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Nutrient Deficiency Mapping in Plants Using Hyperspectral Imaging and Machine Learning

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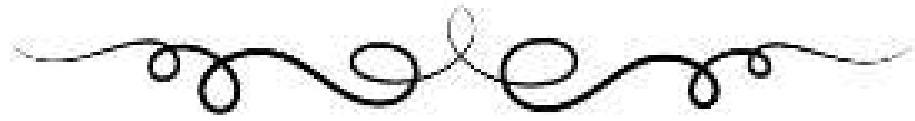
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Abstract

Plant nutrient deficiencies reduce yield and growth and quality of plants. However, The ways currently being used to measure a lack in any of the nutrients required, are costly, lengthy and non applicable for any amount of large scale studies.
This work proposes an integrated approach to early detection and classification of nutrient deficiencies using Hyperspectral Imaging Technology, Machine Learning, Explainable Artificial Intelligence, The proposed system will enable early detection of nutrient deficiency based on spectral data changes in the plant so that crops can be better managed and fertilisers applied more accurately, improving yield, reducing costs and minimising environmental impacts.
Keywords : Hyperspectral Imaging Technology (HSI), Machine Learning (ML), Explainable Artificial Intelligence (XAI), Convolutional Neural Network (CNN), Transfer learning, Nutrient Deficiency.

Résumé

Les carences en nutriments des plantes réduisent le rendement, la croissance et la qualité des cultures. Toutefois, les méthodes actuelles de détection de ces carences sont lentes, coûteuses et ne peuvent être utilisées à grande échelle.
Les travaux présentés ici portent donc sur le développement d'un système intégré pour le dépistage précoce et la classification des carences nutritionnelles, à partir de l'imagerie hyperspectrale (HSI), de l'apprentissage automatique (ML), de l'intelligence artificielle explicable (XAI). Le système proposé permettra une détection précoce des carences nutritionnelles basée sur les changements des données spectrales de la plante, permettant ainsi une meilleure gestion des cultures et une application plus précise des engrais. Cela contribuera à améliorer le rendement, à réduire les coûts et à minimiser les impacts environnementaux.
Mots clés : Technologie d'imagerie hyperspectrale (HSI), Apprentissage automatique (ML), Intelligence Artificielle Explicable (XAI), Réseau Neuronal Convolutif (CNN), Apprentissage par transfert, Carence nutritionnelle.

الملخص

تؤدي نواقص العناصر الغذائية في النباتات إلى انخفاض المحصول والنمو وجودة النباتات. ومع ذلك، فإن الطرق الحالية للكشف عن نقص العناصر الغذائية بطيئة ومكلفة ولا يمكن تطبيقها على نطاق واسع.

يقترح هذا العمل نهجًا متكاملًا للكشف المبكر وتصنيف نواقص العناصر الغذائية باستخدام تقنيات التصوير الطيفي الفائق، وتعلم الآلة، والذكاء الاصطناعي القابل للتفسير. يتيح النظام المقترح الكشف المبكر عن نقص العناصر الغذائية استنادًا إلى التغيرات في البيانات الطيفية للنبات، مما يمكّن من إدارة المحاصيل بشكل أفضل وتطبيق الأسمدة بدقة أكبر، وبالتالي تحسين المحصول، وتقليل التكاليف، وتقليل التأثيرات البيئية.

الكلمات المفتاحية: تقنيات التصوير الطيفي الفائق (HSI) تعلم الآلة (ML) ؛ الذكاء الاصطناعي القابل للتفسير (XAI) ؛ الشبكة العصبية الالتفافية ؛ نقل التعلم ؛ نواقص العناصر الغذائية.

General introduction

Global food security is provided through agricultural production as well as contributing to long term economic stability throughout many countries in the world. In addition to being a significant contributor to worldwide agricultural production, the agricultural sector in Algeria has an important strategic role and has approximately 13.09% of the GDP of Algeria as of 2023[1], which is projected to experience an annual growth rate of 4.4% up until 2025 [2], The production of staple cereal crops (e,g, wheat, barley and potato crops) are critical to Algeria's food sovereignty and thus it will be necessary to continue to improve and preserve the health and productivity of these crops economically and socially.
Maximum yield potential for any individual crop will therefore, largely be limited by the amount of adequate N, P, and K. Of the three nutrient categories identified, these are also identified as being the three macronutrients that are most important. In light of this, the focus of the discussion within this paper is on the use of Precision Agriculture to modernise Algeria's agricultural sector by using digital technologies to enable users to manage their resources more effectively to apply fertiliser at the appropriate time and in appropriate amounts, thereby optimising production while minimising any potential negative impact on the environment.

Problem Statement
Challenge of nutrient deficiencies Nutrient deficiencies can lead to physiological disorders such as (reduced growth and chlorosis), which can significantly impede productivity due to the difficulty in identifying them when they occur, Unfortunately, there are two major challenges when identifying nutrient deficiencies:
First, traditional (laboratory) soil/tissue analysis (soil and tissue testing) takes a long time to complete, can be costly, and is not easily developed/implemented over large geographic areas.
Second, visual symptoms are only observed after the metabolic distress has advanced to the point of being unable to intervene (too late to) so as to reverse the damage from the deficiency. Furthermore, there is no accurate method to map the location of nutrient deficiencies, so fertilisers are often over applied uniformly due to the lack of accurate maps of nutrient deficiencies, which can lead to high costs (due to unnecessary applications) and environmental damage.

Research Question:
How can crop nutrient deficiencies be detected and mapped early and accurately, enabling precise fertilizer application to improve yield, reduce costs, and minimize environmental impacts?

Objective of Work

The purpose of this study is to create a Smart System which will take advantages of Hyperspectral Imaging (HSI) combined with Explainable Artificial Intelligence (XAI) to identify nutrient deficiencies, This system has the following goals :

The Identification of Spectral Signatures: Through high-resolution Hyperspectral imaging, produce an understanding of which types of Spectral Signatures can be identified to be unique to different plant species when exposed to Nutritional Stresses.

Pre-visualization Detection of Nutrient Deficiencies: Create an array of Machine Learning models capable of identifying Nutrient Deficiencies before visible signs (such as wilting, yellowing and spotting) appear in the leaves.

The Development of Explainable Artificial Intelligence (using tools such as SHAP or LIME) to describe how the AI Technology determines the relationship between the Spectral Signature of each type of plant and each of the Physiological Factors that affect their growth.

The Creation of Spatial Distribution Maps of Nutrient Deficiencies that will serve as Guides to produce Variable Rate Applications (VRA's) of Fertilizers for increased Economic Efficiency and decreased Environmental Impact.

General Methodology

The four structured steps used in this study to accomplish the objectives of this research are:

Data collection and preprocessing of hyperspectral data to remove outliers and noise and normalize the dataset.

Feature selection to identify the most informative wavelength bands for evaluating chlorophyll content and cellular structure.

Model development using supervised learning algorithms CNN and Transfer learning

Explainable Artificial Intelligence techniques to provide scientific interpretation of the detected deficiencies.

Thesis Structure

- Chapter 1: Topics include Precision Agriculture, Hyperspectral Imaging, remote sensing and the basics of XAI. The theoretical background for the research.
- Chapter 2: The classification methods based on the classical and deep learning are reviewed and compared. Special emphasis is given to models including SVM, Random Forest, and CNN.
- Chapter 3: The designed system, dataset and CNN model architecture and the training procedure. It also covers evaluation, deployment and the overall prediction workflow.
- Chapter 4: Discusses the implementation details for the developed system; list the technologies used and toolings. Shows the implemented web application with its various users and functionalities.

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Chapter 1

General concepts of precision agriculture and hyperspectral imaging

1.1 Introduction

The document focuses on identifying and mapping out what nutrients are lacking in plants because this will help with food production and food security, The study investigates what the basic factors are about how to conduct that kind of analysis, This includes hyperspectral imaging technologies (HSI), machine learning or algorithms and the extraction of spectral features, It also specifies what the major aims or objectives are of this proposed system, The system was designed to identify when plants first experience nutrient stress before they exhibit symptoms of nutrient deficiency; and, by using hyperspectral imaging with machine learning, to classify exactly which nutrients are missing from major types of crops

A comprehensive case study using crops grown on controlled nutrient deficient soil to demonstrate the practical application of hyperspectral imaging with machine learning for early detection of nutrient stress, This study attempts to develop an improved understanding of the aforementioned technologies and tools to further establish a new and innovative approach to the application of precision agriculture through the use of technology to accomplish more efficient use of fertilisers; less impact on our environment and greater crop yields from a more effective use of nutrients, This process is an example of the sustainable development of technology based agricultural solutions, especially within countries such as Algeria, where having the ability to manage and control nutrients is critical to the country's national food security and economic stability.

The chapter provides a more indepth investigation into the topics discussed above by highlighting how innovation in technology can support the development of a more intelligent, more resilient and sustainable future for the agricultural sector.

1.2 Definition of Precision Agriculture

Precision agriculture, or precision ag, is a management system of growing crops on farms that uses technology and data to collect, measure and evaluate the needs of various crops grown in fields, The goal of precision farm technologies is to produce crops with maximum yield and quality, while at the same time reducing the costs of production and the impact that farming has on the environment; therefore this management system improves the productivity of farms and promotes sustainable farming methods and practices.
Precision ag uses measurement technologies (i.e., sensors) and a proper management information system (MIS) to measure and manage both the inter- and intra-variability of crop systems, Simulation models of crop yield using deep learning and machine learning (ML) support understanding how the combination of different pest pressures, nutritional or moisture deficiencies in the field and/or other types of environmental variability impact a crop during the growing season. Similarly, remote sensing technologies (i.e., lidar imagery, radar, multi and hyperspectral imaging) provide valuable insights that enhance the estimation of crop yields by improving scientists' understanding of the soil, the climate and other types of biophysical characteristics that are necessary to produce healthy and high-yielding crops.
The aim of this research paper is to outline/describe potential areas of research (or further research) for agricultural scientists focusing on ongoing advancements in remote sensing and state of the art machine learning technology such as hyperspectral imaging (HSI) and explainable artificial intelligence (XAI) that have improved accuracy and reliability of crop yield predictions within precision agriculture, It is anticipated with further development and refinement of this technology, as agriculture becomes even more precise using sensor technologies and machine learning methodologies including explainable methods which provide enhanced transparency and interpretability of model outcome results, the application of these new technologies will be to increase the efficiency of agricultural production systems, Furthermore, the future application of hybrid systems developed using various combinations of machine learning methods, hyperspectral imaging, and signal processing will create unique and superior alternative solutions to assist with precision agriculture [3]

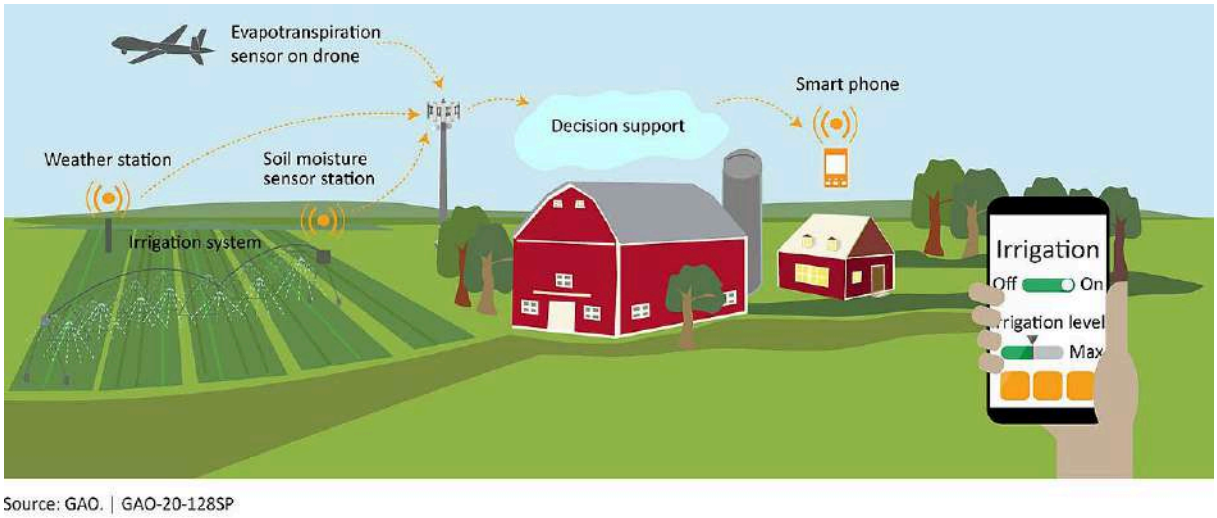


Figure 1.1: Components of a Precision Agriculture System. Image from GAO.

1.3 Challenges of Precision Agriculture

1. **Challenges and limitations in prediction of soil properties and weather pattern**
    - Varying geographical conditions poses a challenge for universal design of the prediction algorithms.
    - Soil parameters prediction is highly dependent on the sample selection philosophy.
    - Dataset selection and filtering is a challenge for researchers with non-computing background.
2. **Challenges and limitations in prediction of crop yield**
    - Varying parameters and complex datasets pose a challenge for universal design of the prediction algorithms.
    - Dataset selection is critical due to the complexity; as an improper selection of data may result in underfit/overfit prediction pattern.
3. **Challenges and limitations in detection of weed and disease in a crop field**
    - The accuracy of prediction depends on the quality of training dataset some of which is available as an open-source dataset, but is applicable to only a limited number of crops.
    - Improperly labelled data may result in a disastrous prediction system, as the training of the system plays a major role in the performance of the system.
    - Overtraining the model may result in a sensitive prediction system.
4. **Challenges and limitations in drip irrigation for an agricultural field**
    - Accurate prediction sometimes depends on the number of sensors and hence increases the initial investment of the farmers.
    - An incorrect sensor placement in the filed affects the accuracy of the system, hence sensor optimization becomes imperative in designing a smart irrigation system.
    - The architecture of prediction system highly depends on the dataset; hence no universal guidelines can be laid out for system design.
5. **Challenges and limitations in intelligent harvesting**
    - The accuracy of the prediction systems largely depends on the training dataset, hence accurately labelled dataset is a primary requirement of implementing an intelligent harvesting system.
    - Inaccurate harvesting recognition system result in economic loss for farmers, as a delay in harvesting might lead to an overripe crop or early harvesting might lead to rejection of the product [4]

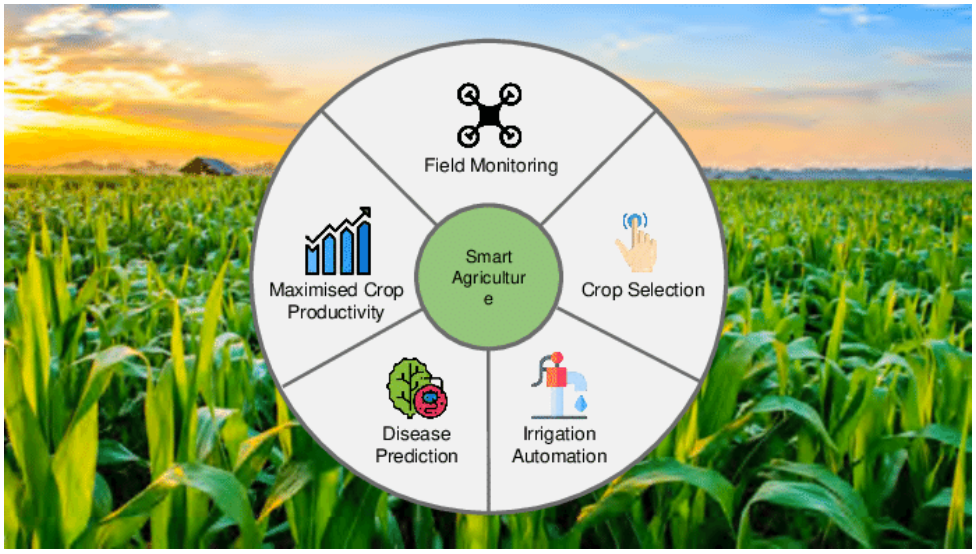


Figure 1.2: Challenges of Smart Agriculture [5]

1.4 Remote Sensing in Agriculture (Satellite and UAV-Based)

A review of the current applications of remote sensing technology to precision agriculture highlighted the differences between the different ways of generating data with either traditional satellites or UAVs. A detailed overview of the various ways the data generated from these two sources has been used within the field of precision agriculture was made available. The use of UAVs versus traditional satellites to generate data has several advantages for users who wish to analyze and apply the data generated by the UAVs.
In addition, precision agriculture can be described as being very broad in scope and therefore, practitioners, researchers, and policy makers must consider a complex value chain that includes multiple stakeholders. As a result, in order to further the dialogue on this topic, the following parts of this paper will provide further analysis of topics that are considered important when discussing the continuing evolution of precision agriculture: a discussion on the significant technological limitations associated with scaling precision agriculture; a list of ideas to address those issues; and a brief depiction of the current socio-economic environment within the agriculture sector [8]

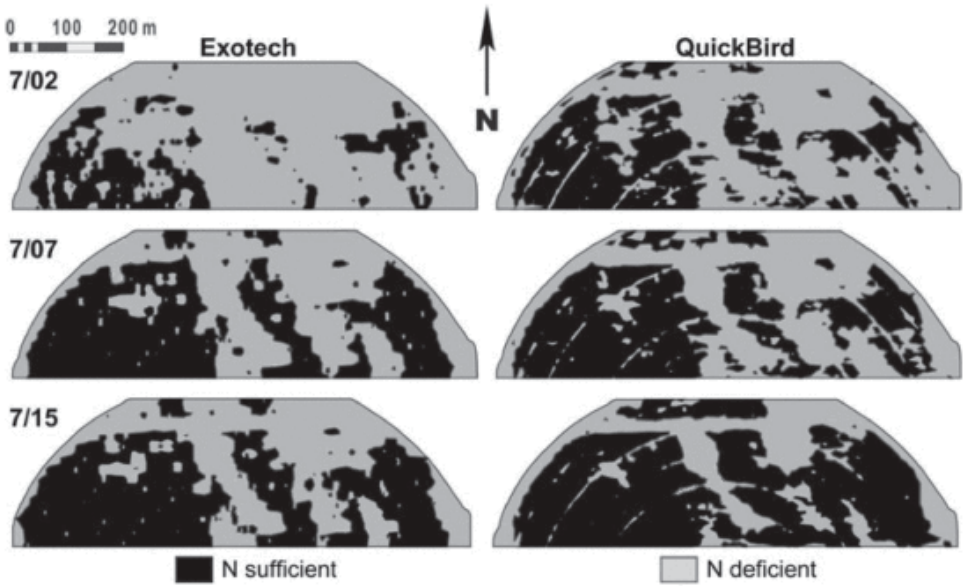


Figure 1.3: Comparison of Nitrogen sufficiency between Exotech ground-based data to the Quickbird Satellite data. The former has pronounced jagged edges due to the lower resolution of the readings [6]

1.4.1 Satellite-Based Remote Sensing

The utilization of satellite remote sensing in agricultural sciences has been very common for many years because satellites provide an abundance of spatial data over wide areas as well as a long period of time. Satellite sensors, such as Landsat, Sentinel-2, MODIS, receive multi-spectral images that have different spatial resolution, spectral resolution, and temporal frequency. The data from these images can be used to accomplish activities such as estimation of vegetation indices (e.g. NDVI), monitor crop growth, identify and quantify environmental stress in crops due to drought, and predict crop yield at both the regional and national level. Satellite imagery is very valuable in the monitoring of agricultural areas and long-term trend analysis of crops[8]

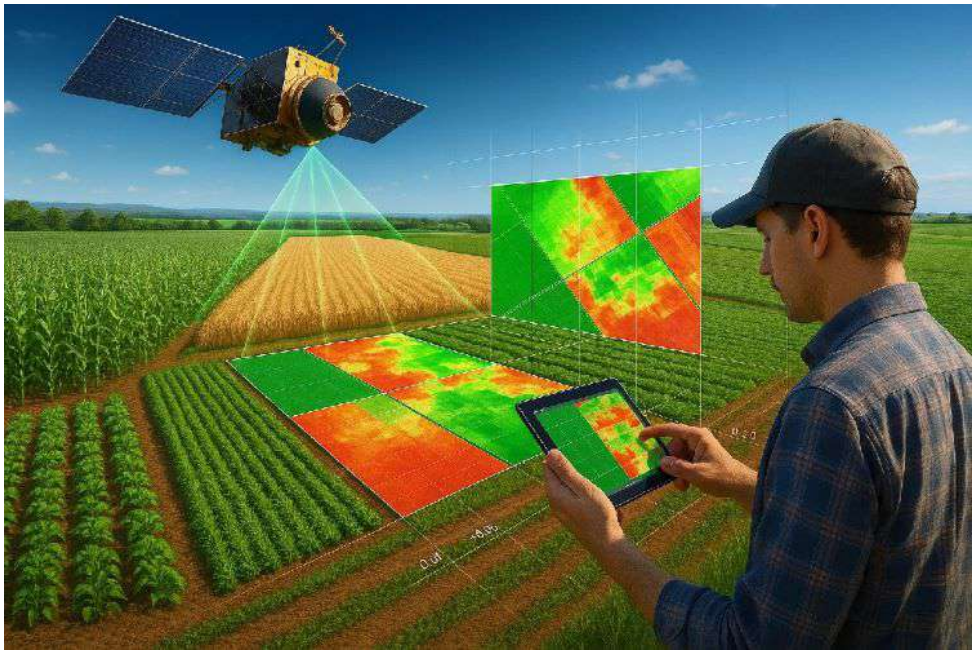


Figure 1.4: Satellite Remote Sensing for Agriculture [7]

The use of satellite remote sensing for crop and land cover classification, soil erosion control, vegetation biomass estimation, soil organic carbon measurement, and predicting crop yields, has provided great success with classification accuracies of 80–90% using multi-spectral and hyperspectral data . The use of advanced analysis methods as well as the fusion of data from multiple satellites were successful in overcoming the issue of coarseness of data; however, the limitations of high cost, limited availability of satellite data, and the use of old satellites (e.g. QuickBird) represent a strong motivation for using remote-sensing methods via UAVs (Unmanned Aerial Vehicles)[8]

Year	Satellite	Data Location	Type of Crops	Type of Analysis	Ref.
2004	IKONOS	USA	Grain	Spatial variability	[28]
2005	QuickBird	USA	Arid land	Image classification	[23]
2005	QuickBird	USA	Sugar beet	Nitrogen concentration	[22]
2007	QuickBird	China	Winter wheat	Nitrogen concentration	[19]
2008	EO-1	India	Cereal	Plant biochemical index (PBI)	[20]
2008	QuickBird	Spain	Olive orchards	Image classification	[21]
2008	EO-1	Australia	Soil	Carbon prediction	[25]
2009	QuickBird	Spain	Mediterranean crops	Object detection	[24]
2009	QuickBird	China	Winter wheet	Variation in soil properties	[29]
2009	Landsat 5	Australia	Cereal	Spatial yield variability	[27]
2010	QuickBird	Spain	Wheat	Image classification	[26]
2010	QuickBird	USA	Corn field	Nitrogen concentration	[18]

Figure 1.5: TABLE 1 Summary of precision agriculture through satellite imagery

1.4.2 UAV(UAS)-Based Remote Sensing

Drones (or UAVs) are a growing technology that complements existing satellite remote sensing technologies for agriculture. They capture high resolution multispectral, hyperspectral and thermal imagery from much lower altitudes than the available satellite sensors

yield, which provides a more granular level of detail about individual plants and planting areas (plots). This user friendly technology is well suited for use in agriculture for quickly identifying localised problems including: nutrient deficiencies, weeds, insect infestations and disease outbreaks.

Using remote sensing from UAVs gives farmers and researchers a lot of flexibility when it comes to collecting imagery because they can have the UAV fly to any location whenever they need collected imagery and can do so under the best possible weather conditions at that time. Very high-resolution imagery creates a precise assessment of within-field variability, which can be used to implement site-specific management activities (e.g. variable rate of fertilization and irrigation). Yet, UAVs are limited by battery life, regulations of flights, and the relatively small area that they can cover in respect to satellites[9]

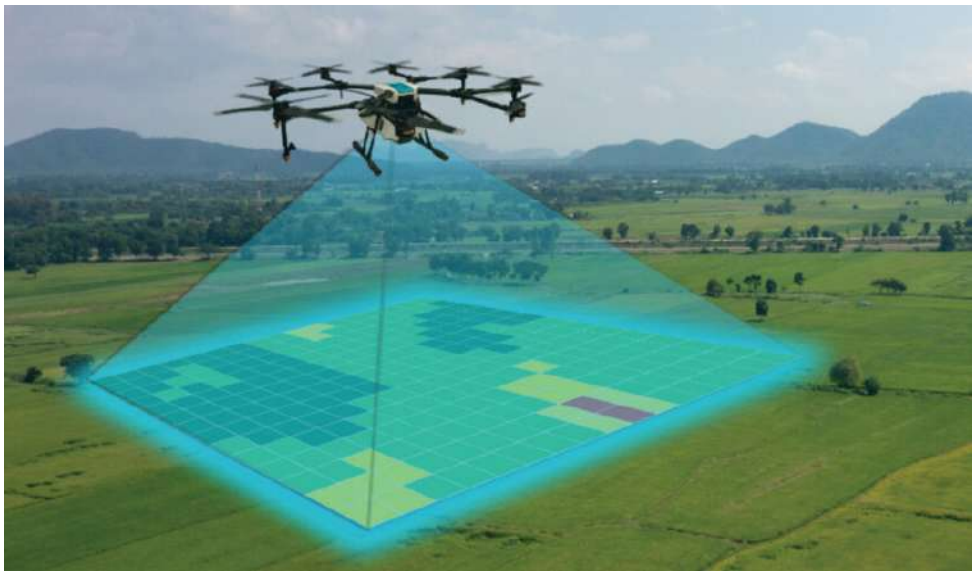


Figure 1.6: UAV-Based Remote Sensing for Agriculture

1.4.3 Integration in Precision Agriculture

Observation of precision agriculture is accomplished by employing a remote sensing technology system that can utilize satellite and unmanned aerial vehicle (UAV) images for record-keeping. Continuous (i.e. time series) and large-area coverage is acquired through satellite observation, whilst UAV observation records a greater quantity of more detailed and accurate images of the crop's growth, obtaining over 10x of recorded image data compared to satellite images, at critical times within the crop's growth cycle.
Remote sensing data, when combined (i.e., fused) with machine learning (ML) and artificial intelligence (AI), can automate crop classification, detect crop stress . Consequently, by integrating these technologies together, the efficiency, sustainability and resiliency of agricultural production systems will be greatly improved[10]

1.5 Principles of Hyperspectral Imaging

Over the last three decades, hyperspectral imaging (HSI) has been an effective technology for military, civilian and environmental applications along all spectral wavelengths, thanks to advances made with remote sensors which provide very high temporal, spatial and spectral resolution of very large areas of the earth s surface. The very fine spectral resolution (0.01 nm to 5 nm) helps to identify materials accurately and to analyse complicated mixtures of surfaces based on their physical characteristics. Now that HSI has been successfully used in food safety and quality assessments, medical diagnostics, and agricultural applications, this review will summarise some fundamental aspects of hyperspectral imaging along with some of its more common applications (food quality assurance laboratory testing, healthcare applications, agriculture, monitoring of fresh water resources, detection of plant stress, discrimination between weeds and crops, flood mitigation) and highlight the current progress being made in the development of automated, HSI-based systems and serves as a basis for the future development of HSI and comparative studies in the field [18]

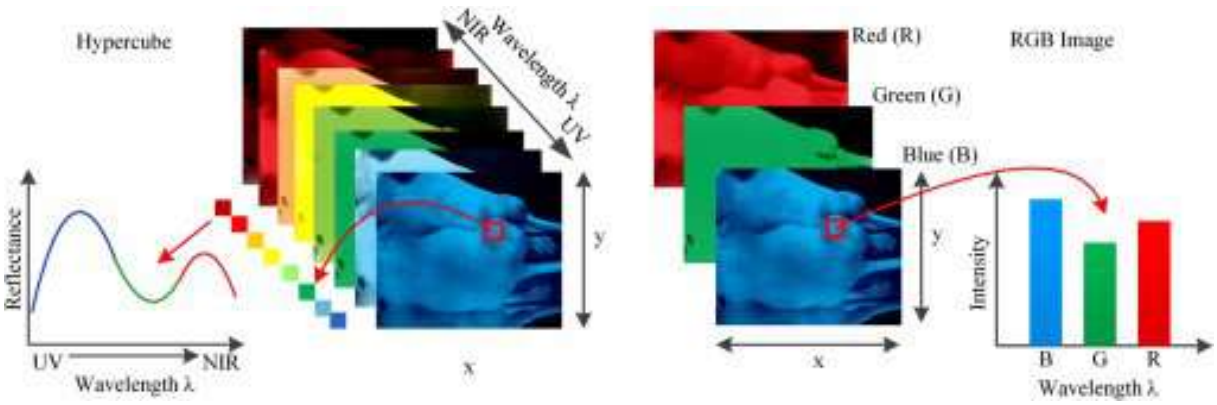


Figure 1.7: Comparison between hypercube and RGB image

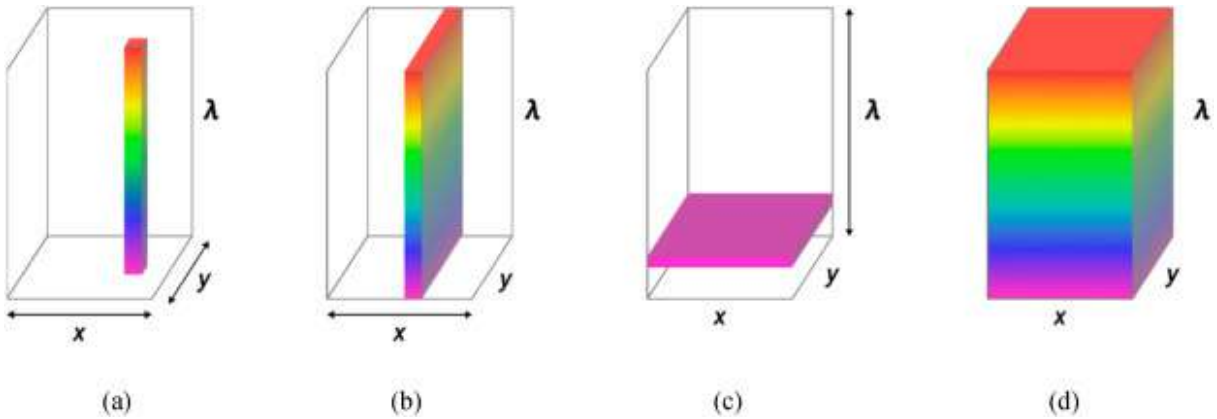


Figure 1.8: Three approaches are used for constructing a hyperspectral image (a) Point Scanning (b) Line Scanning (c) Imagers Staring (d) Imager Snapshot

A. Spatial Resolution

The smallest resolvable or separate object on an image is referred to as its spatial resolution (i.e., how clear your image is), A better measurement of image clarity is spatial resolution than total pixel count. Spatial resolution is determined by the design of the sensor; particularly, the sensor's field of view and the sensor's altitude, Remote sensing uses detectors that capture specific sized ground patches, The smaller the patch being captured by the detector, therefore, the higher the spatial resolution of that captured patch and the finer the level of detail that can be observed, Larger patch sizes will lead to reduced levels of detail.

B. Spectral Resolution

Spectral resolution is the ability of a sensor to discriminate wavelengths of light based upon the range of light wavelengths it can record in a single exposure and the number of spectral bands across which those wavelengths will be captured, A sensor can discriminate across a wide range of wavelengths but have low spectral resolution if it has fewer spectral bands. Conversely, a sensor with many narrow contiguous spectral bands has high spatial resolution, permitting it to make distinctions with respect to materials with similar spectral signatures, wherein multispectral images will only capture low levels of detail with respect to spectral variation, Hyperspectral imaging (HSI) captures data across numerous, narrow, contiguous spectral bands in the visible, near infrared, and mid-infrared range; therefore, the materials can be accurately identified very exactly using HSI. One HSI pixel can provide more information about the materials on a surface than does a non-hyperspectral image.

C. Temporal Resolution

The term temporal resolution when dealing with hyperspectral imagery refers to how often a sensor can capture and revisit a given 'location', or its 'revisit' (or 'return') time. Sensors of high temporal resolution can capture data from the same geographic location frequently with low temporal resolution depicts infrequently captured data, Generally speaking, temporal resolution is expressed in terms of days and is dependent upon the orbital characteristics of the sensor collecting the images.

