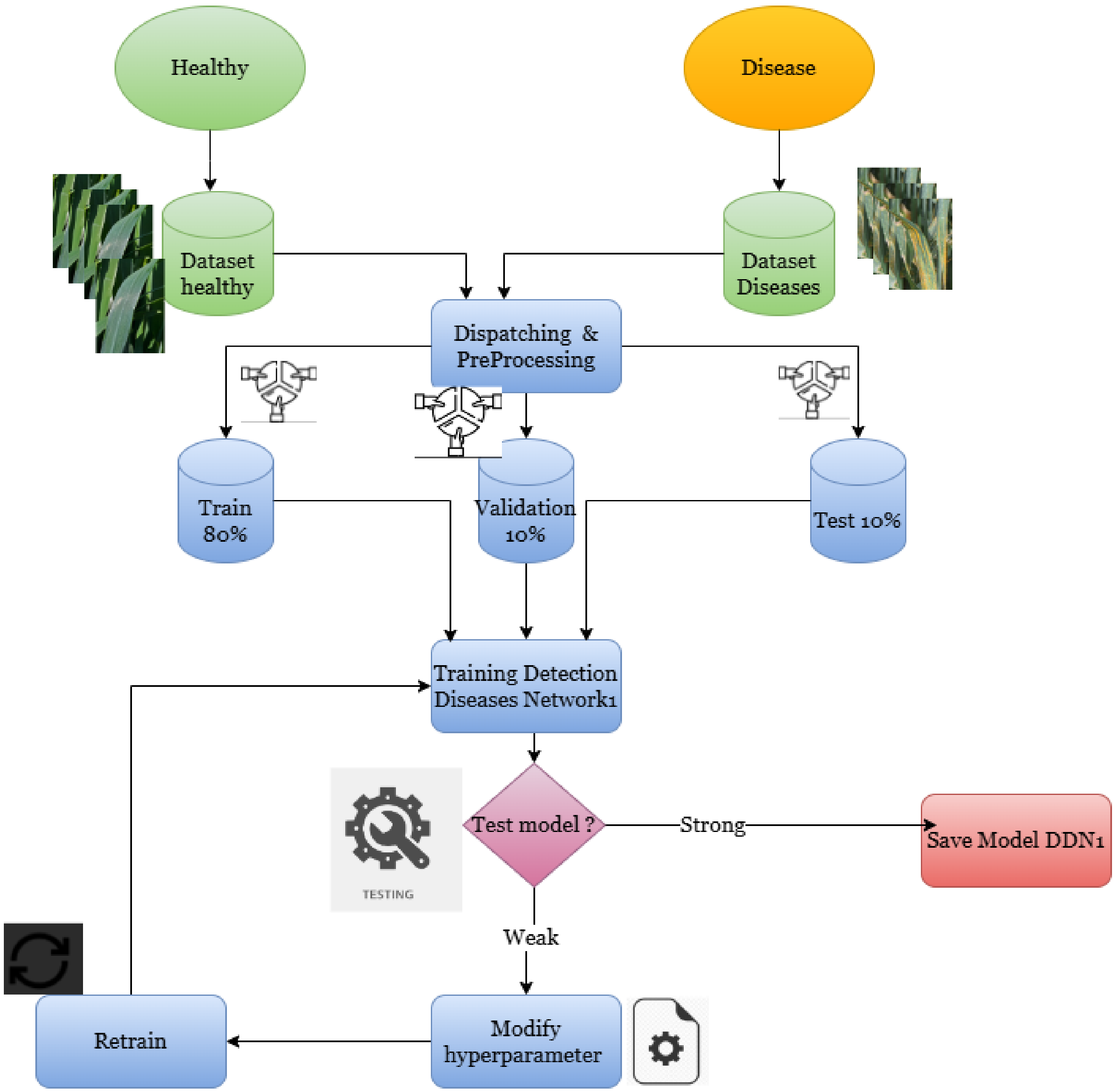


Figure 3.2 : *Train Detection Disease Network (DDN1)*

2.3 Train Diagnose Disease Network

Starting with put the dataset of the Only the diseases wheat and for that we chose 4 classes (septoria , leaf rust ,brown rust ,stripe rust) . Then we dispatching and Preprocessing to the split data (fig 3.3) Our data split to 80% train ,10% validation and 10% for the test.

2.3.1 Image augmentation

Image augmentation for a dataset (fig 3.3) applying various transformations, such as rotation, flipping, and scaling, to the original images to create new, diverse samples in other sense mean take the original image and transformer to other images to make it easy to prediction.

2.3.2 Training data

We consider it a common point with DDN1.Train the model mean that we already put the hyper parameter and split our data

So the results will be Strong or Weak (fig 3.3)

Strong :the strong mean we done and save the Model DNN2

Weak : we need to modify the hyperparamater (fig 3.3) that mean search what is not compatible with the network and replace it (Probably Epoch , Batch size or at level of the pictures of dataset)

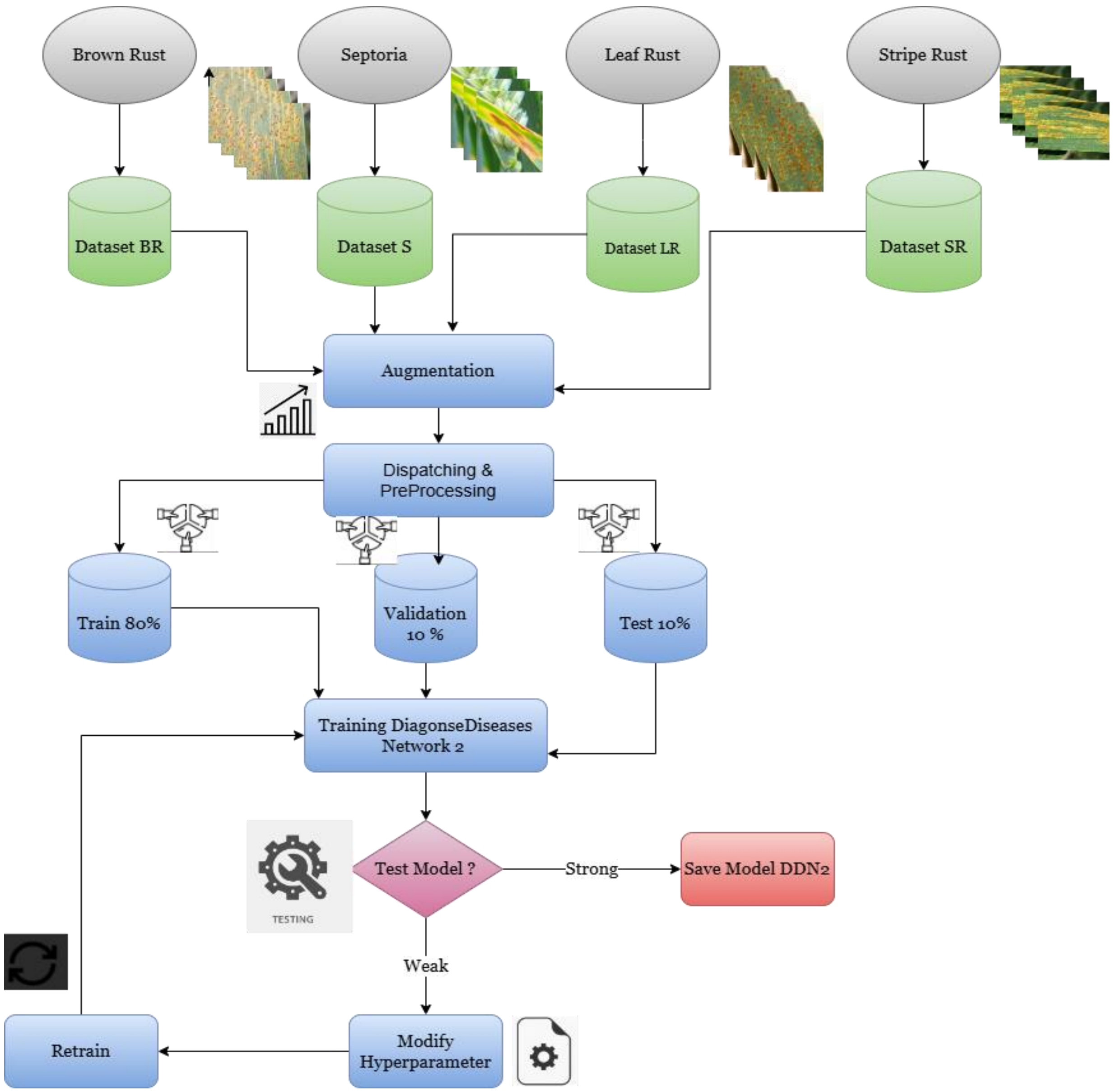


Figure 3.3 : *Train Diagnose Disease Network (DDN2)*

3. Model Architecture

The general structure of the system is as follows :

3.1. Diseases Detection Network

3.1.1 General Model Architecture

acts as the master(DDN1) responsible for verifying the healthy of the wheat grains ,It processes all the sent images by user by resizing them to 255x255 pixels and applying filters (fig 3.4) .The images are then passes through three layers of conv2D and Maxpooling2D and the difference between these layers is the kernel and the output shape .Additionally the images mages are divided into three frames to delve deeper increasing the depth to 32 , then 64 ,and finally 128 (tab 3.1) ,After serial operations at the end the activation will be sigmoid . the output classification label is either 1 or 0 where 0 indicates healthy wheat and 1 indicates disease wheat ,if the final prediction is healthy, however if the wheat is classified as diseases the salve or servant model is invoked to classify the specific diseases

