Journal of King Saud University Computer and Information Sciences (2025) 37:34
https://doi.org/10.1007/s44443-025-00040-3

REVIEW PAPER

A review on automated plant disease detection: motivation, limitations, challenges, and recent advancements for future research

Sajid Ullah Khan[1] · Anas Alsuhaibani[1] · Abdulrahman Alabduljabbar[1] · Fahdah Almarshad[1] · Youssef Altherwy[1] · Tallha Akram[1]

Received: 15 January 2025 / Accepted: 13 April 2025 / Published online: 9 May 2025

Abstract

Developing countries face significant challenges in healthcare, education, technological advancement, and farming, with agriculture playing an important role in economic growth. Ensuring adequate food production is essential for citizens' survival and economic stability. Early detection of plant disease is critical for increasing agricultural yields through efficient control methods. As a result, autonomous plant disease detection models are vital for reducing labor-intensive tasks. Machine learning and deep learning models have recently been introduced to automate disease identification in plants by detecting symptoms on their leaves. This study reviews various publications that use machine learning and deep learning approaches to detect plant and crop diseases. This review provides (i) an automated plant disease detection system, (ii) an automated wheat leaf rust detection system, (iii) publicly available plant disease datasets, (iv) an overview of machine learning and deep learning methods for plant disease detection, (v) remote sensing technology in plant disease detection, and (vi) future trends and research directions. This review is contributing to the literature by establishing a solid foundation for the development of more valuable machine learning and deep learning methods for plant disease detection. This review study critically examines various problems, including model generalization, dataset diversity, and computing factors, to assist prospective researchers in developing robust and scalable solutions. Additionally, this review presented a detailed overview of the limitations, challenges, and recent advancements in plant disease detection, especially in wheat leaf rust detection and remote sensing technology. Furthermore, current challenges and future directions in wheat disease detection are thoroughly discussed. This study provides a fundamental guide for the development of AI-driven algorithms, providing strategies to enhance production, profitability, and sustainability against climate change and population growth.

Keywords Plant disease · Leaf rust · Plant datasets · Machine learning · Deep learning · Remote Sensing

1 Introduction

Agriculture is a critical sector, especially in developing countries, due to its significant economic impact (Chen et al. 2024). It serves as a cornerstone for economic growth. However, traditional crop monitoring through visual examination by farmers and agriculture experts is time-consuming, inefficient, and prone to errors, risking potential future losses. In contemporary agriculture, viral diseases frequently impact plants, severely affecting the economic progress of agrarian nations. Early detection and classification of plant diseases are critical in improving food security and meeting global targets. According to the World Health Organization (WHO), the global population will reach around 7.837 billion in 2021, illustrating the increased demand for food as the population grows.

Advanced technologies such as computer vision (CV), machine learning (ML), deep learning (DL), image processing (IP), and the internet of things (IoT) have the potential to revolutionize agriculture by enhancing production, reducing waste, and increasing profits. Timely implementation of remedial actions and accurate disease diagnosis can significantly boost crop health and yield, ensuring high-quality wheat cultivation and maximizing profits for farmers. The agricultural sector is increasingly reliant on the critical roles played by CV, DL, IP, and IoT (Demilie 2024). Unlike

✉ Sajid Ullah Khan
sk.khan@psau.edu.sa

[1] Department of Information Systems, College of Computer Engineering and Sciences, Prince Sattam Bin Abdulaziz University, 11942 Alkharj, Saudi Arabia

traditional feature-based techniques such as random forests, decision trees, and support vector machines, modern approaches offer a fundamental shift in agricultural practices.

This review provides a detailed overview of the state-of-the-art methods for plant disease detection, with a focus on the most widely used artificial intelligence (AI) techniques, such as ML, DL, and image processing (IP) algorithms. It thoroughly assesses the limitations, challenges, motivations, and future trends and research directions of these methodologies in real-world applications. Multiple studies have demonstrated the value of plant disease detection research. Figure 1 shows the annual publication results of the plant disease detection, retrieved from the Web of Science (WoS) platform, which provides access to several academic databases.

Figure 1 reveals that 4640 articles on plant disease detection have been published since 2011, employing ML and DL methodologies. The increasing publication rate each year reflects the growing demand for automated plant disease detection. In the present study, research publications were retrieved using several search keywords, including'plant leaf disease identification,''plant disease classification,'' ML,''DL,'and'IP'from different academic databases. After accumulating articles from various databases, we used precise selection criteria to decide which ones to include or omit, as shown in Table 1.

Table 1 shows that research publications were retrieved using several search keywords, including “short-length articles or articles without relevant facts” which were disregarded. Publications for additional evaluation were chosen based on their quality assessment standard marks. Numerous review and survey studies have described plant disease detection using ML and DL, each with unique strengths and limitations. Table 2 compares this study with recent state-of-the-art literature evaluations. The specific contributions of the work are highlighted below:

i. Automated plant disease detection systems.
ii. Wheat leaf rust detection systems.
iii. Publicly available datasets.
iv. An overview of ML and DL techniques for plant disease detection.
v. Remote sensing technologies for plant disease detection.
vi. Future trends and research directions.

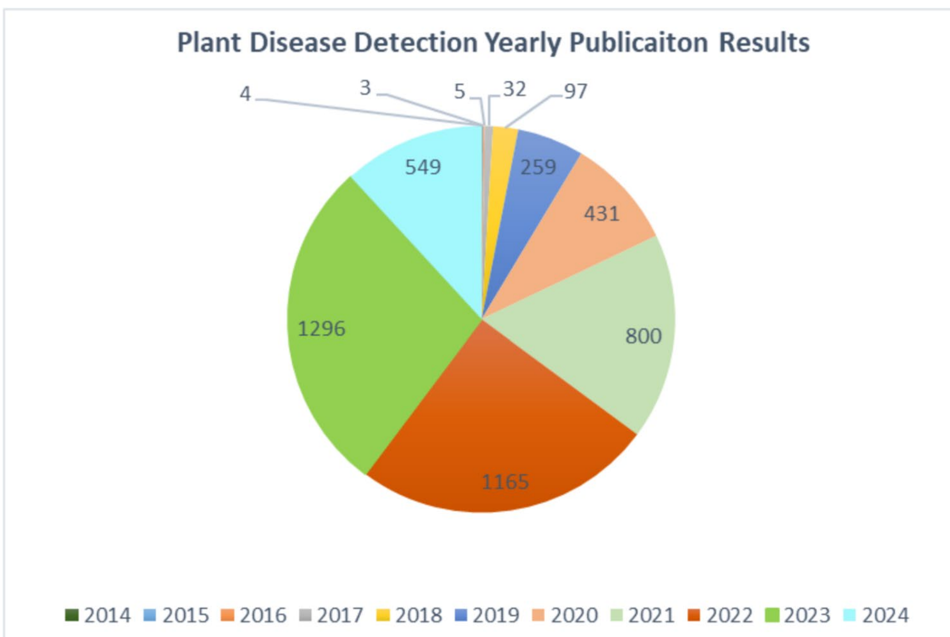


Fig. 1 Number of plant disease detection annual publication results [WoS 2011–2024]

Table 1 Articles selection criteria

Included studies	Excluded studies
Plant disease detection using DL	Articles published in non-indexed journals
Plant disease detection using ML and IP	Short-length articles
Articles published between 2011–2024	Languages other than English
Articles published in WoS and Scopus-indexed journals	Articles without relevant materials

Table 2 shows the prominent review articles covering plant disease detection using ML and DL methods. However, publicly available datasets, detailed studies on comparison of ML and DL models used for plant disease detection, remote sensing technology used in plant disease detection, limitations, challenges, and future work have not been thoroughly discussed. Figure 2 illustrates the overall structure of this review work.

The rest of the paper is organized as follows:

Section 2 discusses an automated plant disease detection system. Section 3 presents the specific area of wheat leaf rust detection using ML and DL methods, and publicly available datasets are discussed in Sect. 4. Section 5 covers a detailed explanation of ML and DL methods for plant disease detection. Section 6 covers remote sensing technology in integration with ML and DL methods, and Sect. 7 presents future trends and research directions in detail. At the end, the review work is concluded in Sect. 8.

2 Automated plant disease detection systems

Automated plant detection systems have dramatically changed environmental monitoring and agriculture by providing accurate, real-time analysis of plant health, species identification, and environmental conditions using advanced technologies (Walsh et al. 2024). These methods provide extensive data from a range of scales and viewpoints. Software tools for image processing improve the quality of the

Table 2 Comparison of recent review articles of literature

Review (Year of Publication)	Plant disease detection using ML, DL	Publicly available datasets	Remote Sensing Technology in Plant Disease Detection	Comparison of ML and DL models used for plant disease detection	Limitations of ML and DL models for plant disease detection	Challenges	Future Work
(Jackulin and Murugavalli 2022)	√	x	x	√	√	x	x
(Shafik et al. 2023)	√	x	x	x	x	√	√
(Prasath 2023)	√	x	x	√	x	√	√
(Ngongoma et al. 2023)	√	x	x	√	√	x	√
(Demilie 2024)	√	x	x	√	x	√	√
This study	√	√	√	√	√	√	√

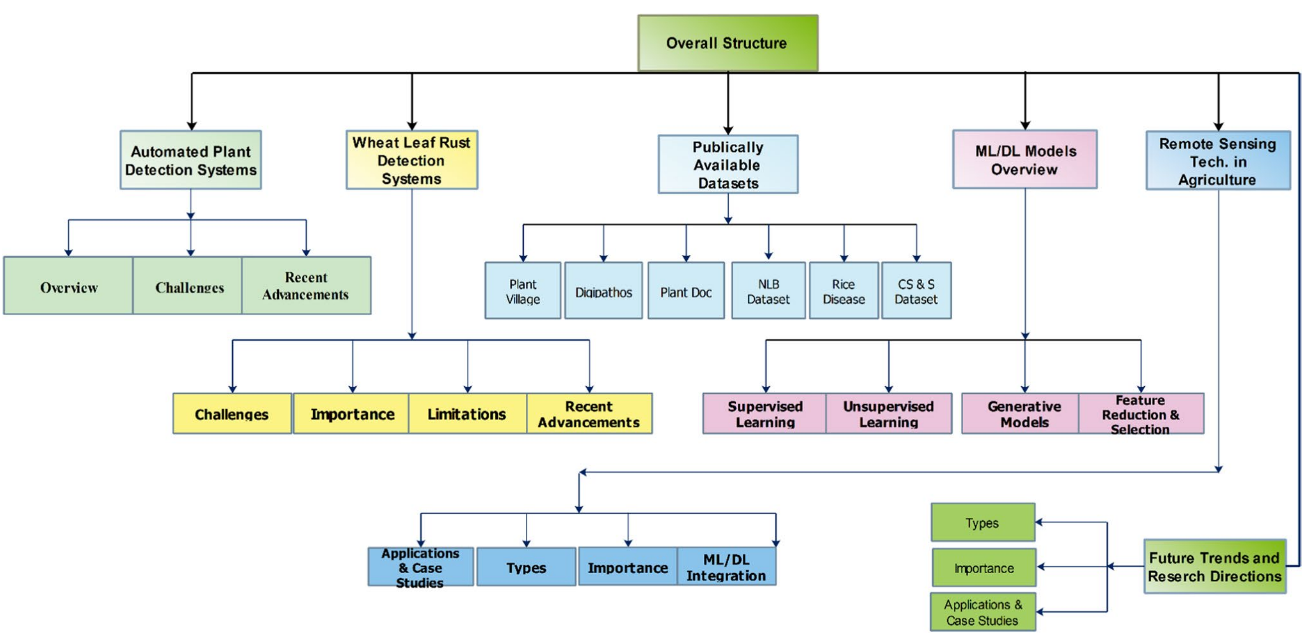


Fig. 2 Overall structure of the paper

input image and algorithms for feature extraction detect and identify the important characteristics of the plants (Walsh et al. 2024). CNNs and RNNs are two examples of machine learning and deep learning algorithms utilized to categorize plant species, identify diseases, and track the phases of plant development (Angamuthu and Arunachalam 2023). Furthermore, time-series graphs, 3D models, and heat maps are just a few of the actionable insights provided by data analysis and visualization technologies. In addition, these systems include automation and control features. Using real-time data, they may be integrated with Internet of Things (IoT) devices to regulate pest management, fertilization, and irrigation. Automated plant detection systems improve agricultural productivity via accurate crop monitoring and management, which raises yields, uses fewer resources, and promotes sustainable farming methods. They are essential resources in agriculture because they monitor biodiversity, forest health, and ecological changes, all supporting attempts to conserve the environment.

2.1 Overview of automated systems

Advanced technologies are used by automated plant disease detection systems to accurately analyze plant health in real-time, identify species, and assess environmental factors. These systems combine high-resolution cameras placed on drones, satellites, and ground-based platforms with hardware components such as optical, light and ranging (LiDAR), and hyperspectral sensors. To analyze and understand data, they use data visualization platforms, as well as machine learning techniques like CNNs and RNNs for classification and the image processing tools on the software side. By automating processes that were previously completed by hand, these systems improve agricultural sustainability, productivity, and accuracy. They also support efficient environmental monitoring and conservation initiatives.