D. Understanding Spectral Signatures

The interaction of incident electromagnetic radiation (sunlight) upon the surface of the Earth is influenced by the type of material from which the surface consists (for example, sand, soil water, minerals and vegetation), The amount of electromagnetic energy (reflected or emitted) from a surface can be measured with the use of hyperspectral sensors. The reflectance of a surface is defined as the percentage of the total incident electromagnetic (light) radiation incident on a surface that has been reflected from the surface back to the sensor, This reflectance can be defined as a function of wavelength, with values from 0% (all incident light absorbed) to 100% (all incident light reflected), Each type of material has its own characteristic reflectance with respect to wavelength, which can be represented in a graph so that these different types of materials can be compared and identified based upon their spectral response or spectral signatures[18]

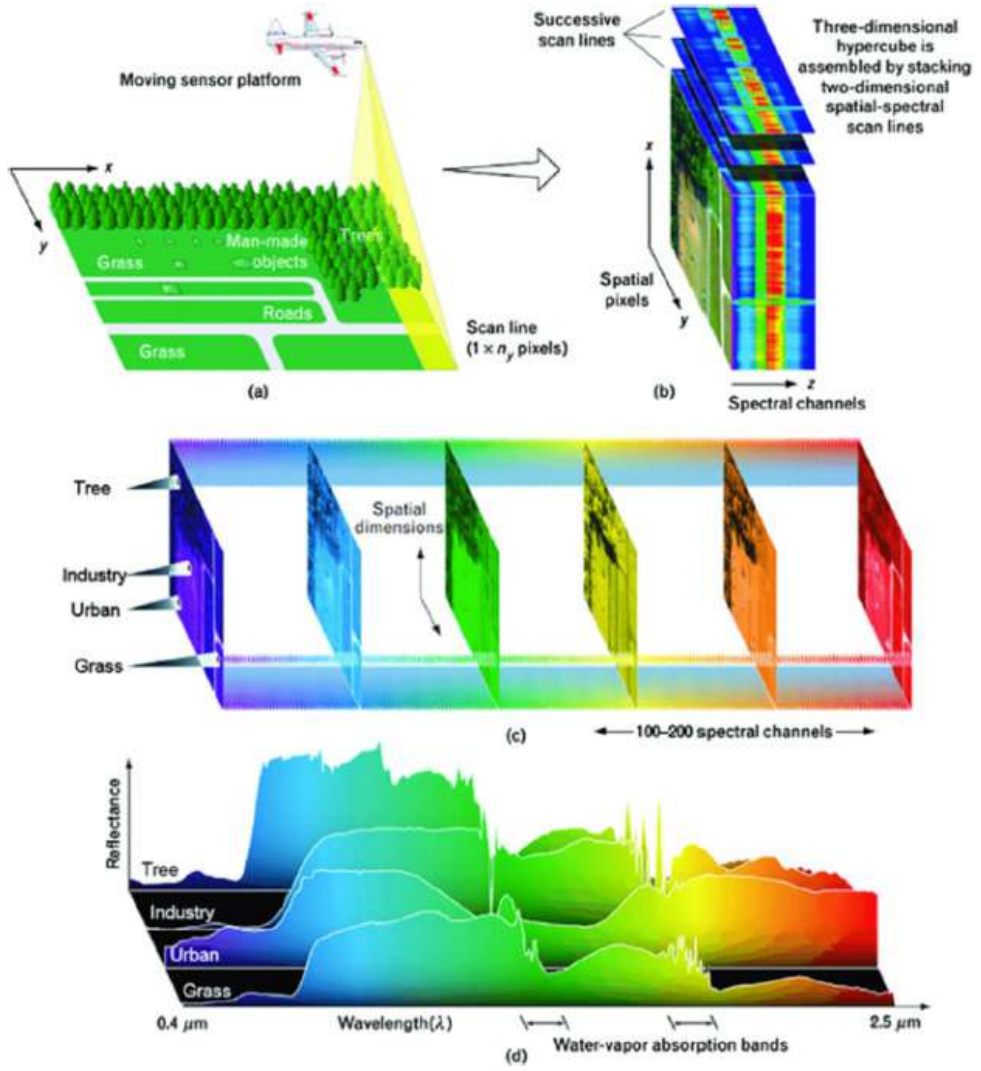


Figure 1.9: Detailed hyperspectral three-dimensional data cube structure

Hyperspectral images are acquired via different image acquisition techniques, which include both spectral (area) and snapshot imaging. Normally, spectral scanning employs two dimensional (2D) detectors to scan a scene and creates the final image from multi-positional exposures of a scene, providing a high resolution image (determined by pixel size and optics) but requiring many images taken at different times, Snapshot imaging (or image scanned) is the direct (single) capture of a full three dimensional (3D) hyperspectral data cube with the use of one integration period, therefore capturing both spatial and spectral data simultaneously without the need for mechanical scanning devices and providing more versatile and generally easier to operate imaging systems.
The primary techniques for generating hyperspectral data cubes have been classified into three major categories according to Qian: HSI Snapshot Method, Spectral Filter-based Method, and Dispersive Element-based Method, To achieve a variety of spatial and temporal resolutions, hyperspectral sensors are typically mounted on various platforms such as: close range systems, manned aircrafts and Unmanned Aerial Vehicles (UAVs), A comparative assessment of these platforms is provided in Table 1[18]

Specifications	Airplanes	Helicopters	Satellites	Fixed Wing UAV	Multi UAV
Example Image					
Operational Altitudes	1–20 km	100 m- 2 km	400–700 km	<150 m	<150 m
Spatial Coverage	~100 km^2	~10 km^2	42 x 7.7 km	~5 km^2	~0.5 km^2
Spatial Resolution	1–20 m	1.1–1 m	20–60 m	1.1–0.5 m	0.01–0.5 m
Temporal Resolution	Depends on operations of flights (Hours to Days)				
Flexibility	Medium (Limited by availability of aviation)		Low (Fixed repeating cycles)	High	
Operational Complexity	Medium (Depending on the sensor operator)		Low (Data provided to users)	High (Software & Hardware of setup by users)	
Applicable Scales	Regional landscape		Global landscape	Canopy landscape	
Cost of Acquisition	High (requires aviation company to fly)		Low to Medium	High (for a large area)	
Limiting Factors	Unfavorable flight speed		Weather	Flight regulations	

Figure 1.10: Comparative Analysis of distinct platforms for hyperspectral imaging

1.6 Spectral Bands and Vegetation Indices (NDVI, GNDVI, Red-Edge, etc.)

1. **Spectral Bands**

   Hyper-spectral imaging (HSI) is utilized in agricultural studies for crop identification through its coverage of the visible (VIS), near-infrared (NIR), and shortwave infrared (SWIR) spectral regions, while also fulfilling the requirements to conduct band selection (BS) in order to determine the most appropriate spectral bands by evaluating both the physical properties of light and plant biology, The spectral bands are classified into fifty bands, fifty bands, and so on, and then evaluated for multifaceted properties (i.e., combinations of entropy and NDVI and MNDWI) to determine the most effective bands for each group, classifying them as HSI spectral regions for determination of crop types. A convolutional neural network (CNN) was trained to classify of the refined sub-cube of HSI through experimentation whereby the results of the experiments for the Indian Pines and Salinas datasets achieved 95.97% and 98.99% by Corn and Soybeans; 94.53% and 100% by Fallow and Romaine Lettuce respectively; indicating that this method of determining the most appropriate spectral bands and using the CNN model correctly classifies the crops [20]

2. **Vegetation indices (VIs)**

   The development of vegetation indices (VIs) for remote-sensing-based measurement and monitoring of vegetation has been a significant study area, and one of the most commonly used indices is the normalized difference vegetation index (NDVI), There are many vegetation indices available for use, however; therefore, this study is concerned with evaluating the degree to which different VIs can be utilized as discriminative features in the agricultural arena. The goal of this study is to evaluate the extent to which different VIs differ from each other and whether they exhibit detectable patterns across multiple modalities of hyperspectral data (i.e.,

from satellite and UAV data) for agricultural uses, To accomplish this goal, we will combine an unsupervised analysis of PRISMA satellite imagery to highlight practical differences between VIs with a supervised classification of UAV hyperspectral imagery. Through this analysis, we will determine if the pattern that differentiates one VI from another is consistent with a given landscape and agricultural use, thus establishing their value as discriminative features in crop segmentation and recognition[19]

1.7 Uses of Hyperspectral imaging in agriculture

Hyperspectral Imaging (HSI) is an innovative technology that has the capacity to change precision agriculture by giving farmers and researchers new ways to assess the health of crops and the environmental conditions surrounding them. This technology uses hundreds of thin-bandwidth spectral signature to collect a detailed map of an object's reflectance at many different wavelengths, which is far greater than any human can discern with their eyes as well as all conventional cameras will allow; therefore, you can target specific treatments rather than just broadly applying them and manage resources more effectively by targeting those areas where conditions would warrant. Here are its key applications in precision agriculture:

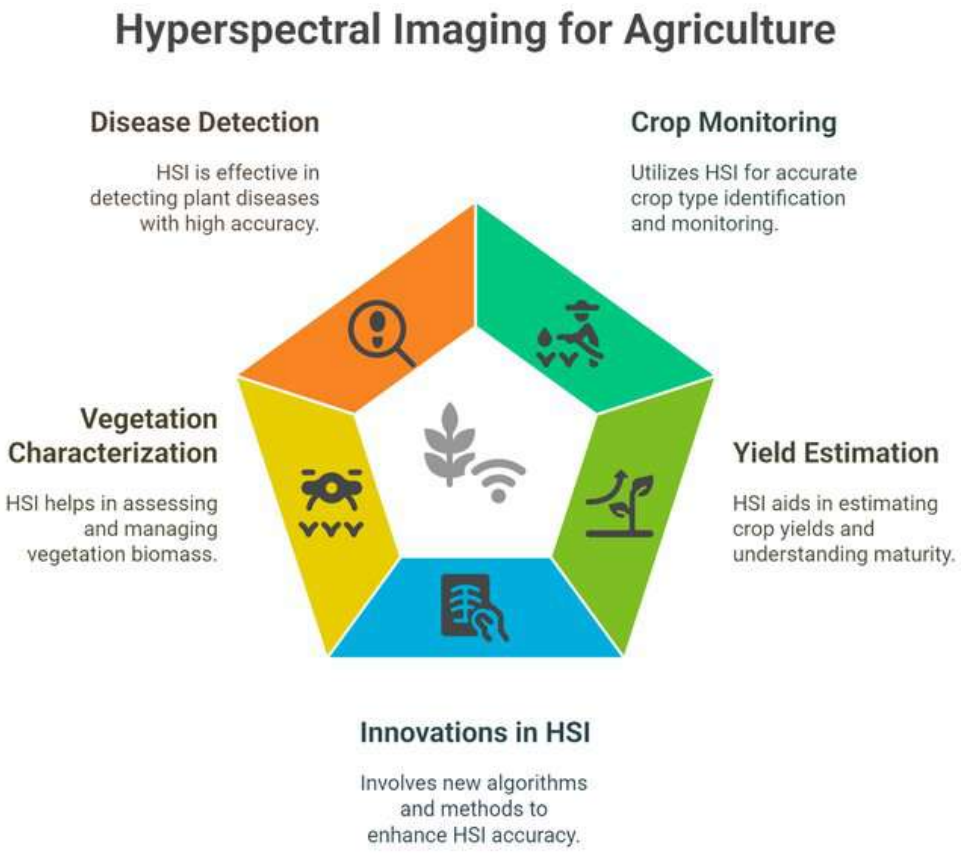


Figure 1.11: HSI in agriculture. HSI also allows a close observation and growth monitor and also diagnose diseases of vegetation as each vegetation species possess characteristic spectral signatures. This help in precise agricultural applications.

- **Crop Health Monitoring**

  Crop stress caused by lack of water, nutrients, or salt can be detected before visual indications are present. This is accomplished by measuring the differences in infrared reflectance of crops using hyperspectral imaging. Measuring chlorophyll absorption and the patterns of water content is a method of quantifying crop growth, and can be used to determine which areas of a field require precision irrigation [11].

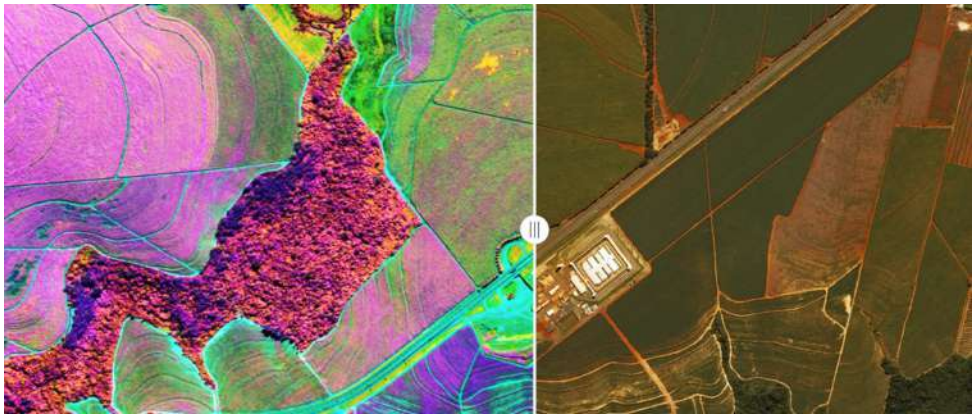


Figure 1.12: Crop Health Monitoring

- **Disease Detection**

  Hyperspectral imaging (HSI) offers plant disease identification several benefits, including using spectral signatures that indicate the existence of disease prior to their exhibiting any visible signs. Through HSI data, plant pathologists can identify the disease before presenting any sign of the problem, differentiate between the various types of the disease, estimate its severity once established, and map the distribution of disease on a large scale for preventative action and reducing crop loss[11]

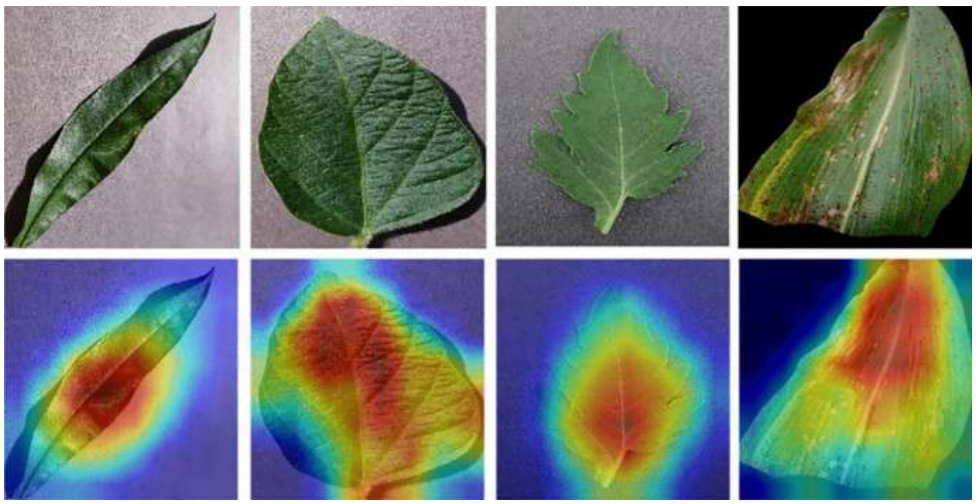


Figure 1.13: HSI for plant disease detection

- **Weed Control**

  HSI also allows the identification of weeds and crop types growing together during the early stages of growth by comparing their spectra with known spectra. This means that farmers can more accurately survey their fields for weed infestations and apply herbicides. By being able to apply herbicides more specifically than before, they will use less chemical herbicide, will spend less money overall and reduce the impact of herbicides on the environment [11]

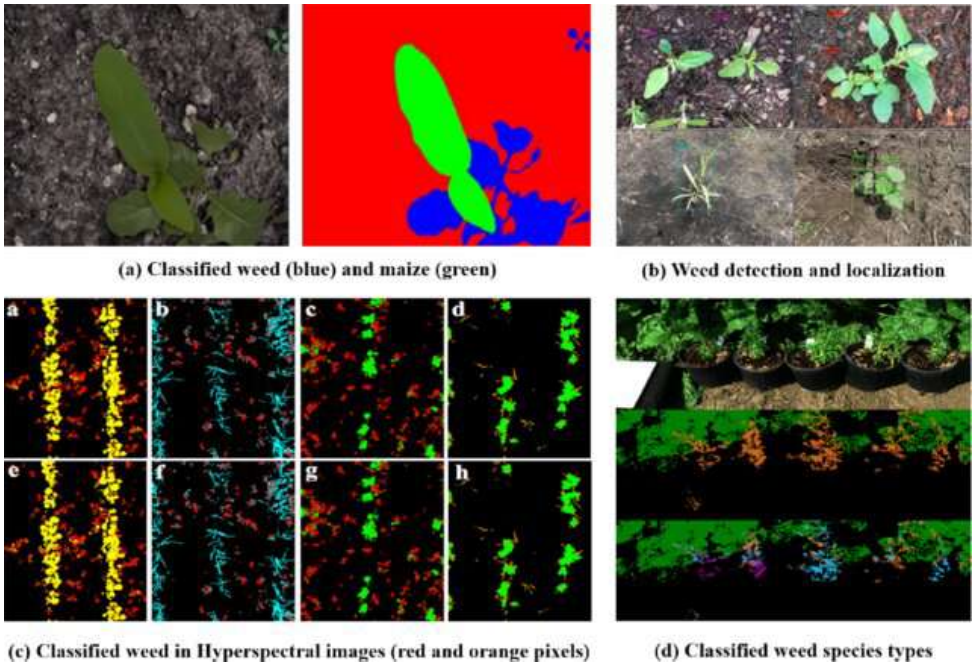


Figure 1.14: Classified weeds as seen in RGB color space (a, b) and hyperspectral images (c, d).

- **Yield Prediction**

  Prediction of crop yields utilizes the HSI and artificial intelligence/machine learning technologies along with the ability to analyze elements such as climatic conditions, soil quality, historical crop yield and farming management practices in order to calculate forecasts for agricultural production. In addition to helping farmers to make better decisions at an individual (farm) level, these predictions also assist with improved utilization of resources, supply chain planning and helping to create a sustainable method of agriculture through precision farming that fits the individual needs of a particular field [12].

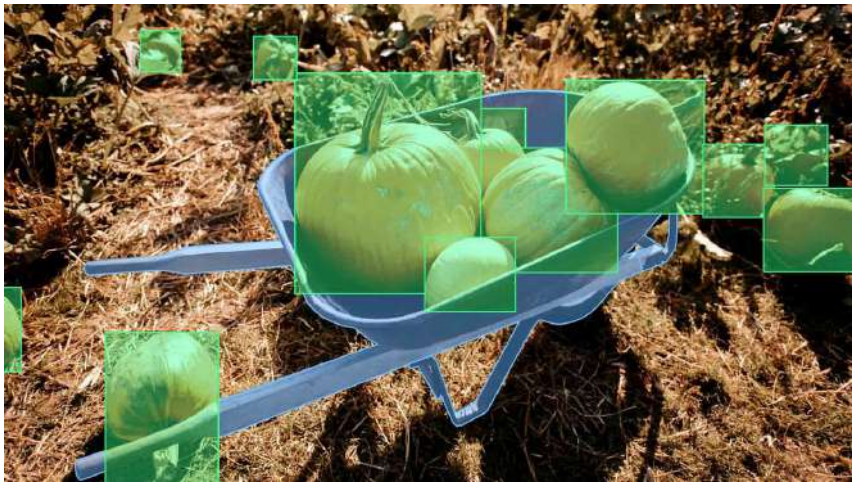


Figure 1.15: AI- for Yield Prediction

- **Soil Property Mapping**

  Hyperspectral remote sensing has shown promise as a means of predicting soil characteristics of alpine grasslands located on the Qinghai-Tibetan Plateau by utilizing both in situ and remotely-sensed hyperspectral data collected at 67 sample points to establish regression equations for the estimation of soil organic carbon, and total nitrogen as well as phosphorus and potassium. Multiple regression analysis using the spectral data produced adequate spatial maps with respect to prediction accuracy (relative root mean square error values ranging from approximately 31% to 69%) indicating that hyperspectral techniques can be used for large area mapping of soil properties [13].

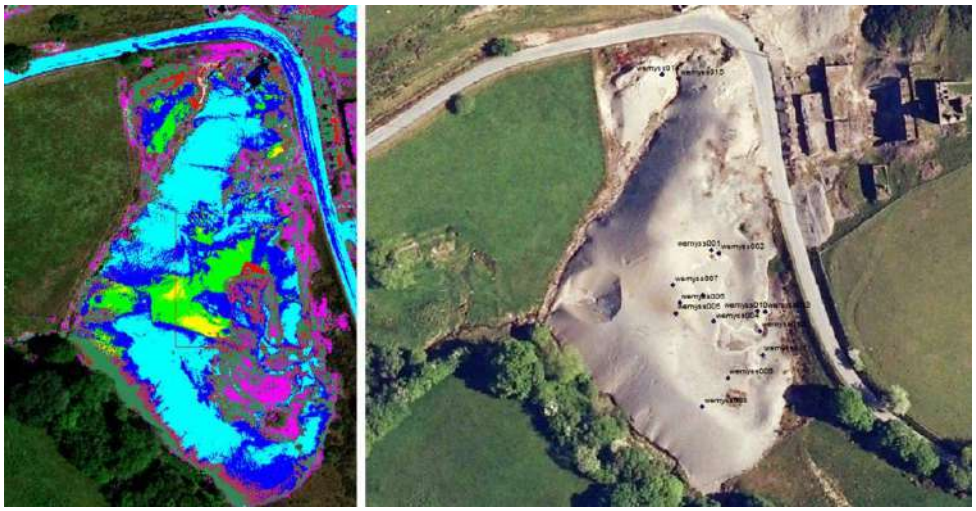


Figure 1.16: HSI for Soil Property Mapping

- **Water Stress and Irrigation Management**

Traditionally, remote sensing technologies used for assessing crop water stress relied on the use of fixed sensors mounted on towers. These systems had limited coverage and spatial extent and were therefore expensive to deploy over greater distances. Hyperspectral imagery from UAVs provides an efficient and economical way to acquire spectral data from all areas of a field in a short period of time. The high-resolution spectral data provided from UAV-based hyperspectral imaging enables producers to calculate CWSI, NDVI, the ratio of canopy nitrogen to leaf area index (CN ratio), LAI, and the ratio of canopy surface area to volume (SAVI) for the entire field. Additionally, UAV-based hyperspectral imaging provides plant-specific "spectral fingerprints," which can assist farmers in optimizing their irrigation, fertilization, and crop management practices far more efficiently than remote sensing methods available via satellite or manned aircraft [14]

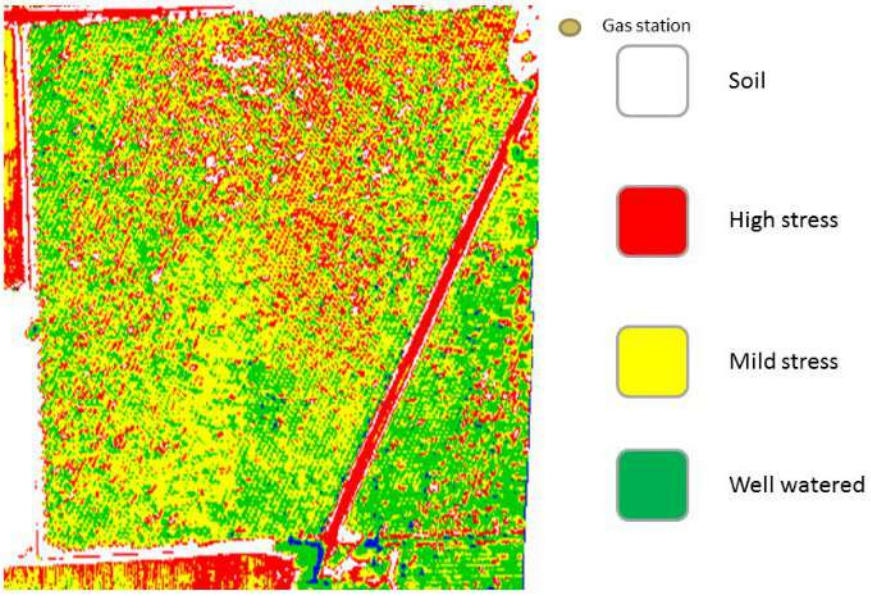


Figure 1.17: Hyperspectral water stress map of 160 acre walnut orchard.

1.8 Challenges and Limitations of Artifical Intelligence in Precision Agriculture

Artificial intelligence has the potential of playing an important role in meeting the food requirement of entire world. However, there are certain challenges which are hampering its adoption in agriculture industries which are outlined as follows:

- A recent government survey in Algeria estimated that literacy rate of Algerian farmers is very low therefore bridging the gap between farmers and technology is a challenging task
- Farmers are less motivated to come out from their comfort zone and learn digital skills to improve their farming standards.

- Agriculture lands are mostly situated in rural areas. Implementation of IoT architecture and WSN which requires cloud services for data storage and analysis is a big issue in rural areas where reliable internet connectivity is not available.
- Accurate prediction and classification through cognitive ability of machines is difficult in varying geographical conditions.
- Initial set up of digital farming which includes hardware and software requires huge investment.
- Deployment of smart sensors and other electronic gadgets requires heavy energy consumption[4]

1.9 Explainable Artificial Intelligence (XAI)

1.9.1 Concepts of transparency and interpretability

Transparency and explainability are especially important with artificial intelligence, because most people (even many that work in IT) do not have a complete understanding of how AI systems produce their results. There is much discussion about transparency and explainability with regard to ethical artificial intelligence, responsible artificial intelligence and governing artificial intelligence. While transparency and explainability are closely related concepts, they mean different things and deliver different benefits with respect to understanding and managing artificial intelligence systems.
Transparency involves providing general information about the artificial intelligence system to a large number of users. Explainability will typically involve providing specific information about a particular decision or outcome to users, developers and/or stakeholders that need to understand how this particular outcome was achieved by the system.
Transparency is aimed at increasing the overall level of trust that all users will have toward the entire artificial intelligence system, while explainability is focused on providing a specific determined value of confidence for that particular outcome to the user(s) that are provided with explanations for this outcome. In other words, overall transparency and specific explainability articulate different components of the overall system [23]

1.9.2 Limitations of "black box" models

Many modern AI designs such as Convolutional Neural Networks (CNN) and Long Short-Term Memory Networks (LSTM) are classed as black boxes and provide extremely accurate predictions without revealing how they arrive at their decision-making processes or predictions.

The level of transparency of a model presents a number of challenges:

- Decreased level of trust by users
- Challenges in scientific validation
- Possibility of undetected failures

- Concerns about ethics and the environment

For example, if predictions made using black box models are inaccurate when used in a precision agriculture setting, it could cause improper fertiliser applications, which would result in financial loss to the farmer and environmental damage.
Thus, relying solely on black-box models where no explanatory mechanisms are applied will limit the use of these models in agricultural systems.

1.9.3 Feature-based XAI methods

Feature Importance

Feature Importance in Explainable Artificial Intelligence (XAI) represents a pivotal method to provide an explanation for how different input variables may affect the output (decision) of machine learning models (ML). The feature importance value assigned to each feature allows for the systematic analysis of the contributions of the various features to the models' predictions; this systematic analysis also yields the quantitative measure of the importance of each feature when determined to be instructive to the model.
As developers perform examination and verification of the actions of their models; they can easily use the feature importance values for various sample data points, so they can understand the influences of different sample data points and their respective contributions to the models' decisions. For example, if a machine learning model is able to determine if a person is preparing to default on their loan, using feature importance may indicate that income and credit history of the borrower are more important in making that prediction than any other factor. This provides all stakeholders with an understanding of how their machine learning model made its prediction [24]

SHAP

SHAP is a post hoc, model-agnostic tool that can be used with any machine learning model. Game theory serves as the theoretical background for the tool which determines the payout of players. In a machine learning model, player and payout are replaced with features and the model's prediction respectively. Each feature of the machine learning model can be given a value that determines its importance towards the output of the model. SHAP takes into account every possible combination between features (i.e. Coalitions) so that all scenarios are tested regarding every possible subset of features that are used. Increasing complexity due to the increase of the number of features made an approximation called Kernel SHAP [25]

LIME

LIME is a local explanation technique that is independent from the model being used. The model provides the influence each feature has on the outcome of a single record. Additionally, in classification models, it provides the probability that the record belongs to a specific class as well as how much each feature contributes to each class in a visualized plot.
On the other hand, LIME produces a local linear model. Then the system outputs the adjusted coefficient values of the new linear model which represent the weightings of the

features in that model. That means if a user uses models that take into account the non-linearity of features with respect to the resulting outcome and LIME generates a surrogate model from that user's models, the model's non-linearity will not be present in the LIME generated explanation of the model due to the non-linearity being lost during the process of creating a surrogate model. Furthermore, LIME is a model-dependent technique meaning whichever model used will determine how LIME will produce an explanation for a record with respect to the same task and dataset [25]

1.10 XAI Methods for Image-Based Models

Deep learning imagebased models such as CNNs can predict with a high level of accuracy; however, because they are considered a "black-box" model, it is very hard to take a look at how they make the resulted prediction. To overcome this challenge, the use of Explainable Artificial Intelligence (XAI) provides not only a visual explanation regarding a model output prediction (i.e., how the input image impacted the model output), but allow to produce an understanding of where in the input image the prediction was derived from. The two most popular and widely used techniques associated with visual explanations for imagebased models are Saliency Maps and Grad-CAM. Each of these methods utilize gradient-based approaches in order to determine which pixels or region of the input image were responsible for the ultimate output of the trained model, improving the transparency of the models, facilitating model validation, and improving trust of computer vision systems, particularly in high-risk situations.

1.10.1 Saliency Maps

The above method of doing experiments about occlusion costs too much time and money. So, it is required to propose other way to calculate how much weight is there of image regions. It should be noted here that a saliency map is an analytical way which gives how much important a pixel is to image, while only require one time forward pass and one time backward pass to pass the network [15].
Saliency Maps are an Analytical Technique for Calculating the Important Pixels Associated with a Deep Learning Model's Class Prediction. A Saliency Map is Less Computationally Intensive Than Occlusion Experiments as a Saliency Map Only Requires One Pass (Forward) and One Pass (Backward) Through the Network to Calculate the Importance of All Pixels in An Image (i.e., at One Time), Thus Reducing the Number of Backward & Forward Passes through the Model by a Factor of 10 or More to Determine Which Pixels Independently the Saliency Map Was Just Calculating The Value of All Pixels From All 256 Colour, Excluding Occlusion Experiment Pixels.
The core intuition is based on sensitivity: if changing a specific pixel leads to a large change in the output score for the ground truth class y, then that pixel is considered important. Mathematically, this importance is represented by the gradient of the output with respect to the input image x. To calculate it, the gradient $G(x)$ is found using the formula:

$$G(x) = \frac{\partial f(x)_y}{\partial x} \tag{1.1}$$

We determine the value of the importance of a pixel x(i,j) taking maximum of the absolute values for each channel. Thus the matrix we will get having dimensions W*H called Saliency Map SM is computed as follows:

$$SM(i,j) = \max\left(|G(0,i,j)|, |G(1,i,j)|, |G(2,i,j)|\right) \tag{1.2}$$

The saliency map can localise well precisely the diseased areas in the input leaf image. Fig. 1.18b, e, f are good cases where the display of the saliency maps show precisely the diseased areas of the leaves. Also, in Fig. 1.18f the two separated diseases area of the leaf mould are presented while it is found only one for the occlusion tests. Beside these good result in a lot of case the saliency maps are unclear because of noisy activation that can easily bother the user. For example Fig.1.18c, d is an example where there are a lot of activation that does notcorrespond to disease areas. The solution of the problem will be the option guided backpropagation.

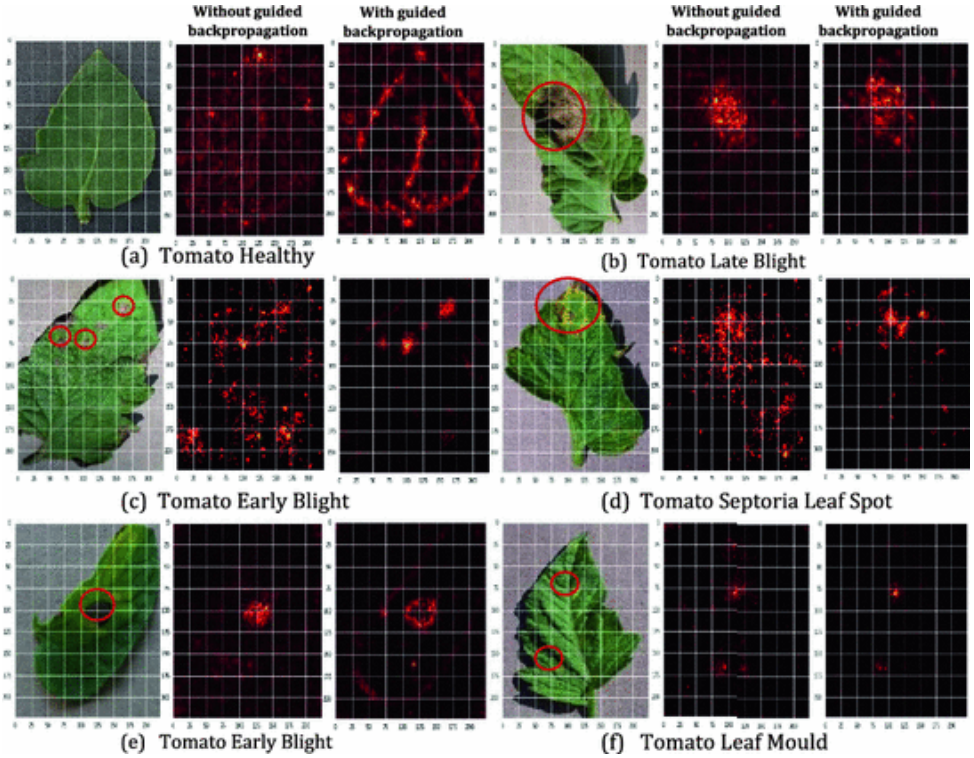


Figure 1.18: Shows a Saliency Map for plant disease classification. Columns 1, 4 represents two types of visualizations for images of leaves. Images on columns 2, 5 represent the visualizations without guided backpropagation. Images on columns 3, 6 represents the visualization with guided backpropagation.