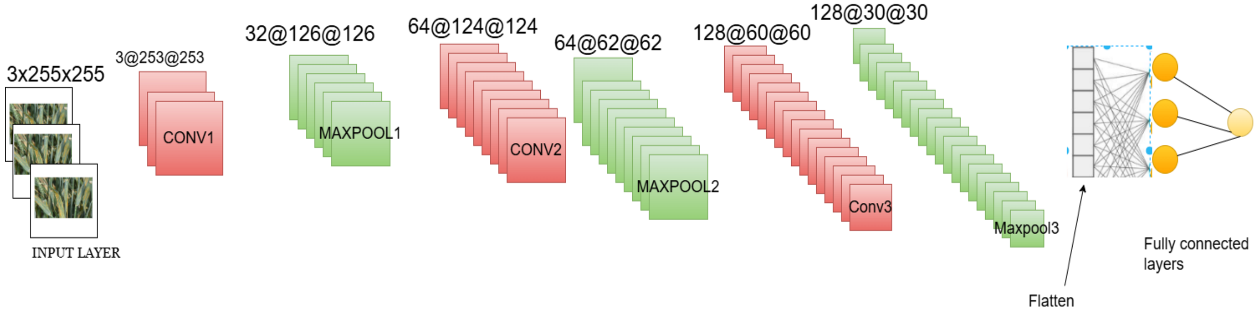


Figure 3.4: *Architecture of Master Network (DDN1)*

3.1.2 Layers of the *Master Network (DDN1)*

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)
MaxPooling 2D	(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)
MaxPooling 2D	(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)
MaxPooling 2D	(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 3.1: Layers of DDN1

```
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(img_size, img_size, 3)))
model.add(MaxPooling2D((2, 2)))
model.add(Dropout(0.2))

model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Dropout(0.2))

model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Dropout(0.2))

model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

***Figure 3.5** : Layers of the DDN1 in python*

3.2 Diagnose Diseases Network

3.2.1 General Model Architecture

Responsible for detect only the diseases wheat and classify it for 4 classes (diseases). It processes all the sent images by user by resizing them to 255x255 pixels and applying filters (fig 3.5). The DDN2 Using Softmax as activation layer by performing similar operations to the first structure but differing in the number of classes. Tthe same input and same beginning with the first model layers but in output will be difference feature map and at level of layer flatten 25088 (tab 3.2), also activation for the layer Dense will be SoftMax not like the first sigmoid

The figure below (fig 3.6) is identical to our second architecture model with noted that we have 4 layers of pooling and conv2D layers:

The Conv2D layer 4 : 128x28x28

The MaxPooling2D layer 4 : 128x14x14

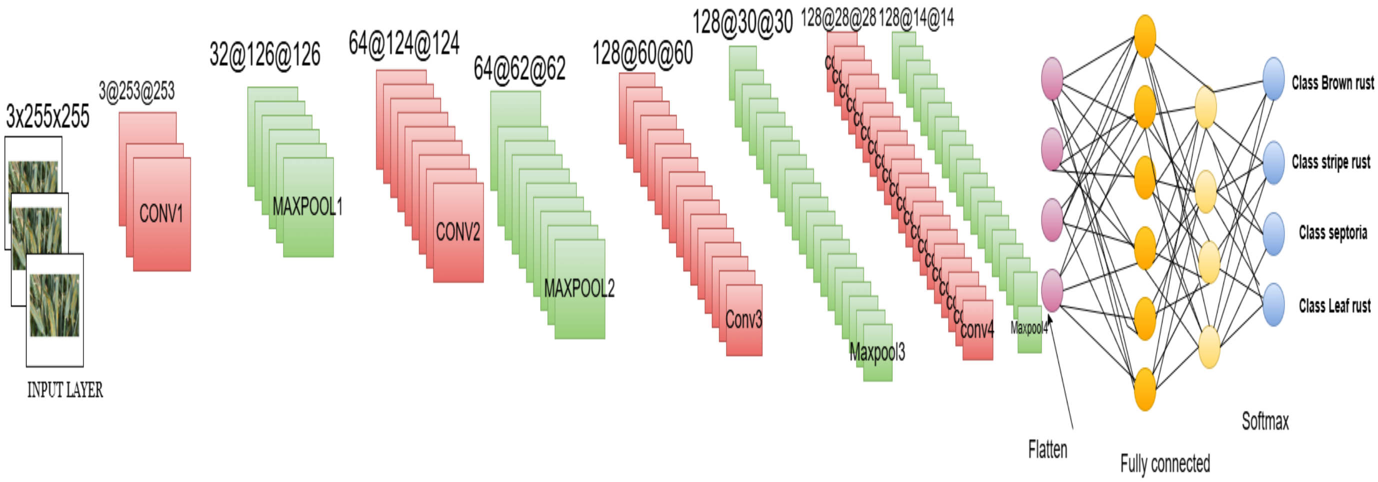


***Figure 3.6**: General Architecture of the Slave Network (DNN2)*

3.2.2 Layers of the Slave Network

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	num_classes	-	-	Softmax	4

Table 3.2: Layer of the DDN2

```python
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(img_size, img_size, 3)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(128, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(128, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(512, activation='relu'),
    Dropout(0.5),
    Dense(num_classes, activation='softmax')
])


model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])