2.1.1 Hardware components

Sensors Optical sensors are normally used for capturing high-resolution images at several wavelengths, such as visible infrared and multispectral bands. These sensors are essential parts of automated plant detection systems. Using these sensors makes it possible to analyze plant features, including leaf color, shape, and reflectance elements critical for classifying species, recognizing diseases, and evaluating general health. Optical sensors collect data on plant health and stress levels by sensing light reflected from plant surfaces. They enable large-scale monitoring and precision agriculture by mounting on platforms such as drones, satellites, or ground vehicles (Ciobotari et al. 2024). This allows farmers to make well-informed choices about irrigation, fertilization, and pest control, eventually improving crop output and sustainability. Moreover, LiDAR and hyperspectral are two different types of sensors used to capture plant images (Ciobotari et al. 2024; Stamford et al. 2024). LiDAR sensors accurately capture three-dimensional (3D) images of plant structures and landscapes. These sensors provide accurate maps of plant height, canopy density, and geographical distribution by releasing laser pulses and timing how long they take to return after striking a surface. LiDAR is used in plant detection systems to monitor growth, evaluate plant health, and identify structural changes over time (Kamarianakis et al. 2024). By delivering precise and valuable data, LiDAR sensors on drones, satellites, or ground-based platforms allow for extensive, high-resolution environmental monitoring (Ciobotari et al. 2024). This helps to enhance forest management, agricultural practices, and ecosystem protection. Hyperspectral sensors provide precise spectral information for every pixel in an image by capturing various wavelengths throughout the electromagnetic spectrum. This makes it possible to distinguish minute variations in plants'properties, such as the amount of pigment, moisture, and nutrients (Stamford et al. 2024). These sensors, which may be installed on drones, satellites, or ground platforms, provide extensive, high-resolution data for well-informed decision-making (Ram et al. 2024). This enables thorough crop health and yield study, enabling environmental monitoring and precision agriculture.

Imaging devices The standard digital as well as the thermal cameras are used for capturing high-resolution images necessary for in-depth analysis[(Kamarianakis et al. 2024). Standard digital cameras, such as DSLRs or even a smart phone camera, capture images in standard RGB format. They have sensors made of millions of tiny light-sensitive elements called pixels. On the other hand, thermal cameras may identify stressors such as water shortages by measuring temperature changes. These cameras, which may be installed on drones, satellites, and ground vehicles, provide a wide range of visual data that makes it easier to accurately identify plant species, detect diseases, and track the health and development of crops in precision agriculture (Kamarianakis et al. 2024). Additionally, thermal cameras capture infrared radiation to assess temperature differences across plant surfaces, and they are vital components of automated plant detection systems (Chelladurai and Sujatha 2024). By detecting the heat plants release, these cameras can identify stressors, including diseases, insect infestations, and water shortages. Thermal cameras aid farmers in the monitoring of plant health, the optimization of irrigation schedules, and the early detection of any problem by viewing temperature changes. Thermal cameras, whether installed on drones, satellites, or ground-based platforms, provide insightful data for precision agriculture. This information enables prompt interventions and well-informed decision-making, improving agricultural yield and sustainability.

Similarly, unmanned aerial vehicles (UAVs), satellites, and ground-based vehicles are used more frequently in plant disease detection systems due to their rapid and practical ability to gather high-resolution data across wide regions. UAVs, outfitted with an array of sensors and cameras ranging from RGB to hyperspectral, multispectral, and thermal, provide comprehensive images and data critical for tracking crop health, evaluating growth phases, and identifying diseases. Compared to satellites, UAVs can fly at low altitudes, providing a closer and more accurate image of the plants (Thakur and Srinivasan 2024). Satellites with sophisticated sensors, such as optical, multispectral, and hyperspectral cameras, are able to gather extensive data on the growth, health, and environmental conditions of plants across large geographic regions (Segarra 2024). Monitoring crop health, identifying stressors, and evaluating biomass and vegetation cover are all made easier with the use of satellite images. Satellites are a priceless tool for monitoring changes in forests, ecosystems, and agricultural fields because of their capacity to gather data across large regions and over time (Najafabadi and Kazemi 2024). ML, DL, remote sensing and crop row technologies are widely used in the field management operations, crop phenotyping, and other fields such as green stormwater infrastructure (Zhang et al. 2024; Xue et al. 2024).

2.1.2 Software components

Image processing software In plant detection systems, preprocessing tools are essential for improving raw data and subsequently improving the accuracy and efficiency of analysis. These tools provide high-quality input for machine learning models by completing noise reduction, image improvement, and distortion correction tasks (Mojaravscki and Graziano Magalhães 2024). Plant characteristics are separated from the background using segmentation techniques, which provide accurate analysis. The preprocessing stages in precision agriculture and environmental monitoring are critical for extracting relevant information from raw sensor and image data. This process ultimately leads to improved accuracy in plant species identification, disease detection, and health assessment. Moreover, feature extraction algorithms for extracting features from raw data are essential to plant detection systems because they help extract the most relevant information and enable precise analysis and classification (Karthickmanoj et al. 2023). These algorithms extract critical properties, including form, texture, color, and spectral fingerprints, from data from various sensors and imaging equipment. To identify diseases and stress situations, plant surfaces are examined using texture analysis tools, such as the Gray-Level Co-occurrence Matrix (GLCM). By examining color changes, color analysis, which makes use of color histograms and color space transformations, helps determine nutrient deficits and plant health (Diker et al. 2024). Furthermore, spectral analysis is used to extract features from multispectral and hyperspectral data to ascertain plants'physiological state and biochemical characteristics. Tasks like species classification, disease diagnosis, and growth monitoring are made possible by these extracted characteristics, which are essential for training machine learning and deep learning models. Efficient feature extraction contributes to precision agriculture and environmental conservation by strengthening the resilience and accuracy of plant disease detection systems.

2.1.3 Data analysis and visualization tools

Data analysis and visualization are essential parts of plant disease detection. Various statistical analysis tools are essential for plant detection systems. With the aid of this program, agronomists and researchers may use a variety of statistical methods to comprehend connections, spot patterns, and find irregularities in plant data. Regression analysis, for instance, may be used to simulate the link between environmental conditions and plant health, while cluster analysis aids in the classification of plants according to shared traits. Variance analysis and hypothesis testing make it possible to evaluate the effects of various farming techniques on crop productivity and health. Statistical analysis tools (Morchid et al. 2024) allow users to improve crop management techniques, maximize resource use, and make data-driven decisions. This results in improved plant ecosystem monitoring and conservation, as well as increased agricultural output and sustainability.

Moreover, plant detection systems need visualization platforms because they convert complicated data into easily understood visual representations that speed up comprehension and decision-making. These platforms use sophisticated tools to produce time-series graphs, heat maps, and 3D models that facilitate the interpretation of data from various sensors and imaging equipment. Heat maps, for example, may be used to identify stressed regions in a field, and 3D models can be used to show the intricate details of plant development patterns and structures. Time-series graphs help identify patterns and abnormalities by tracking plant growth and health changes over time. These platforms provide farmers, researchers, and agronomists the capacity to monitor crop health, evaluate the efficacy of treatments, and make well-informed choices to improve agricultural production and sustainability via the use of interactive and clear visualizations. Thus, visualization systems are essential for converting unprocessed data into meaningful insights that can be used to further environmental preservation and precision farming (Diker et al. 2024; Morchid et al. 2024).

2.1.4 Control and automation systems

Modern plant disease detection systems rely heavily on automated decision-making systems to enable data-driven, real-time operations without the need for human interaction. These systems evaluate data gathered from sensors and imaging devices using sophisticated algorithms like machine learning and artificial intelligence. Automated decision-making systems may detect problems and suggest or carry out remedial activities by analyzing data on plant health, growth patterns, and environmental variables. For instance, they may start pest management procedures when they see indications of an infestation, administer fertilizers in response to nutritional deficits found in plants, or activate irrigation systems when soil moisture levels are low (Mohammad et al. 2024). By guaranteeing timely and effective resource usage, these technologies improve precision agriculture and eventually increase agricultural yields and sustainability. Additionally, automated decision-making systems lessen the need for human monitoring, freeing up farmers to concentrate on other essential duties and improving farm management as a whole. Similarly, automated plant detection systems capabilities significantly increase when they are integrated with IoT devices (Mohammad et al. 2024). IoT devices continually gather and communicate data on a variety of environmental factors. These devices include weather stations, intelligent irrigation systems, and soil moisture sensors. Real-time data on temperature, humidity, soil conditions, and other important variables can be easily input into machine learning models and decision-making algorithms by combining these sensors with plant detection systems. This integration makes it possible to manage crops holistically and to make timely and accurate interventions. Similarly, IoT-enabled pest sensors and traps may identify early indicators of a pest infestation and initiate automated pest management programs to safeguard crops (Anju and Swaraj 2024). Moreover, integrating IoT devices makes remote field administration and monitoring easier. Farmers and agronomists may get up-to-date information and insights with mobile applications or online dashboards, facilitating decision-making from any location (Anju and Swaraj 2024). Precision agriculture is supported by this networked ecosystem of tools and systems, which also increase production, decrease resource waste, and encourage sustainable agricultural methods.

2.2 Challenges with automated plant disease detection systems

Automated plant disease identification with ML and DL provides appealing details to agricultural challenges, but it also has significant limitations that must be addressed in order to improve its effectiveness and dependability. Here are several major limitations:

- High-quality and well-labelled datasets are required for training ML and DL techniques. However, collecting a huge volume of precisely labeled data is difficult due to resource constraints and is also time-consuming. Similarly, class unbalancing results in biased models.
- Lighting variations such as images captured with low or high lighting conditions and background noise, shadows, and blurriness can have a major impact on image quality, making it difficult for the ML and DL techniques to identify initially and later classify.
- Multiple diseases at the same time can make diagnosis more difficult.
- Model generalization leads to an overfitting problem. Models trained on specific datasets may not generalize well to new and unseen data, particularly if there are major variations in environmental conditions.
- Computational resources, interpretability and explainability, scalability and development, and practical considerations are the major limitations occurring in plant disease detection using ML and DL.

Addressing these limitations requires a multi-faceted approach, including the development of better data collection methods, robust algorithms capable of handling diverse conditions, improved model interpretability, and practical solutions for field deployment. Collaborative efforts between researchers, agricultural experts, and technology developers are essential to overcome these challenges and fully realize the potential of automated plant disease detection (Figs. 3 and 4).

3 Wheat leaf rust detection

The fungus Puccinia triticina is the source of wheat leaf rust, which may result in severe yield losses and decreased grain quality. It poses a serious danger to the world's wheat supply. Food security and the mitigation of disease impacts rely on early detection and treatment. Traditional detection methods rely on proficient pathologists or agronomists to inspect the leaves for rust-colored pustules, which indicate the disease. This method is labor-intensive, time-consuming, and prone to human mistakes, even if it works well. Although laboratory-based methods such as pathogen cultivation and microscopy are accurate, they are time-consuming and necessitate specialized expertise. Recent technological developments have brought automated solutions that improve wheat leaf rust detection by using ML and DL algorithms (Kumar et al. 2024a). The CNN family is extensively used in image classification that automatically identify healthy and unhealthy leaves based on the features extracted from the images. With the use of these automated methods, wheat leaf rust could be accurately monitored, which in turn facilitates prompt and efficient disease control. These methods increase the

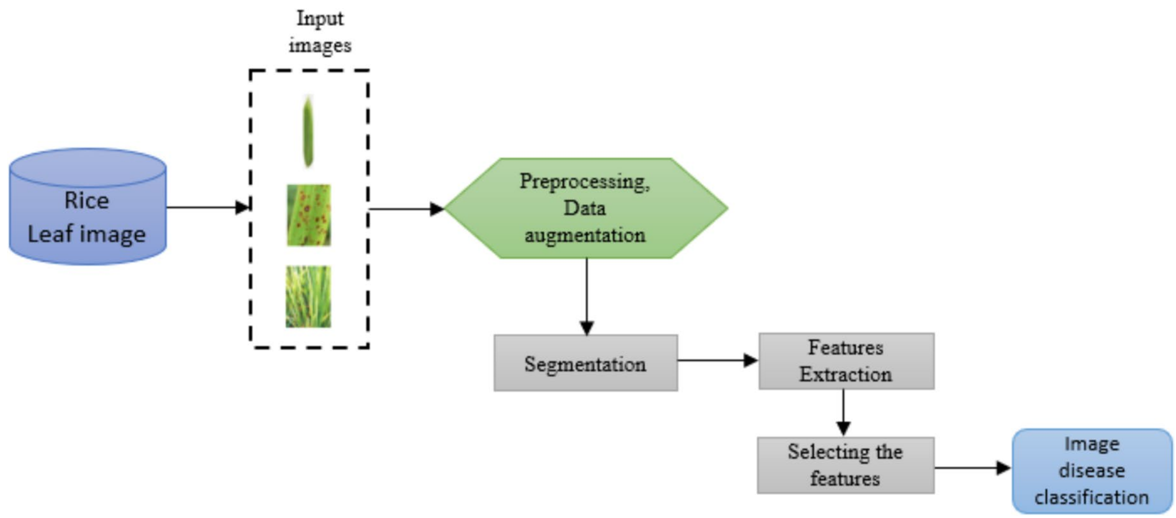


Fig. 3 The fundamental procedure for identifying images of rice plants

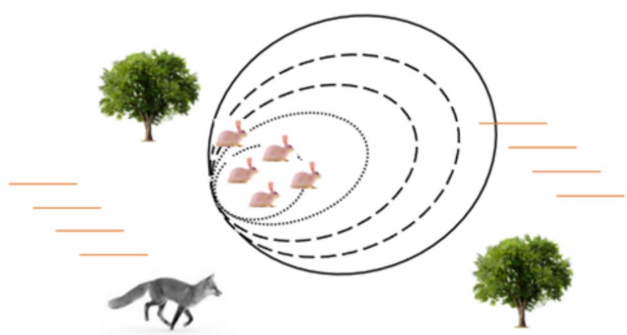


Fig. 4 Red fox hunting habits (Dubey and Choubey 2024)

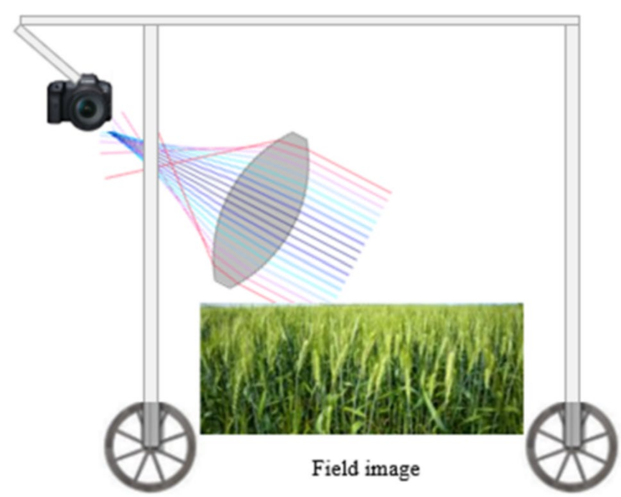


Fig. 5 A vehicle positioned on the ground to gather wheat images from various perspectives

efficacy and efficiency of disease control tactics in wheat production by decreasing the dependence on labor-intensive, conventional approaches. Figure 5 displays images of wheat plants at various phases of growth and under various meteorological circumstances (Kumar et al. 2024a).