1.10.2 Grad-CAM

One important aspect of Explainable AI, particularly in relation to the black-box nature of deep learning models, is the use of Grad-CAM; a widely-used technique for providing a

visual interpretation of model predictions. This is done by identifying areas in relation to the target that produced output from the model's predictions through highlighting these areas (focus areas) of the input image.
Grad-CAM employs heatmaps that are produced by computing feature map gradients a linear sum method from all of the last convolutional layers of the model with respect to the predicted output class (prior to the activation function on the last layer) to highlight the features of the input that are significant in relation to the output class (prediction). Once calculated; the heatmap is overlayed on the original input to highlight the input features that affect the model's prediction.
Each feature map's correlation weight with respect to the output class is obtained by calculating the global average of the individual gradient values for each of the feature maps. The global average value for each feature map's correlation weight gives the relative weight for that feature with respect to how much it contributed (or how influential it was) in the computation of the model's final output class prediction. The calculated output class feature map correlation weight for that particular input is then thresholded using a Relu activation function so only the positive influences are retained [16].

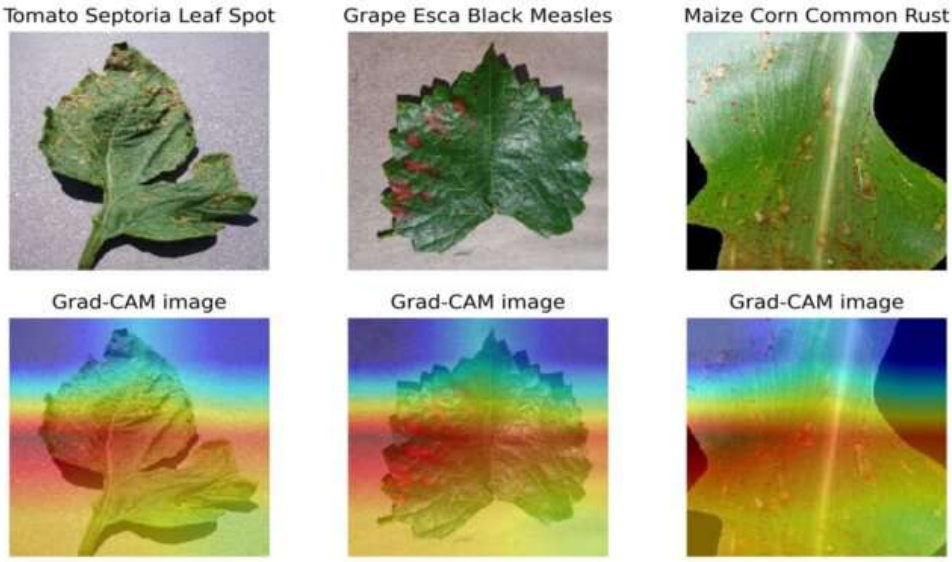


Figure 1.19: 10 Grad-CAM visualization of some sample leaf images

Grad-CAM also allows for the diagnosis of model output failure cases. By allowing for better insight into why the model makes a prediction, the model can be more easily interpreted by a human viewer thereby providing both greater transparency and potentially better accuracy in classification tasks.

The steps to compute the Grad-CAM heatmap are as follows: [17].

1. Let y^c be the score for class c (before the softmax). Compute the gradients of y^c with respect to the feature maps A of a convolutional layer:

$$\frac{\partial y^c}{\partial A^k} \tag{1.3}$$

where k is the index of the feature map.

2. Perform Global Average Pooling on the gradients to obtain the weights α_k^c for each feature map:

$$\alpha_k^c = \frac{1}{Z} \sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}^k} \tag{1.4}$$

where Z is the number of elements in feature map A^k, and i, j are spatial indices.

3. Compute the weighted combination of the feature maps to obtain the raw Grad-CAM heatmap $L^c_{\text{Grad-CAM}}$:

$$L^c_{\text{Grad-CAM}} = \sum_k \alpha_k^c A^k \tag{1.5}$$

4. Apply the ReLU activation function to the raw heatmap to obtain the final Grad-CAM heatmap:

$$L^c_{\text{Grad-CAM}} = \max(0, L^c_{\text{Grad-CAM}}) \tag{1.6}$$

1.11 Role of Explainable AI in Precision Agriculture

XAI, or explainable artificial intelligence, is becoming an important part of the new use of machine/deep-learning algorithms in agriculture, particularly as a way of using data from spectroscopy to help evaluate various aspects of crop health, food quality, and postharvest processes [21, 22]. These algorithms have been able to provide improved accuracy in predictive models; however, the fact that they are "black boxes" does not allow for enough information to be provided to allow users to interpret how the algorithms come to the decisions they do. In addition to potentially impacting the ability for innovation, the lack of interpretable information does not give confidence for users of XAI in agricultural applications, which could slow down the development of lower cost portable devices to be used for agricultural evaluation[21]. XAI attempts to provide users with interpretable information associated with the spectral wavelength and spectral features that provide the rationale for each model's decision, thus improving transparency/credibility in the evaluation of agricultural quality [21]
The article acknowledges that XAI can help to make better decisions, assist in creating an environment for farmers and regulators to approve of XAI, and help in the development of efficient and cost-effective spectroscopic measurement tools for application in the field[21]. However there is still the challenge of the complexity of the computations needed to achieve this outcome and a lack of coordination in how agriculture uses XAI, as well as needing to balance the needs of accurately representing data with the ability to be able to use it. In light of these challenges and obstacles, it is anticipated that XAI will have a major impact on the development of safe and trustworthy non-destructive means of evaluating agricultural quality in the near future[21].

1.12 Conclusion

This chapter discussed Hyperspectral imaging which is considered an important tool to investigate plant health in detail in the context of precision agriculture. Deep learning algorithms such as CNNs are very useful to precisely diagnose diseases and stress.

However, deep learning models are referred to as ”black boxes” as the mechanisms of how they made their decisions are difficult to be interpreted. Hence, this problem was tackled by introducing an approach using Explainable AI (XAI) which enables easy interpretation. Techniques such as Saliency Maps are effective as they are able to point to the pixels that impact the model prediction most while Grad-CAM is effective in generating heatmaps to provide insight into which areas of the image were most relevant to the model's prediction. The contributions of each feature can be seen as Shapley Additive explanations, SHAP, and LIME. All these techniques aim to explain how the model worked to generate a prediction. With the usage of XAI, model trust and validity as well as user convenience are enhanced and user decision making in crop management is improved.

However, few of these techniques still have disadvantages such as noisy output, complexity and calculation cost.

Chapter 2

State of the Art in Classical and Deep Learning Methods for Crop Classification

2.1 Introduction

This chapter aims at the summarisation of current developments of machine learning with respect to the usage of hyperspectral imagery for both identification of crops and classification of stressed plants regarding their nutrient levels. The major advantage of hyperspectral imagery (HSI) is that it provides a series of high-frequency signals (high spectral resolution), so that it is possible to detect physiological based changes. The complicated structure of hyperspectral data has created difficulties in applying machine learning (ML) techniques to hyperspectral studies, therefore there is an absence of academic literature applying traditional ML methods applied to HSI studies. Therefore many researchers are using traditional ML techniques such as the Support Vector Machine (SVM) and Random Forest (RF), since they produce good output with less computational load than more contemporary computer vision type approaches. Modern computer vision based methods have resulted in researchers building on earlier developments in traditional ML methods (with regard to HSI data analysis) to enable the more effective use of computer vision based methodologies. As such this chapter will present a sampling of literature on various types of HSI based data and discuss current trends.

2.2 Classical Machine Learning Techniques

2.2.1 Overview of Classical Techniques

Prior to the development of deep learning, most classification and regression problems were solved using classical machine learning techniques; however, Support Vector Machine (SVM) and Random Forest (RF) are still frequently applied in agronomy and hyperspectral remote sensing because of the robustness, the ability to generalize well, and compatibility with Explainable Artificial Intelligence (XAI) perspectives.
When it comes to nutrient deficiency mapping based on hyperspectral images of plants, SVM and RF, as classical machine learning techniques that handle high dimensional data

(a large number of spectral bands), the nonlinear relationships between plant physiological condition and spectral signatures, and the limited amount of learning data which is often encountered in agricultural applications.

2.2.2 Support Vector Machine (SVM)

Overflow Support Vector Machine

A support vector machine (SVM) is a supervised machine learning algorithm that classifies data by finding an optimal line or hyperplane that maximizes the distance between each class in an N-dimensional space
SVMs are commonly used within classification problems, They distinguish between two classes by finding the optimal hyperplane that maximizes the margin between the closest data points of opposite classes, The number of features in the input data determine if the hyperplane is a line in a 2-D space or a plane in a n-dimensional space. Since multiple hyperplanes can be found to differentiate classes, maximizing the margin between points enables the algorithm to find the best decision boundary between classes. This, in turn, enables it to generalize well to new data and make accurate classification predictions, The lines that are adjacent to the optimal hyperplane are known as support vectors as these vectors run through the data points that determine the maximal margin [26]

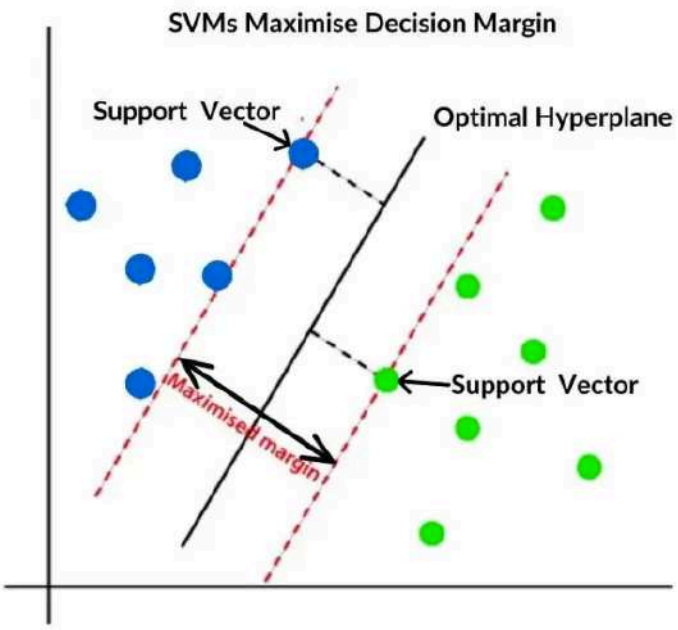


Figure 2.1: Support Vector Machine (SVM) maximizing the decision margin

SVM Classifiers Classification

Classification using SVM classifiers

Classification done using Support Vector Machines (SVM) is a very efficient way of classifying observations into two different classes, when you have a linearly separable dataset,

by using a hyperplane, using an optimal separating boundary that maximizes the margin between your two classes. With SVM classifiers, when you are classifying a new sample or new observations your classification on the original data set will provide better generalization and for data sets that have increased dimensionality will maintain performance levels. When you are classifying data into different classes that is not linearly separable SVM will apply the use of different kernel functions that will allow you to transform your low dimensional feature space into higher dimensional feature spaces. At this state you could use multiple hyperplanes to classify the data, therefore you could use an SVM with a non-linear kernel, to help you classify real world problems that may not be clearly separated by class boundary lines that are very regular or not clearly defined. Following is an example of some of the most commonly used kernel functions:

1. Linear
2. Polynomial
3. Radial Basis Function
4. Sigmoid

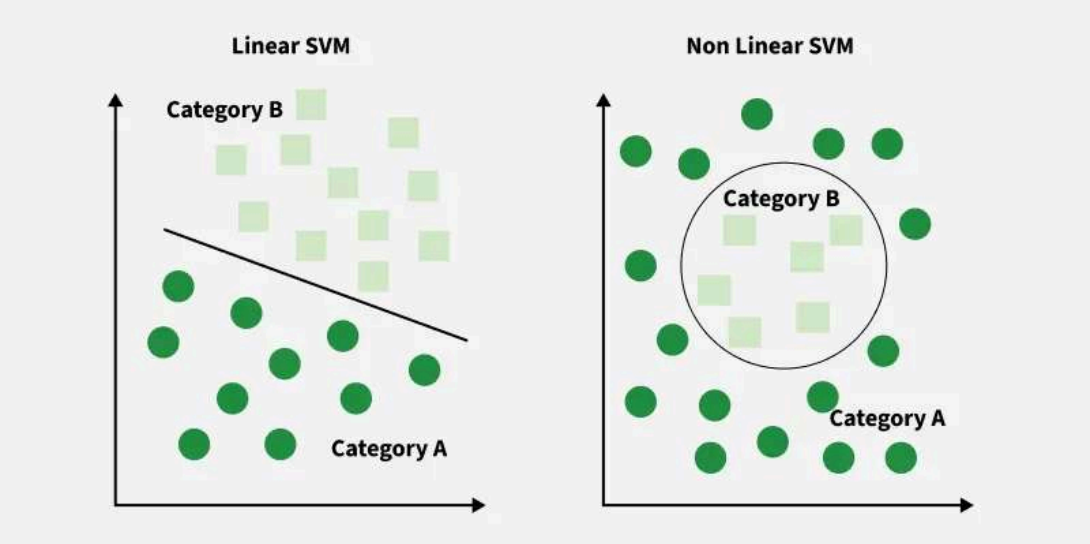


Figure 2.2: Linear SVM vs Non-Linear SVM classification

Important Hyperparameters

The two main hyperstructures in SVMs are C and Gamma. The C hyperstructure defines the balance between minimizing classification errors and maximizing margin. If C is set to be high , it forces the SVM to predict each data point in the training data to be correct which can lead to overfitting in the testing phase. Conversely, a small value of C allows for some classification to fail , making it possible to generalize better with respect to other data.
Gamma defines how much a single data point influences the decision boundary with respect to the RBF kernel, a kernel used with SVMs. When you increase the value of Gamma, the decision boundaries will become more complex, if you reduce the value of

Gamma, the decision boundaries will be more linear (smoother).
To reduce the risk of overfitting and optimize performance, the values for the hyperstructures C and Gamma are typically established by using cross-validation.

Advantages of Using Support Vector Machines (SVM)

- Very big data mining ability from multiple dimensions
- Very little risk for model overfitting
- Very capable in developing models from few training examples
- Very lightweight model (memory utilization is mainly of support vectors)
- Very versatile (utilizing kernels).

Disadvantages of Using Support Vector Machines (SVM)

- Can have high computational costs when processing large datasets
- Highly reliant on the proper kernel and set of hyperparameters
- Interpretability is very low (a major limitation with respect to nonlinear SVMs)
- Requires feature scaling

Applications of SVM in Hyperspectral Imaging

Support Vector Machines (SVM) have been extensively utilized for analysing hyperspectral image data for classification of plant stress, identifying nutrient deficiencies and analysing large, high dimensional datasets where there are few labelled samples. Furthermore, SVM can be combined with Explainable Artificial Intelligence (XAI) techniques such as spectral band weighting and SHAP values.

2.2.3 Random Forest (RF)

What is a Random Forest (RF)?

The Random Forest (RF) algorithm is an all-rounder when it comes to data science problems! Random Forests can be used for classification and regression tasks, while being non-linear and non-parametric, they can handle highdimensional, numerical and categorial variables and they have no special requirements or assumptions for the data to be used – so you do not have to worry about data distributing or standardizing your input features. And the best part: The basic concept is relatively easy to understand!
The RF is a representative of the so called “ensemble learning” methods. The word ensemble means nothing more than group in this context: A standard RF is based on generating a large number (ntree) of decision trees (DT) during the training phase (we will discuss those in a second), each constructed using a different subset (n) of your training dataset (N). Those subsets, also called bootstrap samples, are selected randomly and with replacement. After the training of the algorithm, each of those DTs is capable to map input data X (e.g., reflectances within Landsat 8 bands) to an ouput response y (e.g.,

class labels, like urban, water and forest). The Random Forest algorithm listens to all the responses of the DTs and make its final prediction on the basis of the most frequenty given response (majority vote). In case of regression, the RF takes the average of all the DT responses [28]

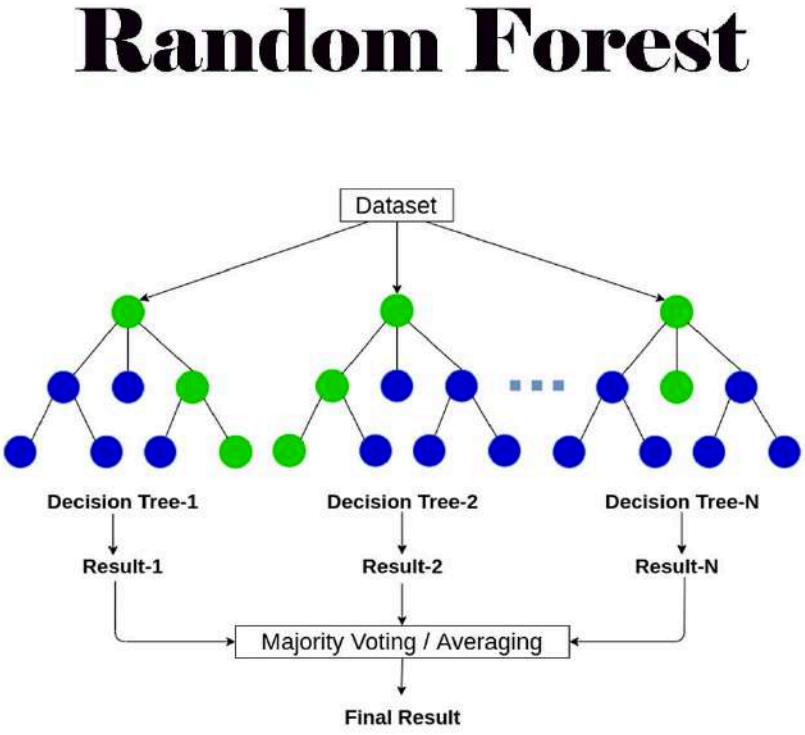


Figure 2.3: Random Forest algorithm combining multiple decision trees

Benefits of Random Forests

- Has an excellent level of immunity to noise
- Can model non-linear relationships
- Requires very little pre-processing
- Can be used to perform Meta-analysis for the purpose of assessing the importance of variables for the purpose of explaining their results (XAI)

Drawbacks of Random Forests

- High computation costs
- Can provide very little information about global trends
- Decreased performance with large/huge datasets

Applications of Random Forests for Hyperspectral Imagery

Random Forests are very common in hyperspectral rim-analysis for detecting nutrient stress in plants. Random Forests can also be used to choose and group the best bands within a hyperspectral rim to monitor and evaluate agricultural and environmental results.

2.2.4 Examples of XAI's Contribution to Mapping Nutrient Deficiencies

XAI has provided new ways of mapping nutrient deficiencies by creating insight into how nutrient deficiencies are identified through providing greater transparency during the interpretation of machine learning algorithms that perform the function of identifying nutrient deficiency, as well as providing insight into which spectral bands and other variables are critical in identifying whether stress is caused by nutrient deficiency or by sources unrelated to nutrient deficiency. As a result, users can have confidence in the information and evidence that support their decision to use models to interpret or manage the impact of nutrient deficiency. In addition, providing users with easy methods for interpreting and displaying spatial patterns, that is, giving users straightforward tools to analyze and understand spatial patterns of nutrient deficiencies and benefits, will enhance users' opportunity to use precision agriculture (PA) as a tool to monitor and manage their crop health as they apply PA methods in crop production. Lastly, XAI's role in providing users with the opportunity to verify that the data created by models used to determine nutrient deficiencies is supported by graphical evidence (how the graphic was created) will increase the level of user trust and increase confidence in AI-based systems, thereby contributing to more trustworthy food production methods.

2.3 Deep learning methods

2.3.1 Overview of Deep learning methods

Due to their capacity to automatically identify intricate patterns within large amounts (and high dimensionality) of raw hyperspectral data, deep learning techniques have become a key component of hyperspectral image analysis for crop type identification. Traditional machine learning methods typically require manually identifying and extracting features, while deep learning architectures can automatically identify and extract both spatial and spectral features from raw hyperspectral data (Convolutional Neural Network , Short Long-Term Memory). CNN and LSTM have successfully been used to capture spatial relationships and spectral dependencies within the data, thus greatly improving classification performance of hyperspectral datasets for the quantifica- tion of agricultural crops.

2.3.2 Convolutional Neural Networks (CNNs)

A convoluted Image processing with CNNs Convolutional Neural Networks can be denoted as Deep Learning Neural Networks where Convolutional Neural Networks (CNNs) excel predominantly on Classification Tasks and Object Recognition Tasks using Images. The CNN is comprised of an Input image converted into a Feature Map, this Feature Map

is frequently passed through several Convolutional layers and Pooling layers,finally,it produces a prediction of the output image representation.

Benefits of Convolutional Neural Networks

- Automated extraction of features; no need for human intervention.
- High accuracy in identifying both classes of objects and drawing boundaries around them.
- Very user-friendly because they handle the large size of optical images easily.

Drawbacks of Convolutional Neural Networks

- Need large quantities of labelled data.
- Require a high level of computing power.
- Frequently require explainable artificial intelligence methods due to their inability to explain why they make particular decisions.

2.3.3 Recurrent Neural Networks and LSTM

RNNs and Long Short-Term Memory (LSTM) networks are types of Neural Networks designed for processing sequential data. LSTMs were developed to successfully address some shortcomings of RNNs. While standard RNNs use a single hidden state that is passed through time, Long Short-Term Memory add a memory cell which contains a memory that can span over an extended period of time which allows LSTMs to solve the problem of learning long-term dependencies. In this way, Long Short-Term Memory are well-suited for modeling long-term dependencies between sequential patterns found within the same sequences of data.

LSTM Structure Architecture

Three gates control computations in the LSTM cells

- Input Gate: Controls writing of new data into memory cell.
- Forget Gate: Indicates to delete information from memory cell
- Output Gate: The result from hidden state output.

LSTMs have two types of states within them.

- Ht : Short-term memory
- Ct : Long-term memory

This dual memory structure of LSTM means it can store records of all relevant information for longer than any other type of RNN.

Using an LSTM to Model Hyper-Spectral Data

In this project, LSTMs can be used to:

- Model Spectral signatures as sequences of bands
- Model Temporal development of plant nutrition
- Model Multi-temporal Hyperspectral Data

An LSTM's sequential nature is beneficial to modeling data with a sequential or temporal pattern.

Benefits

- Able to manage dependencies well over time.
- Can resolve the issue of gradients vanishing.
- Remembers the past information for a significant period.
- Remembers the past information for a significant period.
- Has great precision when performing tasks such as natural language processing and speech generation.

Drawbacks

- Architecture is very complicated.
- Training time to cover a single task is long.
- Larger amounts of data will need to be collected.
- High computational requirements.

2.3.4 Why link to Explainable AI (XAI)?

One major limitation of CNN and LSTM models is that they are black box models. In order to build trust in agronomists' use of CNN/LSTM combination models, Explainable Artificial Intelligence (XAI) methods are required for:

- Identifying the contributing spectral bands to the hyperspectral image
- Providing insight about how areas of the hyperspectral image affect the algorithm's ability to find deficiency
- Demonstrating to agronomists how the algorithm made its decisions

Example XAI methods can include Grad-CAM, SHAP, LIME, and attention-based analyses for the results of each of these models.

2.4 Comparative Summary: Classical Methods vs Deep Learning

Traditional Machine Learning	**Deep Learning**
Manually defined features (for example, spectral bands), vegetation indices, expert judgement	Automatically learning to identify features in spectral bands through the use of raw spectral data without defining features
Small/medium datasets can help create a good model	Large datasets with a wide range of spectral band data will create good results; more data is always better.
Accuracy is very high based on linear/non-linear complexity if using the right features	Very high accuracy on complex/non-linear problems through the use of more complex models
Models are based on simple relationships (for example, linearly related/spectral bands)	Function very well at capturing non-linear relationships in spectral bands
Can run models on regular computers	High computing power is required to produce results, typically requiring GPU
Model training usually occurs quickly based only on the model's hyper-parameters	Takes longer to train models due to the multiple hyper-parameters associated with model training
Models are easy to read/interpret	Models are much more difficult to understand and interpret due to black box models that do not provide a way to explain model relationships

Table 2.1: Classical methods vs Deep learning

Overall, from the table we can see that Traditional Machine learning works well for smaller data sets and for cases in which explainability of the model is critical, whereas for complex and huge hyperspectral data sets, deep learning provides a better performance at high computational cost and low explainability.

2.5 Conclusion

It is shown that whereas the classical ML algorithms are more suitable to smaller dataset and applications in which the interpretability of the model is important, DL are more powerful when they are applied on very large and complex data like hyperspectral images, but with a worse interpretability of the model and higher cost for calculation resources. In the current research, using deep learning, hyperspectral imaging (HSI) and explainable artificial intelligence (XAI) provides to the precision agriculture experts and researchers more tools to map nutrient deficiency accurately but keeping the interpretation of the results. Introducing these techniques for monitoring and making decision in a crop management sustainable process could be useful in fostering sustainable agriculture.

Chapter 3

Design of the Proposed Methodology and System Architecture

3.1 Introduction

Plant diseases seriously influence the quality of crops and agricultural production. The intelligent plant disease detection system is presented using the deep learning and transfer learning. 91 classes and more than 80,000 pictures were selected in the dataset for training and testing. Image preprocessing like resizing, conversion into tensor and normalization, was used. ImageNet pre-trained model was applied and fine-tuned for disease classification. It also showed high performance in automatically identifying plant diseases.

3.2 General Design

3.2.1 System Architecture

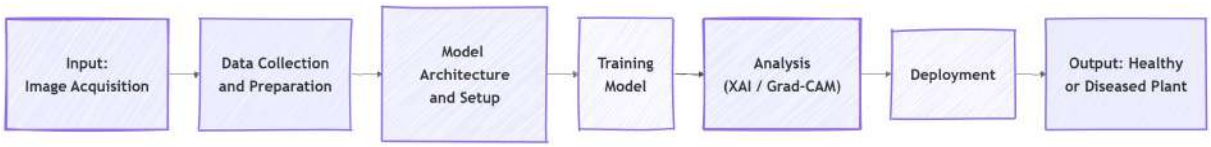


Figure 3.1: General Architecture of the system

- **Image Acquisition :** Obtain camera images of the plant leaf, or dataset containing these images.
- **Data Collection & Preparation :** Apply labeling and image preprocessing (resizing, normalization, augmentation) to the images to enable training.
- **Model Architecture & Setup :** Define a deep learning model (CNN for example) and set up its architecture:
- **Training Model :** Train the model on the prepared datasets in order to learn the patterns of diseases.

- **Analysis (XAI / Grad-CAM) :** Analyze the predictions and display the impacted regions on the leaf.
- **Deployment :** Use the trained model as a working system application.
- **Output:** Classification result: Healthy or Diseased Plant

3.2.2 USE CASE Diagram

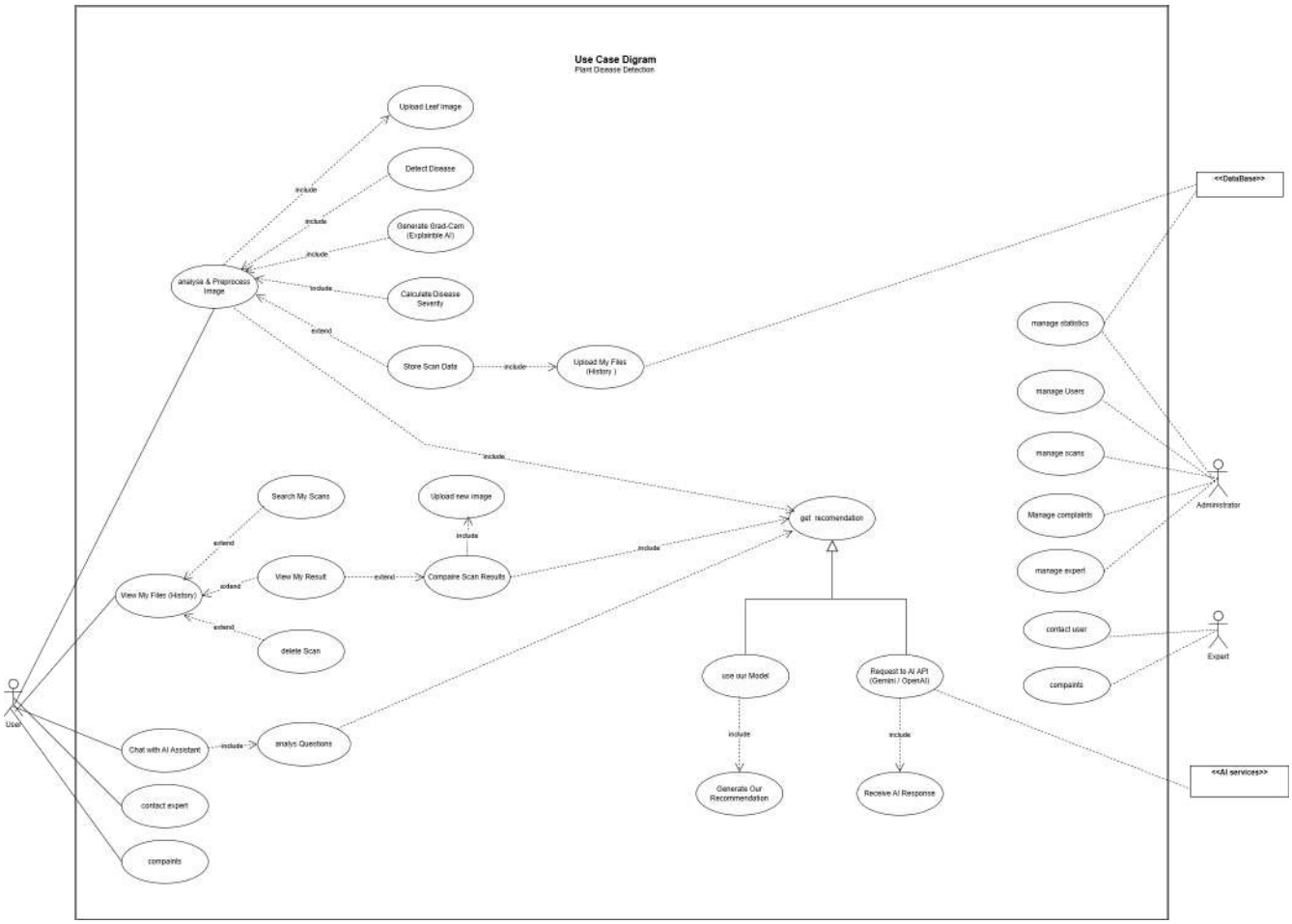


Figure 3.2: System Use Case Diagram

The Use Case diagram displays the major functionalities of the Plant Disease Detection system and the actors involved with it.
Key actors include User, Administrator, Expert, and external systems (Database and AI services).
The system provides five main use cases:

- **image Analysis & Diagnosis:** users upload images to detect disease, apply Grad-CAM, assess severity, and receive recommendations, with optional scan data storage.
- **Manage Scan History:** users can view, search, delete, and compare past scans.

- **Get Recommendation:** recommendations are generated either locally or via external AI APIs.
- **Communication:** users can chat with an AI assistant or contact experts, who can respond and handle complaints.
- **System Management:** administrators manage users, scans, experts, statistics, and complaints through the database.