history = model.fit(
    train_generator,
    epochs=epochs,
    validation_data=val_generator
)
```

Figure 3.7*: Layers of DDN2 in python*

4. Conclusion

We investigated the creation of a deep learning-based system to categorize photographs of wheat and differentiate between harvests that are healthy and unhealthy. We highlighted the use of convolutional neural networks (CNNs), which offer excellent accuracy in identifying wheat illnesses, allowing for efficieent crop management and early intervention.

We described the architecture of the system, which consists of three main parts: prediction, model training, and data processing. The model architecture consists of multiple stages, such as scaling the image, extracting features using filters, and doing computer analysis to produce predictions and classifications. This intricate architecture, which is depicted through diagrams, demonstrates the methodical process of examining and categorizing wheat photos.

CHAPTER 4

Implemantion

1. Introduction

In this era, AI is look like the old technology when it started to early-stage technology; just like as no one in the past could have imagined video calls in 4K quality over vast distances, the potential advancements in AI are beyond our current imagination. For AI to advance, it needs to learn, much like humans learn the alphabet, pray, and acquire various skills. Deep learning follows the same principle, mirroring the human mind's learning process and like the human need to learning to survive also he need to learn the model to solve the problem of food security

This project plays a crucial role in ensuring food security by providing an application that helps farmers detect wheat diseases early in the growth cycle, enabling timely intervention. Early detection of wheat diseases can significantly mitigate crop loss and improve yields, which is vital for maintaining a stable food supply.

The application is available on Windows, offering robust features for comprehensive disease detection and management. Additionally, a simplified version is accessible via Telegram, making it easy for farmers to use the tool on the go, ensuring they have the support they need regardless of their location.

2. Hardware

2.1 LAIG Station

We used the computer of the station of the LAIG (laboratory of automation and computer science) [w16] laboratory in university 8 Mai 1945 with these characteristics:

- Ram: 32 Gb
- GPU: Intel i7 7th generation
- CPU: NVIDIA GeForce GT 1050ti 2 GB
- Windows 10 Pro

2.2 Personal Hardware

TO control the LAIG station from a distance and store a BackUp we used computer:

- Ram: 12 Gb
- GPU: Intel i3 5th generation
- Windows 10 Pro

Smartphone Samsung Meduim (M)

- Ram: 6 Gb
- ROM: 128 Gb
- Android 13.0
- Quad camera 64MP+8MP +2MP+2MP

These components make the execution faster and more efficient.

3. Software

3.1 Pycharm CE

PyCharm is an integrated development environment (IDE) used for programming in Python. It provides code analysis, a graphical debugger, an integrated unit tester, integration with version control systems, and supports web development with Django. PyCharm is developed by the Czech company JetBrains. [w17]

3.2 Programming Language: Python

Is a high-level, interpreted, and object-oriented programming language. It is highly sought after by a large community of developers and programmers. Python is a simple and easy language to learn. The Python library is available for most platforms and can be redistributed freely. [w18] , for our model we used version 3.9 that adapat the librarys