3.1 Challenges in developing ML and DL-based wheat leaf rust detection systems

Although ML and DL techniques for wheat leaf rust detection provide prospective solutions to current agricultural problems, a number of constraints still need to be overcome:

3.1.1 Wheat leaf rust data set collection

The development of powerful ML and DL models for the automated identification and classification of wheat leaf rust caused by Puccinia triticina necessitates the compilation of a comprehensive dataset. The initial phase of identifying wheat leaf diseases involves data collection in both field and greenhouse environments. Figure 6 illustrates the automatic classification of wheat leaf diseases.

Images are captured in the field under diverse climatic conditions to depict real-world scenarios, including varying illumination, moisture levels, and stages of plant growth (Usha Ruby et al. 2024). The regulated environment of greenhouse collections guarantees uniform lighting and backdrop settings, which aid in the capture of sharp and focused images of the disease. High-resolution cameras and smartphones equipped with sophisticated image-capturing functions are

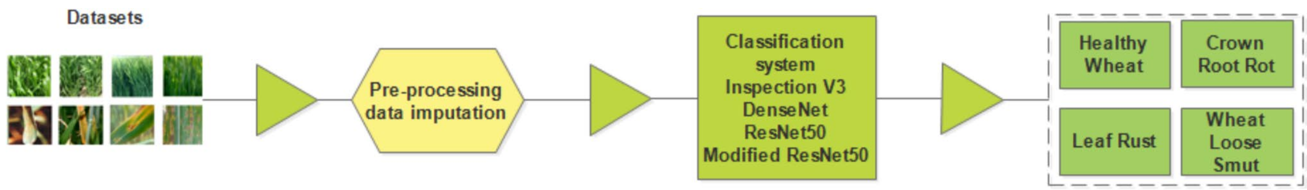


Fig. 6 Framework for automatic classification of wheat leaf diseases

used to capture detailed images (Raja and Nargunam 2024). In addition, camera-equipped drones and UAVs are utilized to cover huge field areas effectively by taking images from various heights and angles. Geographically, the sampling is diverse; images are gathered from several sites to represent a variety of environmental factors and disease prevalence rates. Temporal variety is also ensured by taking images at various points during the growth season to capture distinct phases of disease development. Annotating and labeling data are essential processes. By manually labeling images, specialists can distinguish between healthy and diseased regions and precisely delineate the limits of rust lesions.

Additionally, expert correction may be applied to automated pre-labeling via machine learning models to improve accuracy and efficiency. Preprocessing includes reducing images to a standard resolution for consistent input into models and segmenting images to separate affected areas from the background. To improve model generalization, data augmentation methods, including flipping, rotation, etc., are used to expand the size and variety of the dataset.

Implementing quality control methods involves many rounds of review and verification to guarantee the precision and caliber of the annotated data. To validate the model's performance and ensure it applies well to fresh, untested data, a portion of the dataset is put aside. For research purposes, the final dataset is assembled and made publicly available, together with its annotations and metadata describing the location, time, environmental conditions, and other pertinent information. This extensive and meticulously annotated dataset facilitates the creation of efficacious AI-driven detection systems, hence helping the timely identification and control of wheat leaf rust and, eventually, sustainable farming methods and food security (Joseph et al. 2024). Different wheat leaf diseases are illustrated in Fig. 7.

3.1.2 Model generalization

Due to variations in wheat cultivars, rust strains, and environmental factors, variability in wheat leaf rust symptoms presents a severe difficulty. This fluctuation may make it more difficult for models to make meaningful generalizations across a range of rust appearances and situations. Furthermore, overfitting may occur in deep learning models, especially in those with intricate structures (Jafar et al. 2024). When a model performs very well on training data but is unable to generalize to new and unknown data, this may lead to the problems of overfitting and underfitting. These problems restrict the usefulness of these models, as they may not be able to anticipate or recognize rust symptoms in a variety of real-world scenarios. These difficulties demonstrate the need for robust model construction and abundant training data.

3.1.3 Computational pesources

A major difficulty is that training DL models for wheat leaf rust detection requires a lot of computing resources, including GPUs and large amounts of RAM. This lack of resources might make it more challenging to train and optimize models, especially for small research teams or individual farmers who don't have straightforward access to expensive gear (Pavithra et al. 2023). Further computational hurdles arise when real-time rust detection algorithms are implemented on resource-constrained devices like drones or mobile phones. The inability to identify and respond promptly to rust outbreaks due to the considerable latency in data processing on these devices might pose challenges to the effective management and mitigation of the disease.

3.1.4 Environmental and field conditions

A significant challenge in identifying wheat leaf rust in the field is the variability in image quality due to differing lighting, backgrounds, and weather conditions. Models trained on high-quality images may have difficulties with noisy or fuzzy images obtained under suboptimal conditions, hence adversely impacting model accuracy. Furthermore, the appearance of rust may be influenced by field variability, which includes variations in soil types, moisture content, and other environmental conditions (Ahmad et al. 2023a). Models need to be resistant to these changes to guarantee accurate detection over a variety of domains. It is essential to tackle these obstacles to create rust detection systems that are both efficient and broadly applicable and that function effectively in actual agricultural conditions.

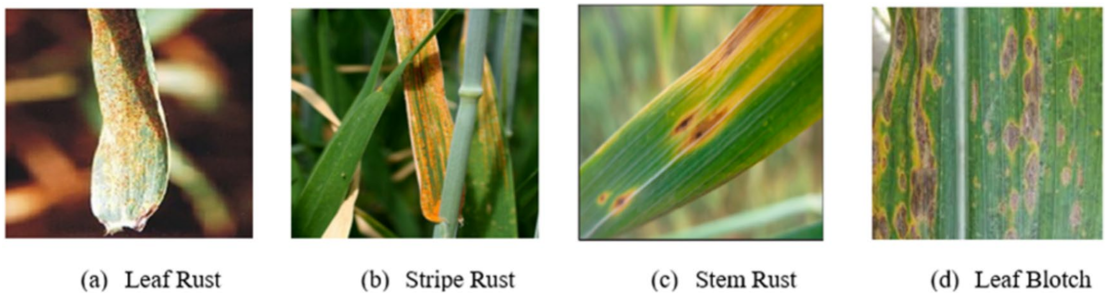


Fig. 7 Various wheat leaf diseases (Joseph et al. 2024)

3.1.5 Integration and deployment

A challenging task is integrating DL and ML models with the current workflows and farm management systems. The successful deployment and acceptance of these advanced technologies by farmers depend on seamless integration since any interruption or additional complication might make it more difficult. It's also crucial to ensure farmers with different degrees of technological ability can efficiently utilize and access detection technologies (Madeira et al. 2024). For improved rust detection technologies to be widely adopted and useful to farmers in their day-to-day operations, these instruments must be simple to use and intuitive.

3.2 Importance of wheat leaf rust detection

Ensuring global wheat production and food security relies on the identification of wheat leaf rust, caused by the fungus Puccinia triticina. This disease significantly diminishes wheat yields by obstructing photosynthesis and harming the plant, as seen by the emergence of rust-colored pustules on the leaves. Figure 8 illustrates the detection methodology for wheat rust diseases in an actual-life scenario, as referenced in (Kumar et al. 2024a; Usha Ruby et al. 2024; Raja and Nargunam 2024; Joseph et al. 2024; Jafar et al. 2024; Pavithra et al. 2023; Ahmad et al. 2023a; Madeira et al. 2024; Patil 2024).

Uncontrolled wheat leaf rust can cause output losses of up to 25%, significantly compromising the survival of farmers and disrupting the global supply chain (Usha Ruby et al. 2024). The effective management of wheat leaf rust relies on early detection, which facilitates targeted fungicide applications, reduces crop losses, and mitigates the disease's spread. Additionally, early diagnosis minimizes the need for broad chemical treatments, which may be expensive and detrimental to the environment, and helps to maximize resource utilization. Conventional detection methods, such as visual inspections and laboratory-based procedures, require a lot

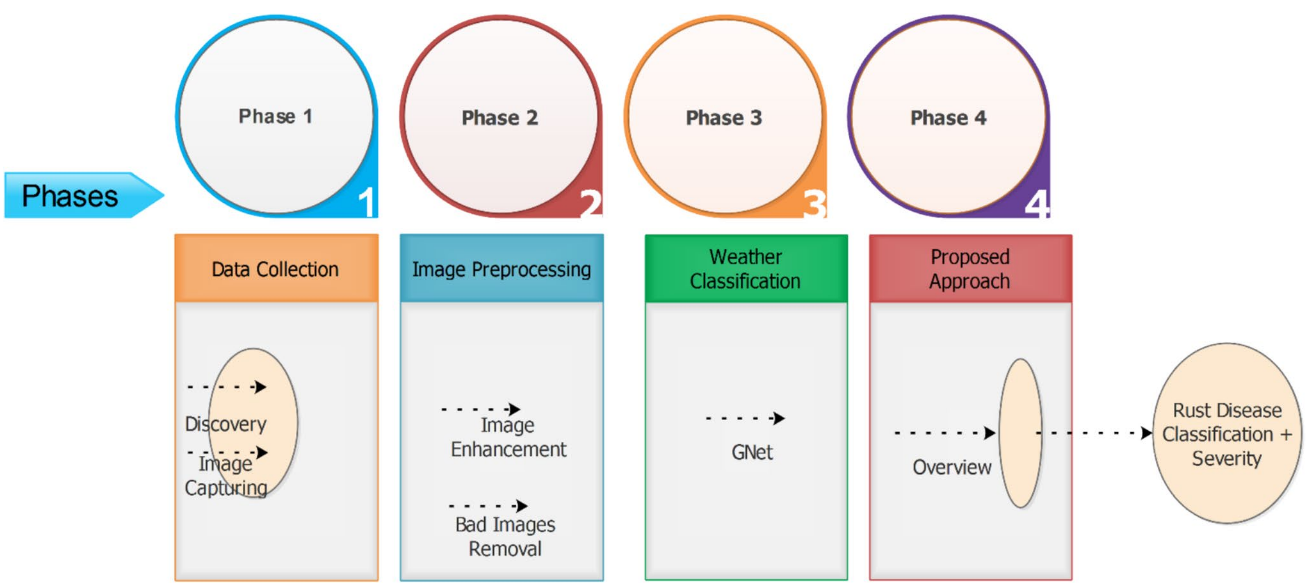


Fig. 8 Detection method for wheat rust diseases in an actual environment

Fig. 9 Classification methodology for wheat leaf disease: a comprehensive review

of time and work. These approaches often lead to delayed reactions, facilitating the disease's continued progression.

Contemporary automated detection systems offer a more effective approach that makes use of ML and DL techniques. These devices allow for faster and more accurate interventions by providing real-time monitoring and identification of unhealthy plants (Chen et al. 2023). Moreover, the ability to identify wheat leaf rust is crucial because it may save wheat fields from large production losses, lessen financial harm, and guarantee a steady supply of food. Modern detection technologies improve the disease's management capabilities, supporting sustainable farming methods and ensuring the world's food security. In contrast, sample images displaying the data for wheat production groups are shown in Fig. 9 (Bhola and Kumar 2025).

3.2.1 Impact on wheat production

Wheat leaf rust has considerable economic implications, as severe outbreaks can lead to yield losses of up to 25% (Usha Ruby et al. 2024). These losses affect individual farmers, the global food supply system, and market pricing. Visual inspections and laboratory testing are two prevalent yet insufficient methods for identifying and managing wheat leaf rust to prevent significant damage. Delays in disease diagnosis and control strategies result from these procedures'labor-intensive and time-consuming nature. Contemporary automated systems with sophisticated algorithms provide a more effective approach, allowing for early identification and prompt action. Table 3 compares pre-trained-based models as listed in (Bhola and Kumar 2025).

3.3 Limitations

3.3.1 Quantity and quality of data

The quality and quantity of data significantly influence the effectiveness of machine learning and deep learning models in detecting wheat leaf rust. Developing dependable and precise models necessitates high-quality, accurately labeled data; nevertheless, obtaining such data presents numerous challenges. A significant challenge with high-quality data is the diverse array of imaging conditions (Ramadan et al. 2024). Variations in illumination, tilt, and resolution may add irregularities and noise to images, impairing the model's capacity to precisely identify rust. Supervised

Table 3 Comparison of pre-trained-based models (Bhola and Kumar 2025)

Pre-trained based	Size/MB	Parameters/Millions	Depth	Time (ms) for each GPU inference step
VGG- 16	527	137.4	15.90	4.19
VGG- 19	548	142.7	18.90	4.39
ResNet- 50-V2	97	25.60	102.90	4.50
ResNet- 152-V2	231.90	59.39	306.90	6.59
DenseNet- 169	56.90	13.93	337.90	6.29
DenseNet- 201	79.90	19.96	401.90	6.8
Inception-V3	91.90	22.90	188.90	6.89
MobileNet-V2	13.99	3.60	104.99	3.79
Xception	87.99	21.99	80.99	7.99

learning algorithms also depend on accurate data labeling. However, manual annotation may be error-prone, particularly when dealing with large datasets. Incomplete or incorrectly classified data can result in poor model performance and erroneous predictions. Furthermore, the signs and symptoms of wheat leaf rust might vary greatly according to the infection stage and surrounding conditions. Although difficult, capturing this variation in training data is essential for the model to perform effectively in a variety of settings. The lack of labeled data for certain plant diseases, such as wheat leaf rust, sometimes restricts the model's learning capacity. Moreover, obtaining high-quality, labeled data is sometimes expensive and time-consuming, which presents a major obstacle to creating complete datasets (Ramadan et al. 2024). Exorbitant expenses linked to data collection, such as using advanced sensors and requiring human annotation procedures, may discourage extensive data collection endeavors, particularly for smaller research organizations and individual farmers. These difficulties emphasize the necessity for better labeling and data-gathering procedures as well as the creation of strategies that may be used for datasets that are noisier or smaller. Improving the precision and dependability of wheat leaf rust detection systems requires addressing these problems.