3.3 Detailed Design

3.3.1 System Architecture

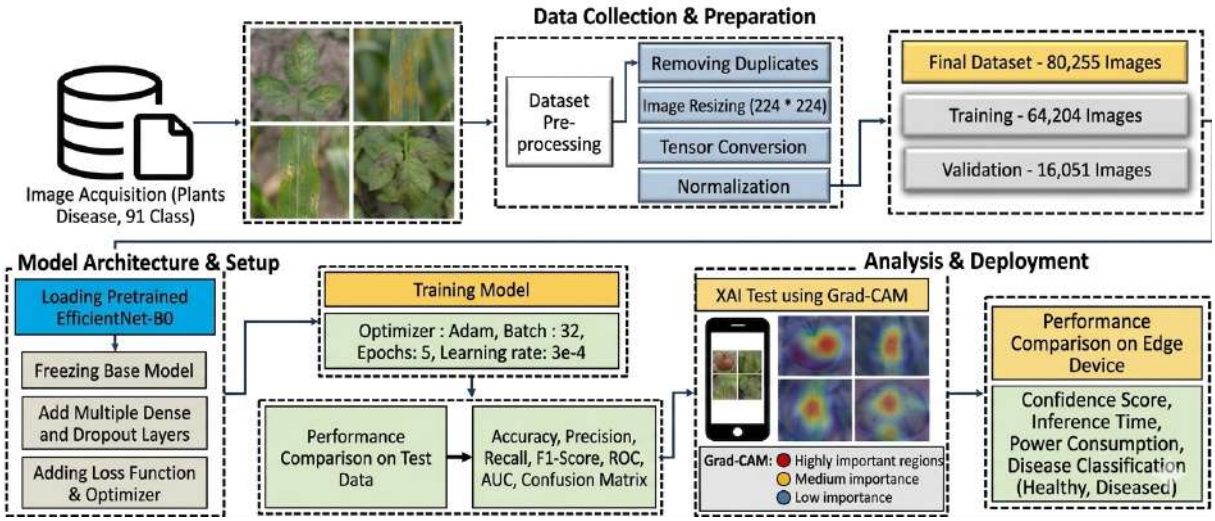


Figure 3.3: Plant Disease Classification with Transfer Learning and Explainable AI

3.3.2 Dataset Description and Image Acquisition

In this study, the data set is composed of crop photographs (i.e plant images) collected from various sources with the objective of gaining diversity among crops to generalize and validate the proposed model. The following crops were selected for this purpose:

- Tomato
- Pepper
- Potato
- Apple
- ...

1. **Images acquisition**
   There are various modalities available for the purpose of providing comparison and educating researchers on how different factors affect the acquisition of images. The following comprises these modalities:

   (a) SmartPhones are typically used at a low cost for field acquisition

   (b) RGB Cameras are the standard form for obtaining images in the visible light spectrum

   (c) HSI (hyperspectral imaging) is a type of camera that allows for the capture and analysis of high-dimensional data through image acquisition

   By having available multiple imaging systems. it is possible to conduct a comparative analysis of both traditional (RGB) imaging systems and hyperspectral imaging systems (HSI) as it relates to the detection of nutrient deficiency in plants.

2. **Dataset Statistics**
   This relative dataset contains 91 classes, 80,255 images with 26 classes of plants and 65 classes of diseases. The data is imbalanced where some classes can have a lot of samples while others can have only very few samples.

```
number of Plants:  26
number of Diseases:  65

name of plants:
['Tomato', 'Tea', 'Rice', 'Soybean', 'Gauva', 'Wheat', 'Pomegranat
e', 'Apple', 'Peach', 'Potato', 'Cherry', 'Mulberry Leaf Rust', 'Jam
un', 'Strawberry', 'Coffee', 'Mango', 'Lemon', 'Pepper_bell', 'Cassa
va', 'Corn', 'Grape', 'Mulberry Leaf spot', 'Sugarcane', 'Cucumber',
'Chili', 'Mulberry Healthy leaves']


                There are 80255 images for training
```

Figure 3.4: Number of (Diseases/Plants/Images) and Plant Categories

Out[6]:

	no. of images
Tomato__septoria_leaf_spot	1782
Tea__anthracnose	300
Rice__hispa	565
Soybean__diabrotica_speciosa	2205
Tomato__healthy	1598
...	...
Wheat__healthy	1225
Sugarcane__red_rot	174
Chili__leaf curl	100
Grape__healthy	470
Tomato__mosaic_virus	382

91 rows × 1 columns

Figure 3.5: Number of Images per Class (Plants / Diseases)

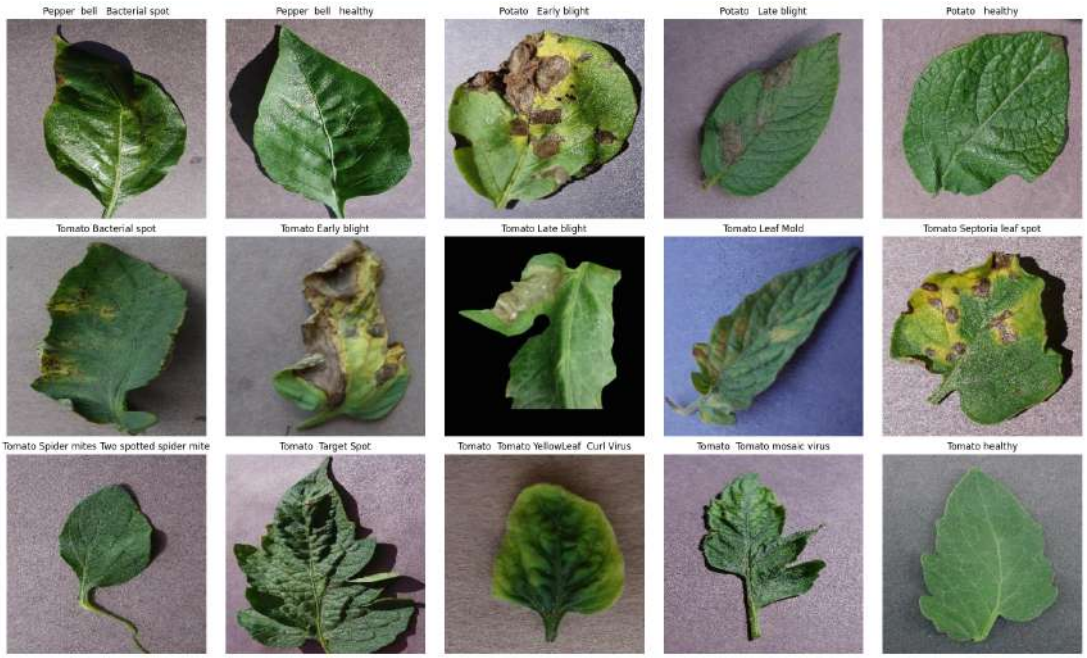


Figure 3.6: Sample images from different plant disease categories:

3.3.3 Data Pre-processing

1. **Image Resizing**

   All images are resized to a same dimension:

   - **224 × 224 pixels**

   The EfficientNet-B0 has a constant size of input images.

2. **Tensor Conversion**

   Images are converted into PyTorch tensors:

   - Converts pixel data into numerical tensors
   - Required for model computation

3. **Normalization** The pixel values are normalized by ImageNet statistics:

   - Mean: [0.485, 0.456, 0.406]
   - Std: [0.229, 0.224, 0.225]

   This is important for the training to be stable and the input distribution to match the weights of pre-trained EfficientNet-B0.

3.3.4 Final Dataset and Split

The dataset ultimately consists of over 80,255 images and includes 91 classes of various plants with an overall size of $\simeq$ 18 GB. The dataset was created by combining several datasets (PlantVillage and PlantDoc) , contains a mix of laboratory images and real world images to ensure that models are constructed in such a way as to generalize well to unseen images.
The data was split into 2 separate sets (training data (64,204 images), validation data (16,051)) using a stratified sampling method after the following preprocessing steps were performed on the data: elimination of poor quality images, poor representation of rare classes in the dataset, and inconsistent labelling.

```
Train size: 64204
Validation size: 16051
```

Figure 3.7: Train–Validation Split

3.3.5 CNN Architecture

A Convolutional Neural Network (CNN) first convolve an input image with a series of feature maps through convolution and pooling layers. Features at different levels, from simple feature maps like edges and texture patterns to high-level semantic features are thus automatically learned. These features are then flattened and fed to fully connected layers for classification, and the prediction of an image's class, such as "healthy leaf" or "diseased leaf," is achieved through the output layer.

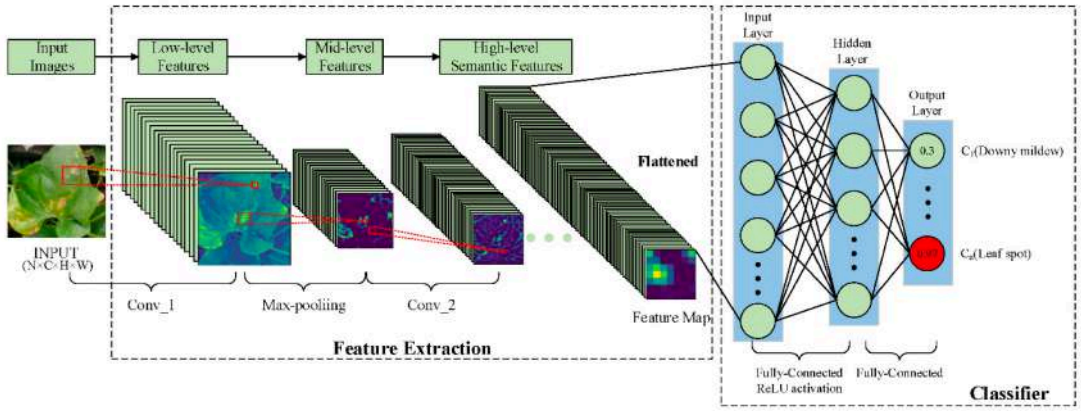


Figure 3.8: Proposed CNN Architecture

3.3.6 Transfer learning Activity Diagram

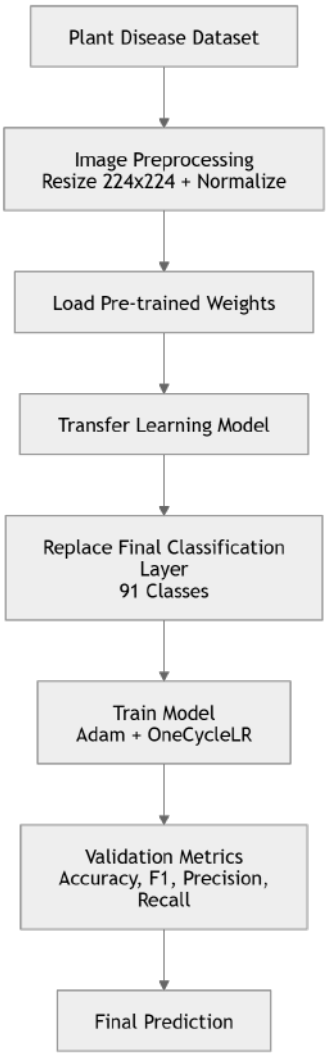


Figure 3.9: Transfer learning Activity Diagram

Transfer learning process is initialized by gathering the plant disease dataset, and then images go through various image processing such as resizing, normalizing and augmenting images, and then training, validation and test data set are created. A pre-trained model is loaded and then the final classification layer of the pre-trained model is replaced with a layer of 91 classes. The model is trained using Adam optimizer and OneCycleLR learning rate scheduler and at this stage we kept tracking validation performance metric like accuracy, precision, recall and F1 score. The trained model is tested by evaluating on test set, the test performance metrics were the confusion matrix and classification report. The prediction of the plant disease using trained model is produced.

3.3.7 Training Model

The model was trained for 5 epochs with a batch size of 32 for each training run, and the image was resized to 224×224 before training. CNN model based on transfer learning was used, and a pre-trained ImageNet model was transferred for the plant disease classification task and the classification layer was replaced with the target classes.
For the optimization, we used the Adam optimizer with a learning rate of 3e-4, and a OneCycle learning rate scheduler to quickly get to a good result and to stabilize the training. We did not use any augmentation or early stopping, we used only the normal preprocessing techniques (resize, to tensor, normalize with ImageNet mean/std).
This CNN transfer learning model gave a good result on training, validation loss is 0.0355%, validation accuracy 97.27%, validation F1 score 97.26%, precision 97.31% and recall 97.27%, that proved a good generalization on the validation dataset.

3.3.8 Model Evaluation

- Final Results (best model):

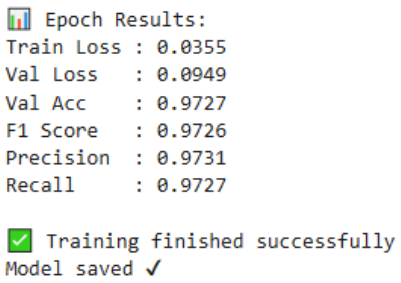


Figure 3.10: Training History

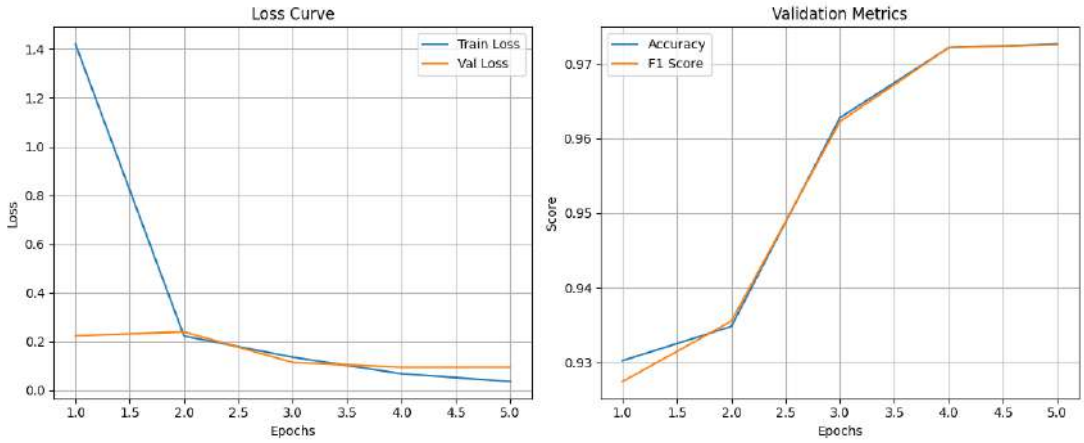


Figure 3.11: Loss Curve and Validation Metrics Vs Epochs

- Testing the Model: A new real-world image was uploaded, this was another image from a different data set and was used to examine the ability of the model to predict and generalize

```
Model loaded ✓
====================================
🔍 Prediction Result
====================================
Class      : Potato__late_blight
Confidence : 56.20%
====================================

:
('Potato__late_blight', 56.20145797729492)
```

Figure 3.12: Testing the Model

3.3.9 Sequence Diagram

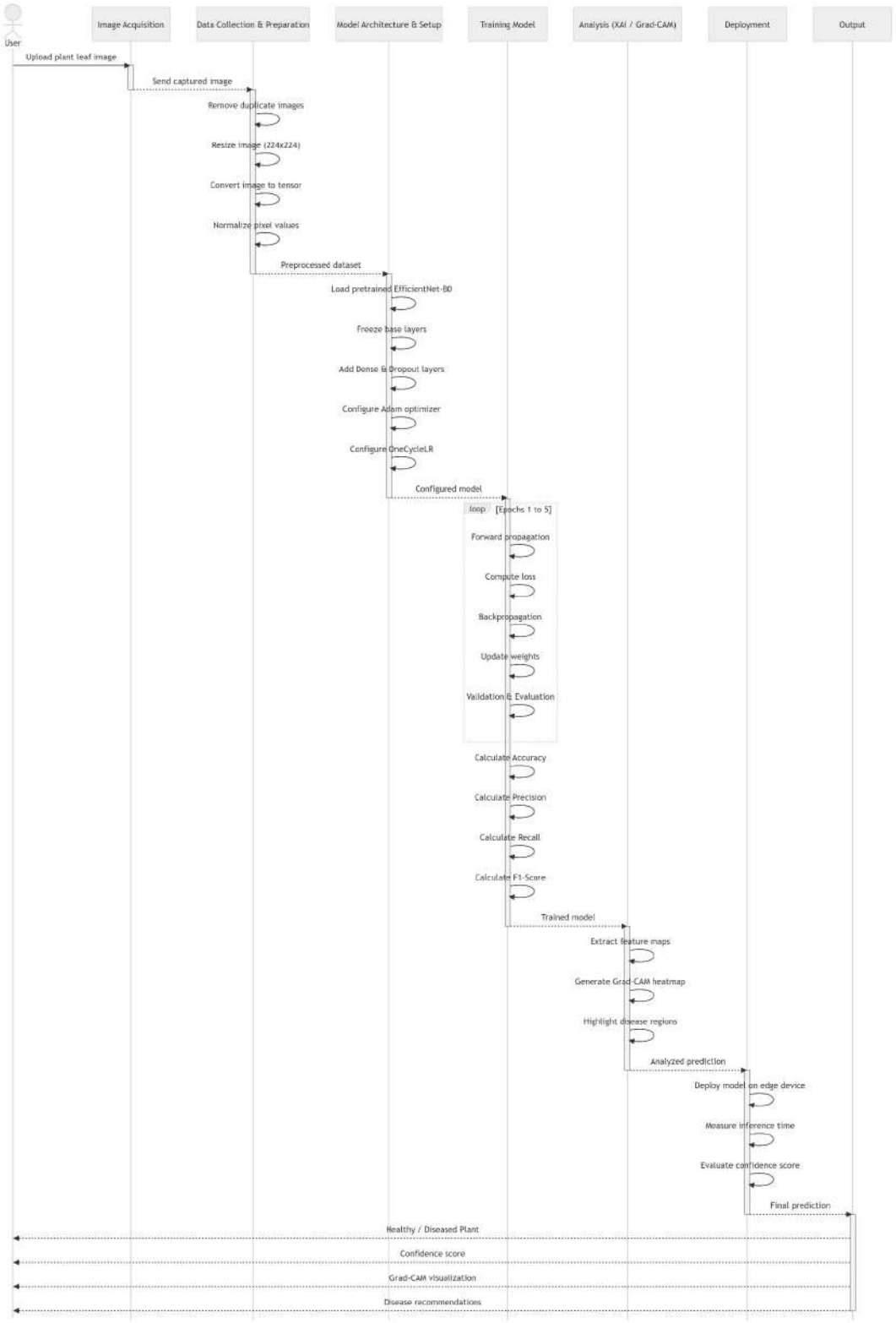


Figure 3.13: UML Sequence Diagram of Plant Disease Detection System

1. User uploads an image of a leaf on his/her plant by the PDA.
2. System would then proceed to the Data Pre-Processing stage where duplicates images would be removed, the image dimensions would be adjusted to 224x224, convert image to tensor and normalize image pixel valu
3. With the completed pre-processing of images, the machine learning model will then compile the 80,255 images, to be used (91 different type of image), for the final dataset that will train the model and then it will then divide this dataset into two, the training and validation dataset.
4. The Model Architecture stage will upload a pre-trained EfficientNet-B0 model and would re-train this model by transfer learning while the whole model base layers are frozen. Then it would add two new layers in the architecture and also set the model's optimizer and loss function.
5. Following, there would be five subsequent processes occurring to the model on each respective epoch: forward propagation, loss computation, backpropagation, adjustment of weights in the model. All these procedures are carried out for 5 consecutive epochs.
6. During the validation process the metrics such as; accuracy, precision, recall, F1-score, ROC and/or AUC and also confusion matrix of the model would be calculated by the Evaluation module within the PDA.
7. The best performing model would be save in a .h5 format on an epoch if it had an increase in performance at that epoch with the current metrics.
8. The Grad-CAM module will use the predictions the model generates to show the regions of the leaf image that contributed to the disease.
9. The finished model would be deploy to the Edge device to provide predictions and analyse performance on the device itself.
10. After the prediction is carried out, the PDA will decide if the plant which the image is taken from is a Healthy plant or Diseased plant. User would also save the scanned result into database if required.
11. The user would finally display a screen as follow: Classification result, confidence score, Grad-CAM visualization, and treatment suggestions for the plant.

3.4 Conclusion

In this chapter, we explained the system design for plant disease detection using deep learning which involves the whole pipeline from image acquisition and preprocessing, to dataset creation, model training with EfficientNet-B0 and transfer learning and the final evaluation. Our model trained with 80,255 image samples in 91 different classes. We also use Grad-CAM to ensure the interpretability of our model. In addition to a good performance, we design this system to perform plant classification (diseased or healthy) in real-time on the edge.

Chapter 4

Implementation

The topic of this part is how we actually implemented our project. We will first describe what tools (software and hardware) have been used for. Then we will show hardware implementation and software development.

4.1 Hardware tools

Hardware Specifications

Specification	HP Laptop	Dell Latitude E7470
Image		
Device Type	Personal Laptop	Business Laptop
Processor (CPU)	Intel Core i5	Intel Core i5
CPU Generation	5th Generation	5th Generation
CPU Speed	2.4 GHz	2.4 GHz
RAM	8 GB	8 GB
Storage	SSD / HDD	SSD / HDD
Graphics	Integrated Intel Graphics	Integrated Intel Graphics
Operating System	Windows	Windows
Usage in Project	Model Training, Preprocessing, Evaluation	Testing, Deployment, Validation
Role in System	Deep Learning Processing	System Validation & Experiments

Figure 4.1: Hardware tools used

4.2 Software tools

- **Google Antigravity :** an IDE (Integrated Development Environment) provided by Google for development of applications in different programming languages

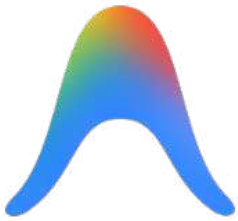


Figure 4.2: Google Antigravity logo [29]

- **Python :** A commonly used and read programming language.

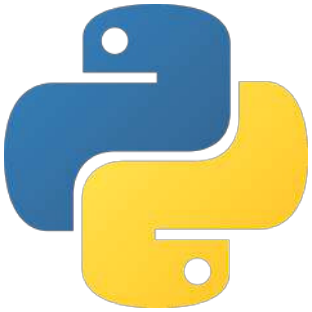


Figure 4.3: Python logo [30]

- **Django :** django makes it easier to build better web apps more quickly and with less code.



Figure 4.4: Django logo [31]

- **HTML :** HTML is the markup language for the creation and structuring of web pages.



Figure 4.5: HTML logo [32]

- **CSS :** A style sheet language which is used to describe how a document written in HTML or XML should be displayed.



Figure 4.6: CSS logo [33]

- **JavaScript(JS) :** Is a lightweight and interpreted programming language used for creating dynamic and interactive functionality for a Web site



Figure 4.7: JavaScript logo [34]

4.3 Web Application

PlantGuard AI is an intelligent application which employs its own AI model for detecting plant disease by the leaf images. It also accurately detect the disease as well as shows the heat maps through which the detection result can be easily understood, with all features model information, file management, AI help, experts' help. It is provided on freemium to the users in order to have accurate and fast information for the benefit of their plants and agriculture.

- **Login Page :** is the secure gateway to the website. The user is required to enter their credentials to access the administrative interface.

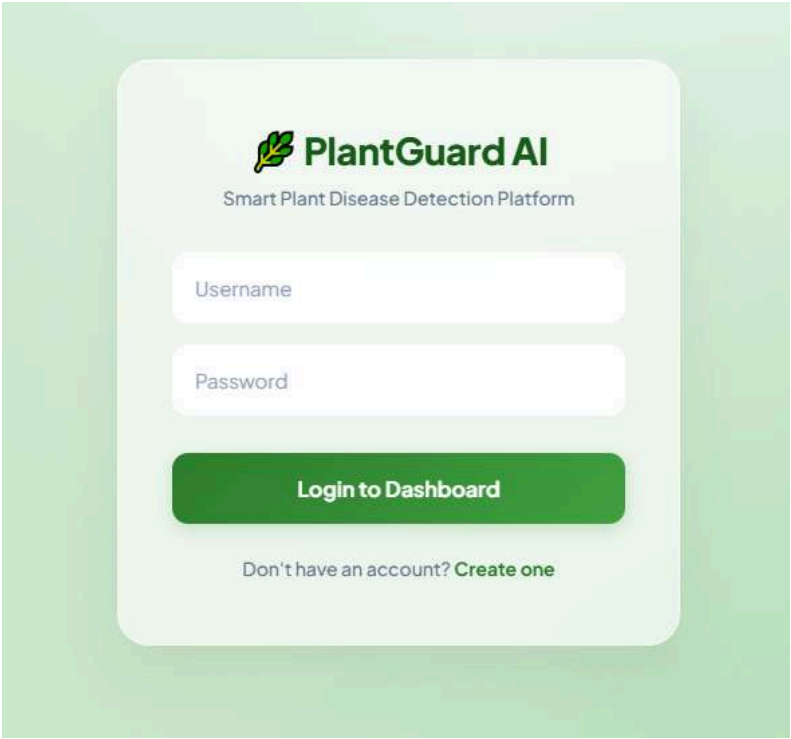


Figure 4.8: The Login Page

- **Sign up Page :** Used to create new accounts for authenticated farmers or companies, and set their authorization within the system.

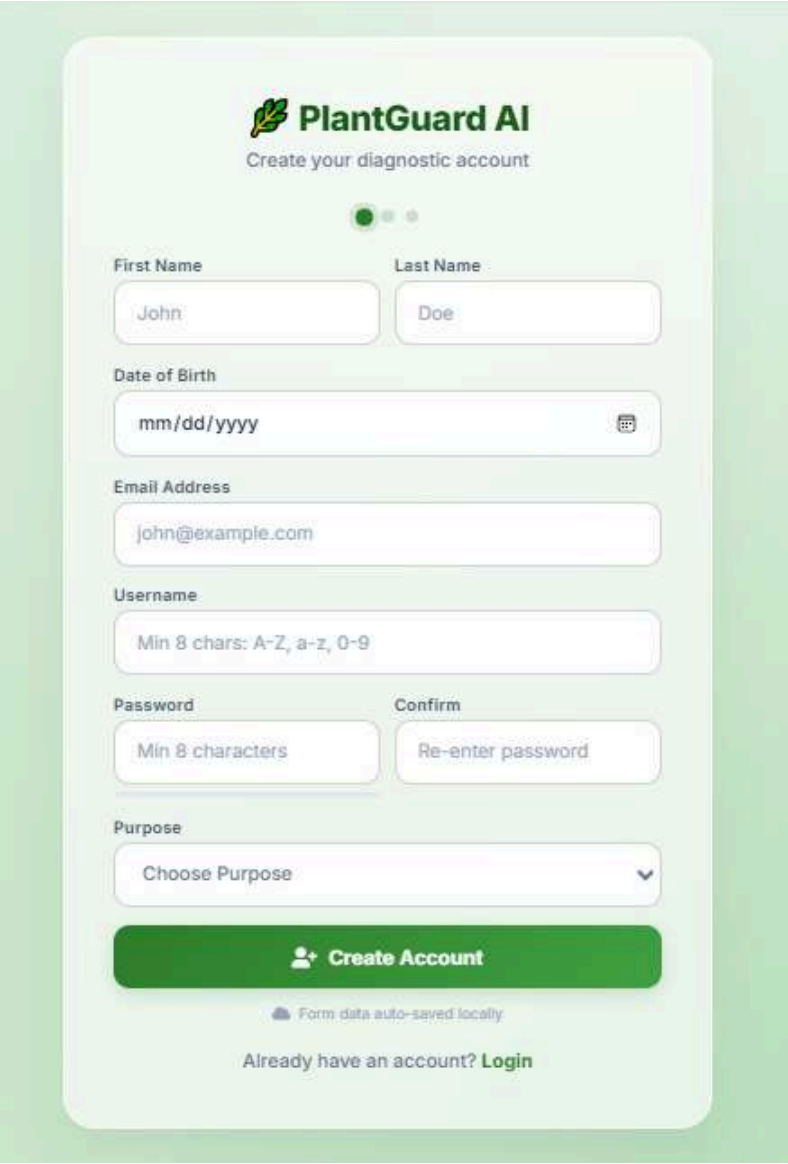


Figure 4.9: The Signup Page

4.3.1 Farmer Account

- **Home page :** This is the core functionality page of the system where real time plant disease diagnoses takes place. A user uploads an image of their crop and the developed AI model which have good accuracy levels due to customized training performs the diagnoses of the disease. It then provides explanations to the users using XAI style confidence levels or heat-maps to foster trust and understanding of the system. The page further guides the users to diagnosis treatment and expert consultations.

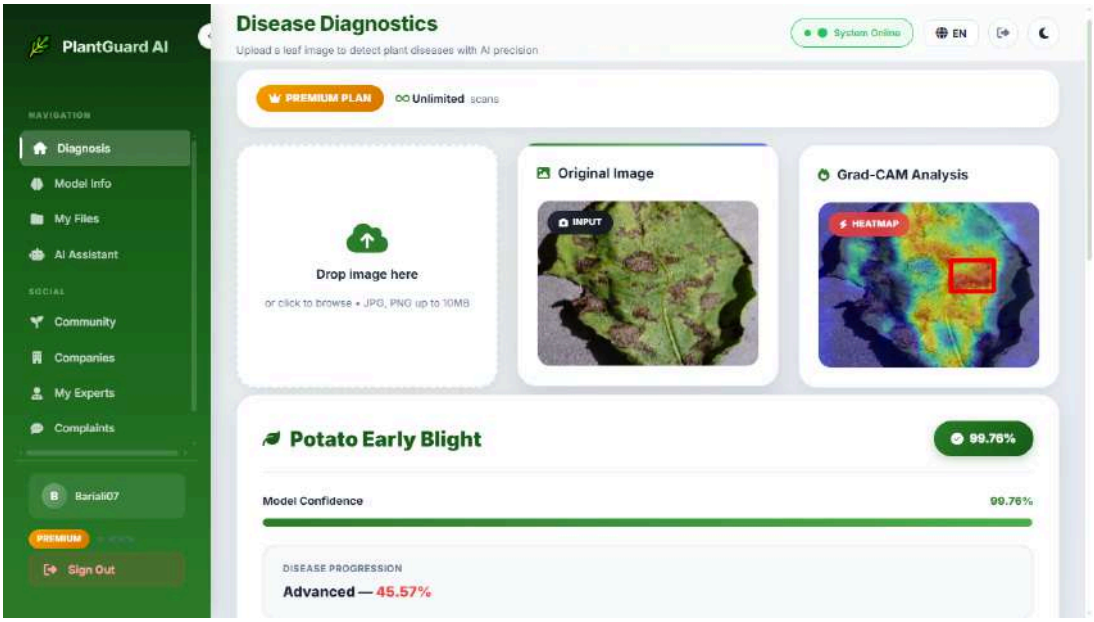


Figure 4.10: Home page

- **My Files page :** A personal archive for users to look at past plant disease scans and to manage them. Shows the images that were scanned, the disease findings, their severity levels, the dates and times and offers access to the in-depth report feature

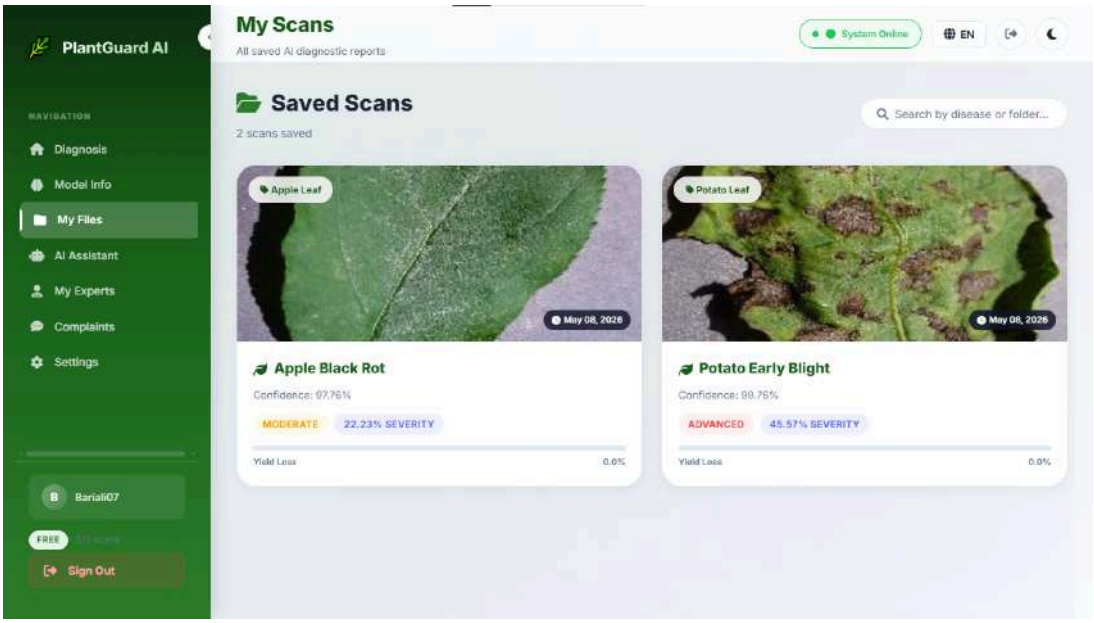


Figure 4.11: My Files page

- **AI Assistant page :** An AI chat system which offers individualised advice for plant diseases and assistance with crop management. Users are able to upload saved scans, manage chats, gain smart suggestions and expert agricultural knowledge.