Figure 4.1: Python logo

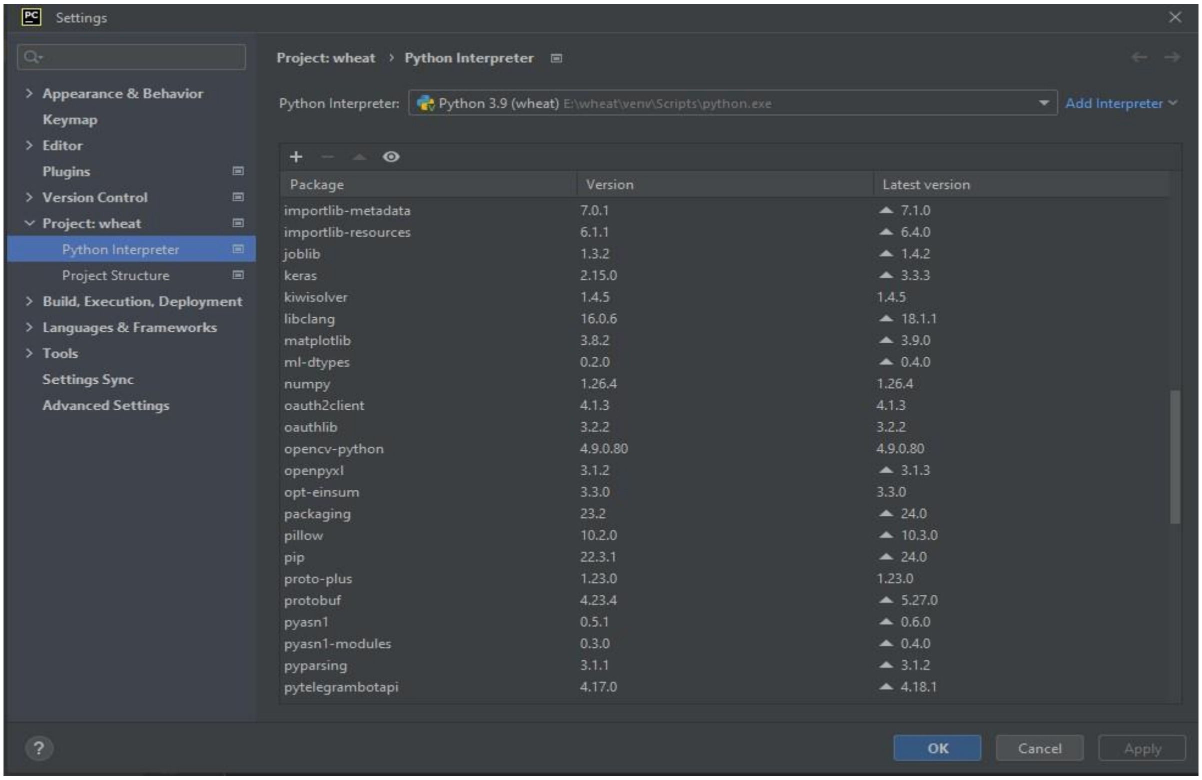


Figure 4.2: Python configuration system

3.3 Kaggle

Kaggle, a branch of Google, serves as a hub for data scientists and developers. Enthusiasts of machine learning and contemporary development can become part of this community, which boasts over 1 million registered users. Within this platform, members can discuss development methodologies, delve into datasets, and connect with peers from 194 different countries worldwide. [w19]

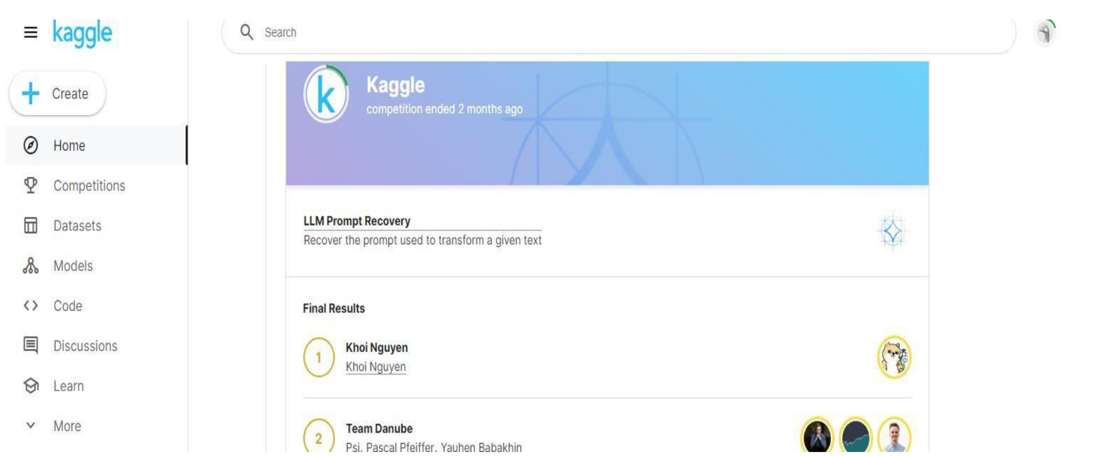


Figure 4.3: kaggle main page

3.4 Google colab

Colab (short for "Colaboratory") enables you to write and execute Python code in your browser with no setup required, free access to GPUs and, easy sharing

Whether you're a student, data scientist, or AI researcher, Colab can streamline your work. Watch the Colab overview to learn more or get started right away.[w20]

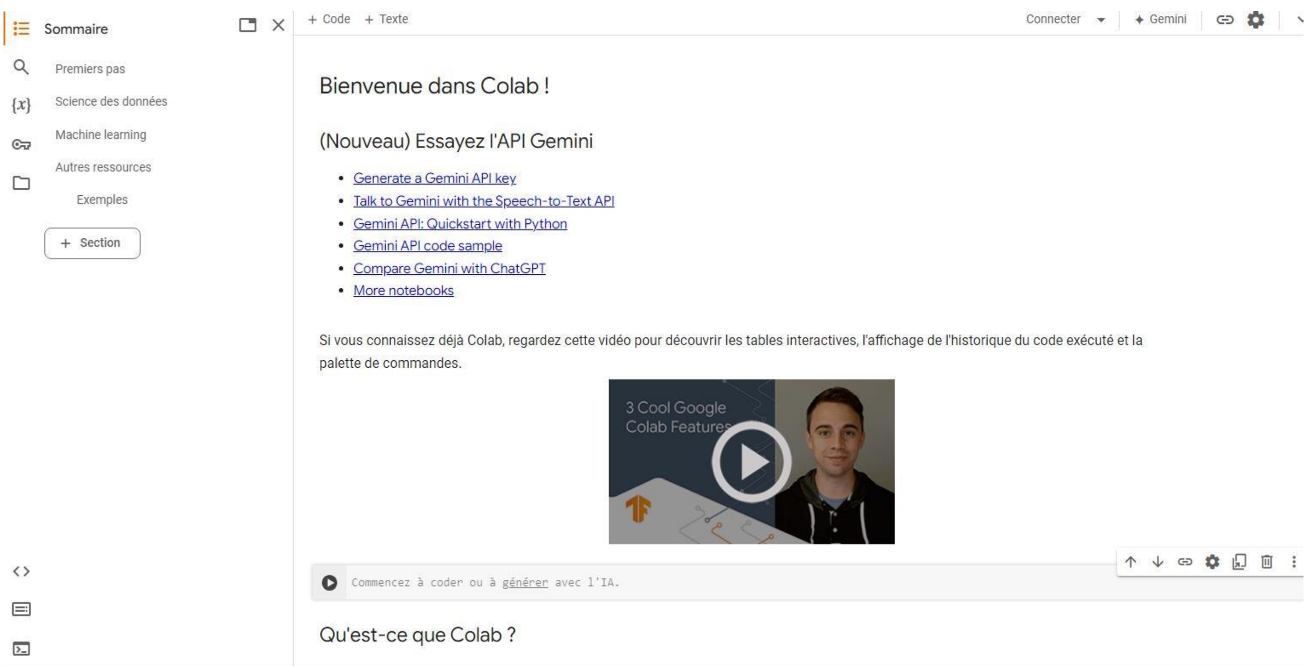


***Figure 4.4**: Main page google colab*

4. Library used

4.1 Tensorflow

TensorFlow stands as an open-source framework crafted by Google researchers, dedicated to executing machine learning, deep learning, and various statistical and predictive analytics tasks. In line with comparable platforms, its purpose is to simplify the journey of creating and running sophisticated analytics applications, catering to users like data scientists, statisticians, and predictive modelers. [w21]

4.2 Keras

Keras functions as an open-source library offering a Python interface tailored for artificial neural networks. Initially developed as standalone software, it was subsequently integrated into the TensorFlow library and expanded its support to other frameworks. The upcoming "Keras 3" represents a complete overhaul, enabling usage as a foundational cross-framework language to construct custom components like layers, models, or metrics. These can seamlessly integrate into native workflows across JAX, tensorFlow, or pytorch, all from a single codebase. Starting from

TensorFlow versioon 2.16 onwards, Keras 3 will become the default version, although Keras 2 will remain usable. Exemple for keras : keras for layers (dense ,dropout),Keras for models (sequential) . [w22]

4.3 Matplotlib

Matplotlib is a Python programming language library designed for plotting and visualizing data in the form of graphs. It can be paired with Python's scientific computing libraries NumPy and sciPy. Additionally, it offers an object-oriented API, facilitating the integration of graphs into applications using versatile graphical interface tools like Tkinter, wxpython, Qt, or GTK. [w23]

4.4 Numpy

NumPy is the fundamental package for scientific computing in Python. It is a Python library that provides a multidimensional array object, various derived objects (such as masked arrays and matrices), and a collection of routines for fast operations on arrays, including mathematical, logical, shape manipulation, sorting, selection, I/O (Input/Output), discrete Fourier transforms, basic linear algebra, basic statistical operations, random simulation, and more. [w24]

4.5 OS