3.3.2 Computational requirements

Substantial challenges and limitations emerge from the computational requirements for DL and ML models in the detection of wheat leaf rust. These models require substantial computational resources during both training and deployment, particularly DL architectures such as RNNs and CNNs. The substantial computational expense associated with training deep learning models constitutes a primary challenge. Specialized hardware, including graphics processing units (GPUs) or tensor processing units (TPUs), is necessary to do the extensive computations required for analyzing large datasets and complex neural networks in model training.

Access to this kind of high-performance computer equipment may be expensive and scarce, particularly for individual farmers, small research teams, and agricultural organizations. This problem is made worse by the need for lengthy training periods; depending on the complexity and amount of the dataset, training deep learning models may take hours, days, or even weeks. A substantial memory capacity requirement is another important restriction. DL models need a lot of memory to store data and perform intermediate calculations, particularly when working with huge datasets and high-resolution images. Inadequate memory may cause sluggish processing and, sometimes, make it impossible to train models properly. This may be a major bottleneck when trying to analyze data in real-time or almost real-time for prompt disease diagnosis and action. Innovative approaches are needed to solve these computational problems, such as designing hybrid models that strike a compromise between speed and complexity using distributed computing and optimizing algorithms for efficiency. A sufficient amount of computing resources must be available for sophisticated wheat leaf rust detection systems to be implemented practically and at scale.

3.3.3 Environmental factors

Environmental conditions significantly influence the reliability and effectiveness of wheat leaf rust detection systems. These components introduce complexity and unpredictability, potentially presenting substantial challenges and limitations for both traditional and contemporary detection methods. The unpredictable nature of weather constitutes a significant environmental concern. Factors such as temperature, humidity, and sunlight can substantially affect the morphology of wheat plants and the manifestation of rust symptoms. For instance, varying lighting conditions may modify an image's hue and shading, complicating the ability of detection algorithms to consistently identify rust indicators. Rust development may be accelerated by high humidity, and it might be more difficult to discover it in time if there are limited visual indications. The variations in soil types and fertilizer availability are other important factors. These variations may impact wheat plants'general health and appearance, which may change how rust symptoms appear. For instance, plants cultivated in nutrient-rich soil can seem harder, which might conceal early rust symptoms that would be more noticeable in nutrient-poor soil. Because of this heterogeneity, in order to increase the resilience and generalization of the models, they must be trained on a variety of datasets that reflect a broad range of environmental variables. Crop management techniques, including fertilization, irrigation, and insect control, also impact the growth and detection of rust. Subsequently, environmental limitations affect data gathering and real-time monitoring in outdoor agricultural situations. The data quality that sensors and cameras capture may be affected by physical obstacles, dust, and rain. Maintaining the accuracy of detection systems depends on dependable and consistent data collection under various field circumstances.

3.4 Recent advancements in wheat leaf rust detection system using ML and DL

The most recent advances in ML and DL for wheat leaf rust detection are driven by innovations in data collection, model design, transfer learning, real-time processing, and determining explainability. The impact of this disease on wheat production is being lessened because of these developments, which are improving the accuracy, effectiveness, and accessibility of rust detection.

Cooperative efforts and ongoing research and development will further enhance the potential and use of these technologies in agriculture (Ramadan et al. 2024). Figure 9 shows the classification methodology for wheat leaf disease: a comprehensive review. The following are the many approaches that researchers in this field have offered, which we have listed here in this section:

In (Mandava et al. 2024), the researcher examines the use of DL and ML methods for the detection and classification of wheat yellow rust disease, which is caused by the fungus Puccinia striiformis. The study shows that DL-based models outperform conventional ML techniques on a large dataset of annotated wheat images using CNN models such as ResNet50, DenseNet121, and VGG19. EfficientNetB3 attains the highest classification accuracy via data augmentation and transfer learning. The results validate the creation of precision agricultural instruments to enable prompt intervention, reducing yield loss and mitigating the financial effect on wheat cultivation. In (Cuenca-Romero et al. 2024), yellow and brown rust detection in wheat is investigated using hyperspectral data and machine learning models, such as ANN, SVM, RF, and GNB. The study uses the SMOTE approach to find that SVM and RF models provide greater accuracy when applied to imbalanced datasets. Without data augmentation, the RF model detected yellow rust with 70% accuracy, whereas the SVM model detected brown rust with 63% accuracy when using SMOTE. The results highlight the potential of spectral data and machine learning approaches in the identification of plant diseases and urge further investigation into data processing techniques such as SMOTE to improve model performance. The researcher (Zenkl et al. 2024) presented a dataset of 422 high-resolution images of wheat leaves taken in different outdoor lighting conditions. The images have been annotated for leaf necrosis, insect damage, and disease indicators such as rust pustules and Septoria tritici blotch (STB). The approach obtained great accuracy in recognizing and quantifying these diseases (e.g., IoU of 0.96 for leaves) by using DL for semantic segmentation and key point identification. The model's functionality was on par with that of human annotators, and it showed strong field generalization without the need for manual assistance. This study demonstrates how precision agriculture may benefit from non-invasive, high-throughput disease screening to support site-specific crop management and resistance breeding. In (Reis and Turk 2024), the authors proposed a method to diagnose wheat plant diseases by merging the integrated DL framework (IDLF) and ensemble learning (EL) with pre-trained deep neural networks and several image-enhancing methods such as contrast stretching, hypercolumn, and CLAHE. Thirteen deep learning architectures, both pre-trained and customized, are used in this method. On the original dataset, 98.33% on the CLAHE-enhanced dataset and 99.58% with transfer learning were the accuracy rates attained by the RegNetY080 model. The hybrid approach, which included random forest with pre-trained RegNetY080, produced an accuracy of 99.58%, while the proposed IDLF and EL models produced an accuracy of 99.72%. With an accuracy of 97.56% on the wheat leaf dataset and 99.43% on the wheat leaf disease dataset, their technique demonstrated a high degree of promise for helping farmers in the early detection of diseases.

Furthermore, with losses of up to 80%, Asian soybean rust (ASR) poses a serious risk to soybean crops. While deep learning and hyperspectral images provide opportunities, the inflexible convolutional architecture of existing models makes them unsuitable for precisely identifying ASR. In (Feng et al. 2024), a neural network called DC2 Net is shown. It extracts spectral and spatial characteristics to enhance detection via the use of deformable and dilated convolutions. Furthermore, channel attention and Shapley value techniques pinpoint important wavelengths, improving accuracy. With its early asymptomatic identification of ASR and 96.73% detection accuracy, DC2 Net is a useful tool for preventative disease treatment. 14.1% of crop loss is estimated to be caused by plant diseases, making agriculture essential for the world's food security. To avoid using ineffective management strategies, it is crucial to identify plant diseases as soon as possible. To address the shortage of raw data for the identification of plant diseases, the researcher (Joseph et al. 2024) created databases for rice, wheat, and maize. After testing eight redefined deep learning models, Xception and MobileNet performed exceptionally well for maize, MobileNetV2 and MobileNet for wheat, and Xception and Inception V3 for rice.

On all three datasets, a recently discussed CNN model also demonstrated excellent accuracy, proving its usefulness for disease identification. Due to wheat diseases'severe risks to output and quality, standard visual diagnosis is no longer adequate for contemporary agriculture. Similarly, the researcher in (Mao et al. 2024) presented DAE-Mask, a deep learning technique that uses a feature pyramid network with attention mechanisms for varied features and DenseNet for feature extraction. The edge agreement head module uses Sobel filters to improve efficiency and reaches a detection speed of 0.08 s/pic. DAE-Mask outperformed other models when tested on the MSWDD2022 dataset, with a mean average accuracy (mAP) of 96.02%. It performed very well, with a 57.68% mAP on the PlantDoc dataset. It offers real-time field recognition with a 92.78% mAP and a 1.43 s return latency per image when deployed on WeChat.

The conventional approaches require professionals to engage in arduous, labor-intensive, and impracticable feature extraction. This study employed the EfficientNet B0 architecture, enhanced with a convolutional block attention mechanism (CBAM), to focus on disease-infected regions in wheat leaf images, therefore improving performance (Nigam et al. 2024). Utilizing the WheatRust21 dataset for evaluation, the EfficientNet B0-CBAM model achieved an F1 score of 98% and a testing accuracy of 98.70%. Grad-CAM representations reinforced the model's focus on the affected regions and demonstrated its potential utility for sustainable crop management and practical agricultural applications. To improve existing methods, the work in (Sharma and Sethi 2024) proposed a CNN-based segmentation model that used the point rend deep segmentation model for accurate pixel-level separation of wheat leaf diseases. The model uses EfficientNet to classify diseases from a 4000-image dataset, including spot blotch, leaf rust, and powdery mildew. With a 99.43% classification accuracy, the suggested model outperforms non-segmentation methods and helps farmers discover diseases early. A hybrid technique based on panoptic segmentation and designed for real-time WRD detection, FERSPNET- 50, is presented in this paper (Kumar et al. 2024a). Images from different weather conditions are first analyzed using the GNet model, and then wheat leaf and stem patches are identified using the FRCNN algorithm. The accuracy of rust identification is further improved with a deep CNN pre-trained model and a pyramid scene parsing network. In WRD identification, the proposed approach outperforms YOLOV4 (0.88) and RetinaNet (0.82) with a high precision of 0.97.

Food security depends on wheat, and countries like Egypt is facing difficulties in managing wheat diseases as a result of climate change. The authors of (Tolba and Talal 2024) offer Mobile-DNN-Net, a unique deep-learning model for early wheat disease diagnosis, to support Egypt's Vision 2030 for sustainable development. The DCNN and MobileNet architectures are combined in Mobile-DNN-Net, which also employs Grad-CAM methods for increased transparency. The model performs better than other deep learning models, such as Xception, MobileNet, InceptionV3, and VGG19, when tested on a dataset including 15 types of wheat diseases. The idea presented in (Dixit et al. 2024) examines a variety of ML methods for the early identification of pests, diseases, and weed infestations in crops. While wheat, rice, and corn are important staple crops in the world, their production is threatened by diseases that may easily affect them. It's critical to diagnose diseases accurately and on time. To identify agricultural diseases, this work in (Bhola and Kumar 2025) proposed a hybrid methodology that combined machine learning with the deep transfer learning. With less data, the model achieved remarkable accuracy by using pre-trained DenseNet201 for feature extraction and support vector machine (SVM) for classification. It performs better than benchmarks with an overall accuracy of 87.23% and a specific accuracy of 99.82% for maize, 98.75% for wheat, and 84.15% for rice. Its effectiveness and lightweight construction make it a useful instrument for real-time agricultural disease diagnosis. Global food security depends on wheat, but diseases endanger its output; thus, early and effective diagnosis is necessary. Through transfer learning and ensemble learning, this study proposes a state-of-the-art approach to identify eight wheat leaf disease classes, outperforming well-known models including CNN, Simple Net, Efficient Net, VGG16, ResNet50, and VGG-FCN-VD16 (Saraswat et al. 2024). With a classification accuracy of 98.08%, the framework suggested in (Saraswat et al. 2024) shows notable advancements over current techniques and contributes to the development of agricultural output and quality. Like other crops, wheat production presented several issues that require nondestructive, dependable remote detection techniques to avoid diseases. DL with hyperspectral imaging provides a potent method for precise mapping, evaluation, and detection of severity and early disease. The study presented in (Abdelkrim 2024) offered a thorough grasp of plant health by combining spectroscopy and imaging. Deep learning improves yield forecast and crop monitoring by automating the interpretation of complicated hyperspectral data. The paper examined current research, datasets, and the advantages and disadvantages of using deep learning for hyperspectral imaging of wheat. It highlights the potential of deep learning to enhance accuracy while also noting the necessity for significant computational resources and comprehensive datasets. Swift and accurate identification of wheat leaf diseases is essential for effective prevention and treatment strategies. The research in (Usha Ruby et al. 2024) offers a deep learning-based classification method and focuses on diseases like loose smut, crown root rot, and leaf rust. The technique employs a collaborative generative adversarial network (GAN) for image imputation, enhancing feature extraction by approximating missing data. For increased accuracy, the technique makes use of a modified version of the ResNet50 architecture that includes extra"Conv,""Batch Normalization,"and"Activation Leaky Relu"layers. After extensive testing, the suggested model achieves 98.44% identification accuracy, outperforming ResNet50, InceptionV3, and DenseNet to help with accurate disease detection and classification. Puccinia Strigiformes, the source of yellow rust, has a detrimental effect on wheat output, making an early and precise diagnosis essential to reducing yield losses and food shortages.