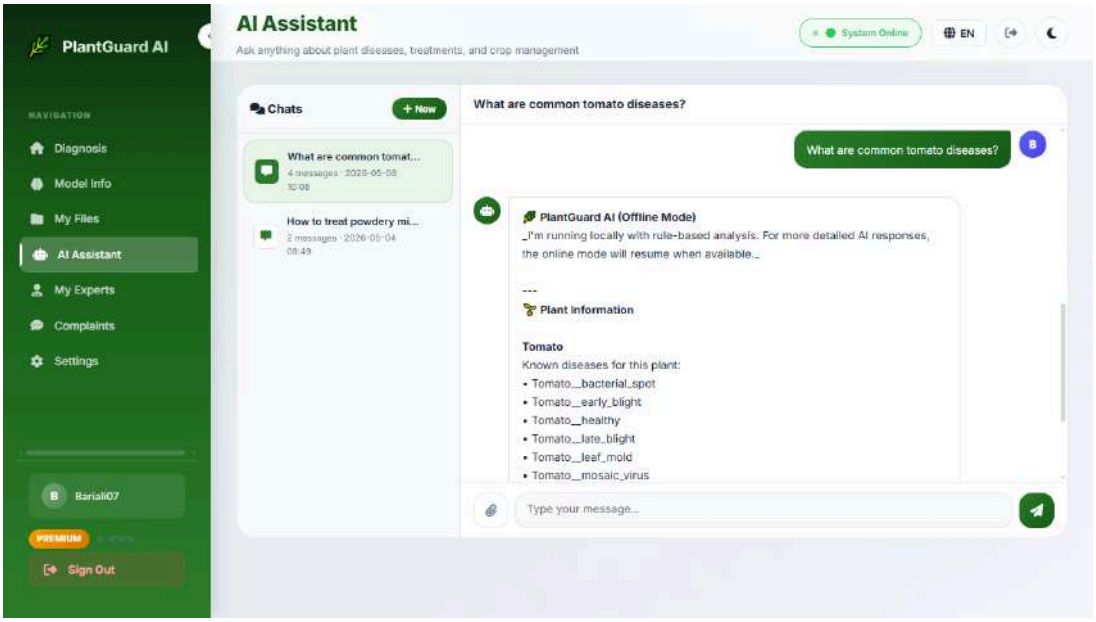


Figure 4.12: AI Assistant page

- **Community page :** This acts as a social portal where individuals, users and experts can share and exchange information related to farming, can ask their plant-health related issues, create and reply on the posts, etc. This section consists of features like article creation, search, user profiles etc, which further make it a interactive medium for sharing and acquiring agricultural knowledge.

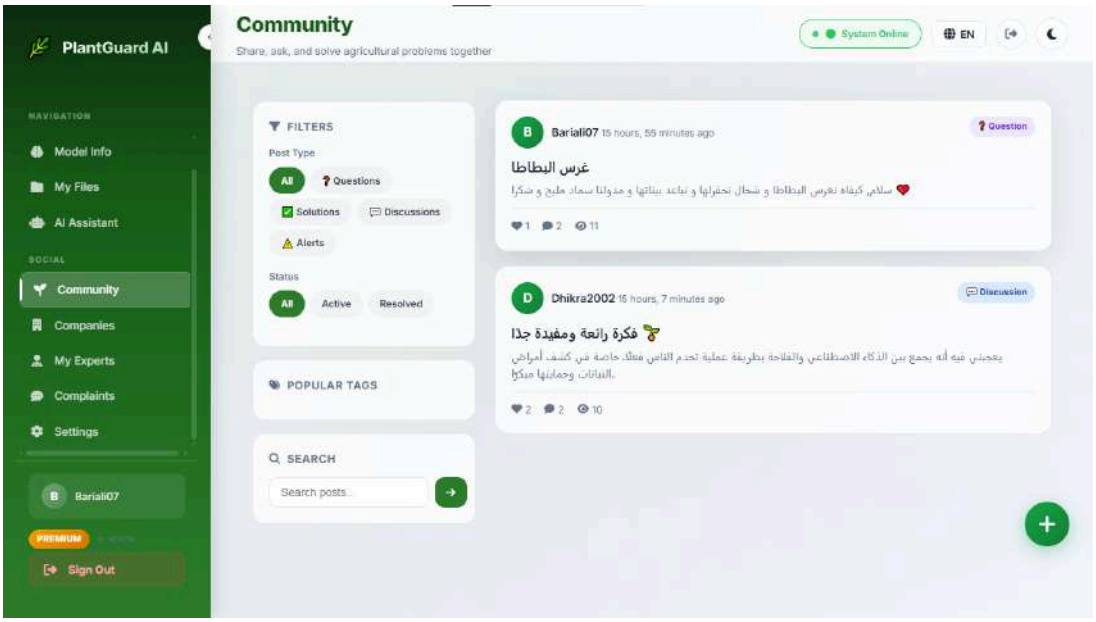


Figure 4.13: Community page

- **Companies page :** The "Industrial Network" is part of the agricultural platform and provides the means for connecting final users to certified agricultural companies. The network works as an exhaustive corporate directory allowing users to find

and contact companies by areas of specialization (fertilizers, pesticides, seeds and equipment), it works to encourage B2B & B2C links via public reviews about each company, offering both detailed information on the corporate profile and private messages to each company representative.

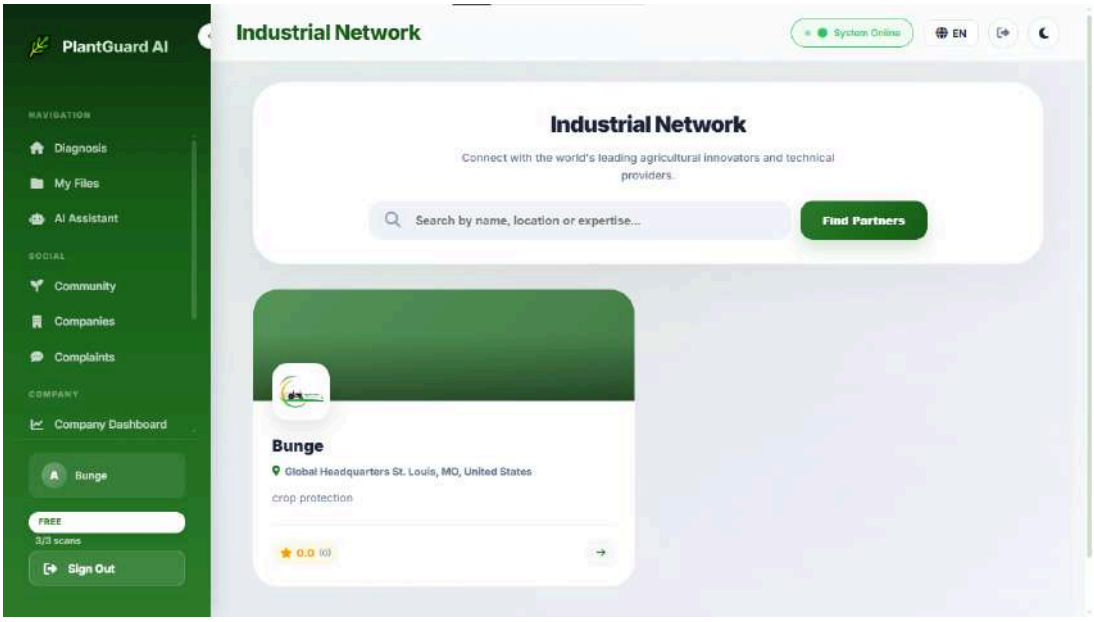


Figure 4.14: Companies page

- **Companies Dashboard page :**

  It is a primary management interface for agro companies, known as "Companies Dashboard". It helps an administrator to perform business management functions such as company profile, products and services, communication to customers, and business image through ratings and reviews.

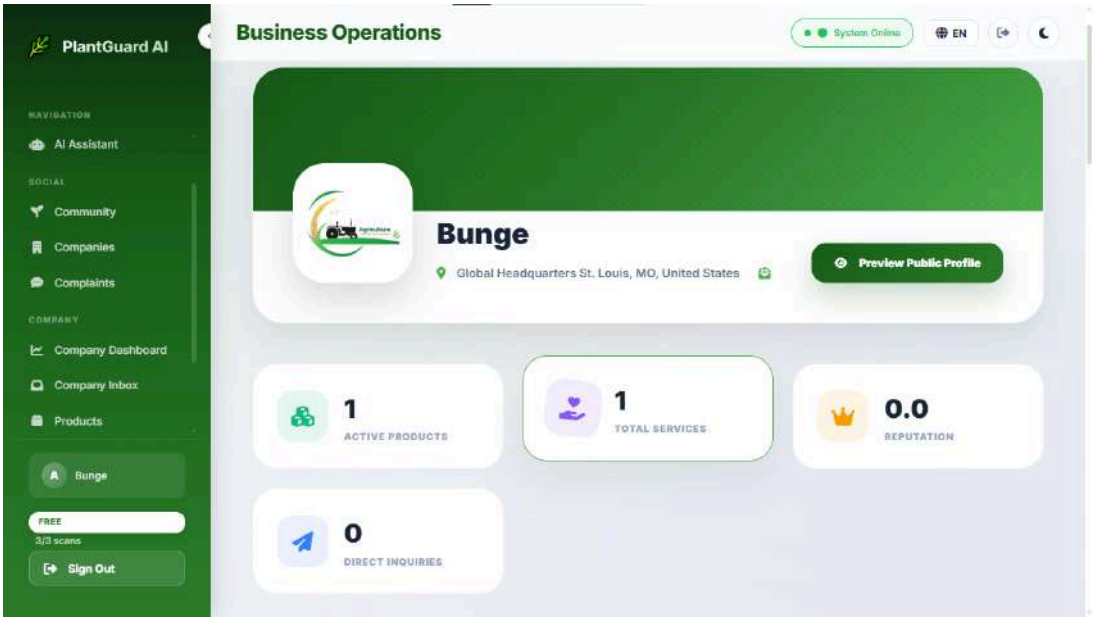


Figure 4.15: Companies Dashboard page

- **Companies Products page :**

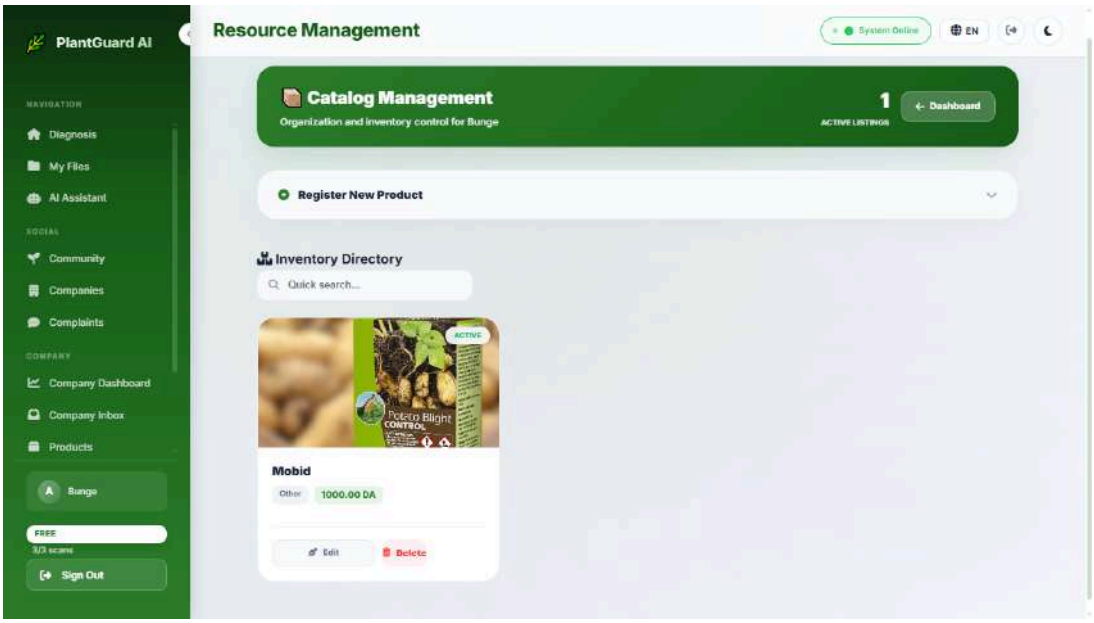


Figure 4.16: Companies Products page

- **Companies Services page :**

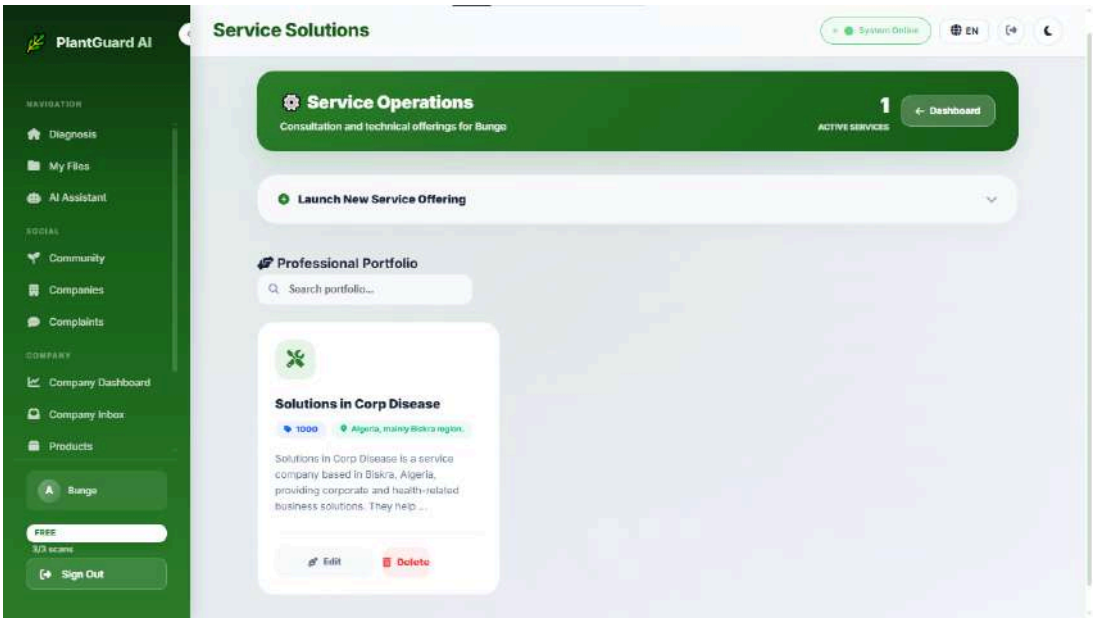


Figure 4.17: Companies Services page

- **My Experts page :** A consultation hub to connect with the allocated experts and get dedicated personal support and professional advice for the plant disease. The features consist of experts profiles, in-app messaging, notification tracking, and onboarding for expert allocation.

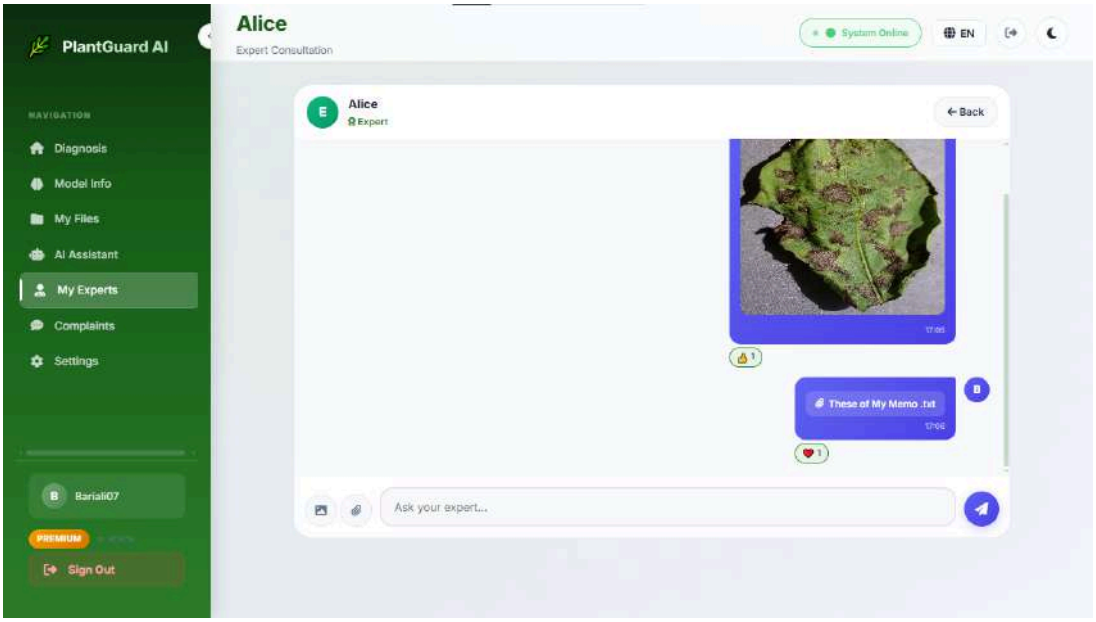


Figure 4.18: My Experts page

- **Feedback & Support page :** A support center that allow the users to create an issue, and check on the updates and complaints in the systems. The support center would consist of the submission form, issue history, check status, view/delete complaint feature.

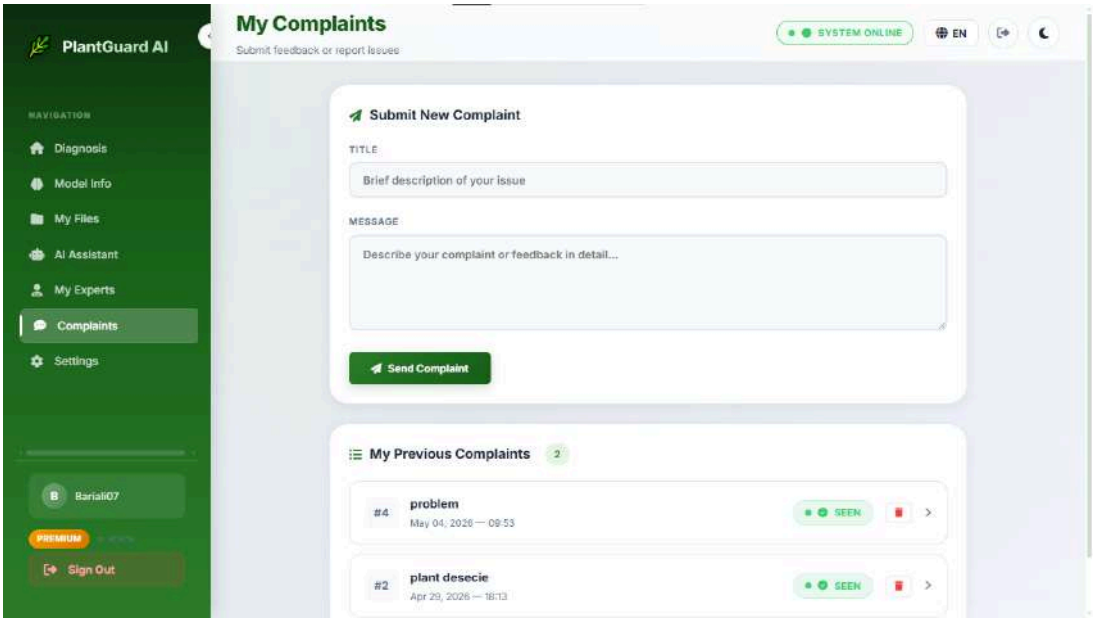


Figure 4.19: Feedback & Support page

- **Plans & Pricing page :** A subscription page that allows customers to choose between three Free, Basic and Premium options based on the usage. It highlights how the feature set differs between the plans, clearly marks out what the current plan is, and has clear ways to upgrade.

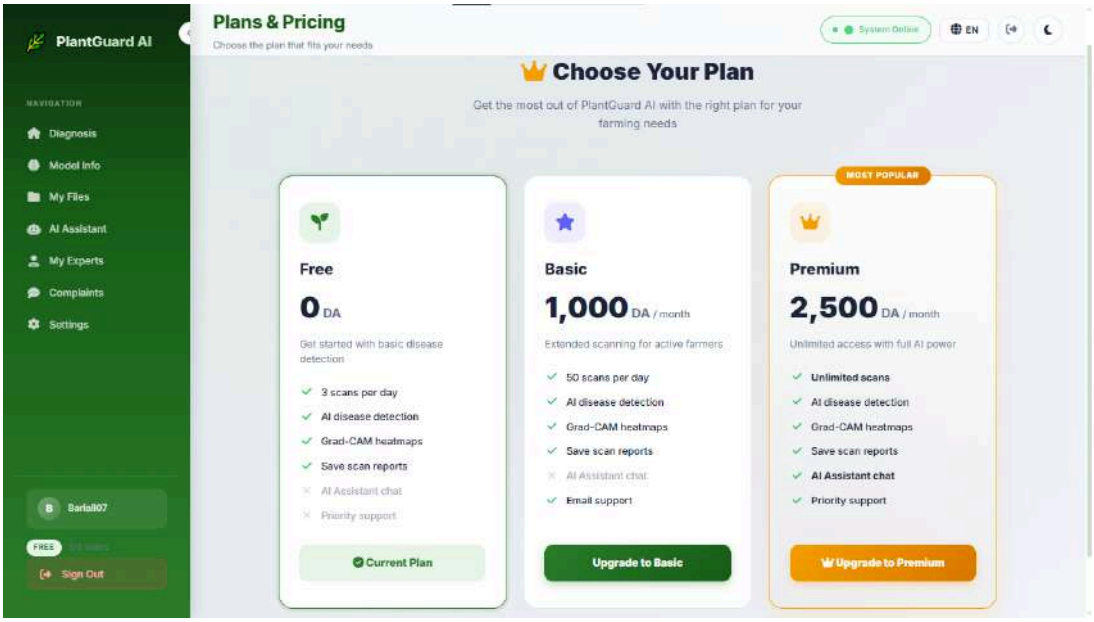


Figure 4.20: Plans & Pricing page

- **Settings page :** An all in one, tabbed panel in the accounts section where users can view their account information, manage security and see their usage activity and subscription details. This includes viewing all their identity data, updating profile and password details and viewing their diagnostic usage information, along with their complete subscription status, payment history and expiry date.

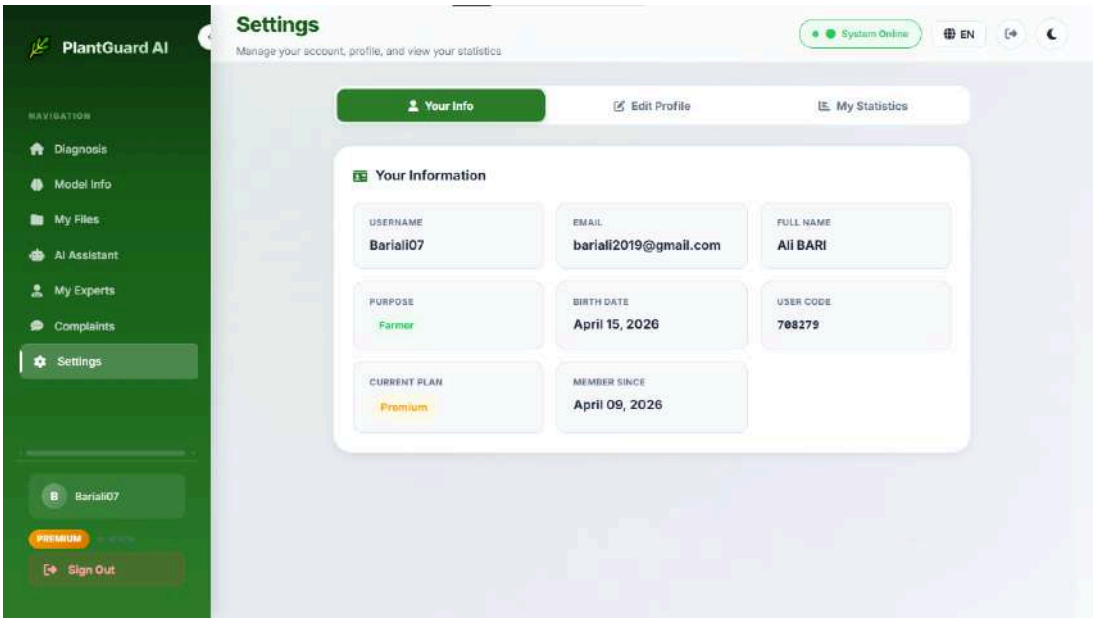


Figure 4.21: Settings page

4.3.2 Expert Account

Agricultural experts workspace that integrate the AI diagnosis with human experts interaction. It helps the experts manage their users, send advise to the users, internal expert

communication, and their profile maintenance. Core Features : **Expert Dashboard, User Consultations, Admin Communications, Expert Settings, Public Profile, My Files, Expert Complaints.**

- **Expert Dashboard Page :** This is the management dashboard where experts will track assigned users and monitor consultations along with managing their messages. It displays the workload statistics, chat history, a list of the assigned users, and the direct chat window for smooth client service.

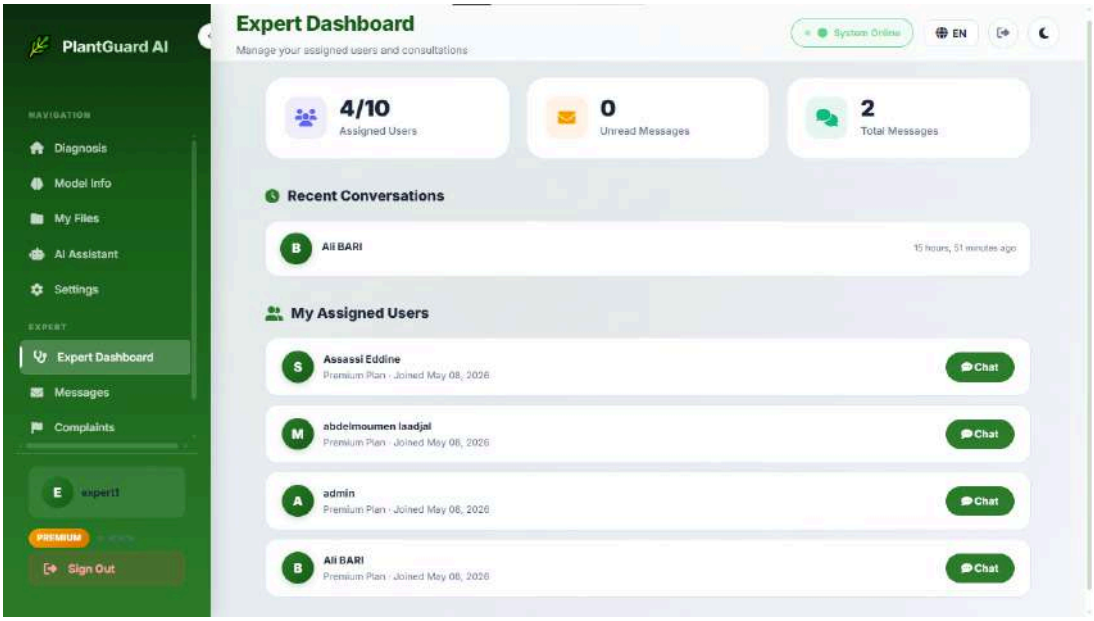


Figure 4.22: Expert Dashboard page

4.3.3 Company Account

4.3.4 Admin Account

The secure administration control center, with ultimate control over the entire platform, users, experts, AI processing, communication channels, support channels, monitoring of all platform operations, administration and performance.

1. **Admin Dashboard Page :**
    - Key Performance Indicators

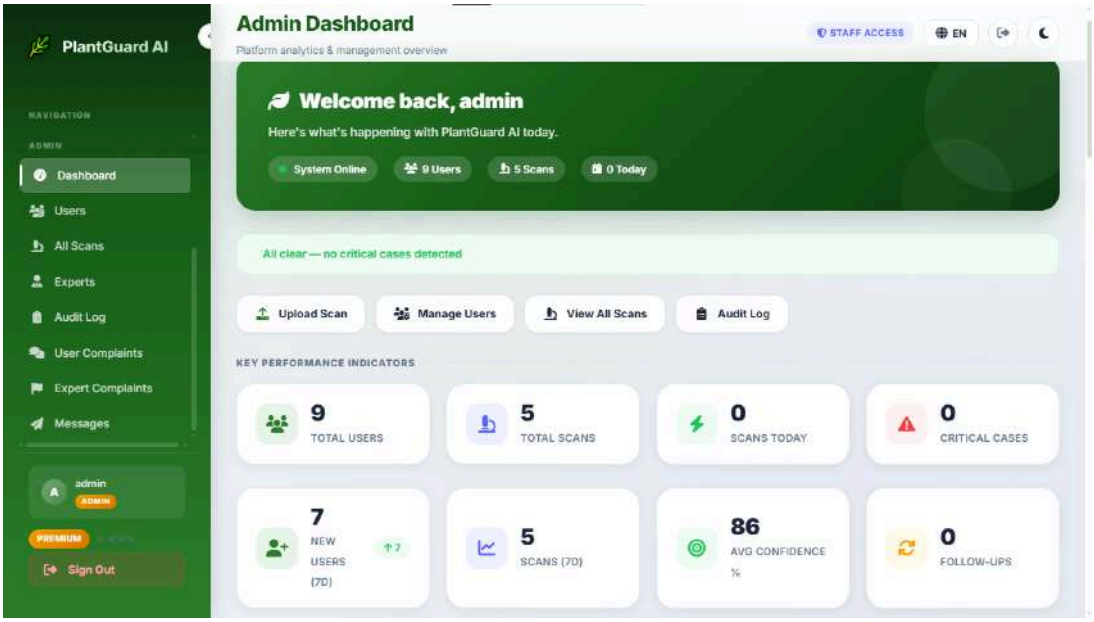


Figure 4.23: Key Performance Indicators Page

- Analytics (Disease Distribution & Scan Volume)