OS The OS module in Python provides functions for interacting with the operating system. The operating system is part of Python's standard utility modules. This module provides a portable way of using operating system-dependent functionality. The *os* and *os.path* modules include many functions for interacting with the file system, such as creating and deleting a directory (folder), retrieving its contents, modifying and identifying the current directory, etc. [w25]

4.6 Open cv (cv2 in python coding)

OpenCV, an abbreviation for Open Source Computer Vision Library, stands as a freely accessible software library for computer vision and machine learning. Initially developed by Intel, it is presently upheld by a collaborative community of developers within the OpenCV Foundation.

OpenCV presents an extensive open-source repository for computer vision, machine learning, and image processing tasks. It accommodates a wide array of programming languages including Python, C++, Java, etc. Capable of analyzing images and videos to detect objects, faces, or even human handwriting, OpenCV enhances its functionality when paired with various libraries like Numpy, renowned for its optimized numerical operations. This integration broadens the scope of possibilities, allowing for the combination of Numpy's capabilities with those of OpenCV. [w26]

4.7 Tkinter

The term "Tkinter" derives from "Tk interface," which references the Tk GUI toolkit upon which Tkinter is constructed. Tkinter facilitates the creation of windows, buttons, labels, text boxes, and other GUI components essential for developing interactive applications.

Importance of Tkinter stands as an integrated Python module utilized for crafting GUI applications. It ranks among the most prevalent modules for GUI development in Python due to its simplicity and user-friendliness. One doesn't need to separately install the Tkinter module as it is inherently bundled with Python. Tkinter furnishes an object-oriented interface to the Tk GUI toolkit. Out of all available options, Tkinter enjoys the broadest adoption. [w27]

4.8 Telebot

TeleBot is synchronous and asynchronous implementation used for create a bot telegram online and control it.[w28]

5. Database of the model

5.1 Database DNN1

For training the network, which we named DNN1, we used the dataset consisting of a total of 1765 images. These images are divided into two directories: one containing 1023 images of diseased wheat and the other containing 735 images of healthy wheat

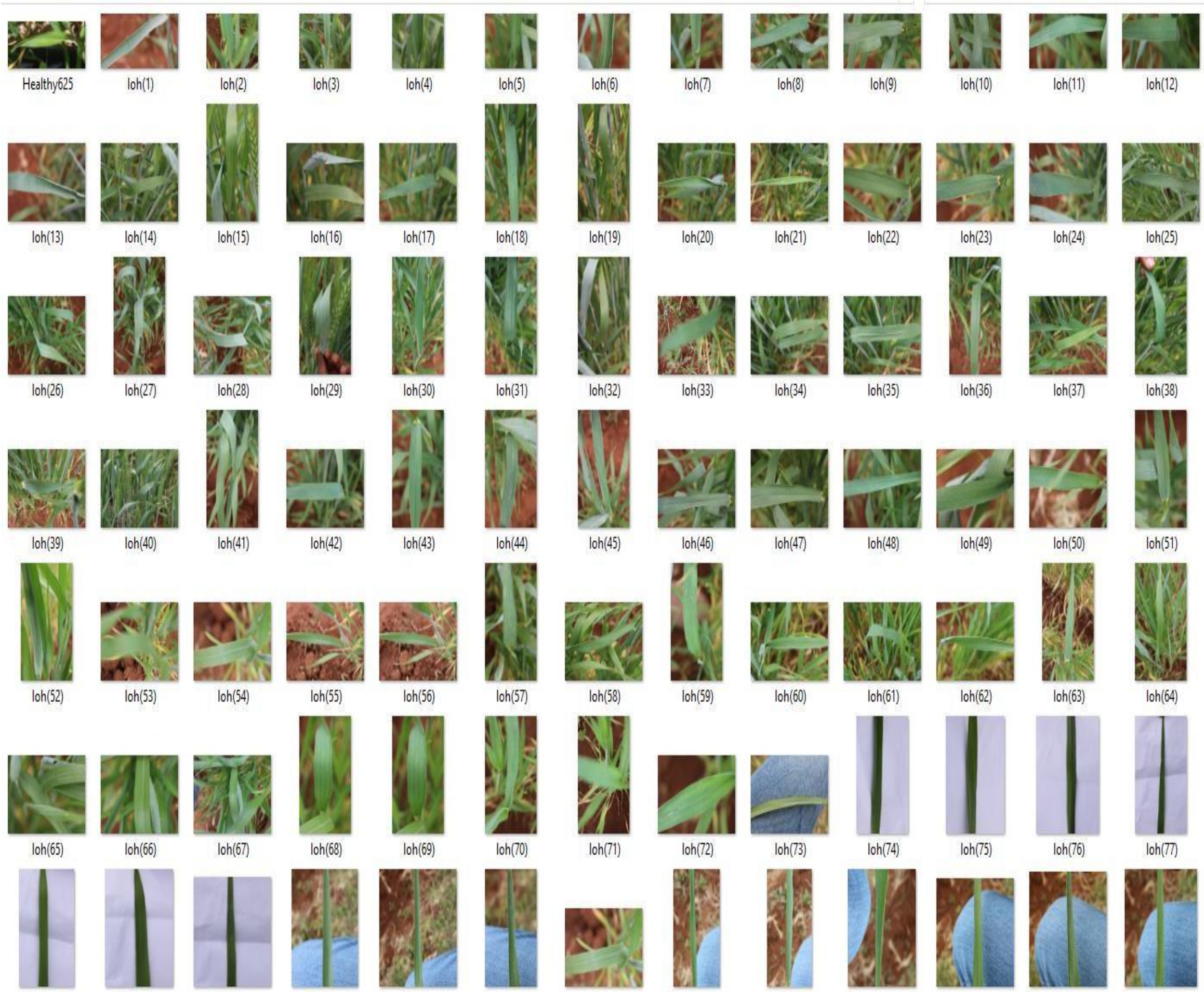


Figure 4.5 *:Wheat healthy dataset for DDN1*

5.2 Database DNN2

The second only model for detect and classification which diseases has infected the wheat, the diseases (tab 4.1) we have chosen four diseases (wheat leaf rust, Septoria ,wheat yellow rust ,wheat brown rust)

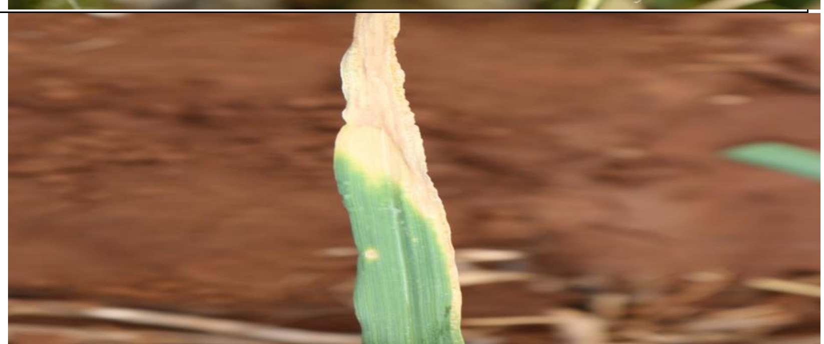
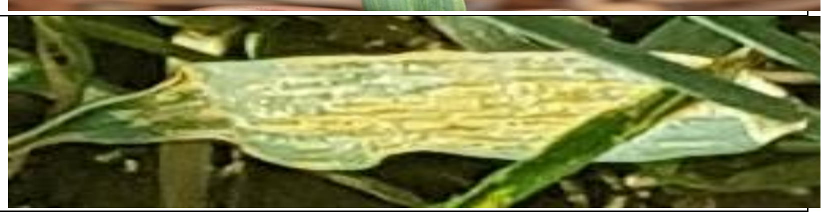
Diseases	Number of pictures	Example
Brown rust	**1128**	
Leaf rust	**36**	
Septoria	**208**	
Yellow rust	**1396**	

Table 4.1 : Split Dataset of DDN2

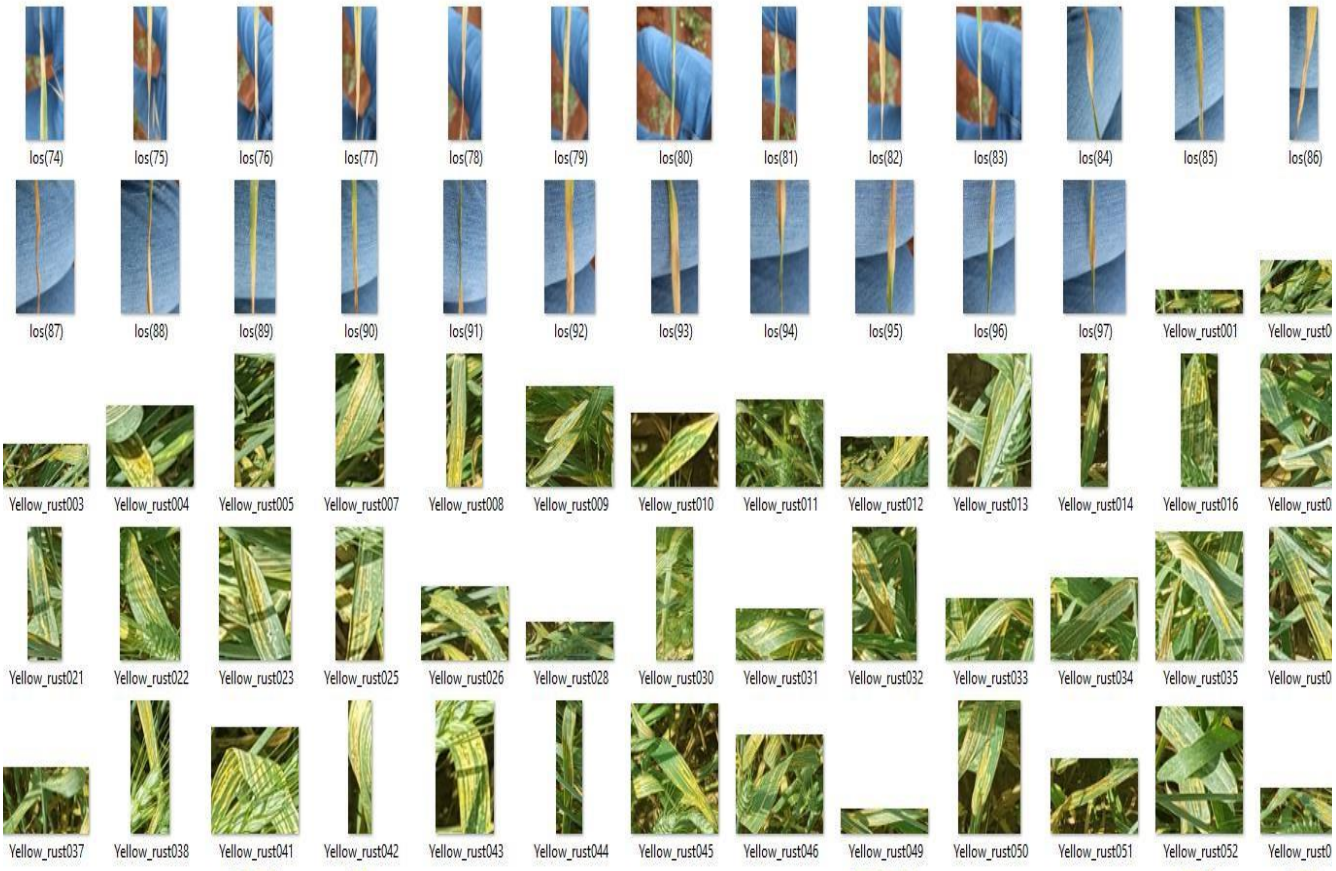


Figure 4.6*: Example of dataset for the diseases network*

6. Data Preprocessing

6.1 Resizing image

All images used for training both networks have been resized to 255 x 255 dimensions for both of the networks of the model DDN1 Master and DDN2

Image resizing is a crucial preprocessing step that prepares images for further analysis or modeling by ensuring consistency in image dimensions and potentially improving computational efficiency.

6.2 Split data