The contemporary methods of manual identification are labor-intensive and prone to errors. To achieve high-precision identification of yellow rust in wheat, the researcher in (Ali 2024) proposed a distinctive automated approach that employed advanced image processing techniques, including CNN, residual networks (ResNet), and MobileNet. The CNN-based model demonstrated remarkable efficacy in disease identification, achieving an accuracy of 0.99, alongside ResNet at 0.84 and MobileNet at 1.0. By eliminating the need for human inspections, these automated models have the potential to change agricultural disease surveillance completely. The integrity of global food security is jeopardized by the emergence of wheat leaf disease, necessitating the development of precise detection and classification methodologies. The study in (Ramadan et al. 2024) used CycleGAN and ADASYN for data augmentation to demonstrate the promise of deep learning for automated disease identification. When it came to enhanced datasets, MobileNetV2 proved to be a better classifier by attaining 100% accuracy and lowering errors. CycleGAN has shown remarkable efficacy in improving classifier performance, mitigating data scarcity, and correcting class imbalances. The study emphasizes how crucial these methods are for correctly classifying wheat diseases; going forward, research will concentrate on enhancing computational effectiveness and incorporating cutting-edge technologies like edge computing. A vital crop for the world's food supply, wheat is susceptible to a number of diseases that lower its quality and productivity. Figure 10 shows the Cycle GAN architecture for a wheat leaf.

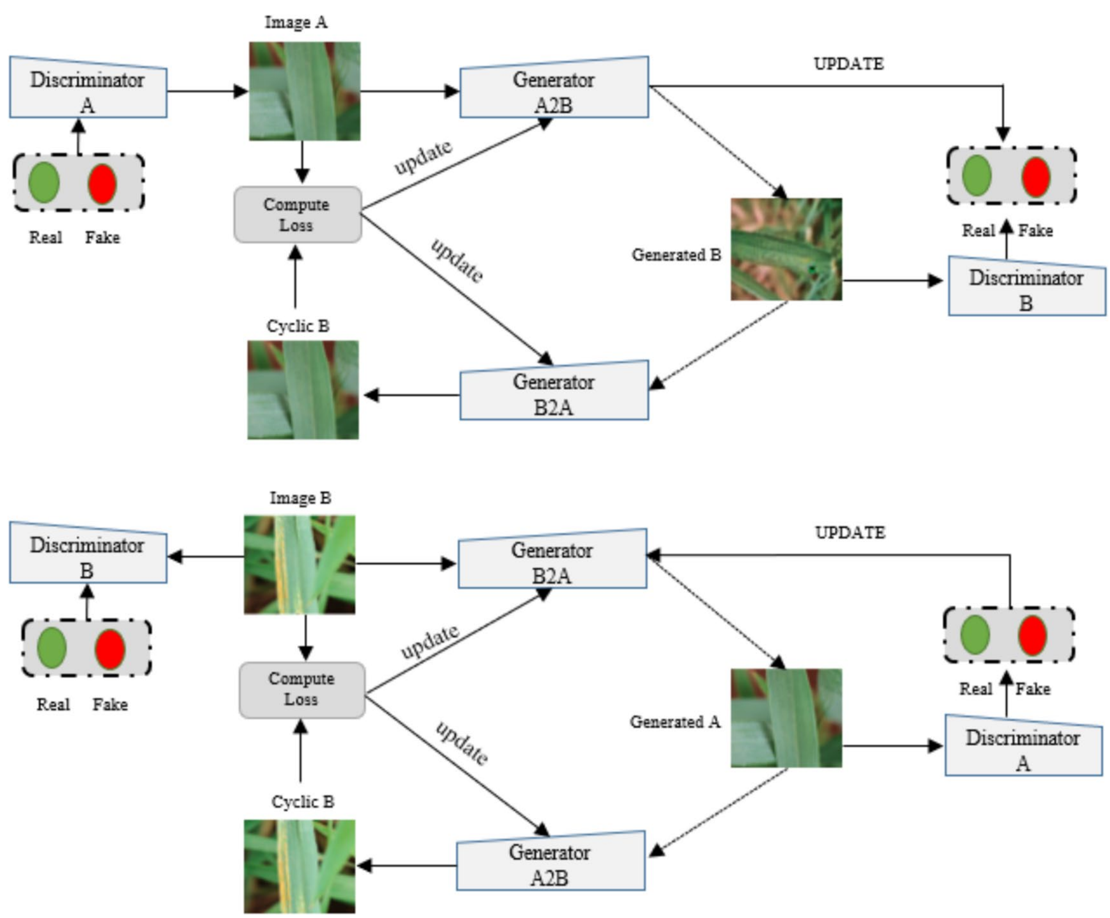


Fig. 10 Cycle GAN architecture for a wheat leaf

The authors of (Jagadeeshan et al. 2024) proposed using convolutional filter layers to identify disease patterns and classify wheat rust disease using a three-dimensional convolutional neural network (3D-CNN). The 1486 images in the CGIAR dataset are pre-processed using a Gaussian filter for noise reduction and smoothing, and feature extraction is carried out using the computationally efficient Discrete Wavelet Transform (DWT). With 99.83% accuracy, 98.89% recall, 98.81% F1 score, and 98.79% precision, the 3D-CNN outperforms other methods like GNet + FERSPNET- 50 and Efficient Net. Figure 11 visually represents the CNN model.

Moreover, a classification system intended to predict effect levels across 10 classes is evaluated by the authors of (Kumar et al. 2024b), who show good performance metrics. The authors in (Kumar et al. 2024b) proposed a framework that achieved precision and accuracy of 92.79% and 95.07%. The F1-Score continuously falls between 93.38% and 94.43%, striking a balance between recall and accuracy. Support values ranging from 1096 to 1175 ensured the balanced representation across classes. With a micro average of 93.66% and macro and weighted averages of around 93.66%, the total accuracy is 83.9979%, demonstrating consistent and dependable performance in prediction. Wheat is important to the world, but diseases like tan spot, yellow rust, stem rust, and leaf rust lower yields, making early and accurate disease identification necessary. Even with deep learning advances, class imbalance, limited RGB images, and difficulty with feature extraction make it impossible to identify numerous diseases at once. To overcome these problems, (Maqsood et al. 2024) proposed a unique approach for data augmentation utilizing transfer adversarial networks. 99.20% test accuracy and 97.95% F1-score were attained using a customized vision transformers (ViT) architecture working with graph neural networks and an ensemble classifier based on model-agnostic meta-learning (MAML). The proposed framework, proposed to include new diseases, pests, and weeds, and it exceeds current approaches in accuracy and multi-pathogen identification as future work. Wheat diseases need precise detection techniques because they substantially influence production and quality. Because of their fixed IoU thresholds, current deep learning approaches are not well suited to diseases' images with different orientations and aspect ratios. A convolutional neural network-based approach for identifying these wheat diseases is presented in (Liu et al. 2024). It includes a localization potential evaluation scheme and an auto-adjustment label assignment technique based on aspect ratio similarity. With the WDF2023 dataset, the proposed approach attained a mean average precision (mAP) of 60.8% and a mean recall (mRecall) of 73.8%, surpassing current-oriented object identification detectors and performing better than traditional detectors in accurately localizing disease locations. The research in (Subbiah and Nagappan 2024) presented the APLDD-ESOSDL technique to identify plant leaf diseases. The stacked long short-term memory (SLSTM) model is used for classification, while the inception ResNet-v2 model is used for feature extraction. The enhanced symbiotic organism search (ESOS) method optimized parameter values. Extensive tests demonstrated the APLDD-ESOSDL method outperformed six advanced systems in disease classification by achieving 99.22% accuracy, 98.52% precision, 98.06% sensitivity, and 99.54% specificity.

A prediction model with the capacity to predict the severity of wheat leaf disease across ten stages is examined in the research in (Banerjee et al. 2024). Metrics like precision, recall, F1-score, support, support proportion, and accuracy are used to assess the model's performance. Its excellent recall (89.44% to 92.31%) and precision (86.22% to 91.91%) showed that it accurately classified the disease's samples. The F1-score, which reflected a fair trade-off between the precision and recall, spans from 88.25% to 91.78%. Support values provided a reasonable depiction of each intensity level by indicating the composition of the dataset. With a 98% total accuracy rate, the model demonstrated how well it can classify disease severity levels. The crop yield estimated at the field scale must be accurate to maximize agricultural productivity and ensure food security. This size is a challenge for the conventional data-driven models because of the difficulty in acquiring trustworthy ground truths and also geographical relationships across various fields. To solve these problems, the research in (Han et al. 2024) used a graph-based architecture using Sentinel- 1,− 2, and − 3data to integrate deep learning with knowledge of crop physiology and geography. The Seq_Gra_Gd model efficiently predicts winter wheat growth (Leaf Area Index, LAI) and yield by combining graph convolution with the best available meteorological data. It improved yield estimated accuracy by accounting for the geographical distribution features of agricultural catastrophes and achieved acceptable accuracy ($R2 = 0.73$, $RMSE = 590.43$ kg/ha). The hybrid model that combined CNN and random forest obtained good classification accuracy for eight wheat diseases, such

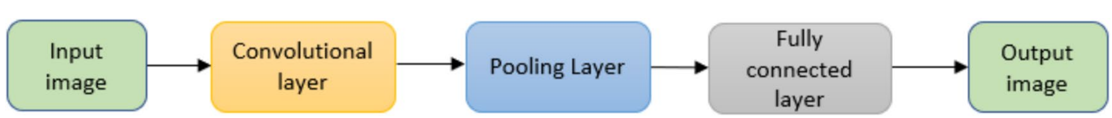


Fig. 11 CNN model

as fusarium head blight, powdery mildew, and rust diseases (Kumar et al. 2024c). Across all diseased classes, the model showed remarkable accuracy (95.24%− 95.95%), recall (95.42%− 95.92%), and F1-Scores (95.62%− 95.79%). With constant weighted and macro F1-Scores of 95.67%, it attained an overall classification accuracy of 99%. Additionally, 95.67% is the micro-average F1-Score, highlighting the model's dependability. This development emphasized how the model's accurate and automated classification of wheat diseases may boost agricultural output and guarantee the world's food security.

The authors in (Sonmez et al. 2024) investigated the use of AI for wheat variety and hybrid classification, with an accuracy of 99.26% and 97.41%, respectively, using MobileNetv2 and GoogleNet. With the SVM, the classification accuracy achieved is 99.91% with the MobileNetv2-SVM hybrid model. This methodology offered a quick and precise way to identify wheat, that helped with crop management and breeding initiatives. In (Tang et al. 2023), a neural network-based classifier called RustNet, which was developed using transfer learning, and ResNet- 18 are presented for the purpose of early identification of stripe rust in images and videos taken by UAVs or cellphones. Efficiency is increased by RustNet's semi-automated labeling, which produces cross-validation AUC values ranging from 0.72 to 0.87 under different circumstances. Accuracy values ranging from 0.79 to 0.86 were observed in an independent validation on a German dataset, indicating the potential of RustNet for effective and timely stripe rust monitoring. An advanced machine learning system designed for the identification and classification of wheat diseases, particularly brown and yellow rust, has been developed by the researcher cited in reference (Khan et al. 2022). The technique entailed gathering data from fields in Pakistan, segmenting and resizing it, and then training machine learning models. Several performance measures showed that the framework outperformed several ML frameworks by achieving an accuracy of 99.8%.

The researcher in (Mohapatra et al. 2021) also presented a deep learning model for detecting three different kinds of wheat rust diseases: yellow rust, stem rust, and leaf rust. The model utilized color code segmentation to extract relevant information from images of wheat fields and differentiate healthy from diseased crops. Extensive testing of variables such as train-test split ratio, dropout rate, and learning rate yields a fantastic accuracy of 99.76%, indicating the model's efficacy in diagnosing wheat rust diseases. Because of the significant resemblance between the spores and spots and also the difficulty in differentiating edge contours, wheat stripe rust damaged leaves provide obstacles for automated disease index computation. Similarly, in (Li et al. 2022), authors resolved these problems and produced the first comprehensive dataset of 33,238 images of wheat stripe rust from the Qinghai region. The research outperformed PSPNet, DeepLabv3, and U-Net using the Octave-UNet model, which enhanced feature assignment by octave convolution. The Octave-UNet model improved the segmentation accuracy of spores, leaves, and backgrounds with 83.44% mean intersection over union, 94.58% mean pixel accuracy, and 96.06% total accuracy. An EfficientNet architecture-based methodology for automatically identifying the main wheat rusts is proposed by the researchers in (Nigam et al. 2023). Several CNN-based models were evaluated using the WheatRust21 dataset, which consists of 6556 images of both healthy and diseased leaves taken in a natural field setting. The models'accuracy ranged from 91.2% to 97.8%.

The optimized EfficientNet B4 model outperformed previously published findings, achieving an accuracy of 99.35%. Stakeholders may utilize this approach in the field by integrating it with mobile apps. In (Shafi et al. 2023), the authors proposed a method for identifying and grouping wheat rust into four groups: resistant, susceptible, moderate, and healthy. The dataset was gathered from the National Agricultural Research Centre in Islamabad. Background removal is done using a pre-trained U2-Net model, and then classification is done using Xception and ResNet-50 models. With 96% accuracy, ResNet- 50 received the highest score. The work in (Singh et al. 2023) showed how ML models may be used to predict WYR non-destructively utilizing images. In (Nigus et al. 2024), a modified Cobbs scale set of recommendations is used to propose an automated approach for the classification of wheat stem rust. The system used Gabor filters to extract features and adaptive thresholding to segment data. It then used a deep learning model with a 12-way Softmax for classification, obtaining 92.01% testing and 92.02% training accuracy. The technology helped with proactive disease management and effective resource allocation by improving real-time monitoring and grade accuracy.