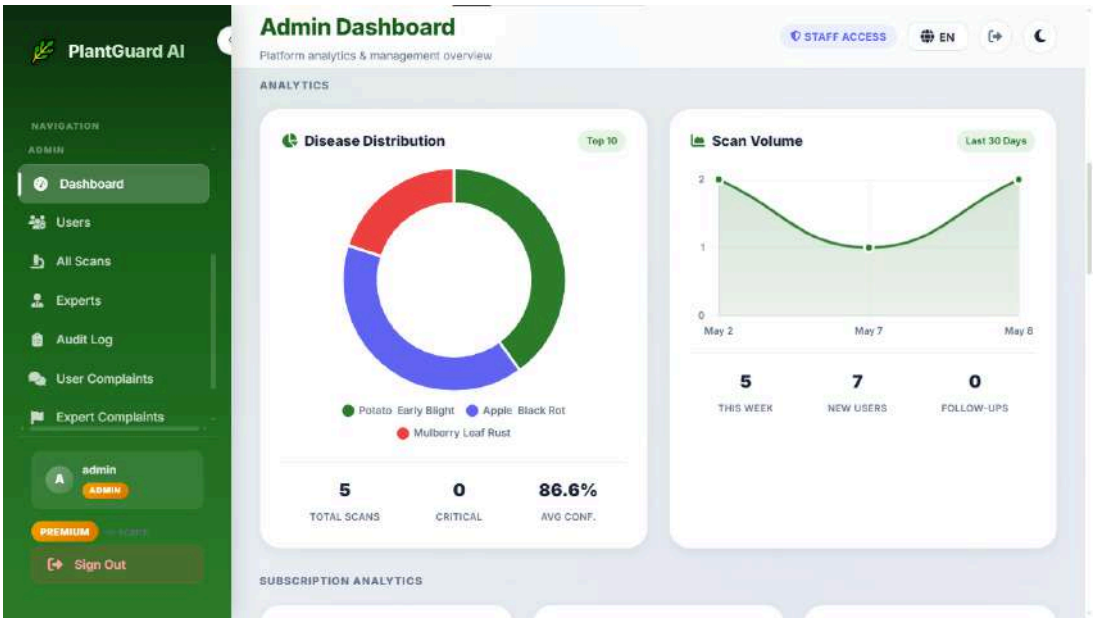


Figure 4.24: Disease Distribution & Scan Volume page

- Subscription Analytics

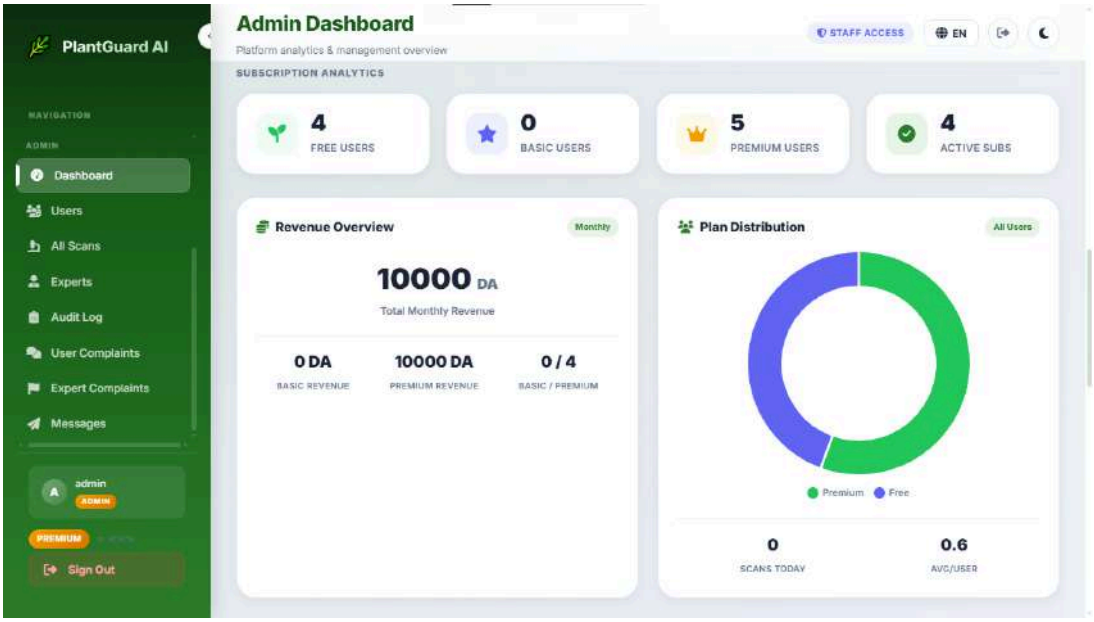


Figure 4.25: Subscription Analytics Page

- Top Users by Scan Count & Payment Upgrades (Demo) & Recent Payments

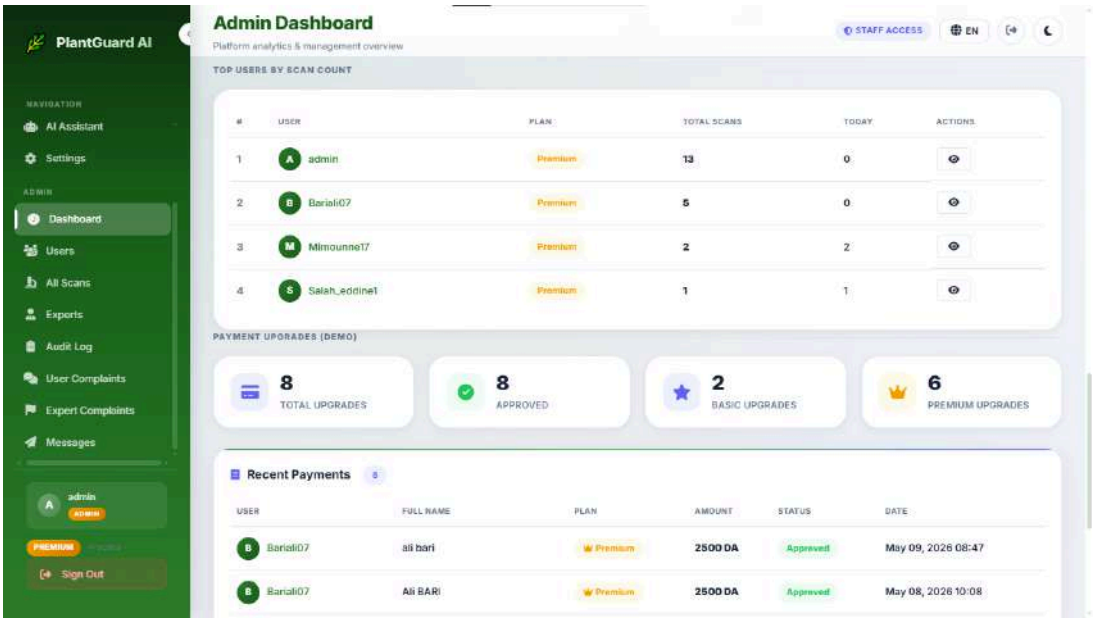


Figure 4.26: Top Scan Count & Upgrades & Recent Payments Page

2. Users Management

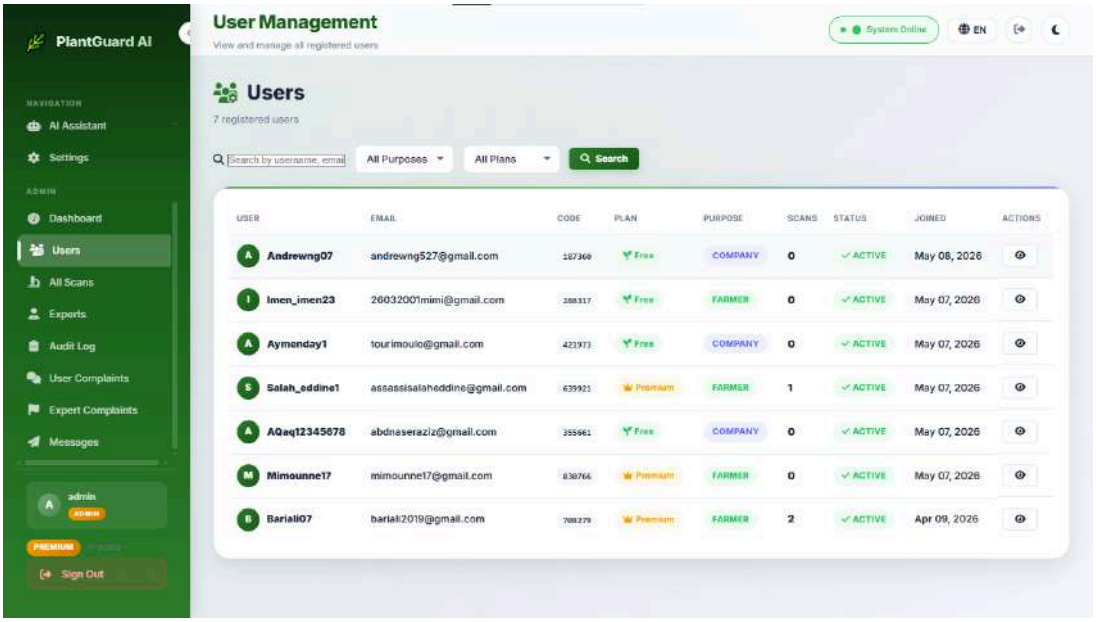


Figure 4.27: Users Management Page

3. All Scans (Scan Management)

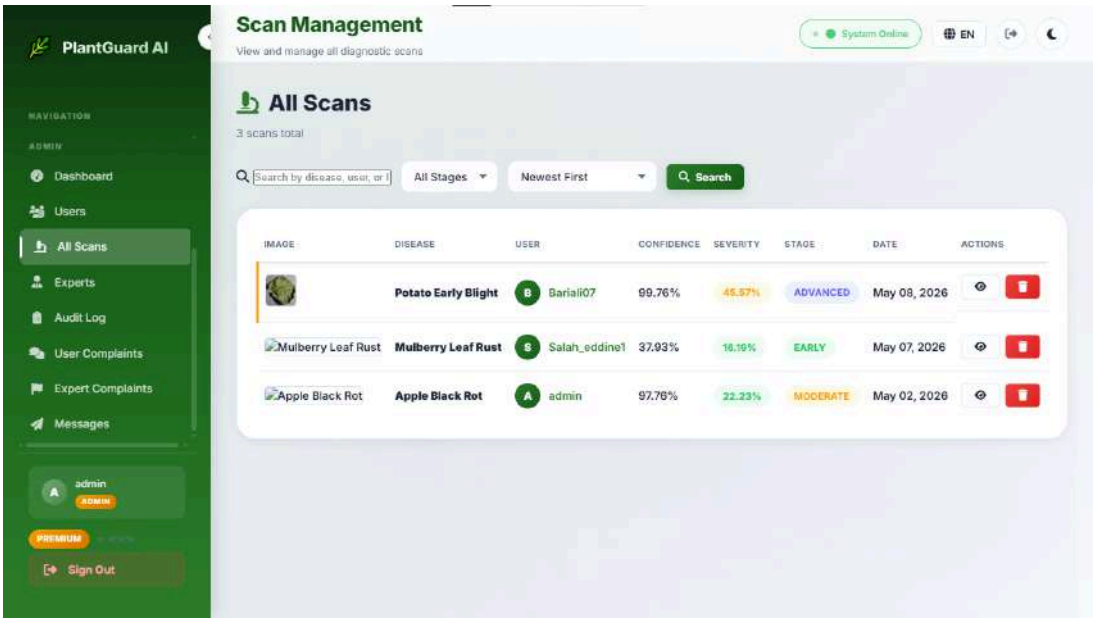


Figure 4.28: All Scans Page

4. Expert Management

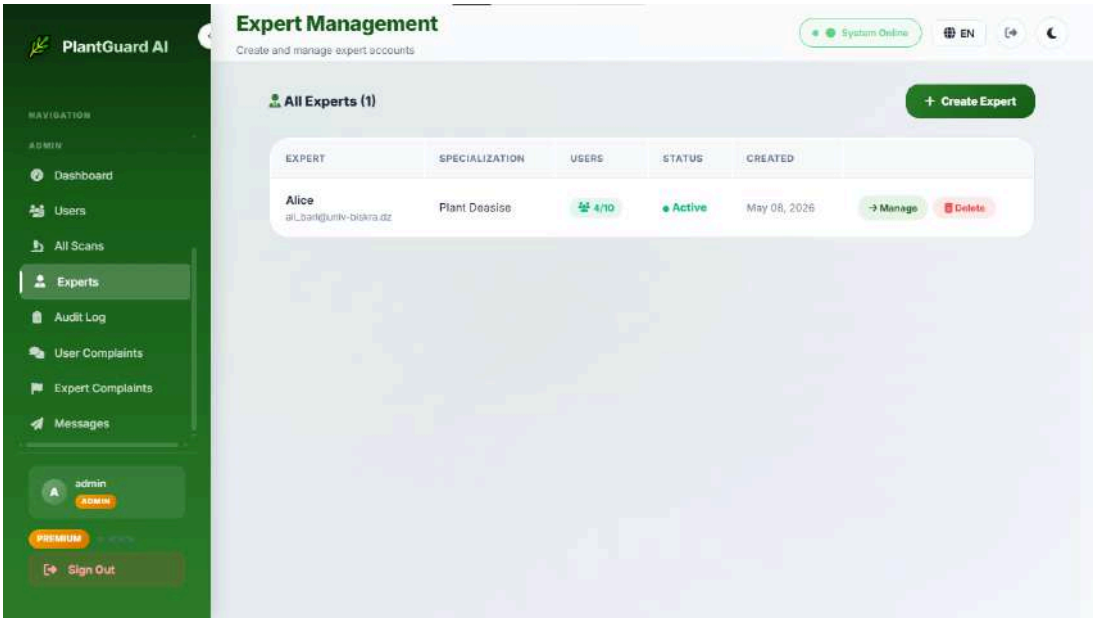


Figure 4.29: Expert Management Page

- Create Expert Account

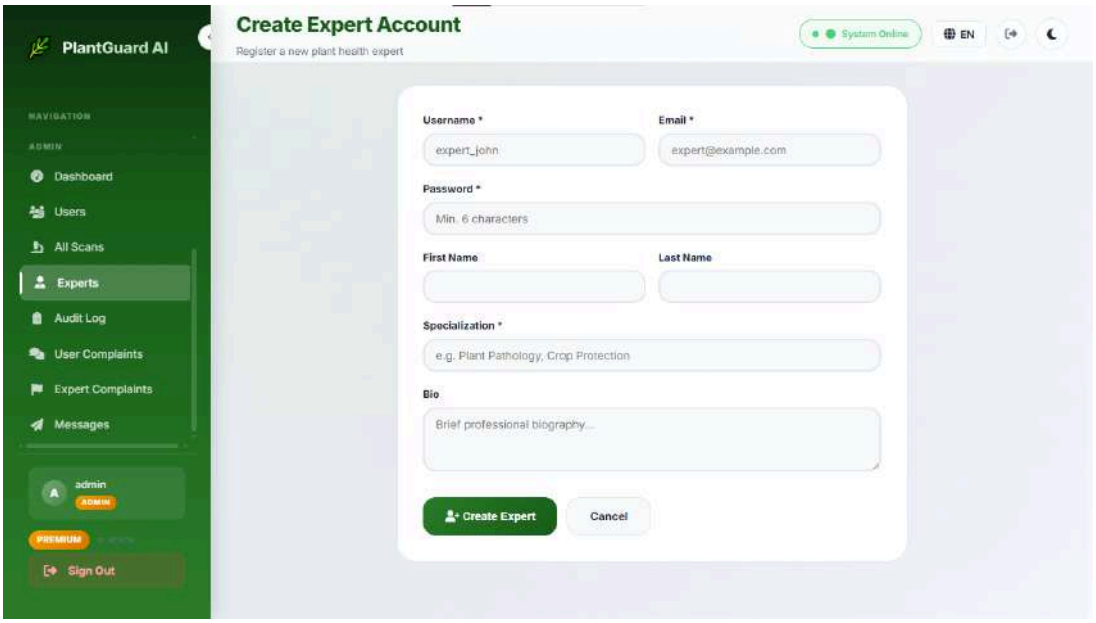


Figure 4.30: Create Expert Account Page

- Profile Expert Account

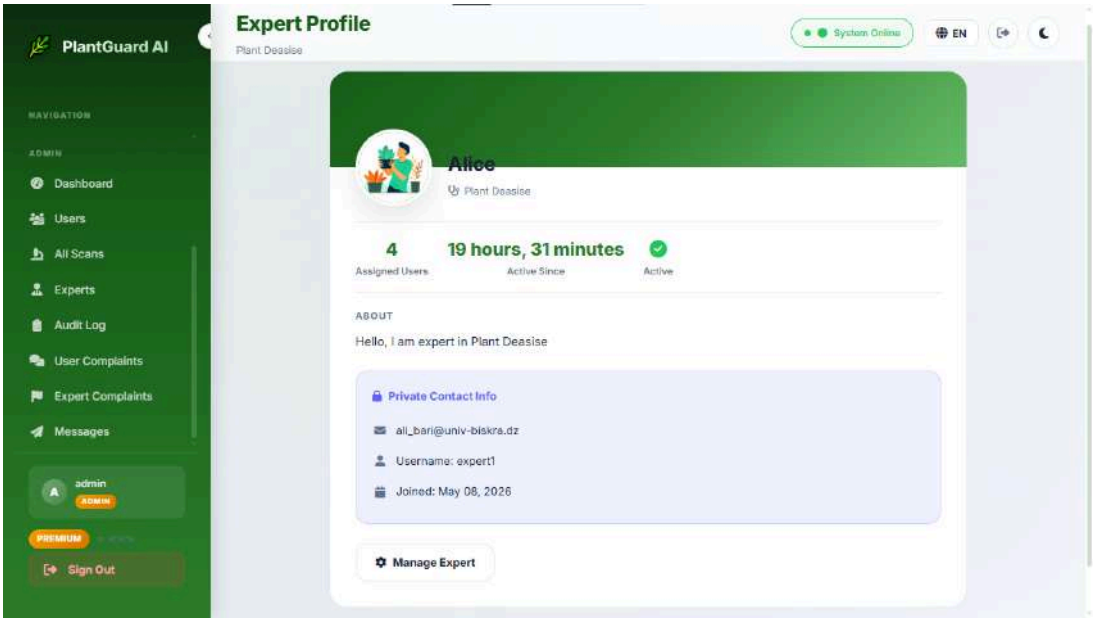


Figure 4.31: Profile Expert Account Page

5. Users Feedback (Complaints)

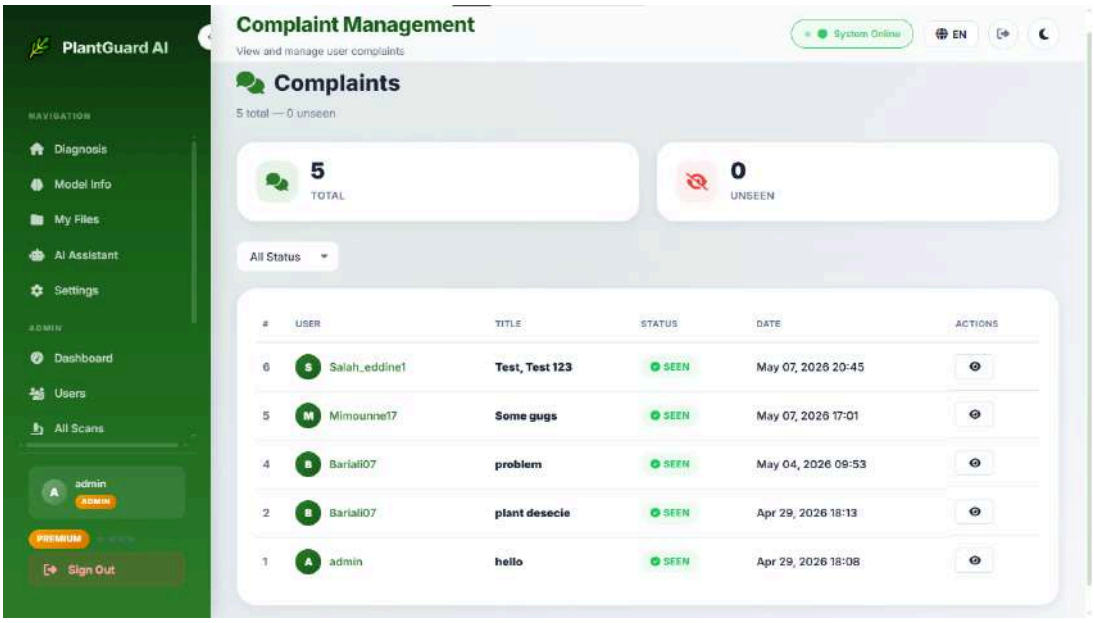


Figure 4.32: Users Feedback Page

6. Experts Feedback (Complaints)

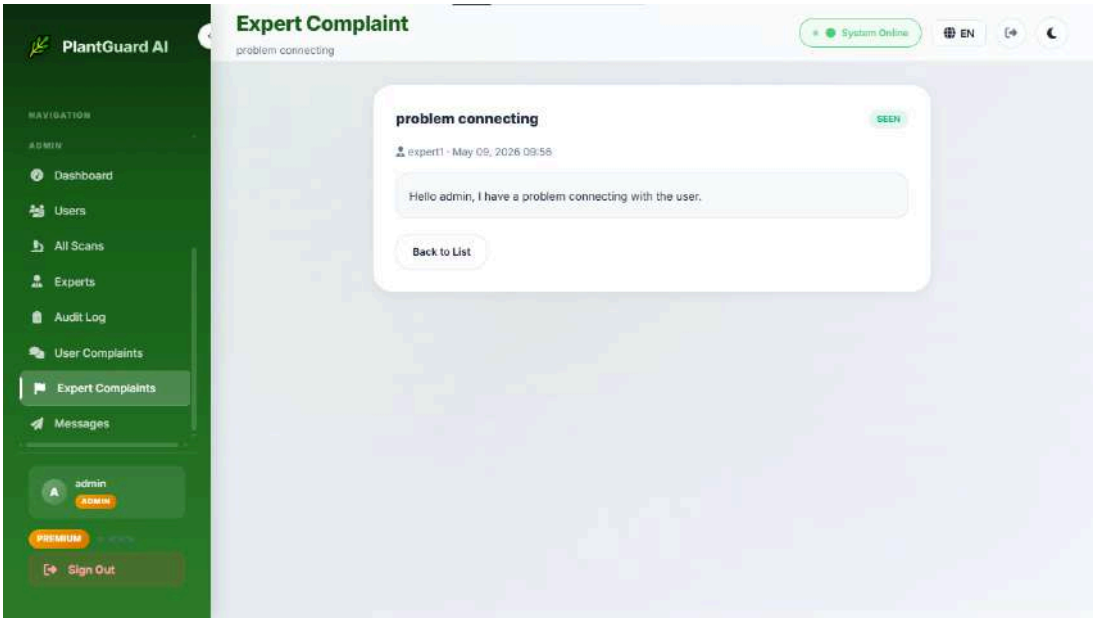


Figure 4.33: Experts Feedback Page

7. Audit Log

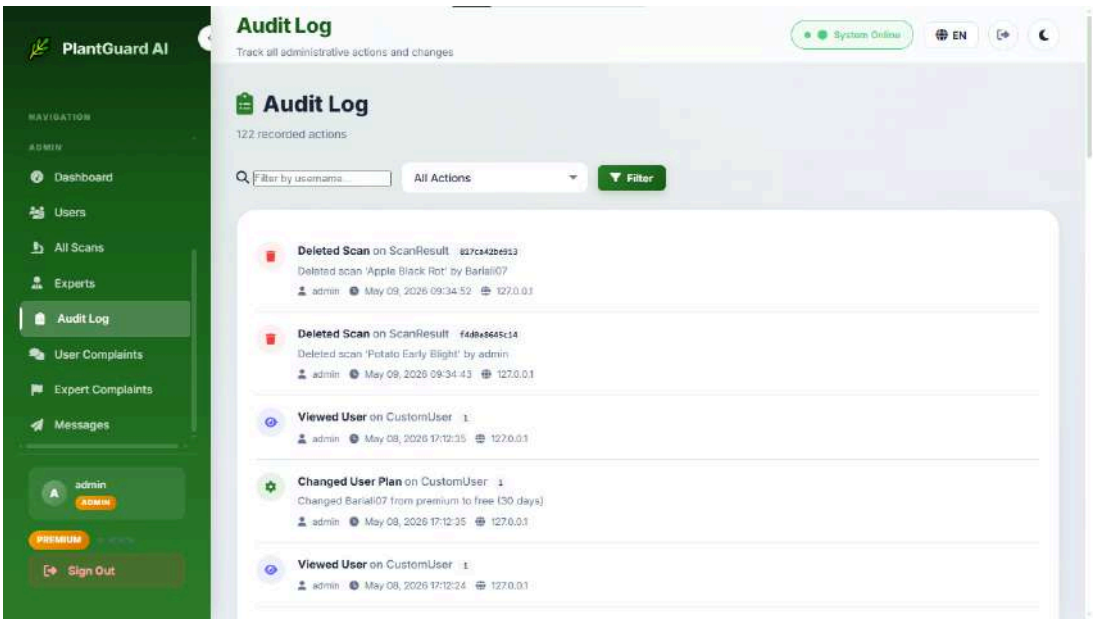


Figure 4.34: Audit Log Page

Chapter 5

Conclusion

Project PlantGuard AI (PlantsXAIHSI_Detection) embodies a revolution that will undoubtedly redefine the digital transformation of agriculture in Algeria. It goes far beyond a simple software application to become the first national comprehensive system and smart device that combines advanced artificial intelligence and field agronomy. Designed at the forefront of defending national plant heritage, its objective is to guarantee food sovereignty for Algeria, eliminate foreign technological dependency and propose a 100% local solution perfectly suited to the climate and diseases prevalent in the country.
From a technical point of view, the system overcomes the "black box" of AI through the implementation of XAI methods (Grad-CAM) in order to provide absolute certainty to the farmer and agronomist of the decisions made by the machine thanks to heatmaps identifying precisely the outbreak of infection. Along with a high diagnostic accuracy (91 types of diseases classified by EfficientNet-B0), the platform is equipped with modern and secure microservice and AJAX API architecture, state-of-the-art security to guarantee the security of data and servers, and is crowned by a high-end Emerald Executive UX/UI.
On an economic and agricultural level, it does not stop at diagnosis but also proposes a treatment set and accurate recommendations perfectly aligned with Algerian registered pesticides. The addition of smart Yield Loss Prediction algorithms transforms a simple scan into an economic tool and enables farmers, investors and cooperatives to anticipate, manage the risk and prevent agricultural disasters, thereby encouraging the optimal use of chemical pesticides.
Finally, the economic and agricultural development of the system will only be possible thanks to the implementation of an excellent network of strategic partners uniting government bodies, research centers (ITGC, INRAA), specialists in telecom and hardware manufacturing as well as in agrochemicals, so that it may reach the farmlands in the North and the Sahara, confirming it as the "cornerstone" and "milestone" of smart agriculture in Algeria.

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ملحق مشروع مؤسسة ناشئة

PlantGuard AI

منصة ذكية لرصد نقص العناصر الغذائية وأمراض النباتات



في اطار انجاز مذكرة تخرج " مؤسسة ناشئة " وفقا للقرار 1275

حاضنة أعمال جامعة بسكرة

قسم : الإعلام الآلي

تخصص : شبكات و تكنولوجيا الإعلام و الإتصال

PLANTGUARD AI

السنة الجامعية: 2026/2025

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المشرف الرئيسي

علوي إيمان

المشرف المساعد

تيبرماسين أحمد

فريق العمل/2

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تخصص : شبكات و تكنولوجيا الإعلام و الإتصال

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مقليد محمد الأمين

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كلية العلوم الدقيقة و علوم الطبيعة و الحياة

PLANTGUARD AI

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PLANTGUARD AI

مقدمة

يُعدّ القطاع الزراعي من أهم القطاعات الحيوية التي تساهم في تحقيق الأمن الغذائي والاستقرار الاقتصادي، خاصة في الدول التي تعتمد على الإنتاج المحلي لتلبية احتياجاتها الغذائية. وفي الجزائر، يلعب هذا القطاع دورًا استراتيجيًا من خلال إنتاج المحاصيل الأساسية مثل القمح والشعير والبطاطا...إلخ.

غير أن الإنتاج الزراعي يتأثر بعدة عوامل من بينها نقص العناصر الغذائية في التربة وانتشار أمراض النبات، مما يؤدي إلى انخفاض الإنتاجية وتدهور جودة المحاصيل. وتُعد هذه المشاكل من التحديات الرئيسية التي يصعب اكتشافها مبكرًا بالطرق التقليدية.

ومع تطور تقنيات الذكاء الاصطناعي والتعلم العميق، أصبح من الممكن تطوير أنظمة ذكية تعتمد على الشبكات العصبية الالتفافية (CNN) وتقنية التعلم بالنقل (Transfer Learning) لتحليل بيانات النباتات والكشف المبكر عن الإصابات ونقص العناصر الغذائية بدقة عالية، مما يساهم في تحسين الإنتاج الزراعي وتقليل الخسائر.

بناءً على ذلك، يهدف هذا العمل إلى تطوير نظام ذكي يعتمد على تقنيات التعلم العميق لتحليل بيانات النباتات والكشف المبكر عن نقص العناصر الغذائية وأمراض النبات، مما يساهم في تحسين لإنتاج الزراعي، وتقليل الخسائر، ودعم اتخاذ القرار في المجال الزراعي بشكل أكثر دقة وفعالية.

PLANTGUARD AI

المحور الاول:

تقديم المشروع



PLANTGUARD AI

1-فكرة المشروع:

PlantGuard AI هو مشروع ناشئ مبتكر في قطاع التكنولوجيا الزراعية (AgriTech)، يهدف إلى تمكين المزارعين والشركات الزراعية من الكشف المبكر والدقيق عن أمراض النباتات والآفات الزراعية ومكافحتها بكفاءة.

المنصة عبارة عن منظومة رقمية سحابية متكاملة تعمل عبر تطبيقات الويب والهواتف الذكية، وتعتمد على دمج تقنيات التعلم العميق (Deep Learning) مع الذكاء الاصطناعي القابل للتفسير (Explainable AI - XAI).

المنصة لا تكتفي بتقديم تشخيص فوري للمرض من خلال تحليل صور الأوراق المصابة المرفوعة بكاميرا الهاتف، بل تمهد الطريق لعهد جديد من الثقة والشفافية عبر توفير دليل بصري تفاعلي (Grad-CAM Heatmap) يوضح للمزارع أو الخبير أين يكمن موضع الإصابة ومبررات التشخيص بالتحديد على الورقة، مدعوماً بتقرير إرشادي زراعي فوري وشامل يغطي كافة جوانب العلاج الموصى به، خطة الري المخصصة، توقعات الفاقد، ومطابقة المبيدات الكيميائية والبيولوجية .

أولاً: خطوات رحلة المستخدم

- يقوم المستخدم بالدخول إلى لوحة التحكم التفاعلية لـ PlantGuard AI، ثم يقوم بتحميل صورة ورقة النبات المصابة أو التقاطها مباشرة عبر كاميرا الهاتف في منطقة الرفع المخصصة (Upload Zone) التي تدعم الصور حتى 10 ميجابايت.

- يعالج النظام الصورة خلال أجزاء من الثانية، وفي حال كانت الصورة غير واضحة أو لا تحتوي على نبات، يتم عرض تنبيه فوري (Low Confidence Warning) يطلب إعادة التقاط الصورة أو إجراء فحص يدوي.

- بعد ذلك، تُعرض واجهة تحليل ثنائية تُظهر الصورة الأصلية بجانب خريطة حرارية (Grad-CAM Heatmap) توضح مناطق الإصابة التي اعتمد عليها النموذج في التشخيص.

- كما يقدم النظام تقريرًا إرشاديًا متكاملًا يتضمن اسم المرض، نسبة الثقة، وصفًا للمسبب البيولوجي، توصيات للري، مؤشر خسارة المحصول المتوقعة (Yield Loss)، وجدولًا بالمبيدات المقترحة وآلية عملها.

- وأخيرًا، يمكن للمستخدم حفظ التقرير باسم محدد داخل نظام تخزين سحابي، مع إمكانية مشاركته مع الخبراء الزراعيين أو الاطلاع على توصيات العلاج المتاحة لإنقاذ المحصول.

ثانياً: رحلة الشركات والموردين

- تسجل الشركة الزراعية أو المورد حساباً تجارياً معتمداً عبر منصة المؤسسات للوصول إلى لوحة تحكم متطورة تمكنها من إدارة منتجاتها وتتبع عملائها.

- تقوم شركات الأدوية والمستلزمات الزراعية بعرض منتجاتها ومبيداتها المعتمدة في دليل المنتجات لكي يقوم الذكاء الاصطناعي بربطها تلقائياً بالتقارير العلاجية للمزارعين لحظة تشخيص المرض.

- تتابع الشركات الزراعية الكبرى وملاك المزارع الشاسعة مؤشرات أداء حقولهم ونسب انتشار الأوبئة وحالة المزروعات عبر لوحة بيانات إحصائية تفاعلية موحدة ورسم الخرائط الحرارية لمستوى الإصابات.

- تستقبل شركات الموردين طلبات الشراء المباشرة للمستلزمات والمبيدات الزراعية التي يرسلها المزارعون فور فحص محاصيلهم، وتقوم بتأكيد الطلبات وإصدار الفواتير وشحن المنتجات بشكل سريع.

- تتلقى الشركات شكاوى واستفسارات المزارعين وتقوم بحلها وتقديم التغذية الراجعة والدعم الفني المباشر لضمان تقديم أفضل تجربة خدمة عملاء وبناء علاقات تجارية مستدامة.

2-القيم المقترحة :

يسعى مشروع " PlantGuard AI " لتقديم العديد من القيم المقترحة نذكر منها :

الوصول

تمكين صغار المزارعين وأصحاب الحقول البعيدة من الوصول إلى خدمات التشخيص الزراعي عبر حل سحابي يزيل العوائق الجغرافية ويتيح الفحص في أي وقت ومن أي مكان عبر الهواتف الذكية.

تعزيز المساواة

ضمان المساواة في جودة ودقة التشخيص الزراعي والتوصيات العلاجية بين صغار المزارعين وكبرى الشركات عبر تكييف تقنيات الذكاء الاصطناعي لتناسب مختلف الإمكانيات والاحتياجات.

تعزيز الاستقلالية

تعزيز استقلالية صغار المزارعين عبر توفير أدوات تكنولوجية متقدمة تمكّنهم من تشخيص أمراض محاصيلهم بشكل مستقل وتقليل اعتمادهم على الخبراء والوسطاء.

الكفاءة و السرعة

تعزيز كفاءة وسرعة صغار المزارعين في رصد ومكافحة الآفات الزراعية عبر توفير تشخيص فوري ودقيق يساهم في تقليل الوقت والجهد والحد من انتشار الأمراض، وتمكينهم من اتخاذ قرارات علاجية سريعة ومستقلة.