We have split data :80% for train the training set is used to train the model, 10% for the validation the validation set is used for hyperparameter tuning and model evaluation during training, and 10% for the test that set is used to assess the final performance of the trained model.

Class	Train 80%	Validation 10%	Test 10%
Healthy	588	74	73
Sick	2215	277	276

Table 4.2: Split dataset for DDN1 model

Class	Train	Validation	Test
Septoria	166	21	21
Leaf rust	20	8	8
Brown rust	902	113	113
Stripe rust	1116	140	140

Table 4.3: Split dataset for the DDN2 for each disease

7. Training of our system

For training our system, we followed these steps:

- Preparing the library, we need
- Preparing PyCharm environment (package and versions)
- Set the path of the dataset that already split
- Importing the necessary libraries.
- Training the model.
- Evaluating the model.
- Saving the obtained model.
- Store another copy at google colab and save it

8. Results

8.1 Trainig of the DDN1

After tests and changes to the model Detection Diseases Network we achieved the results below (fig 4.7-fig 4.9) with the following configurations:

- Optimizer: "Adam"
- Batch size: 32
- Relu For all convolutional layers function except the output layer use Softmax
- Epochs: 30

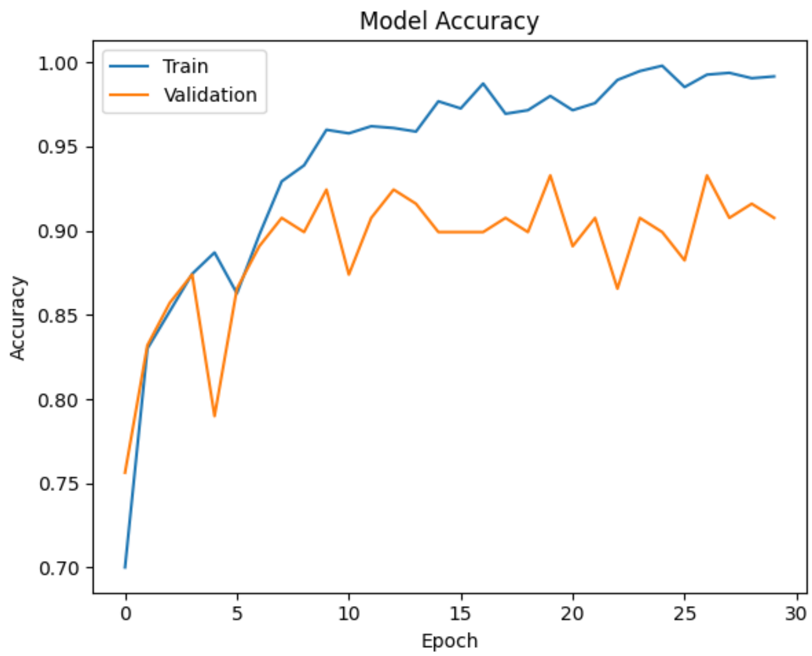


***Figure 4.7**: Graph of the accuracy train and validation for DDN1*

We note that the training accuracy improves steadily with each epoch, reaching close to 98%. This indicates that the model is learning the training data very well, almost perfectly by the end. For the validation accuracy improves initially, but after about 5 epochs, it starts to fluctuate and down but it is temporary. It doesn't show the same smooth improvement as the training accuracy. In the end the validation accuracy achieved 90%.

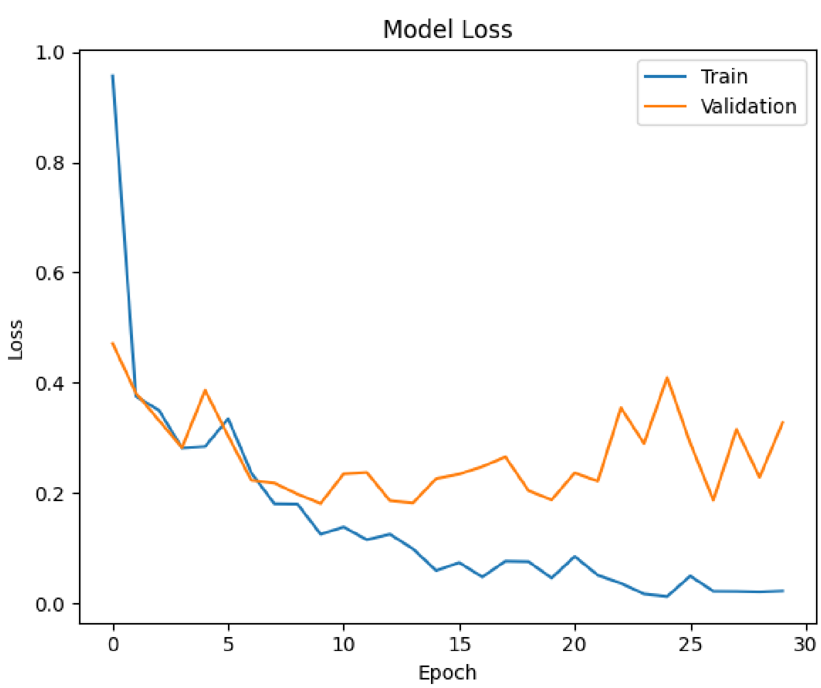


***Figure 4.8**: Graphe of the train and validation loos for the DDN1*

- The training loss decreases steadily and significantly, starting from a high value and dropping to nearly zero. This indicates that the model is fitting the training data very well over the epochs.
- The validation loss decreases initially but starts to fluctuate after a few epochs.
- Despite the fluctuations, the validation loss remains higher than the training loss and even starts to increase slightly towards the end of the training process.

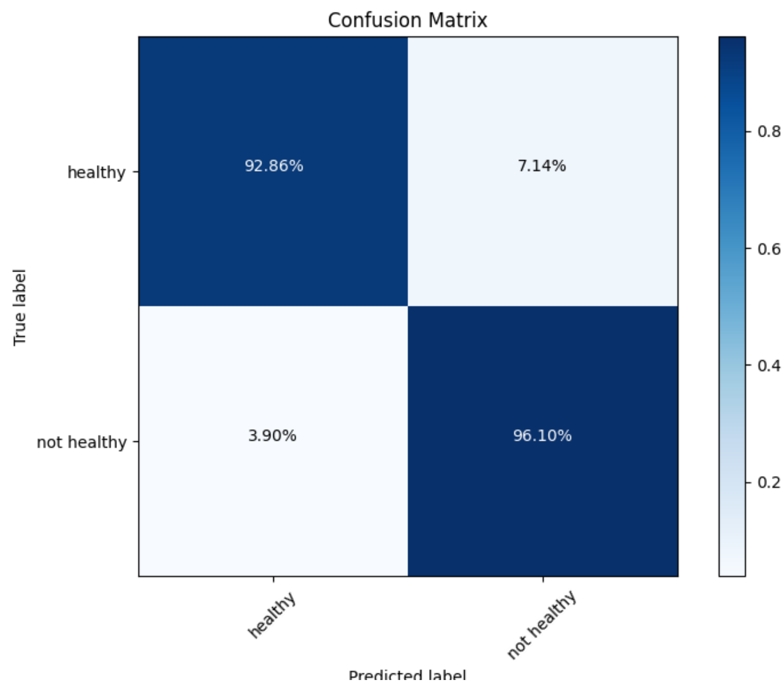


Figure 4.9: *Confusion matrix for the Master Network (DDN1)*

➢ The model performs very well in distinguishing between healthy and not healthy classes, with both classes showing high correct classification rates.

➢ The relatively low rates of false positives and false negatives suggest the model has good precision and recall for both classes.

8.2 Training of the DDN2

After tests and changes to the model Diagnose Diseases Network we achieved the results below (fig 4.10-fig 4.12) with the following configurations:

✓ Optimizer: "Adam"
✓ Batch size: 32
✓ Relu For all convolutional layers function except the output layer use Softmax
✓ Epoch number : 50

Figure 4.10: *Graphe of train and validation accuracy for the Slave Network (DDN2)*

- Both training and validation accuracy start around 50% at epoch 0.
- We note that the training accuracy and validation accuracy improves steadily with each epoch, reaching close to 91%

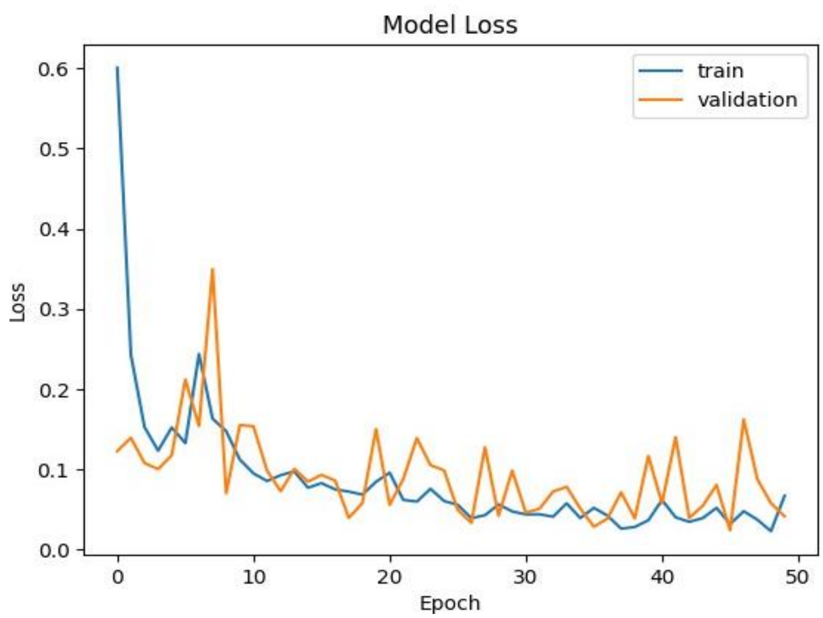


Figure 4.11: *Train and validation loss for DNN2*