Recent innovations in ML and DL algorithms have considerably enhanced the accuracy as well as reliability of wheat leaf rust detection systems. The diversity and innovation in data collection enable the acquisition of high-quality images from various locations, hence ensuring effective model training. Cutting-edge algorithms such as Vision Transformers and EfficientNet employed attention mechanisms and spectral-spatial feature extraction, attaining an accuracy of 99.35%. The data augmentation and transfer learning characteristics of algorithms, including deep learning models such as DenseNet121, VGG19, and ResNet50, along with EfficientNetB3, have enhanced classification accuracy. In addition, ensemble and hybrid deep learning algorithms, such as the integrated deep learning framework (IDLF), enhance accuracy by up to 99.72%. Real-time processing models and explainability techniques, including DAE-Mask and RustNet, markedly enhance model decisions and facilitate quick detection (0.08 to 1.43 s per image), hence increasing trust and accessibility for farmers. These advancements enhance precision agriculture by minimizing production loss and promoting sustainable agricultural practices. Future initiatives promote collaboration on different global datasets, edge computing, and streamlined algorithms to provide rapid, precise, and equitable solutions that improve food security through effective and sustainable disease management.

4 Publicly available datasets

It is necessary to have appropriate datasets in order to develop algorithms and train machines to diagnose plant diseases from images. DL-based solutions require big datasets with thousands of images (Ahmad et al. 2023b). This section summarizes various publicly available datasets from the reviewed studies. The number of studies using images of plant diseases from different databases is shown in Fig. 12. It was discovered that the "PlantVillage" dataset is the most often used. However, several of the researchers in the examined studies chose to build unique datasets that are not publicly available.

4.1 Plant village

The PlantVillage dataset is a huge, publicly available image collection used to build and test plant disease detection systems. It was designed to assist researchers and developers in training ML and DL models to detect various plant diseases using images of plant leaves (Shafi et al. 2023). The PlantVillage dataset includes 54,309 images that depict 38 distinct diseases across 14 crops (Ahmad et al. 2023b). The majority of images were taken in a controlled laboratory setting with uniform background, as seen in Fig. 13. Additionally, the PlantVillage dataset is an unbalanced dataset, as shown in Table 4.

4.2 Digipathos

Digipathos, a recently released huge plant disease dataset, comprises approximately 46,000 images spanning 171 diseases that impact 21 distinct crops (Barbedo et al. 2018). In this dataset, only 2326 images with similar backgrounds processed in the lab show leaf diseases, as illustrated in Fig. 14(a). The remaining 44,187 images show clipped disease lesions, as shown in Fig. 14(b). It is evident from this that over 95% of the images in this dataset do not appropriately represent plant diseases in their natural environments.

4.3 PlantDoc

PlantDoc, a plant disease dataset of 2,598 images spanning 17 diseases impacting 13 distinct crops, was recently obtained (Singh et al. 2020). As Fig. 15(a) illustrates, most of the images were shot in the field; however, Fig. 15(b) displays a few images that were taken with a uniform background. Deep learning models may be less able to identify important disease leaves in this dataset, though, as several images (Fig. 15(c)) show entire crops or multiple damaged leaves. Table 5 shows the summary of the PlantDoc dataset.

4.4 NLB dataset

The NLB dataset contains approximately 18000 images of corn crops (Wiesner-Hanks et al. 2018). This dataset is not suitable for multiple disease detection as it only shows corn leaf images with a single disease. This dataset can also be used to evaluate how well DL models generalize their capacity to diagnose diseases across various datasets. Figure 16 below shows examples of images taken with normal cameras, boom technology, and drone technology.

4.5 Rice disease dataset

This dataset consists of approximately 3365 images, including four (4) categories such as unaffected, sesame leaf spot, rice hispa, and rotten neck (Prajapati et al. 2017). Table 6 shows the details of these diseases. However, the images were taken only with white backgrounds, as seen in Fig. 17. As a result, this dataset presents problems for developing robust deep learning models capable of properly identifying rice diseases in the field.

5 An overview of machine learning and deep learning algorithms for plant disease detection

Various machine learning (ML) and deep learning (DL) methods are now being employed for plant disease detection. DL is a new ML trend that has produced revolutionary results in a variety of academic areas, including computer vision, medicine, and biotechnology. This section reviews numerous supervised learning, unsupervised learning, deep learning, generative models, feature reduction and selection algorithms widely used for plant disease identification and detection.

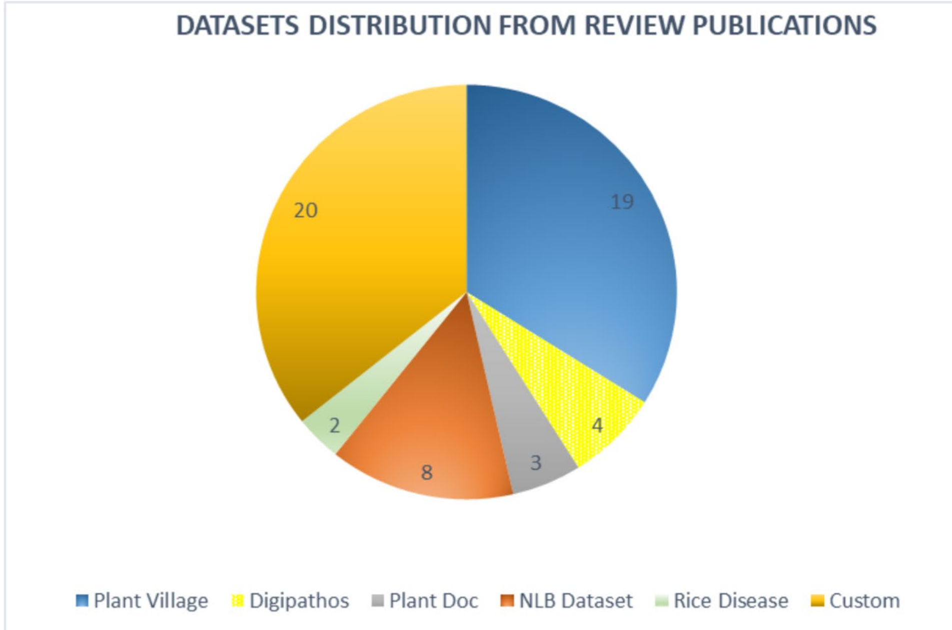


Fig. 12 Research work uses both custom and publicly accessible databases to detect diseases in various crops

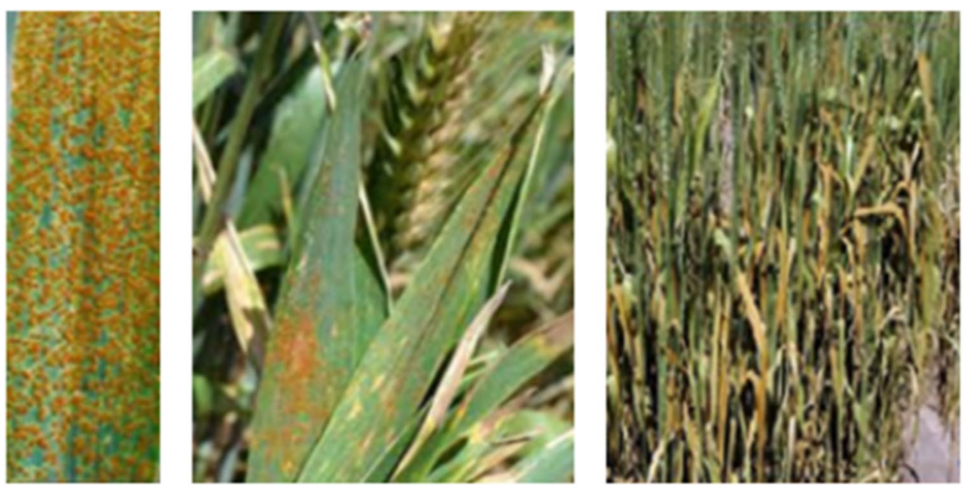


Fig. 13 Wheat leaf rust disease

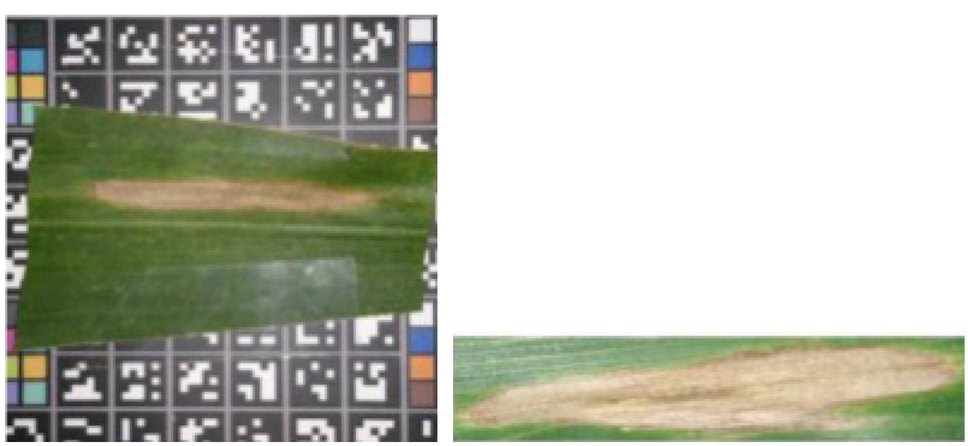
5.1 Supervised learning algorithms

Plant disease identification and detection commonly employ supervised learning algorithms because the algorithms are capable of categorizing and predicting solutions according to labelled data (Chen 2024). These algorithms have proved to be highly efficient in tasks such as disease diagnosis and detection, species classification, and crop status evaluation, which has led to the development of precision farming. Conventional supervised classical machine learning methods used for plant disease identification include decision trees (DT), random forests (RF), support vector machines (SVM), neural networks (NN), K-nearest neighbors (KNN) and naïve bayes (NB) (Demilie 2024; Walsh et al. 2024; Angamuthu and Arunachalam 2023; Ciobotari et al. 2024; Stamford et al. 2024; Kamarianakis et al. 2024; Ram et al. 2024; Chelladurai and Sujatha 2024; Thakur and Srinivasan 2024; Segarra 2024; Najafabadi and Kazemi 2024; Zhang et al. 2024; Xue et al. 2024; Mojaravscki and Graziano Magalhães 2024; Karthickmanoj et al. 2023; Diker et al. 2024; Morchid et al. 2024; Mohammad et al. 2024; Anju and Swaraj 2024; Stephen et al. 2024; Routis et al. 2024; Khalid and Karan 2024; Thivya Lakshmi et al. 2024; Pujari et al. 2024; Subbiah and Krishnaraj 2024; Mahadevan et al. 2024;

Table 4 PlantVillage Dataset details

Crop type	Disease name	No. of images
Blueberry	Unaffected	1604
Apple	Unaffected	1712
	Rotted	719
	Rust	262
	Scab	643
Cherry	Unaffected	821
	Powdery Mildew	1092
Grape	Unaffected	418
	Black Rot	1202
	Measles	1380
	Leaf Spot	1110
Corn	Unaffected	1099
	Leaf Spot	524
	Rust	1190
	Leaf Blight	983
Orange	Citrus Greening	5,674
Peach	Unaffected	410
	Infectious	3021
Bell Pepper	Unaffected	1521
	Infectious	885
Potato	Unaffected	181
	Initial Blight	1100
	Severe Blight	1100
Soybean	Unaffected	5,110
Squash	Powdery Mildew	1645
Tomato	Unaffected	1611
	Infectious	2214
	Initial Blight	1100
	Severe Blight	1899
	Mold	984
	Infectious ted	1802
	Arachnid Lice	1680
	Mark Infectious	1521
	Yellow Twist	5641
	Medley Disease	389

Rani et al. 2024; Pawar et al. 2024; Dohare and Khan 2024; Gautam et al. 2024; Dubey and Choubey 2024; Bouacida et al. 2025; Kumar et al. 2024a; Usha Ruby et al. 2024; Raja and Nargunam 2024; Joseph et al. 2024; Jafar et al. 2024; Pavithra et al. 2023; Ahmad et al. 2023a; Madeira et al. 2024; Patil 2024; Chen et al. 2023; Bhola and Kumar 2025; Ramadan et al. 2024; Mandava et al. 2024; Cuenca-Romero et al. 2024; Zenkl et al. 2024; Reis and Turk 2024; Feng et al. 2024; Mao et al. 2024; Nigam et al. 2024; Sharma and Sethi 2024; Tolba and Talal 2024; Dixit et al. 2024; Saraswat et al. 2024; Abdelkrim 2024; Ali 2024; Jagadeeshan et al. 2024; Kumar et al. 2024b; Maqsood et al. 2024; Liu 2024; Subbiah and Nagappan 2024; Banerjee et al. 2024; Han et al. 2024; Kumar et al. 2024c; Sonmez et al. 2024; Tang et al. 2023; Khan et al. 2022; Mohapatra et al. 2021; Li et al. 2022; Nigam et al. 2023; Shafi et al. 2023; Singh et al. 2023; Nigus et al. 2024; Ahmad et al. 2023b; Barbedo et al. 2018; Singh et al. 2020; Wiesner-Hanks et al. 2018; Prajapati et al. 2017; Reddy and Adimoolam 2024). For instance, we applied decision trees, which are simple machine learning techniques employed in the identification and detection of plant diseases. These models give a very straightforward and easy-to-understand representation of plant condition monitoring as well as decision-making information flow. Random Forest algorithms enhance the precision and reliability of PDID and PD because they generate several DTs. These algorithms were effective at pointing out tiny symptoms of the ailment in question. These models are widely used in precision agriculture and ecological monitoring as they can and are effective in handling information (Macuácua et al. 2024). SVM and its families are another common supervised learning model applied for plant disease identification (Sharma et al. 2024). SVM and its families are another preferred method of supervised learning used in the identification of plant diseases (Sharma et al. 2024). SVM is able to handle data in high- dimensions as well as draw boundaries.