3-فريق العمل:



باري علي

- دورة تكوينية حول المؤسسات الناشئة
- دورة تكوينية حول نموذج العمل التجاري BMC
- دورة تكوينية حول التطبيقات المالية والمحاسبية
- دورة تكوينية حول تطبيقات واستخدامات التسويق الرقمي في المشاريع
- دورة تكوينية حول كيفية الدراسة التقنية والاقتصادية للمشاريع المبتكرة
- مكلف بالجانب التقني



مقليد محمد الأمين

- دورة تكوينية حول المؤسسات الناشئة
- دورة تكوينية حول نموذج العمل التجاري BMC
- دورة تكوينية حول التطبيقات المالية والمحاسبية
- دورة تكوينية حول تطبيقات واستخدامات التسويق الرقمي في المشاريع
- دورة تكوينية حول كيفية الدراسة التقنية والاقتصادية للمشاريع المبتكرة
- مكلف بالجانب التقني

4-أهداف المشروع:

الأهداف المراد تحقيقها من خلال مشروعنا PlantGuard AI هي :

رؤية نشر وتطوير المشروع ميدانياً :

- نهدف إلى نشر هذا المشروع في كافة المستثمرات الفلاحية الخاصة والعامة، والمعاهد والمدارس الوطنية العليا للفلاحة، والمزارع التجريبية التي تضم الفلاحين والمهندسين الزراعيين في الجزائر، وذلك من خلال التعاون وإبرام الصفقات والشراكات مع الجهات الحكومية والتعليمية والوصية (مثل وزارة الفلاحة والتنمية الريفية، ووزارة التعليم العالي والبحث العلمي، والغرف الفلاحية الوطنية).

تطوير المشروع وإضافة تقنيات جديدة كالذكاء الاصطناعي:

- نسعى لتحسين وتطوير المشروع باستمرار من خلال دمج تقنيات متقدمة مثل الذكاء الاصطناعي التفسيري (XAI)، والتصوير فوق الطيفي (Hyperspectral Imaging - HSI)، وتكنولوجيا إنترنت الأشياء (IoT). هذا سيشمل تحسين قدرات المشروع على التعرف الدقيق الفوري على أعراض الأمراض، وتوفير تفاعلات وتقارير زراعية ذكية تتكيف مع احتياجات ومستوى كل مزارع أو مهندس ميداني.

التمكين والأثر التنموي:

- من خلال هذه التحسينات، سيتمكن المشروع من تقديم تجربة إرشادية وتوجيهية أكثر فاعلية ودقة، مما يعزز من استقلالية المزارعين والمهندسين الزراعيين وقدرتهم على حماية محاصيلهم واتخاذ القرارات العلاجية السليمة فوراً لتحقيق النجاح الإنتاجي والاقتصادي المستدام.

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5-جدول زمني لتحقيق المشروع :

	الشهر 1-3	الشهر 4	الشهر 4-13	الشهر 14	الشهر 15
دراسة السوق و الأبحاث	✓				
اقتناء مكونات الجهاز		✓			
تركيب الجهاز			✓		
اختبار الجهاز				✓	
التسويق					✓

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المحور الثاني:

الجوانب الابتكارية للمشروع



1- طبيعة الابتكارات:



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2-مجالات الابتكارات:

مجالات الابتكارات في هذا المشروع تشمل عدة مجالات، منها :

- **تقنيات التعلم العميق والذكاء الاصطناعي:**

استخدام تقنيات الذكاء الاصطناعي والتعلم العميق لتحليل صور النباتات والكشف المبكر عن أمراض النبات ونقص العناصر الغذائية بدقة عالية وسرعة في التشخيص.

- **تقنيات التصوير فائق الطيف (HSI):**

اعتماد التصوير فائق الطيف لاستخراج الخصائص الطيفية للنباتات ومراقبة حالتها الصحية بشكل دقيق قبل ظهور الأعراض المرئية.

- **النماذج القابلة للتفسير (XAI):**

تطبيق تقنيات الذكاء الاصطناعي القابل للتفسير لتوضيح قرارات النموذج وتحسين فهم نتائج التشخيص الزراعي وزيادة موثوقيتها.

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المحور الثالث:

التحليل الاستراتيجي للسوق

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1-عرض القطاع السوقي:

يمكننا ان نحدد السوق المستهدف لمشروعنا PlantGuard AI كمايلي :

السوق المستهدف هو الفئة الرئيسية التي يستهدفها المنتج مباشرة والتي ستستفيد بشكل كبير من الحل المقدم و نذكر منهم :

المستثمرات والمزارع الفلاحية الخاصة (الكبرى والصغرى)

- أصحاب الأراضي الفلاحية الكبرى والمستثمرون الزراعيون في ولايات الجنوب (مثل الوادي وبسكرة وورقلة) والولايات الشمالية (مثل معسكر، ميلة، والشلف) الذين يحتاجون لحماية محاصيلهم ذات القيمة العالية (كالحبوب، البطاطس، الطماطم، والتمور) من الأمراض الفطرية والبكتيرية لتقليل الخسائر المالية

المعاهد والمراكز الوطنية للبحث والإرشاد الفلاحي بالجزائر

الجهات الحكومية والبحثية والرقابية التابعة لوزارة الفلاحة، وعلى رأسها:

- ITGC (المعهد التقني للمحاصيل الواسعة - لتشخيص محاصيل الحبوب كالقمح والشعير).
- INRAA (المعهد الوطني للبحث الزراعي بالجزائر).
- ITMAS (المعاهد التقنية المتوسطة الفلاحية المتخصصة) لتوفير أداة تعليمية وعملية لطلبة التخصص الفلاحي.



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التعاونيات والجمعيات الفلاحية الجزائرية

- تعاونيات الحبوب والبقول الجافة (CCLS) والغرف الفلاحية الولائية والوطنية التي تسعى لتوفير أحدث التقنيات وأجهزة الفحص الذكية للفلاحين لرفع كفاءة الإنتاج والتصدي الجماعي للآفات.

الشركات الزراعية وموزعو المدخلات الكيميائية والمبيدات

- الشركات الموزعة لمبيدات الفطريات والأسمدة (مثل شركة أسيدال أو موزعي الكيماويات المعتمدين في الجزائر)، والتي تستخدم الجهاز كأداة قيمة لتقديم خدمة تشخيص دقيقة وعلمية لعملائها من الفلاحين لترشيح واختيار المبيد المناسب بنسبة 100%.

مكاتب الاستشارات الفلاحية والمهندسون الزراعيون الأحرار:

- الخبراء الزراعيون الأحرار والمهندسون المستقلون الذين يقدمون خدمات فحص تقني واستشارات فلاحية دورية للحقول والمستثمرات الكبيرة لتوجيه المزارعين علاجياً.



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2-قياس شدة المنافسة:

- **التطبيقات الأجنبية العالمية (مثل Plantix و Pl@ntNet):**
  - نقاط القوة لديهم: امتلاك خوادم ضخمة وقواعد بيانات شاملة على المستوى الدولي.
  - الثغرات وعيوب المنافس: نقص التخصيص للمحاصيل والآفات المحلية الجزائرية، وعدم توافق مقترحاتهم العلاجية مع الأدوية ومبيدات الفطريات المرخصة تجارياً في الجزائر، بالإضافة لغياب الدعم الميداني المباشر وانعدام التفسير البصري (XAI) الذي يبني ثقة المزارع.



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3-الاستراتيجية التسويقية:

لضمان نجاح مشروع PlantGuard AI في السوق الزراعي الجزائري، يجب تطوير استراتيجية تسويقية متكاملة تهدف إلى نشر الوعي بالتقنيات الزراعية الذكية، جذب المزارعين والمؤسسات الفلاحية، وتعزيز الاعتماد على حلول الذكاء الاصطناعي في حماية المحاصيل.

تحليل السوق وتحديد الجمهور المستهدف

- دراسة السوق: تحليل احتياجات القطاع الزراعي والمشاكل المرتبطة بنقص العناصر الغذائية وتأثيرها على الإنتاجية الزراعية.
- تحديد الجمهور المستهدف: التركيز على المهندسين الزراعيين، التعاونيات الفلاحية، مستثمري البيوت البلاستيكية، وأصحاب الزراعات ذات القيمة العالية.

تطوير عرض القيمة

- رسالة واضحة: التركيز على تحسين دقة التشخيص الزراعي وتقليل الخسائر الزراعية باستخدام الذكاء الاصطناعي والتصوير الطيفي.
- مزايا المنتج: سهولة الاستخدام عبر الهاتف الذكي، تشخيص سريع ودقيق، خرائط ذكية تفاعلية، وتوصيات زراعية مخصصة.

استراتيجية التسعير

- تسعير تنافسي: تقديم أسعار مناسبة للمؤسسات الزراعية والفلاحين مع مراعاة القدرة الشرائية.
- خطط تسعير متنوعة: توفير اشتراكات شهرية أو سنوية، تقارير مدفوعة، وعروض خاصة للمؤسسات والتعاونيات.

قنوات التوزيع

- البيع المباشر: التعاونيات والمؤسسات الزراعية.
- الشراكات: مديريات الفلاحة وشركات AgriTech.
- البيع عبر الإنترنت: تطبيق الهاتف ومنصة إلكترونية للخدمات الزراعية.

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استراتيجية الترويج

- برامج التوعية: توفير فيديوهات تعليمية قصيرة ومبسطة داخل التطبيق وعلى يوتيوب تشرح كيفية التقاط الصور الصحيحة للنباتات المصابة للحصول على أدق تشخيص.
- تدريب المرشدين: تقديم دورات تدريبية للمرشدين الفلاحيين ليصبحوا سفراء للمنصة ويساعدوا الفلاحين الأقل خبرة تقنياً في استخدامها.

التعليم والتدريب

- دعم متعدد القنوات: توفير دعم فني سريع عبر قنوات سهلة الاستخدام بالنسبة للفلاح (مثل دعم عبر WhatsApp) ومدمج داخل التطبيق.
- التغذية الراجعة: تشجيع المستخدمين على تقييم نتائج التشخيص داخل التطبيق، واستخدام هذه الملاحظات لتحسين دقة خوارزميات الذكاء الاصطناعي بشكل مستمر.

الدعم الفني وخدمة العملاء

- قصص النجاح: نشر مقاطع فيديو ومقالات توثق قصص نجاح حقيقية لمزارعين تمكنوا من إنقاذ محاصيلهم بفضل التشخيص المبكر لمنصة PlantGuard.
- التغطية الإعلامية: التنسيق مع البرامج التلفزيونية والمجلات المتخصصة في الزراعة لتسليط الضوء على دور المنصة في رقمنة القطاع الفلاحي.

العلاقات العامة

- توسيع قدرات المنصة: الاستمرار في تدريب نماذج الذكاء الاصطناعي للتعرف على أنواع جديدة من النباتات والأمراض والآفات.
- التوسع في الأسواق ودمج التقنيات: استكشاف أسواق زراعية في دول جديدة، والعمل مستقبلاً على دمج بيانات الطقس أو مستشعرات التربة (IoT) لتقديم توصيات زراعية استباقية وأكثر شمولية.

المحور الرابع:

خطة الانتاج و التنظيم



PLANTGUARD AI

1-خطوات استخدام التطبيق:

- يقوم المستخدم (الفلاح أو المهندس الزراعي) بفتح تطبيق « PlantGuard » على الهاتف الذكي أو عبر منصة الويب.
- يختار المستخدم لغة الواجهة المناسبة له: العربية أو الفرنسية أو الإنجليزية.
- يضغط المستخدم على زر « فحص جديد » (Scan) لالتقاط صورة لورقة النبات المصابة أو رفع صورة من المعرض.
- ينتظر المستخدم بضع ثوانٍ بينما تقوم خوارزميات الذكاء الاصطناعي بتحليل الصورة وتحديد نوع المرض المحتمل.
- تعرض المنصة نتيجة التشخيص متضمنة اسم المرض، نسبة دقة التشخيص، والعلاجات والتدابير الوقائية المقترحة.
- يمكن للمستخدم حفظ نتائج الفحص في سجله الخاص أو مشاركة النتيجة في قسم « المجتمع » (Community) للحصول على استشارة إضافية.
- يستطيع المستخدم تكرار العملية لفحص نباتات أخرى أو الاطلاع على إحصائيات المزرعة الخاصة به.

2-اليد العاملة:

الفريق التقني

- مهندسو البرمجيات (Software Engineers): تطوير الواجهات الأمامية والخلفية للمنصة (مثل العمل على إطار Django)، وإدارة قواعد البيانات لضمان سرعة واستقرار التطبيق.
- مهندسو الذكاء الاصطناعي ورؤية الحاسوب (AI & Computer Vision Engineers): بناء، تدريب، وتحسين نماذج التعلم العميق (Deep Learning) الخاصة بالتعرف على أمراض النباتات من خلال الصور.
- مهندسو الاختبار وضمان الجودة (QA Engineers): اختبار المنصة ونماذج التشخيص في بيئات وظروف إضاءة مختلفة للتأكد من دقة النتائج وخلو التطبيق من الأخطاء التقنية.

الفريق الاستشاري الزراعي.

- خبراء أمراض النباتات والمهندسون الزراعيون: مراجعة وتدقيق نتائج نماذج الذكاء الاصطناعي، صياغة التوصيات العلاجية بدقة علمية، وتقديم الاستشارات في قسم " المجتمع " داخل المنصة.

الفريق الإداري

- مدير المشروع: تنسيق جميع جوانب المشروع التقنية والزراعية، وضمان الالتزام بالجداول الزمنية والميزانية.
- مدير الموارد البشرية: توظيف الكفاءات (سواء تقنية أو زراعية) وإدارة شؤون فريق العمل.

الفريق التسويقي

- مدير التسويق والمبيعات: وضع الاستراتيجية التسويقية للوصول إلى المزارعين والتعاونيات الفلاحية، وعقد شراكات مع الجهات الحكومية والخاصة.
- صانع محتوى زراعي: إنشاء محتوى ترويجي وإرشادي (فيديوهات ومقالات مبسطة) لتعليم الفلاحين كيفية حماية محاصيلهم وكيفية استخدام المنصة.
- مسير حسابات مواقع التواصل الاجتماعي: إدارة الحملات الإعلانية الموجهة، وتنشيط التفاعل مع الفلاحين على منصات مثل فيسبوك والمنصة الداخلية للتطبيق.

فريق دعم العملاء

- فرق الدعم الفني: تقديم المساعدة التقنية للمستخدمين وحل أي مشكلات برمجية قد تواجههم أثناء الفحص.
- مرشدون فلاحيون رقميون (ممثلو خدمة العملاء): الإجابة على استفسارات المستخدمين وتوجيههم لأفضل الطرق لالتقاط صور واضحة تضمن تشخيصاً دقيقاً.

البحث والتطوير (R&D)

- باحثون في الذكاء الاصطناعي: العمل على تطوير قدرات المنصة للتعرف على أنواع جديدة من المحاصيل والأمراض، ودمج تقنيات جديدة للتحليل.
- محللو البيانات (Data Analysts): تحليل بيانات الفحوصات والخرائط الجغرافية لتتبع انتشار الآفات الزراعية وتوجيه الإنذارات المبكرة لتطوير المنتج مستقبلاً.

PLANTGUARD AI

3-الشراكات الرئيسية:

لتطوير وتسويق منصة " PlantGuard " للذكاء الاصطناعي الزراعي، من المهم إقامة شراكات استراتيجية مع مجموعة من الكيانات المختلفة لتعزيز قدرات المشروع، إثراء قاعدة البيانات، وضمان نجاحه وانتشاره. إليك الشراكات الرئيسية التي تعتبر محورية للمنصة:

شراكات تقنية

- مزودو الخدمات السحابية والذكاء الاصطناعي: مثل Amazon Web Services (AWS) أو Google Cloud، للحصول على بنية تحتية قوية لاستضافة قواعد البيانات الضخمة (صور النباتات) وتشغيل نماذج التعلم العميق بكفاءة عالية.
- شركات التكنولوجيا الزراعية (AgriTech): التعاون مستقبلاً مع شركات تصنيع طائرات الدرون الزراعية أو مستشعرات التربة لدمج بيانات إضافية تزيد من دقة التشخيص.

شراكات أكاديمية وعلمية

- المعاهد والجامعات الزراعية: التعاون مع كليات الهندسة الزراعية والبيولوجيا لتجربة المنصة في المزارع التجريبية، وتزويد المنصة بالمعرفة الأكاديمية الموثوقة حول الأمراض والعلاجات.
- مراكز البحوث الزراعية (INRAA مثلاً): للتعاون في تحسين خوارزميات التعرف على الآفات بناءً على أحدث البحوث والبيانات المناخية والبيولوجية المحلية.

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شراكات مع الجمعيات والتعاونيات الفلاحية

- التعاونيات الفلاحية: الشراكة المباشرة مع تعاونيات منتجي الحبوب، الأشجار المثمرة، وغيرها، لتسهيل وصول المنصة للمزارعين المنضوين تحتها وتقديم اشتراكات جماعية.
- المنظمات غير الحكومية المهتمة بالأمن الغذائي: للتعاون في المبادرات التي تهدف إلى مساعدة صغار المزارعين على تحسين مردوديتهم وحماية محاصيلهم من التلف.

شراكات حكومية

- وزارة الفلاحة والتنمية الريفية: للحصول على الدعم المؤسسي، وتبني المنصة كأداة رسمية مساعدة في برامج التنمية الزراعية.
- الغرف الفلاحية (الوطنية والولائية): لتسهيل اعتماد المنصة كوسيلة معتمدة للإرشاد الفلاحي الرقمي وتسهيل التواصل مع شريحة واسعة من الفلاحين في مختلف المناطق.

شراكات تجارية وتسويقية

- موردو المواد والمعدات الفلاحية: الشراكة مع شركات إنتاج وبيع الأسمدة والمبيدات الزراعية المعتمدة (لعرض إعلانات موجهة داخل المنصة أو رعاية المحتوى التوعوي).
- وكالات التسويق الرقمي: للمساعدة في تصميم حملات إعلانية فعالة تستهدف المزارعين والمهندسين على منصات التواصل الاجتماعي لزيادة قاعدة المستخدمين.

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شراكات في الدعم والإرشاد الميداني

- مراكز الإرشاد الفلاحي: تدريب المرشدين الفلاحيين التابعين للدولة ليصبحوا سفراء للمنصة، بحيث يقومون بتدريب الفلاحين الأقل خبرة تقنياً على كيفية استخدام التطبيق.
- المهندسون الزراعيون المستقلون: شراكات مع مهندسين لتقديم استشارات مخصصة (مدفوعة أو مجانية) للفلاحين عبر قسم "المجتمع" داخل المنصة.

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المحور الخامس:

الخطة المالية



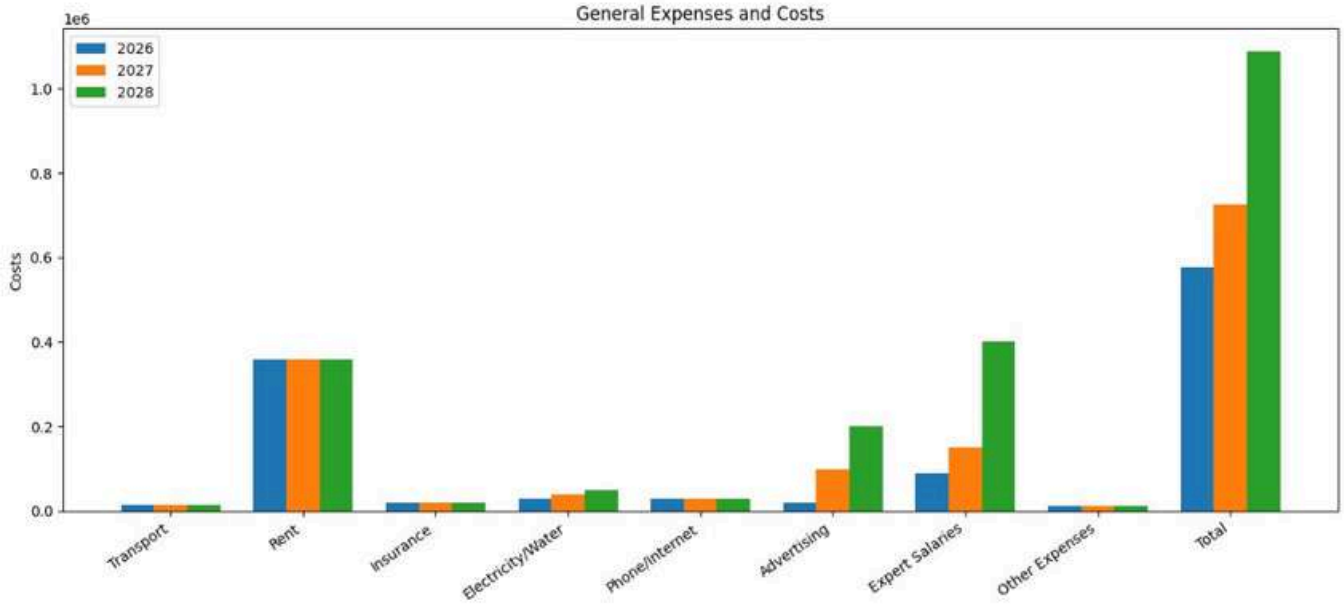
المواد الأولية و المخزونات:

حالة شراء المادة الأولية والتجهيزات

المنتجات الإستهلاكية والتقنية	السنة الأولى	السنة الثانية	السنة الثالثة
تراخيص وأدوات التطوير	20000 DA	20000 DA	20000 DA
خوادم سحابية	60000 DA	80000 DA	100000 DA
بيانات زراعية للتدريب	20000 DA	20000 DA	20000 DA
واجهات الذكاء الاصطناعي	30000 DA	0 DA	0 DA
حواسيب محمولة للمطورين	200000 DA	0 DA	0 DA
أجهزة ذكية للاختبار الميدانية	100000 DA	0 DA	0 DA
ذاكرة وصول عشوائي للتطوير المحلية	40000 DA	0 DA	0 DA
لقواعد البيانات SSD لأغراض تخزين	20000 DA	0 DA	0 DA
قرص صلب خارجي للنسخ الاحتياطي	60000 DA	0 DA	0 DA
مطورو ذكاء اصطناعي	60000 DA	60000 DA	60000 DA
مهندسون زراعيون	60000 DA	60000 DA	60000 DA
مكتب	30000 DA	0 DA	0 DA
كرسي	30000 DA	0 DA	0 DA
مكيف	80000 DA	0 DA	0 DA
المجموع	810000 DA	240000 DA	260000 DA

بيان المصروفات العامة

البند	السنة الأولى	السنة الثانية	السنة الثالثة
النقل	15000 DA	15000 DA	15000 DA
الإيجار (أمن مكتب)	360000 DA	360000 DA	360000 DA
التأمين	20000 DA	20000 DA	20000 DA
الكهرباء/الغاز/الماء	30000 DA	40000 DA	50000 DA
اشتراك الهاتف/الإنترنت	30000 DA	30000 DA	30000 DA
الإعلان (التسويق)	20000 DA	100000 DA	200000 DA
أجور الخبراء	90000 DA	150000 DA	400000 DA
المصاريف المالية أخرى	12000 DA	12000 DA	12000 DA
المجموع	577000 DA	727000 DA	1087000 DA



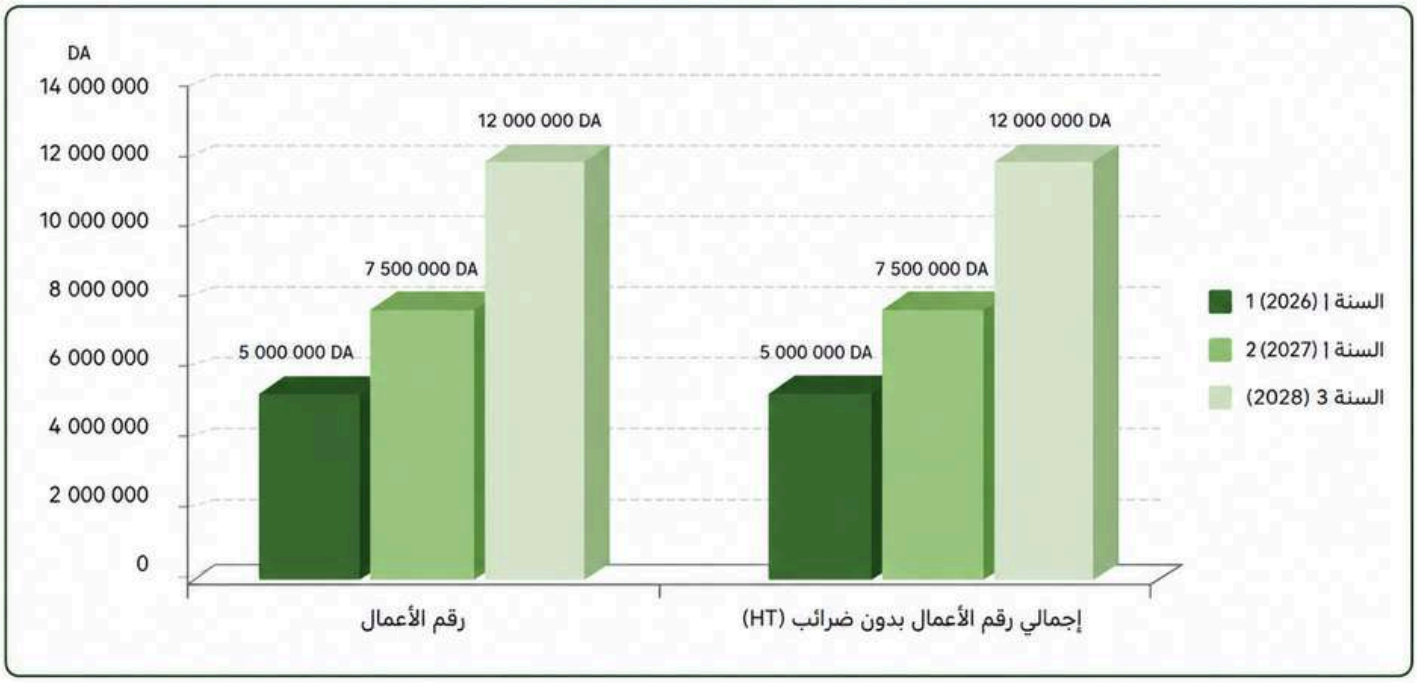
PLANTGUARD AI

رقم الأعمال:

3. حالة رقم الأعمال التقديري

البند	السنة 1 (2026)	السنة 2 (2027)	السنة 3 (2028)
رقم الأعمال	5 000 000 DA	7 500 000 DA	12 000 000 DA
إجمالي رقم الأعمال بدون ضرائب (HT)	5 000 000 DA	7 500 000 DA	12 000 000 DA

الشكل يمثل رقم الأعمال



4. جدول حساب النتائج المتوقع

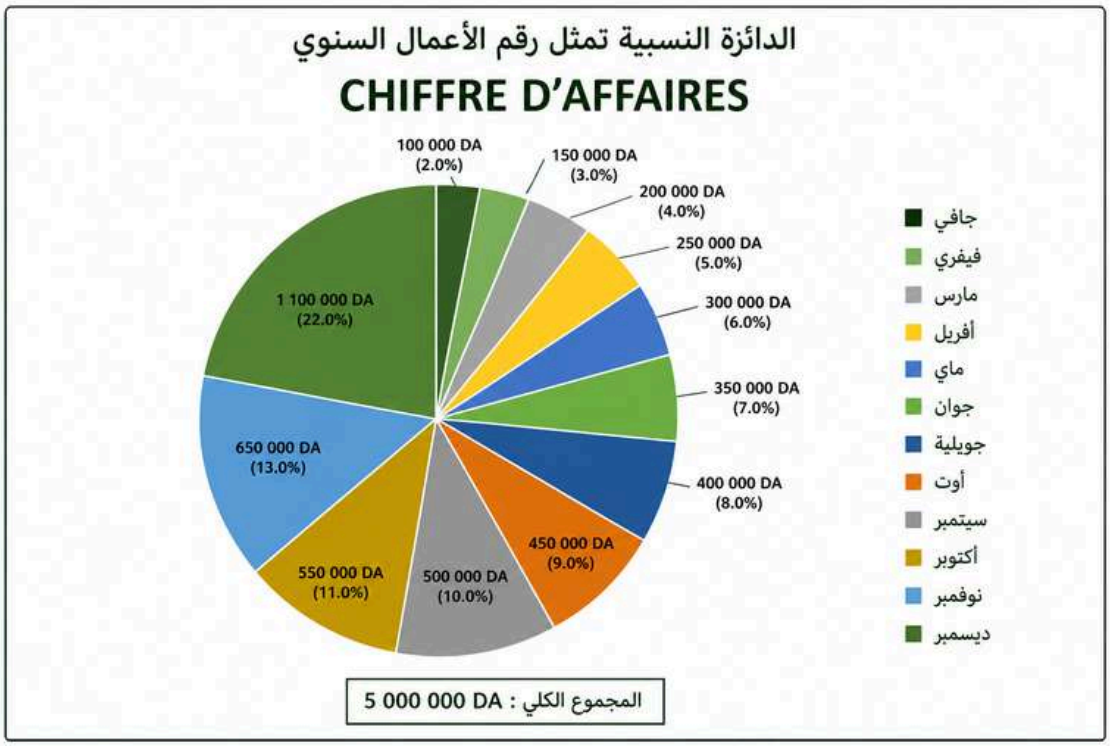
الحساب والبيان	السنة 1 (2026)	السنة 2 (2027)	السنة 3 (2028)
70 المبيعات والمنتجات المنحقة (رقم الأعمال)	5,000,000.00	7,500,000.00	12,000,000.00
I إنتاج السنة المالية	**5,000,000.00**	**7,500,000.00**	**12,000,000.00**
60-61-62 استهلاك السنة المالية (الاستهلاك الوسيط)	605,000.00	685,000.00	815,000.00
II استهلاك السنة المالية (الاستهلاك الوسيط)	**605,000.00**	**685,000.00**	**815,000.00**
III القيمة المضافة للاستغلال (II – I)	**4,395,000.00**	**6,815,000.00**	**11,185,000.00**
63 أعباء المستخدمين (رواتب المهندسين والخبراء)	210,000.00	270,000.00	520,000.00
64 الضرائب والرسوم	30,000.00	35,000.00	50,000.00
IV إجمالي فائض الاستغلال (EBE)	**4,155,000.00**	**6,510,000.00**	**10,615,000.00**
75 المنتجات العملياتية الأخرى	10,000.00	15,000.00	20,000.00
65 الأعباء العملياتية الأخرى	80,000.00	100,000.00	140,000.00
68 المخصصات للاهتلاكات والمؤونات (إهلاك الحواسيب والأجهزة)	112,000.00	112,000.00	112,000.00
78 الاسترجاعات عن خسائر القيمة والمؤونات	0.00	0.00	0.00
V النتيجة العملياتية (IV – 68)	**3,973,000.00**	**6,313,000.00**	**10,383,000.00**
76 المنتجات المالية	5,000.00	6,000.00	7,000.00
66 الأعباء المالية (المصاريف المالية الأخرى)	18,000.00	20,000.00	25,000.00
VI النتيجة المالية (76 – 76)	**- 13,000.00**	**- 14,000.00**	**- 18,000.00**
VII النتيجة العادية قبل الضرائب (V + VI)	**3,960,000.00**	**6,299,000.00**	**10,365,000.00**
695-698 الضرائب الواجب دفعها - (IBS) - معفي)	990,000.00	1,575,000.00	2,610,000.00
IX صافي تتيجة السنة المالية (النتيجة الصافية)	**2,970,000.00**	**4,724,000.00**	**7,755,000.00**

قدرة التمويل الذاتي (CAF / Cash-Flow)	**3,082,000.00**	**4,836,000.00**	**7,867,000.00**
معدل الربحية (هامش الربح %)	**35 %**	**40 %**	**45 %**

الشكل يمثل رقم الأعمال مقارنة بالمصاريف



الدائرة النسبية تمثل رقم الأعمال السنوي



PLAN DE TRÉSORERIE MENSUEL 2026

LIBELLÉ	JUILLET 2026	AQÛT 2026	SEPTEMBRE 2026	OCTOBRE 2026	NOVEMBRE 2026	DÉCEMBRE 2026
I. ENCAISSEMENTS						
Ventes	416 666,67	416 666,67	416 666,67	416 666,67	416 666,67	416 666,67
Capitaux propres	0,00	0,00	0,00	0,00	0,00	0,00
TOTAL ENCAISSEMENTS	**416 666,67**	**416 666,67**	**416 666,67**	**416 666,67**	**416 666,67**	**416 666,67**
II. DÉCAISSEMENTS						
Frais généraux	68 916,67	68 916,67	68 916,67	68 916,67	68 916,67	68 916,67
Investissements (hors développement application)	17 500,00	17 500,00	17 500,00	17 500,00	17 500,00	17 500,00
Développement de l'application	100 000,00	150 000,00	150 000,00	100 000,00	0,00	0,00
TOTAL DÉCAISSEMENTS	**186 416,67**	**236 416,67**	**236 416,67**	**186 416,67**	**86 416,67**	**86 416,67**
Solde début	0,00	230 250,00	410 500,00	590 750,00	821 000,00	1 151 250,00
Solde mensuel	230 250,00	180 250,00	180 250,00	230 250,00	330 250,00	330 250,00
SOLDE MENSUEL	**230 250,00**	**180 250,00**	**180 250,00**	**230 250,00**	**330 250,00**	**330 250,00**
SOLDE CUMULÉ	**230 250,00**	**410 500,00**	**590 750,00**	**821 000,00**	**1 151 250,00**	**1 481 500,00**