Figure 4.11 shows the Model Loss for both training and validation datasets over 50 epochs. The training and validation loss decrease significantly during 60% the initial epochs and then stabilize at low values, indicating effective learning and good model performance with minimal 0.08 overfitting.

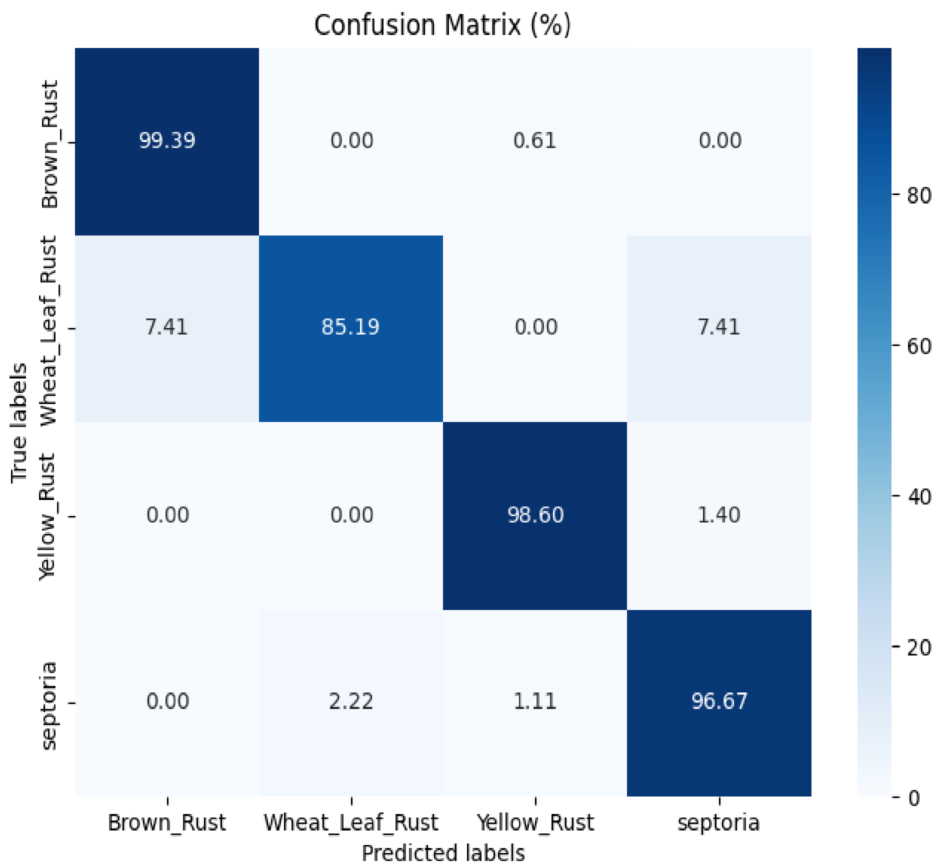


Figure 4.12: *Confusion matrix for the slave model*

The model demonstrates high accuracy across all disease categories, with minimal misclassification rates. The highest accuracy is observed in identifying Brown Rust (99.39%), while Wheat Leaf Rust (85.19%) has the lowest accuracy misclassifications include 7.41% of Wheat Leaf Rust samples misclassified as Brown Rust and another 7.41% as Septoria due to notable visual confusion with Brown Rust and Septoria.

9. Interface of our system

A description of the main buttons available in the interface of our system is illustrates in figure 4.13 as follow:

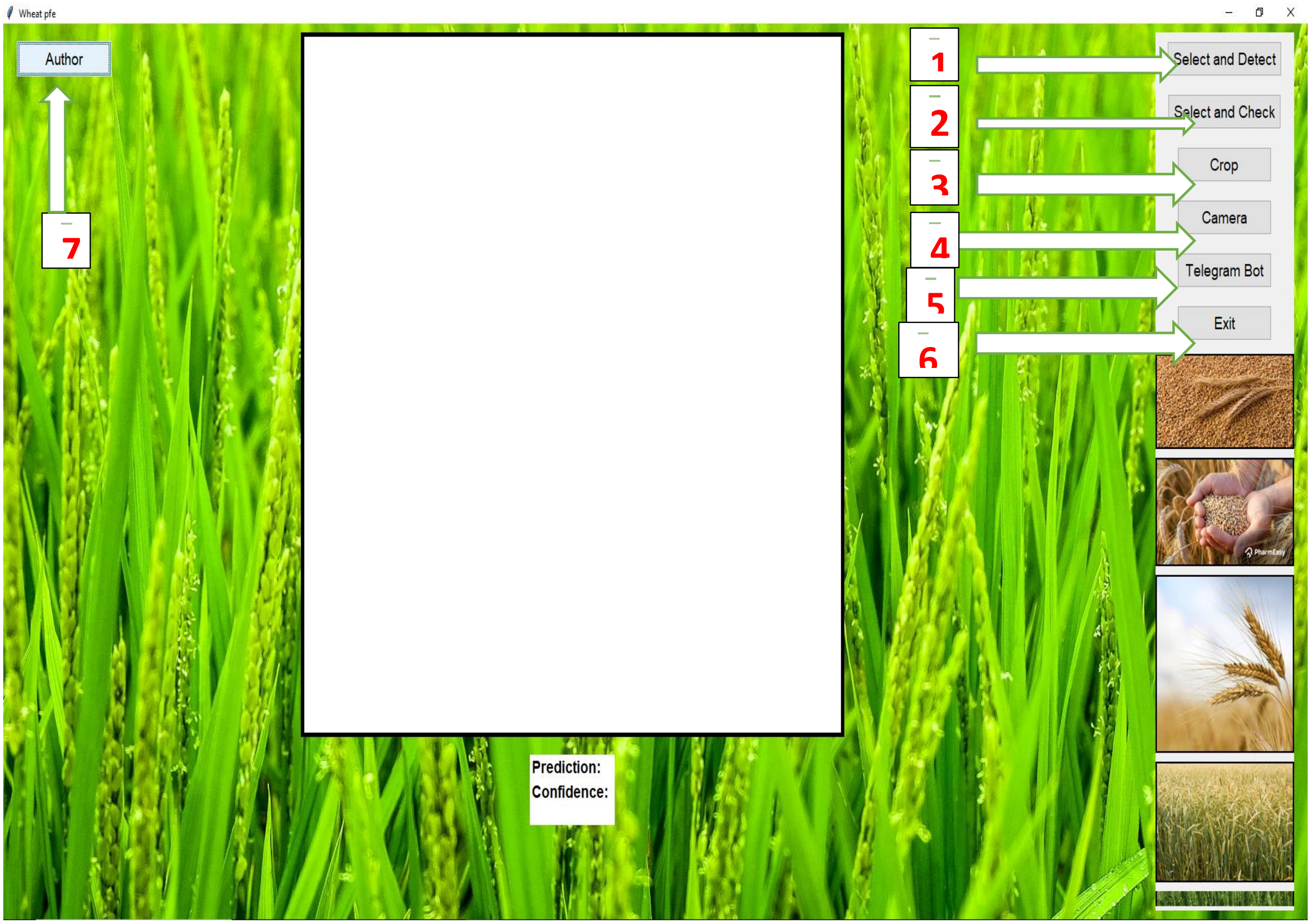


Figure 4.13: *main interface system*

1. Button Select and Detect: Allows the user to directly detect the disease affecting their wheat. The diseases that the system can detect are: Leaf rust, Brown rust, Septoria, and yellow rust.

2. Button Select and Check: Allows the user to verify if the wheat is healthy or sick.

3. Button Crop: Allows the user to set the selected part of the image, which helps to achieve a more accurate result.

4. Button camera: Allows the user to open the camera and take photo for the wheat.

5. Button Telegram: Takes the user to the bot, which allows the use of the camera and offers more advantages in online mode. It is also available in the interface of the main page.

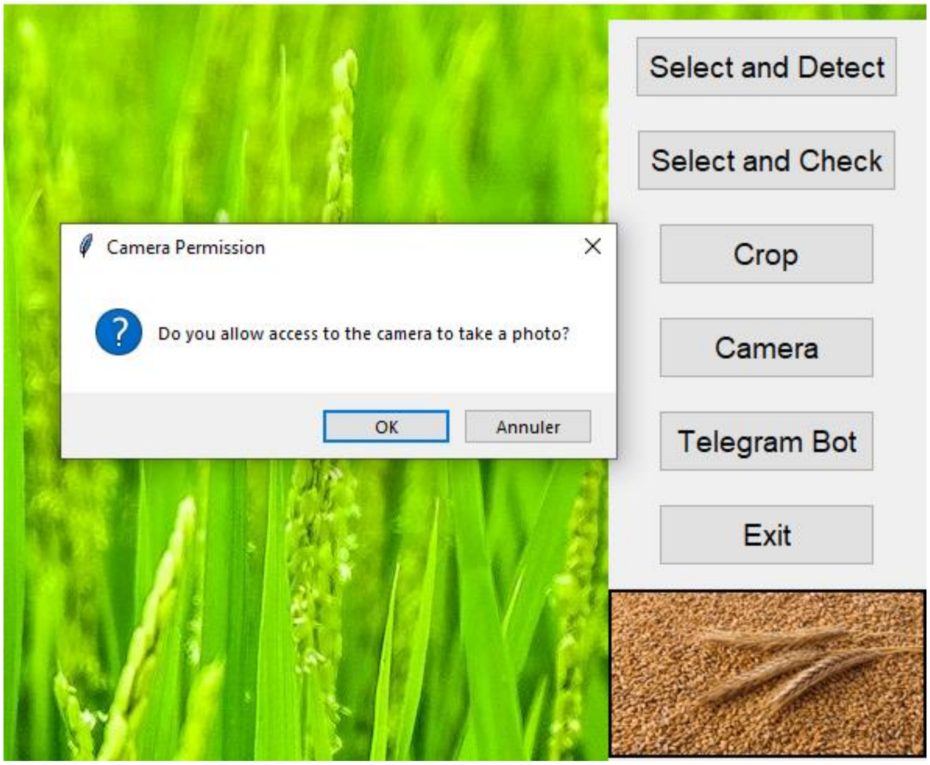


Figure 4.14 : *Camera Permmision*

6. Button Exit: Allows the user to leave the system.

7. Button author : To show the responsible of this project

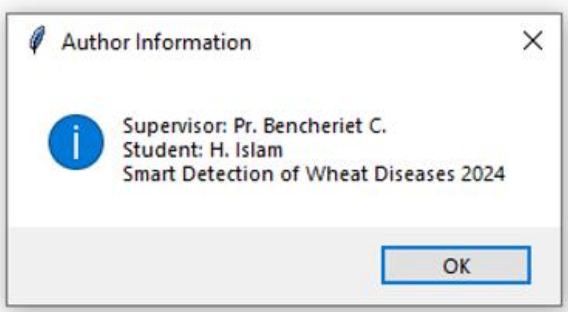


Figure 4.15 *:Button authors*

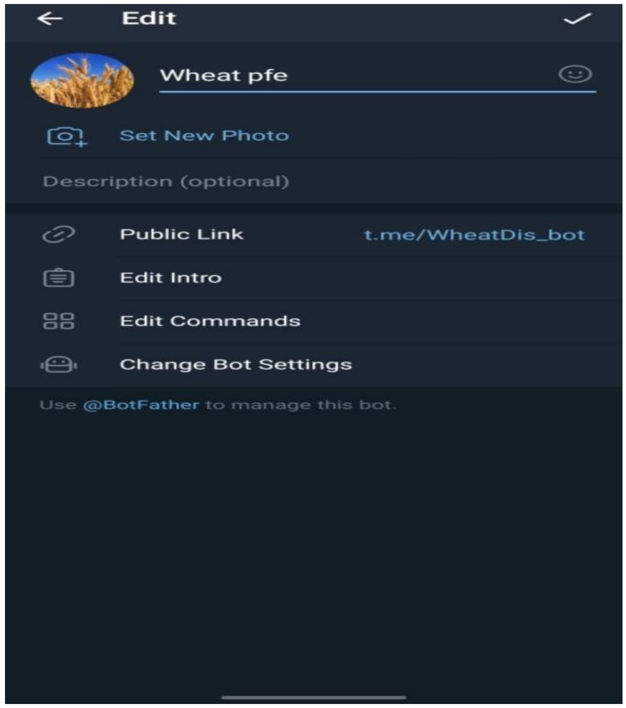


***Figure 4.16**: Interface phone telegram bot*

-Set new photo: to change the background (not allows to the users)

-Public link: @WheatDis_bot allows to acces to the bot by research or by copy and share the link directly

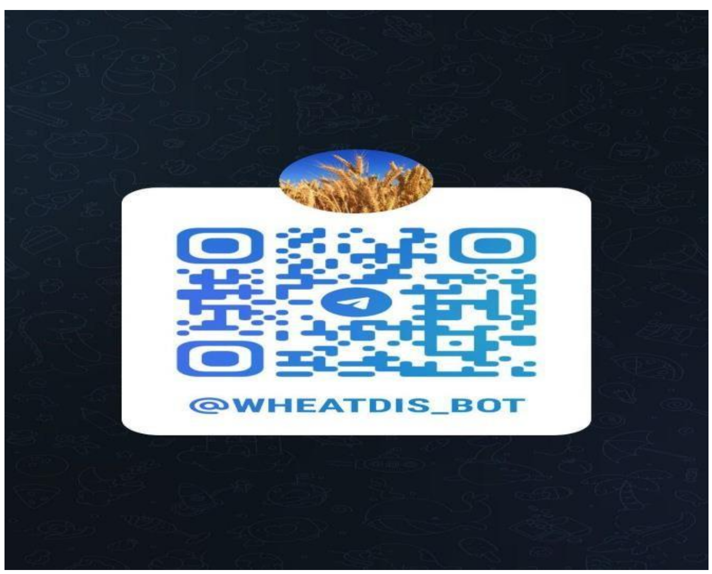


***Figure 4.17**: Acces via Qr code*

-Edit intro: The introduction in the main page (only for admin) when we click, we get to Botfather to change it

-Edit commands: Same like before but in the commands line

-Change Bot Settings: To get another api token or make some service payements or delete bot

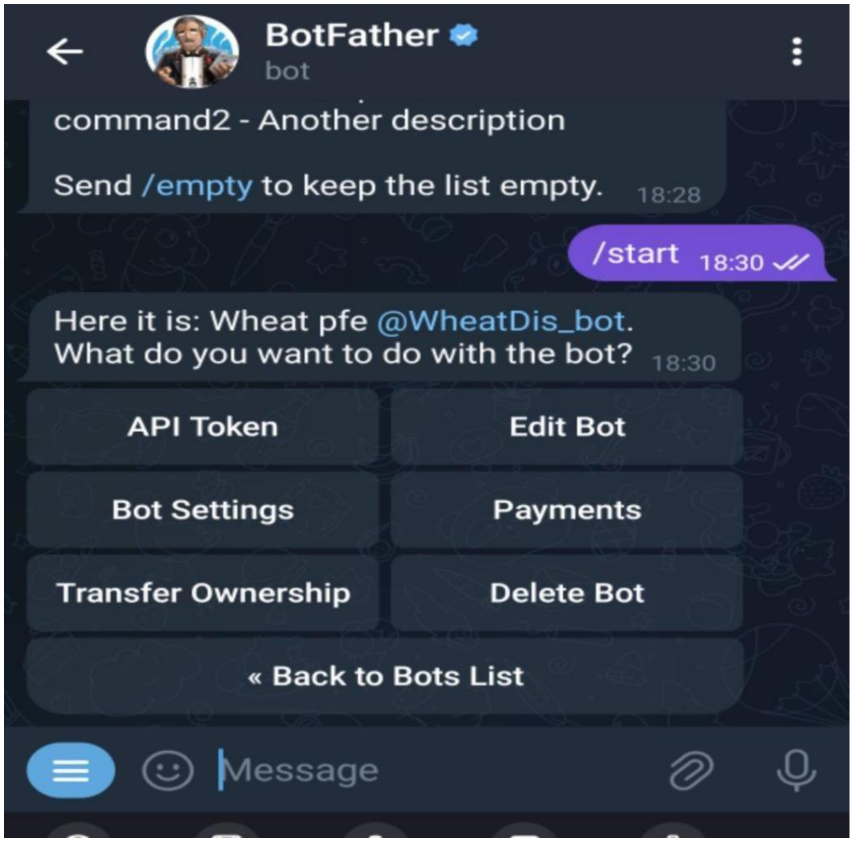
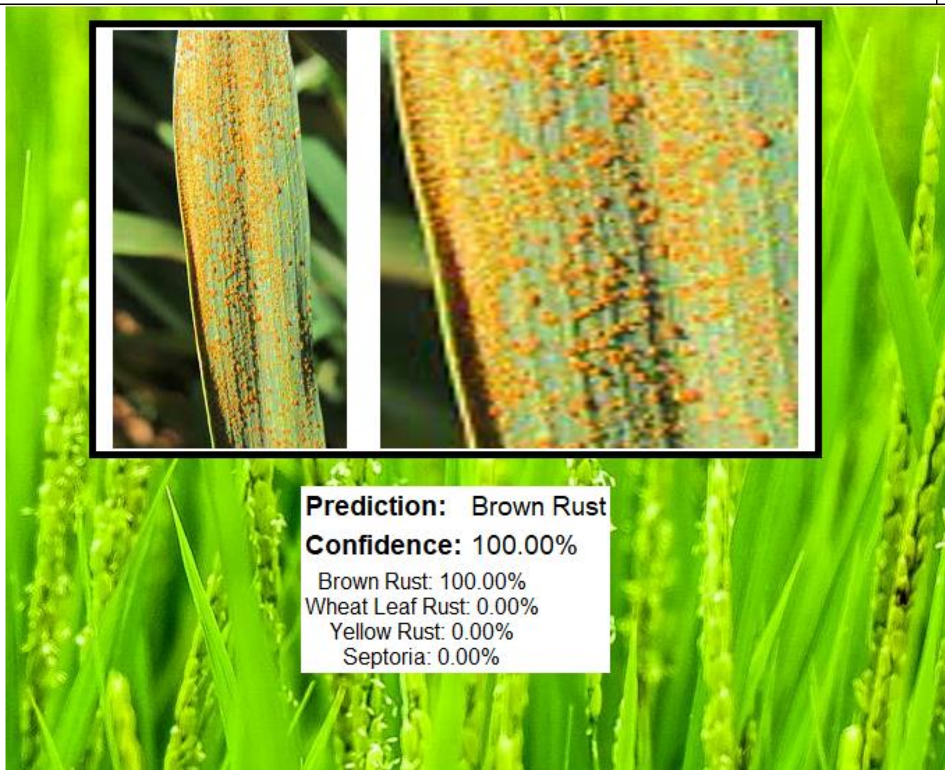


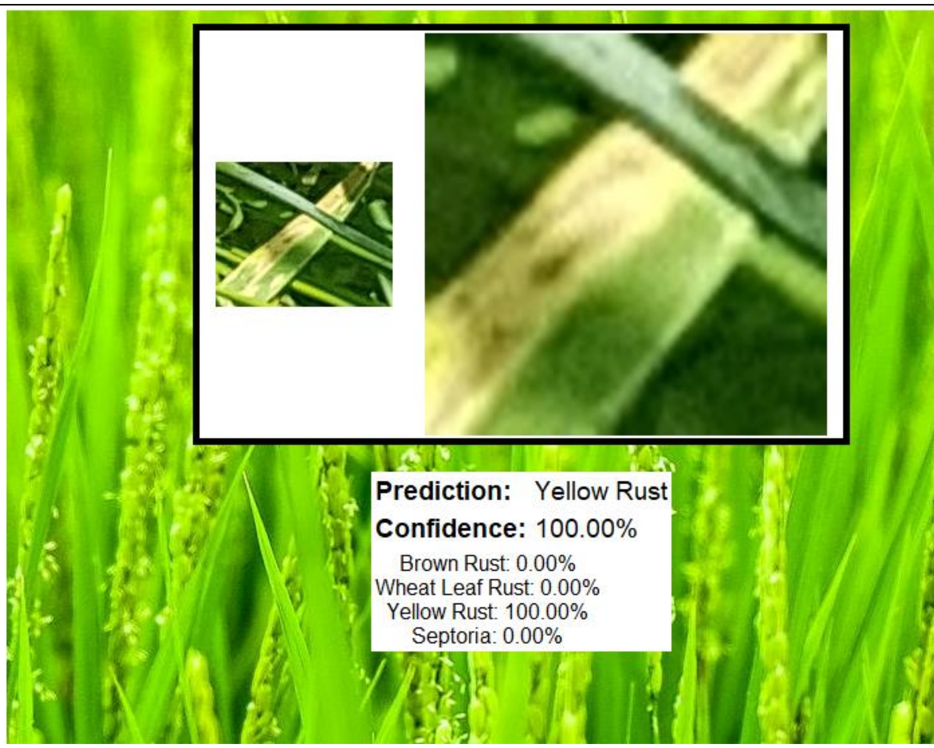
Figure 4.18: *Admin option*

10. Test on External Selected Images

10.1 Tests on the main interface system

We Have chosen different pictures for test the our system (tab 4.3):

Disease	Test picture	Results
Brown rust		Success
Septoria		Success

Healthy		**Success**
Yellow rust		**Success**

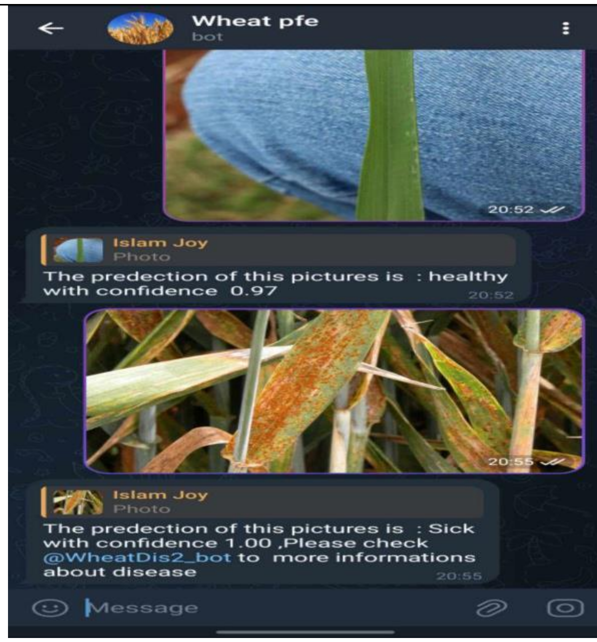
Healthy		**Failed**
Leaf rust		**Success**

Leaf rust		**Success**
Brown rust		**Success**

Table 4.3: External test pictures in main interface

11.2 Tests on the Smartphone

To simplify more for the farmers, we insert our system in telegram to be available and online, the frames need just to use the camera and put there in the bot to check there wheat. Table 4.4 illustrates some tests.

Disease	Test picture	Results
Bot1:Check		Success ,Success
Bot 2 :Detecte Disease,Leaf rust		Success

Brown rust		Success