(a) (b)

Fig. 14 Digipathos Dataset (**a**) Controlled Background (**b**) Lesion of Corn from Digipathos Dataset [https://www.redape.dados.embrapa.br/dataset.xhtml?persistentId=doi:https://doi.org/10.48432/XA1OVL]

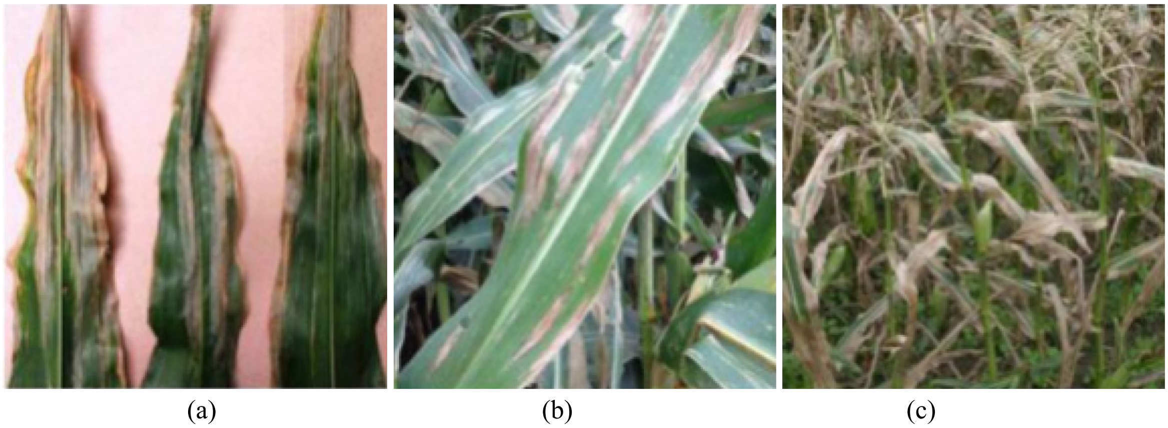


Fig. 15 PlantDoc Dataset (**a**) similar background (**b**) PlantDoc dataset with natural condition (**c**) whole infected corn plants [https://www.kaggle.com/datasets/abdulhasibuddin/plant-doc-dataset]

Table 5 PlantDoc Dataset details

Crop type	Disease name	No. of images
Malus pumila	Unaffected	88
	Scab	91
	Rusted	91
Sweet Pepper	Unaffected	58
	Infectious	69
bilberry	Unaffected	122
Cherry	Unaffected	62
Corn	Leaf Blight	189
	Infectious	71
	Rusted	221
Grape	Unaffected	72
	Black Rot	61
Peach	Unaffected	109
Potato	Initial Blight	221
	Severe Blight	111
Raspberry	Unaffected	220
Soybean	Unaffected	71
Squash	Dry Fungus	129
Tomato	Unaffected	59
	Infectious	121
	Early Blight	91
	Late Blight	109
	Spray Mold	89
	Septoria Leaf Spot	161
	Mosaic Disease	62
	Yellow Disease	62
	Wanderer Nit	3

SVM is used to specify the most appropriate hyperplane that enlarges the distance between different classes of the feature space (Sharma et al. 2024). Therefore, SVM is very effective in the recognition of plant species. With the increasing trend of using SVMs, environmental monitoring and crop management by means of precision agriculture have become useful in stress identification and plant disease diagnosis (Saxena et al. 2024). Due to the ability of the NN models to recognize complex patterns, these models are applied in plant disease detection and identification systems. The convolutional neural networks (CNNs) get better results in handling visual data and therefore can be used for identification of plant species, assessing plant diseases, and generally assessing the health status of plants by using aerial and satellite images (Saraswathi 2024). Elements of neural networks (NNs) consist of an extraordinary ability to detect intricate patterns and features; hence, precision and flexibility. This makes them beneficial, especially for precision agriculture, since through a robotic system, crop assessment and management can be done in real time to increase productivity and profitability. KNN and Naïve Bayes are two strong models still in use for plant disease diagnosis (Reddy and Adimoolam 2024; Macuácua et al. 2024; Sharma et al. 2024; Saxena et al. 2024; Saraswathi and Faritha Banu 2024; HR and KM 2024). KNN would assign labels to a test instance and then use the most frequently occurring class among the neighbors to make the prediction. Because of that, it is found to be suitable for processing small datasets only according to the trends identified in (HR and KM 2024). Naïve Bayes is actually a probability model based on the assumption of feature independence (Reddy anf Adimoolam 2024). This is particularly important when used in ensembles where more complex models can be its counterpart.

5.2 Unsupervised learning algorithms

The capability of the unsupervised learning models for detecting features in unlabeled data makes it applicable in plant disease diagnosis (Sajitha et al. 2024). These types of

(a) (b) (c)

Fig. 16 NLB Dataset (**a**) camera (**b**) boon (**c**) drone [https://www.kaggle.com/datasets/rabbityashow/corn-leaf-diseasesnlb]

Table 6 Rice dataset details

Class	No. of images
Unaffected	780
Sesame leaf spot	172
Rice hispa	410
Rotten neck	192

Fig. 17 Rice disease leaf

unsupervised learning models allow the plant types to be discovered and distinguished and the disease to be tracked and unveiled without pre-labelling because these methods are capable of uncovering hidden structures and patterns within the big data (Demilie 2024), (Walsh et al. 2024). An effective way to process and understand complex environmental and data acquired in farming is used by unsupervised learning. Unsupervised techniques that proved effective in plant disease detection comprise of clustering techniques (CT), principal component analysis (PCA), stochastic neighbor embedding with t-distribution (t-SNE), frequent pattern growth (FP-Growth), and others. It is used to provide a mechanism to aggregate plants in groups with and without reference to theoretical classifications (Demilie 2024; Walsh et al. 2024; Angamuthu and Arunachalam 2023; Ciobotari et al. 2024; Stamford et al. 2024; Kamarianakis et al. 2024; Ram et al. 2024; Chelladurai and Sujatha 2024; Thakur and Srinivasan 2024; Segarra 2024; Najafabadi and Kazemi 2024; Zhang et al. 2024; Xue et al. 2024; Mojaravscki and Graziano Magalhães 2024; Karthickmanoj et al 2023; Diker et al. 2024; Morchid et al. 2024; Mohammad et al. 2024; Anju and Swaraj 2024; Stephen et al. 2024; Routis et al. 2024; Khalid and Karan 2024; Thivya Lakshmi et al. 2024; Pujari et al. 2024; Subbiah and Krishnaraj 2024; Mahadevan et al. 2024; Rani et al. 2024; Pawar et al. 2024; Dohare and Khan 2024; Gautam et al. 2024; Dubey and Choubey 2024; Bouacida et al. 2025; Kumar et al. 2024a; Usha Ruby et al. 2024; Raja and Nargunam 2024; Joseph et al. 2024; Jafar et al. 2024; Pavithra et al. 2023; Ahmad et al. 2023a; Madeira et al. 2024; Patil 2024; Chen et al. 2023; Bhola and Kumar 2025; Ramadan et al. 2024; Mandava et al. 2024; Cuenca-Romero et al. 2024; Zenkl et al. 2024; Reis and Turk 2024; Feng et al. 2024; Mao et al. 2024; Nigam et al. 2024; Sharma and Sethi 2024; Tolba and Talal 2024; Dixit et al. 2024; Saraswat et al. 2024; Abdelkrim 2024; Ali 2024; Jagadeeshan et al. 2024; Kumar et al. 2024b; Maqsood et al. 2024; Liu 2024; Subbiah and Nagappan 2024; Banerjee et al. 2024; Han et al. 2024; Kumar et al. 2024c; Sonmez et al. 2024; Tang et al. 2023; Khan et al. 2022; Mohapatra et al. 2021; Li et al. 2022; Nigam et al. 2023; Shafi et al. 2023; Singh et al. 2023; Nigus et al. 2024; Ahmad et al. 2023b; Barbedo et al. 2018; Singh et al. 2020; Wiesner-Hanks et al. 2018; Prajapati et al. 2017; Reddy and Adimoolam 2024; Macuácua et al. 2024; Sharma et al. 2024; Saxena et al. 2024; Saraswathi and Faritha Banu 2024; HK and KM 2024; Sajitha et al. 2024; Rahman et al. 2024). Cluster analysis techniques can be applied for natural clustering and pattern recognition that involves several fields such as phenotyping, crop classification, and others related to biodiversity. Clustering methods improve the detailed analysis of extensive and integrated data to provide profound insights into the location, well-being and distinction of the plants (Rahman et al. 2024). Likewise, PCA is a data reduction technique that can help paleontologists to analyze large and complicated data sets but retain meaningful information (Rahman et al. 2024; Zhao et al. 2024). It is mainly used to reduce the first set of underlying variables into a new set of unrelated ones, capturing a greater portion of the data transformation effort in features. PCA also reveals some important features for disease diagnosis and plant species classification and thereby enhances the analysis and interpretation of large ecological as well as agricultural data. One of the methods for visualizing such data is t-distributed stochastic neighbour embedding (t-SNE) which transforms the data into low-dimensional scale, namely, 2D or 3D, which helps to simplify the complicated plant dataset and make them visually beautiful. This makes it easier for the farmers and researchers to interpret disease outbreaks, species distribution, and other biological and ecological occurrences (Zhao et al. 2024). FP-Growth is a common algorithm for extracting frequent item sets and obtaining association rules in big data over large datasets without candidate generation (Houetohossou et al. 2024). FP-Growth helps pinpoint relationships between attributes of plants and other factors such as the environment and the farming techniques used in the plant detection process. Other familiar unsupervised methods are SOM, Markov model, K-means clustering, and deep belief network, among others.

Machine learning along with the deep learning approach has been identified as the most often used technique for disease identification simply because of the speed, availability of capacity for data storage, and the availability of larger datasets (Mng'ombe et al. 2024; Dey et al. 2024). CNNs and RNNs are effective in plant disease diagnosis by images and the analysis of sequential data which will be helpful in long-term surveillance of plant disease (Dey et al. 2024). It is due to convolutional layers which allow CNNs to extract spatial features from images using data in a method that is completely autonomous, thus making CNNs useful in identifying plant species, diseases, as well as the condition of plants (Adekunle et al. 2024). CNN's layered design enhances their precision and longevity by accumulating intricate patterns and features (Tiendrebeogo 2024). In the same way, in monitoring plant development, recognizing stress signs, and predicting crop yields where the time-ordered sequences of data are discovered, RNNs can learn temporal relations, including Long Short-Term Memory (LSTM) (Kareem 2024). A transfer learning process is based on deep learning, where a model employed in identifying plant diseases is trained on large data sets and then fine-tuned. When information from models learned on large, varied databases is used, it simplifies the training of models and improves their performance on the target task. Plant detection utilizes the transfer learning approach in which such models are tweaked slightly using minimal more training for specific purposes like species segmentation, disease identification, and stress detection (Srivastava and Meena 2024).

5.3 Generative models

These models are widely used in plant disease identification and detection due to its ability to manipulate limited and insufficient label data. The recent models include generative adversarial networks (GANs); the model comprises both a discriminator and a generator neural network. Remarkably, the discriminator checks the credibility of the false output produced by the generator with actual data (Paul Joshua et al. 2025). GANs could mimic various plant conditions, development stages, diseases, and effects of external factors improves efficient model training (Paul Joshua et al. 2025). Finally, GANs enhance the chances of building better and more reliable mechanisms for identification of plant diseases, and thus enhanced agricultural control and surveillance. Similarly, Transformers are a core part of modern deep learning algorithms. In this context, processing of input data is based on the use of self-attention which allows for parallelism and more precise control over long-term dependencies (Barman et al. 2024; Sarkar et al. 2023). Transformer models employ sophisticated computational mechanisms, referred to as attention or self-attention, to demonstrate the flow and interconnection between data components present within a sequence and irrespective of the positions of these components. The use of methods based on deep learning and remote sensing for disease identification and detection has many benefits for plant diseases, such as differentiation of disease symbols, identification of different types of diseases and occurrences, evaluation of disease severity, and development of economical medication (Zhang et al. 2019; Zhang and Zhu 2023).

5.3.1 Transformer-based architecture

a. **Self-supervised learning:** Many Transformer-based architectures like ViTs and BERT utilize self-supervised learning (SSL) methods for pre-training. These architectures require huge datasets for pre-training through mechanisms such as mask modelling, enabling the prediction of the missing pixels in an image. SSL-based methods are particularly productive in situations with limited labelled data. BERT uses masked language modelling to predict masked words in a sentence. ViTs use intrinsic information regarding the image structure and can be successfully used for plant disease detection.
b. **Encoder/decoder architectures:** Transformers-based models use the encoder to compute input image or text

and the decoder to produce an output in the form of classification or segmentation. For example, BERT and ViTs use an encoder for classification, Generative Pre-Trained Transformer (GPT) employs only a decoder for text creation, and DETR uses both encoder-decoder to detect any object.

5.4 Feature reduction and selection

These methods are vital to drive high dimensional data and enhance the efficiency of ML algorithms. Few widely used models include PCA, t-SNE, and FP-Growth. PCA is essential model to reduce the dimensionality of huge datasets and could preserve meaningful features. It is frequently used in plant disease identification and detection of various species. Similarly, t-SNE is a visualization tool. However, it effectively assists in feature reduction by converting high dimensional data into fewer dimensions, therefore, improving image analysis and understanding. Moreover, FP-Growth method could effectively identify correlations between plant features and environmental factors, enabling in feature selection for disease identification and detection.

A few plant diseases, broadly categorized into biotc and abiotic, are shown in Fig. 18, and commonly used ML and DL techniques used for plant disease detection are shown in Fig. 19.

Table 7 outlines the main distinctions and uses of ML and DL for plant disease detection, particularly regarding identifying wheat leaf rust disease.

Next, Figs. 20 and 21 show the method for leaf disease detection using ML and DL and Fig. 22 depicts a comparative analysis of ML and DL techniques. The comparison is evaluated, and the findings are displayed graphically.