4. BILAN PRÉVISIONNEL

Intitulé	2024			2025	2026
	Brut	Amortissement	Montant net	net	net
Actif immobilisé net					
Immobilisations incorporelles	512 000,00	4 000,00	508 000,00	504 000,00	500 000,00
Immobilisations corporelles	800 000,00	130 000,00	670 000,00	540 000,00	410 000,00
Autres immobilisations financières	0,00	0,00	0,00	0,00	0,00
Total actif immobilisé	**1 312 000,00**	**134 000,00**	**1 178 000,00**	**1 044 000,00**	**910 000,00**
Actif circulant					
Stock de marchandise			0,00	0,00	0,00
Stock de matière première, fourniture			0,00	0,00	0,00
Stock de production			0,00	0,00	0,00
Stocks et en cours			0,00	0,00	0,00
Créances Clients			0,00	0,00	0,00
Banque			1 681 500,00	3 101 250,00	3 942 250,00
Comptes de tiers			0,00	0,00	0,00
Total actif circulant			**1 681 500,00**	**3 101 250,00**	**3 942 250,00**
TOTAL ACTIF			**2 859 500,00**	**4 145 250,00**	**4 852 250,00**
Passif					
Capitaux propres					
Capital			810 000,00	810 000,00	810 000,00
Réserves et report à nouveau			0,00	280 250,00	560 500,00
Résultat de l'exercice			280 250,00	280 250,00	280 250,00
Subvention investissement			0,00	0,00	0,00
Total Capitaux propres			**1 090 250,00**	**1 370 500,00**	**1 650 750,00**
Dettes					
Emprunts et dettes financières			0,00	0,00	0,00
Dettes fournisseurs			0,00	0,00	0,00
Autres dettes			0,00	0,00	0,00
Dettes rattachées			0,00	0,00	0,00
Total dettes			**0,00**	**0,00**	**0,00**
TOTAL PASSIF			**1 090 250,00**	**1 370 500,00**	**1 650 750,00**
TOTAL PASSIF			**2 859 500,00**	**4 145 250,00**	**4 852 250,00**

الملحق

1. Frais de personnel

Désignation	Montant 2026	Montant 2027	Montant 2028
Salaires bruts (Rémunérations Ingénieurs et Experts)	210 000,00	270 000,00	520 000,00
Total	**210 000,00**	**270 000,00**	**520 000,00**

2. Etat des investissements :

Nature des investissements	Montant année 1 (2026)	Montant année 2 (2027)	Montant année 3 (2028)
Licences et outils de développement	20 000,00	20 000,00	20 000,00
Serveurs cloud (AWS / DigitalOcean)	60 000,00	80 000,00	100 000,00
Données agricoles pour entraînement	20 000,00	20 000,00	20 000,00
APIs et interfaces IA	30 000,00	0,00	0,00
Ordinateurs pour développeurs	200 000,00	0,00	0,00
Appareils de test intelligents	100 000,00	0,00	0,00
Disques SSD & sauvegarde	80 000,00	0,00	0,00
Mobilier et aménagement bureau	60 000,00	0,00	0,00
Développement de l'application	**500 000,00**	**0,00**	**0,00**
Total	**1 070 000,00**	**120 000,00**	**140 000,00**

3. Etat des amortissements des investissements

Nature des investissements	Durée (Années)	Montant	Amortissements Annuels
Ordinateurs et équipements informatiques	5	200 000,00	40 000,00
Appareils de test intelligents	5	100 000,00	20 000,00
Disques SSD & sauvegarde	5	80 000,00	16 000,00
Mobilier et aménagement	5	60 000,00	12 000,00
Application mobile/Web	**5**	**500 000,00**	**100 000,00**
Total		**940 000,00**	**188 000,00**

4. Plan de financement

Actif	Montant	Passif	Montant
Licences et outils de développement	20 000,00	Financement propre	1 310 000,00
Serveurs cloud (AWS / DigitalOcean)	60 000,00		
Données agricoles pour entraînement	20 000,00		
APIs et interfaces IA	30 000,00		
Ordinateurs pour développeurs	200 000,00		
Appareils de test intelligents	100 000,00		
Disques SSD & sauvegarde	80 000,00		
Mobilier et aménagement bureau	60 000,00		
Mémoire et accessoires techniques	40 000,00		
Développement de l'application	**500 000,00**		
Total actif	**1 310 000,00**	**Total passif**	**1 310 000,00**

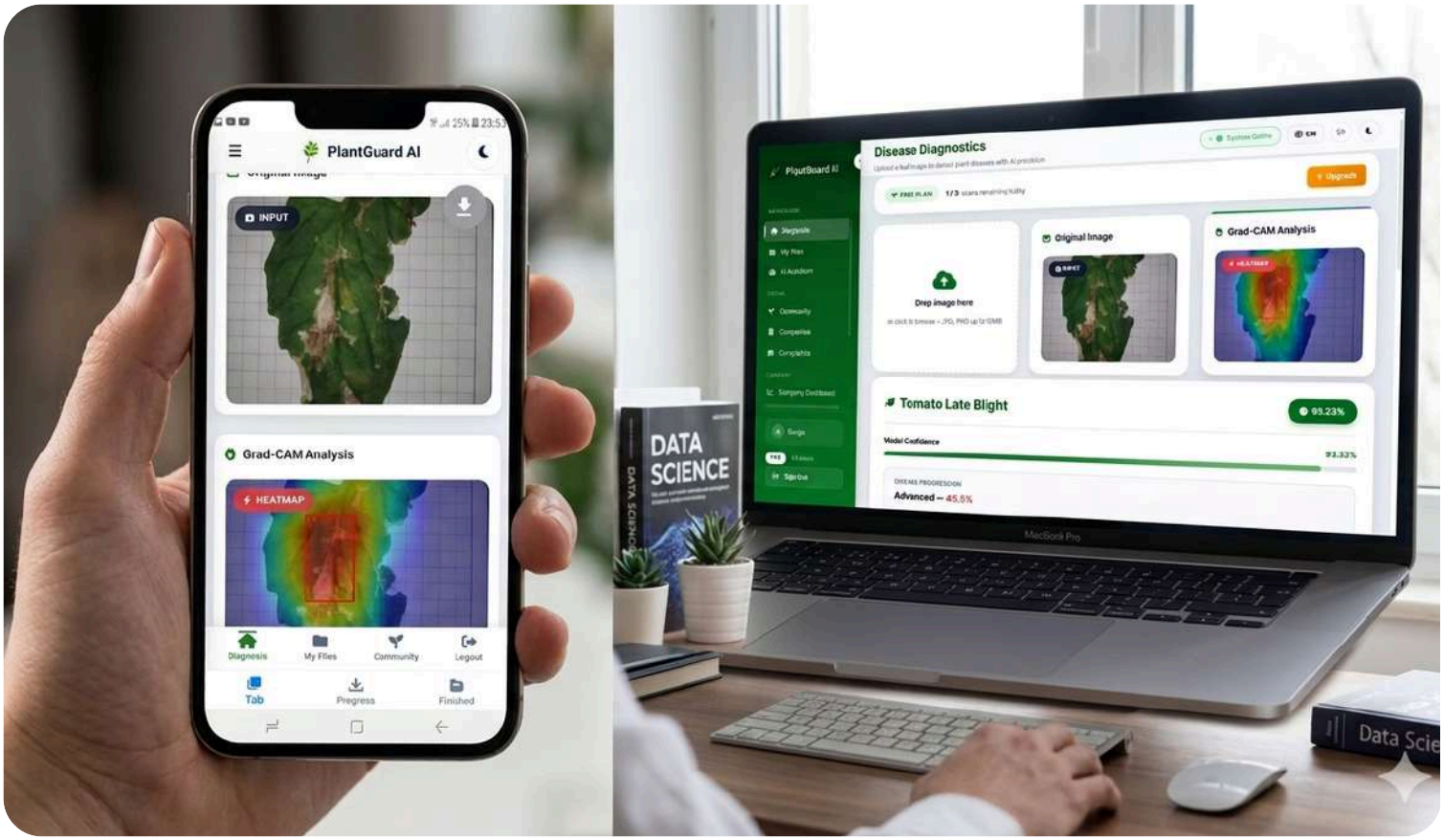
PLANTGUARD AI

المحور السادس:

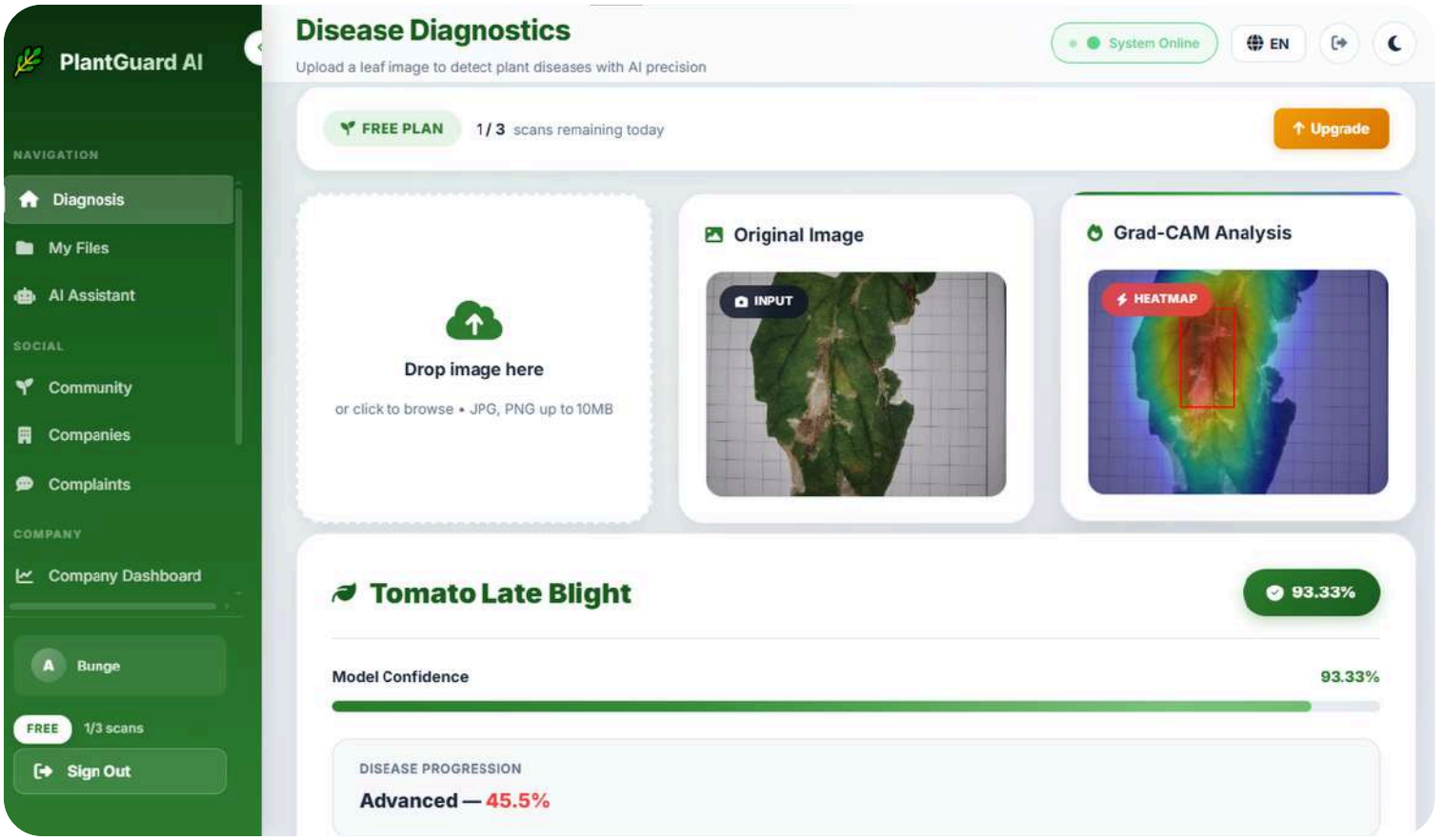
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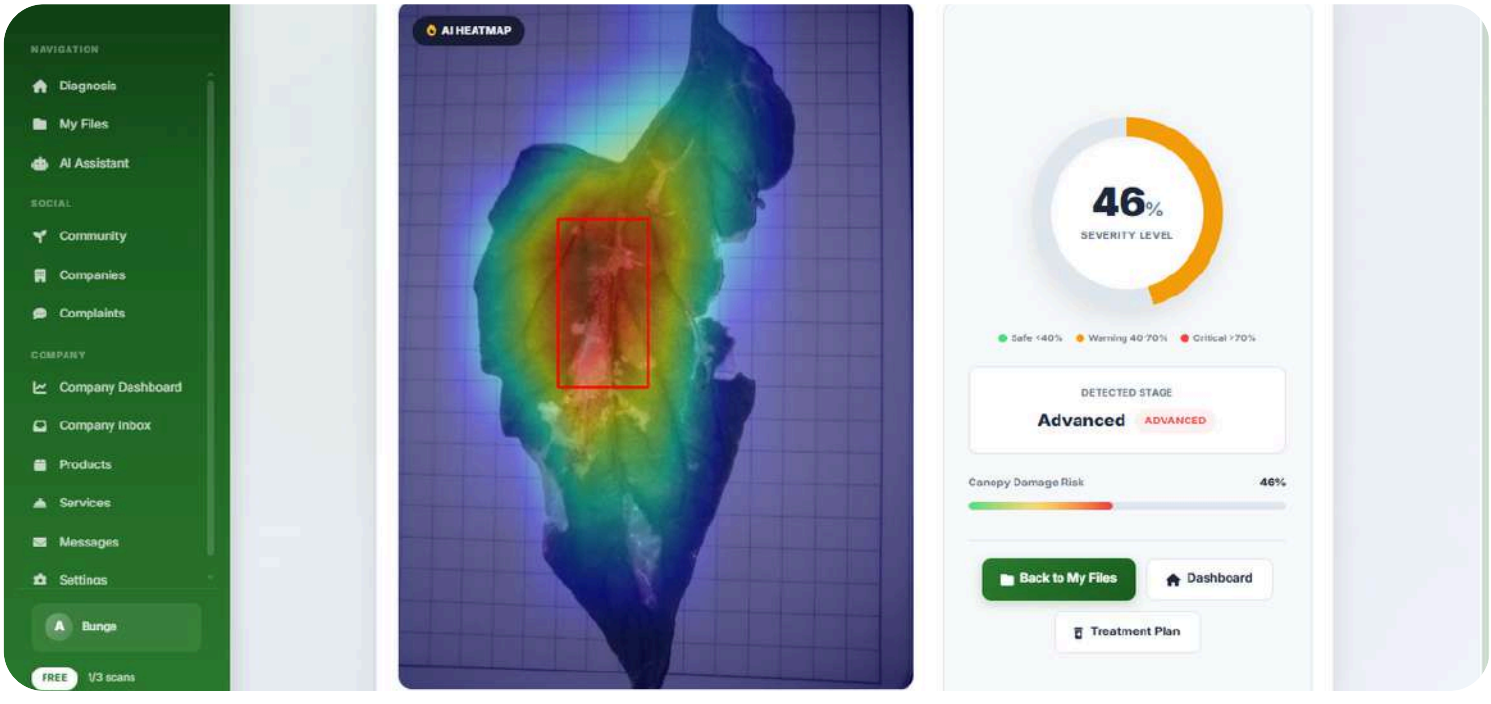


واجهة التطبيق (هاتف + حاسوب)

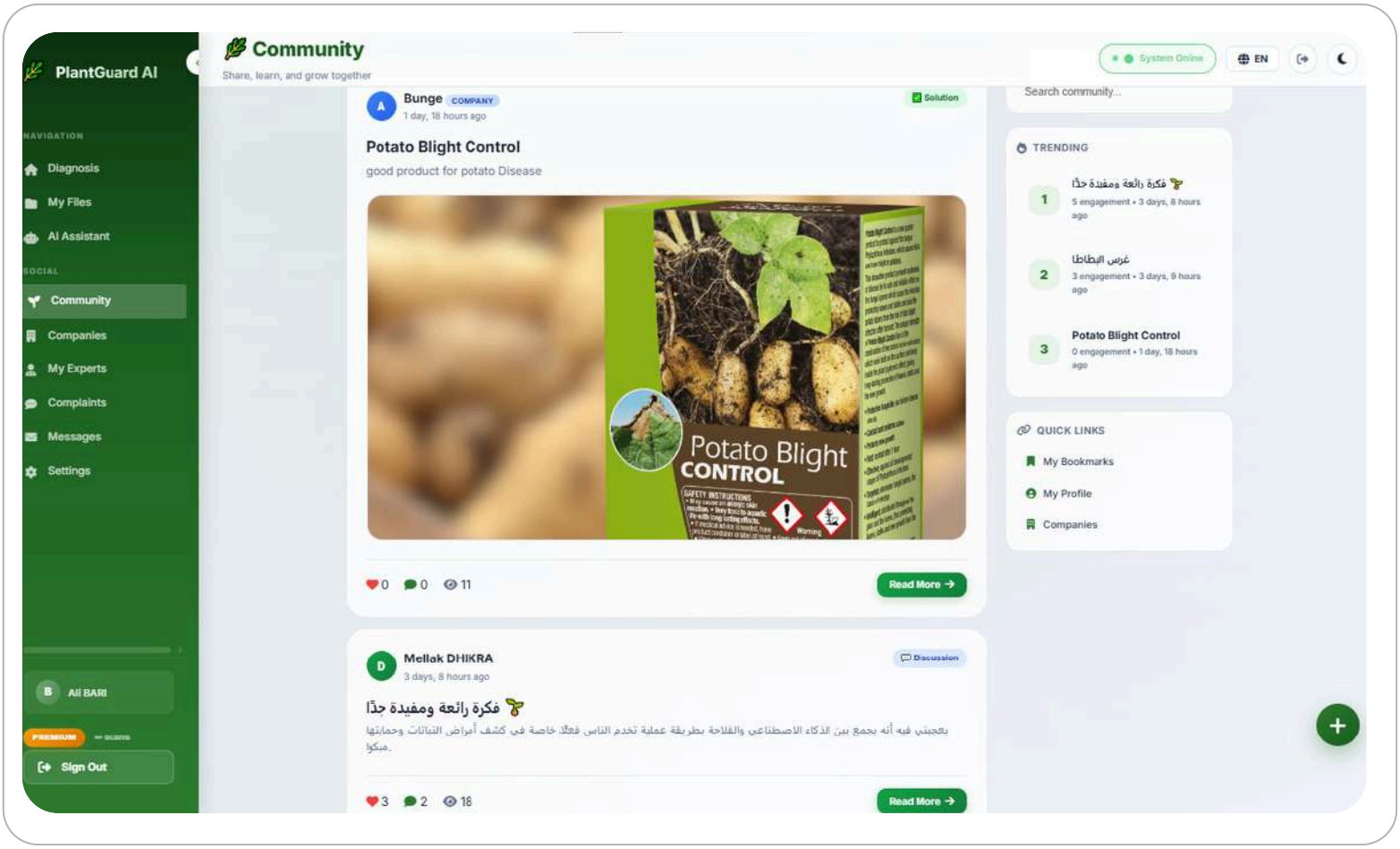


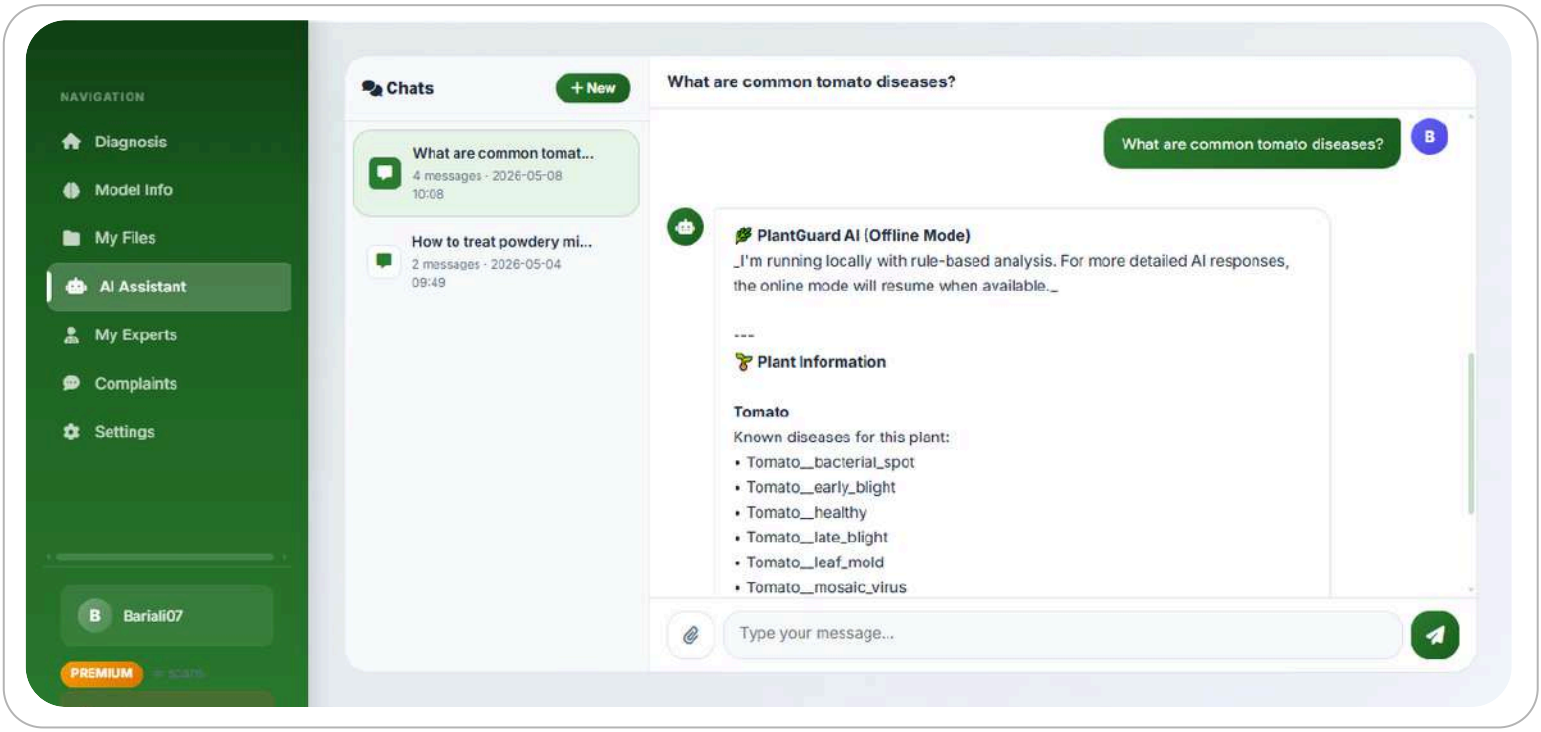
واجهة التطبيق PlantGuard AI



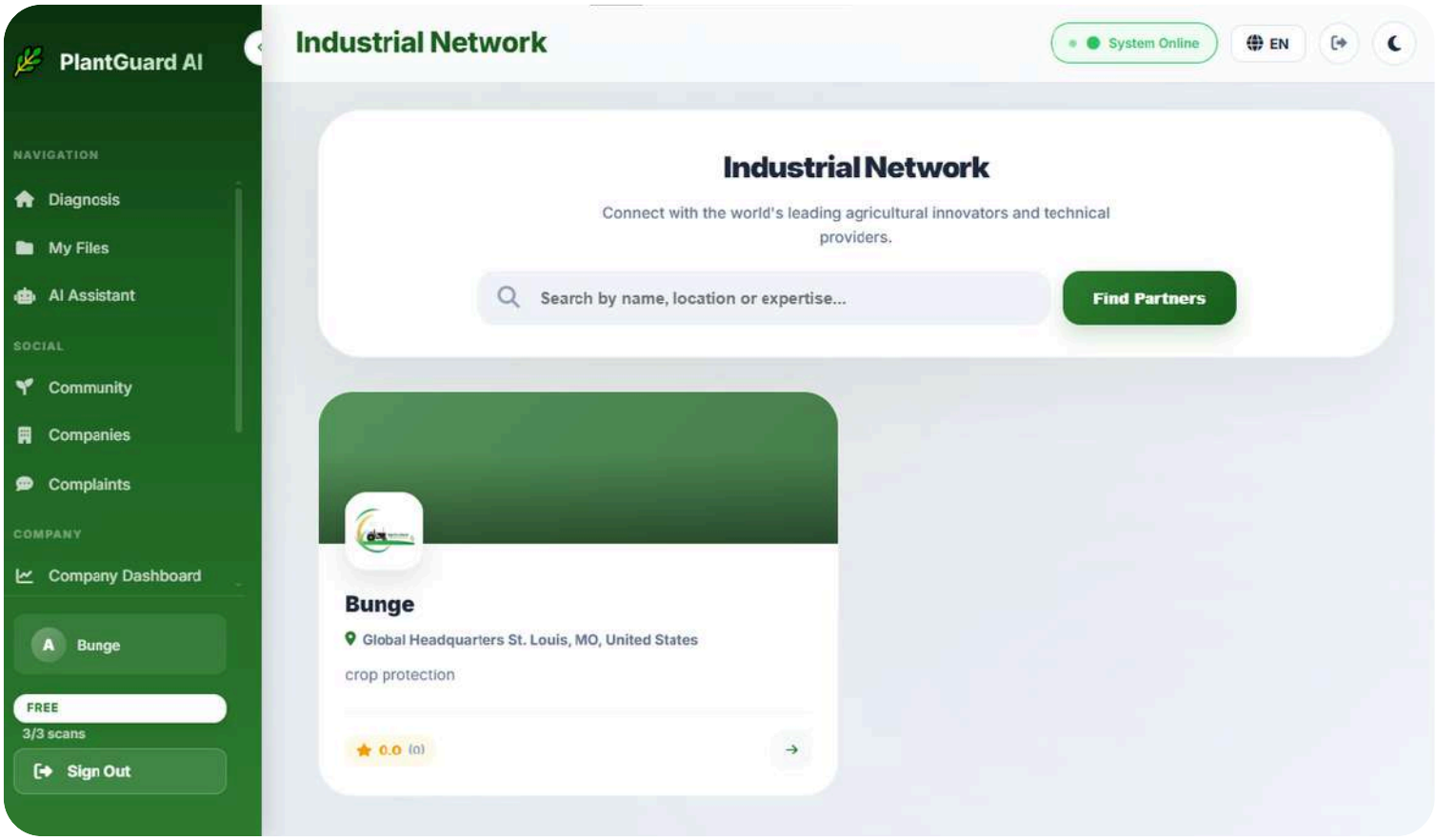


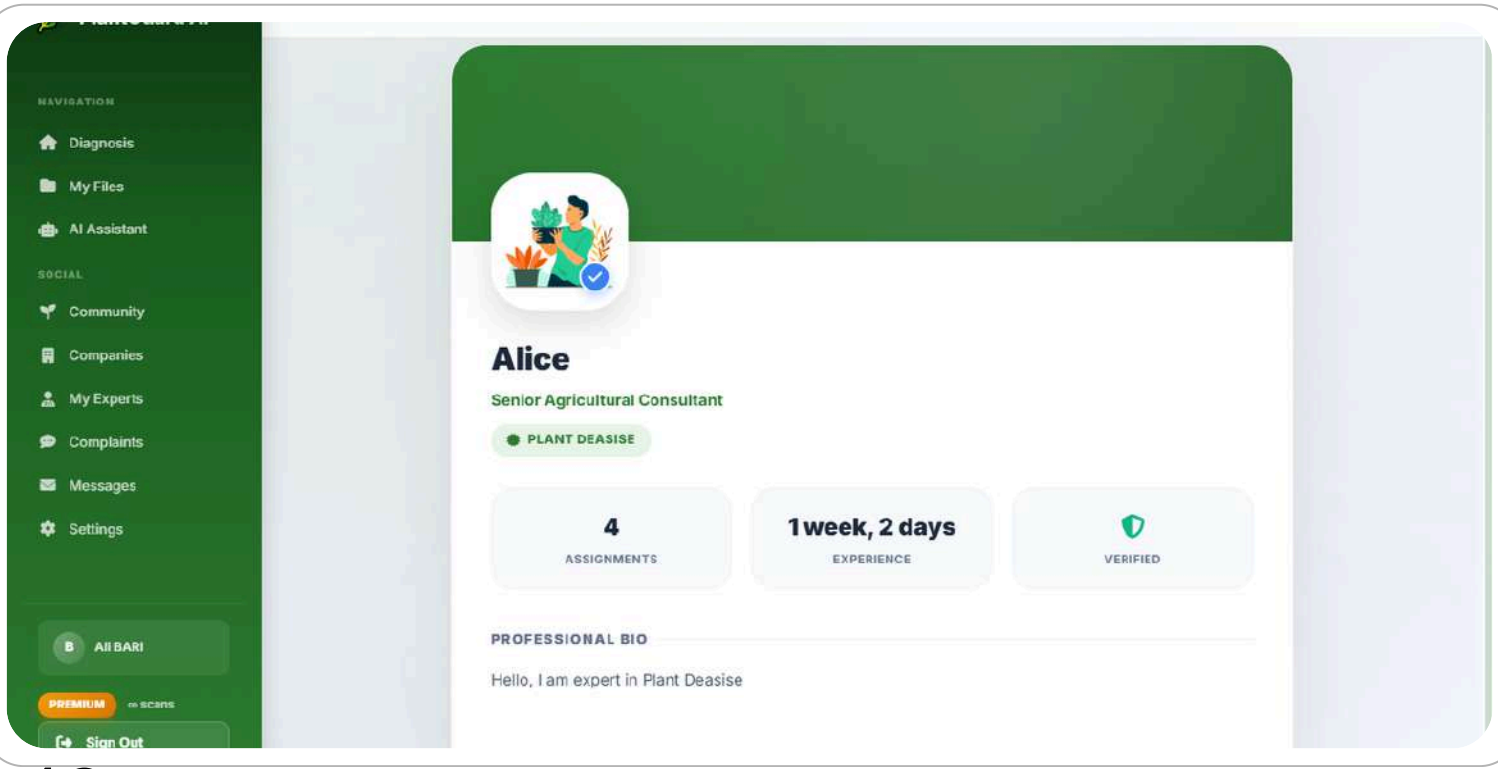
واجهة المجتمع و Chatbot





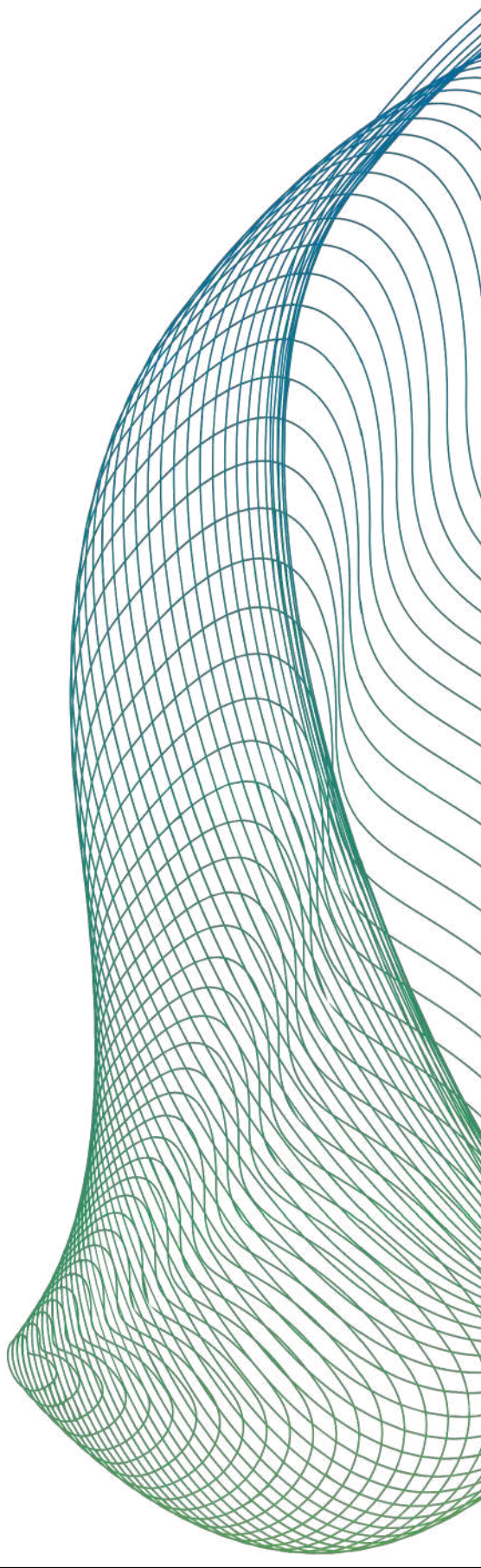
واجهة الشركات والخبراء





PLANTGUARD AI

قائمة الملاحق



نموذج العمل التجاري

BUSINESS MODEL CANVAS