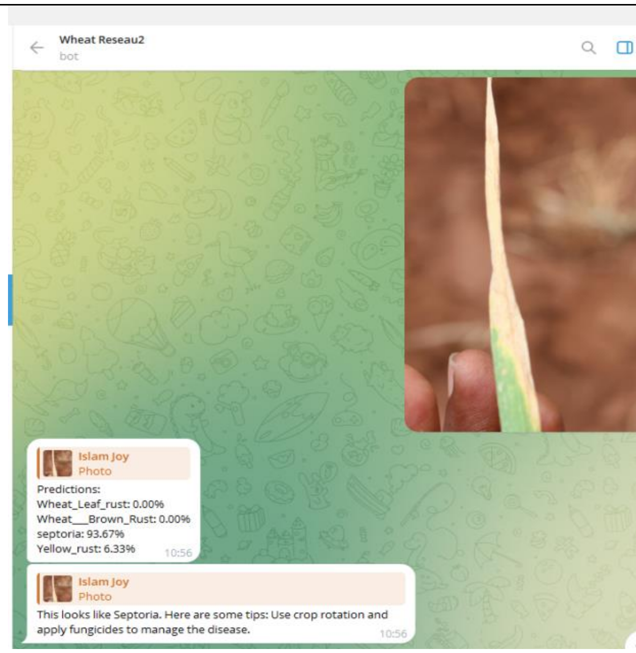
Septoria		Success

Table 4.4: Test on external images in smartphone

11. Conclusion

Smart systems for detecting wheat diseases represent a significant advancement in agriculture. By leveraging cutting-edge technologies like Convolutional Neural Networks (CNNs), these systems can precisely identify and diagnose diseases in wheat crops, ensuring prompt and effective intervention. Accessible interfaces, such as a Python-based platform for in-depth analysis and a Telegram bot for real-time updates, render these systems user-friendly for farmers and agricultural professionals. This technology not only streamlines the disease detection process but also facilitates proactive crop management, ultimately leading to healthier crops and higher yields.

General Conclusion

The importance of wheat in food safety cannot be overstated, as it is a staple food for a significant portion of the global population. Ensuring the health and productivity of wheat crops is crucial for maintaining food security and preventing shortages. Smart systems for wheat disease detection play a vital role in this context by enhancing the accuracy, efficiency, and sustainability of agricultural practices.

In this work, we have developed a system capable of distinguishing between four types of diseases (brown rust, yellow rust, leaf rust, sptoria) and detecting healthy wheat before ripening by training on about 2800 images. The choice of the model, its development, and its training was a very important phase that took us more than three months to achieve the expected results. Our system utilizes a dual CNN architecture operating in a master-slave configuration. The primary CNN (DDN1) identifies the presence of disease, while the secondary CNN (DDN2) classifies the type of disease only if a disease is detected. This approach ensures efficient processing and accurate classification of diseases, including septoria, brown rust, yellow rust, and leaf rust. The high classification rates achieved by our system validate its effectiveness.

This system is a first step toward addressing agricultural problems and finding solutions. The development of this program, along with its integration with artificial intelligence technology and the provision of extensive information about our country such as the types of new diseases, their seasons, the amount of wheat produced, and annual losses enables the organization of a robust system.

Looking ahead, future work will focus on integrating our diagnostic application with a smart camera mounted on a drone, enabling real-time monitoring and diagnosis in the field. Moreover, integrating these systems with drone technology further amplifies their effectiveness. Drones equipped with advanced sensors can cover large areas quickly, providing real-time data for smart systems to analyze and detect diseases early. This synergy between smart detection systems and drones allows for rapid, targeted interventions, reducing crop loss and ensuring a stable food supply.

The development of advanced smart systems for detecting wheat diseases is revolutionizing agriculture by improving crop health and productivity. The integration of these systems with drone technology marks the beginning of the "SMART Agriculture" era, significantly contributing to food safety and security by enabling precise, efficient, and sustainable agricultural practices.

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