The review of various research publications using ML and DL approaches is examined and compared in the bar graph visualization in Fig. 23.

6 Remote sensing technology in plant disease detection

In today's era, remote sensing technology is widely used in agriculture to gain detailed information of plant growth and environmental conditions using satellite and UAV (drone) technologies (Zhang et al. 2019; Zhang and Zhu 2023). Commonly, hyperspectral, optical, and thermal sensors are used to get large datasets across broad areas. However, UAVs provide high-quality, real-time, and crop condition monitoring data (Zhang and Zhu 2023; Peña et al. 2015). Pre-processed data is processed using ML and DL algorithms such as CNNs, SVMs, GAN's, and transformer-based models to accurately identify and classify plant disease and environmental conditions (Lu et al. 2023; Royimani et al. 2019). These approaches are

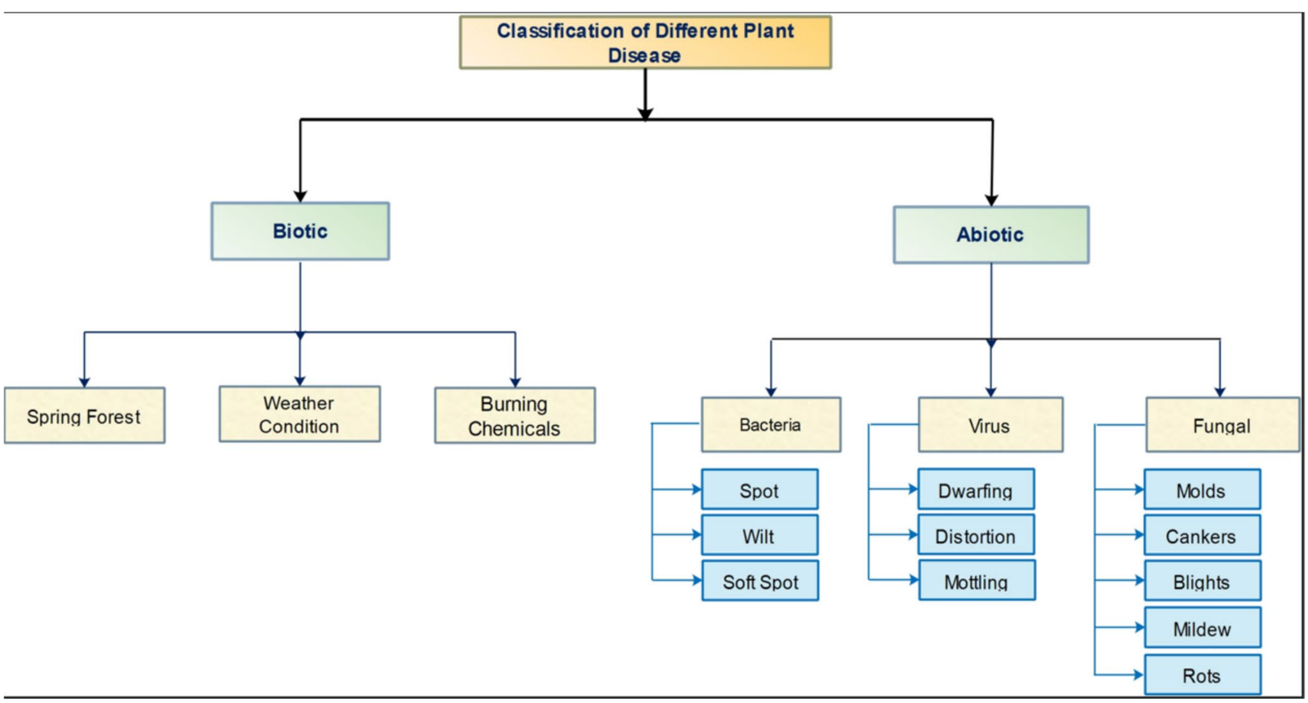


Fig. 18 Classification of different plant diseases

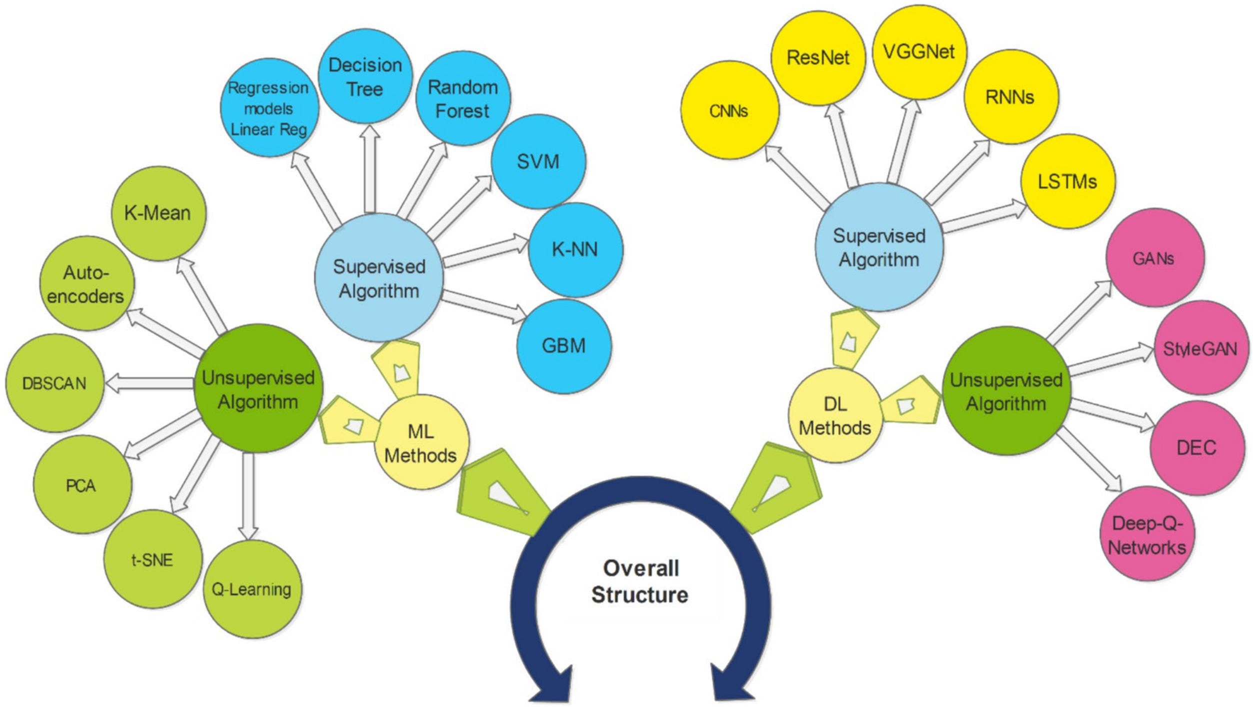


Fig. 19 Common ML and DL techniques used to detect plant diseases

utilized in domains like water management, yield forecasting, disease detection, and crop health evaluation (Peña et al. 2015). This section reviews different types of remote sensing technologies, usages, and case studies in plant disease detection and identification.

6.1 Types of remote sensing

In DL and ML-based plant identification systems, remote sensing plays a crucial role in gathering essential data (Cavender-Bares et al. 2020; Lu et al. 2023; Royimani

Table 7 An overview of the major differences and uses between ML and DL in the context of plant disease detection, with a focus on wheat leaf rust disease detection

Attributes	Machine Learning	Deep Learning
Feature Extraction	Requires manual feature extraction	Automated feature extraction from unprocessed data
Data Requirement	Less data is needed than with DL	needs a lot of data that has been labeled
Model Complexity	Less complex models (e.g., SVM, k-NN, Decision Trees)	intricate models (such as CNNs, RNNs, and GANs)
Training Time	Learning time is faster	needs time to learn and more computational power
Performance	Excellent performance with low data; mostly dependent on feature quality	High efficiency, particularly when working with big information and intricate data structures
Example Algorithms	k-NN, Random Forests, Decision Trees, and SVM	CNN, GAN and RNN
Plant disease detection application	uses manually extracted aspects from images, such as color, texture, and design	directly learns from and detects patterns in disease using raw images
Wheat leaf rust detection application	Requires preprocessing procedures to extract features such as the color, shape, and texture of lesions	detects rust by automatically picking out characteristics from images of affected leaves
Advantages	Simpler models are easier to comprehend and require fewer computational resources and data	Improved accuracy and the ability to automatically handle complicated data patterns
Disadvantages	Manual feature extraction may be laborious and may fail to collect all relevant data	High demand for data and processing power; complicated models are sometimes seen as"black boxes."

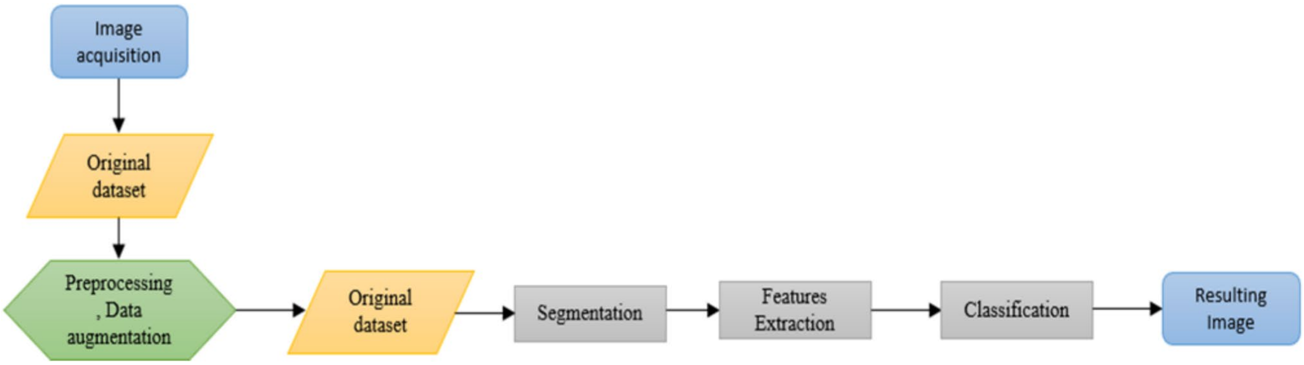


Fig. 20 Methods for detecting leaf diseases using ML

et al. 2019; Abdullah et al. 2023; Jung et al. 2023; Gogoi et al. 2018). There are various types of remote sensing, including satellite, aerial, and ground-based methods, each offering distinct advantages and specific applications. To fully harness their potential and enhance the accuracy and efficiency of plant detection systems, a deep understanding of these different remote sensing types is required (Cavender-Bares et al. 2020). Figure 24 provides an overview of the technologies used in remote sensing for plant detection, outlining the processes and components involved, such as the technology types and data sources, as well as information on applications, advantages, limitations, and examples of usage.

6.1.1 Satellite remote sensing

As previously discussed, the collection of extensive data and imagery from satellites equipped with advanced sensors such as optical, multispectral, hyperspectral, and thermal sensors is referred to as satellite remote sensing (Cavender-Bares et al. 2020). This technology plays an important role in long-term agriculture monitoring due to its reliability and wide range coverage (Peña et al. 2015; Cavender-Bares et al. 2020; Lu et al. 2023; Royimani et al. 2019). Using this technology, we can track crop growth, diseases, and environmental conditions because it provides systematic and continuous data across multiple seasons (Peña et al. 2015; Cavender-Bares et al. 2020; Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023). Satellites use optical sensors for image acquisition in visible light which are helpful in evaluating the overall crop conditions and the plant canopy (Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023). Hyperspectral and multispectral sensors, which detect light outside the visible spectrum at a number of wavelengths, provide rich information regarding plant growth, nutritional levels, and symptoms of stress (Peña et al. 2015; Cavender-Bares et al. 2020; Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023). Thermal sensors facilitate the evaluation of the surface temperature and soil moisture and can identify water stress (Peña et al. 2015; Cavender-Bares et al. 2020; Lu et al. 2023).

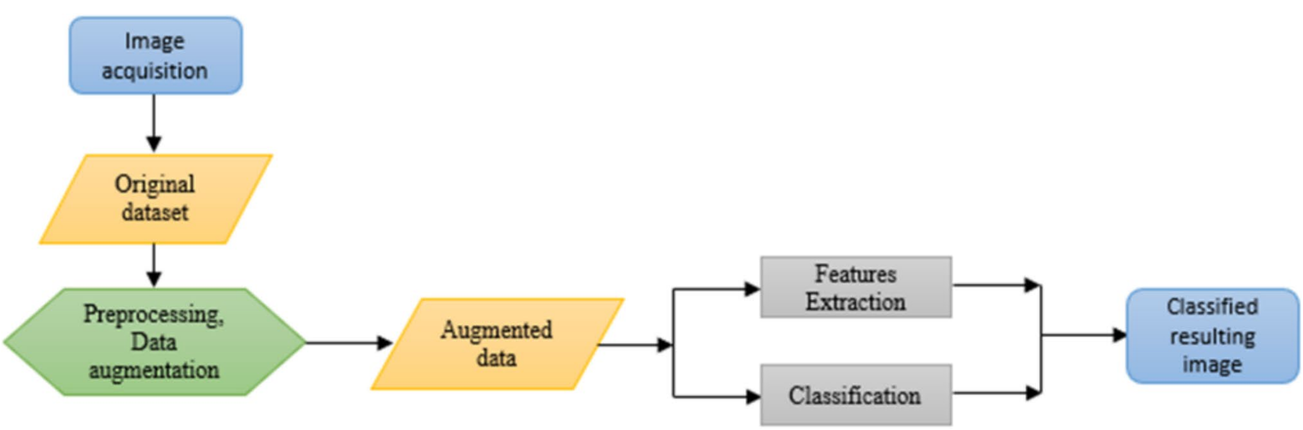
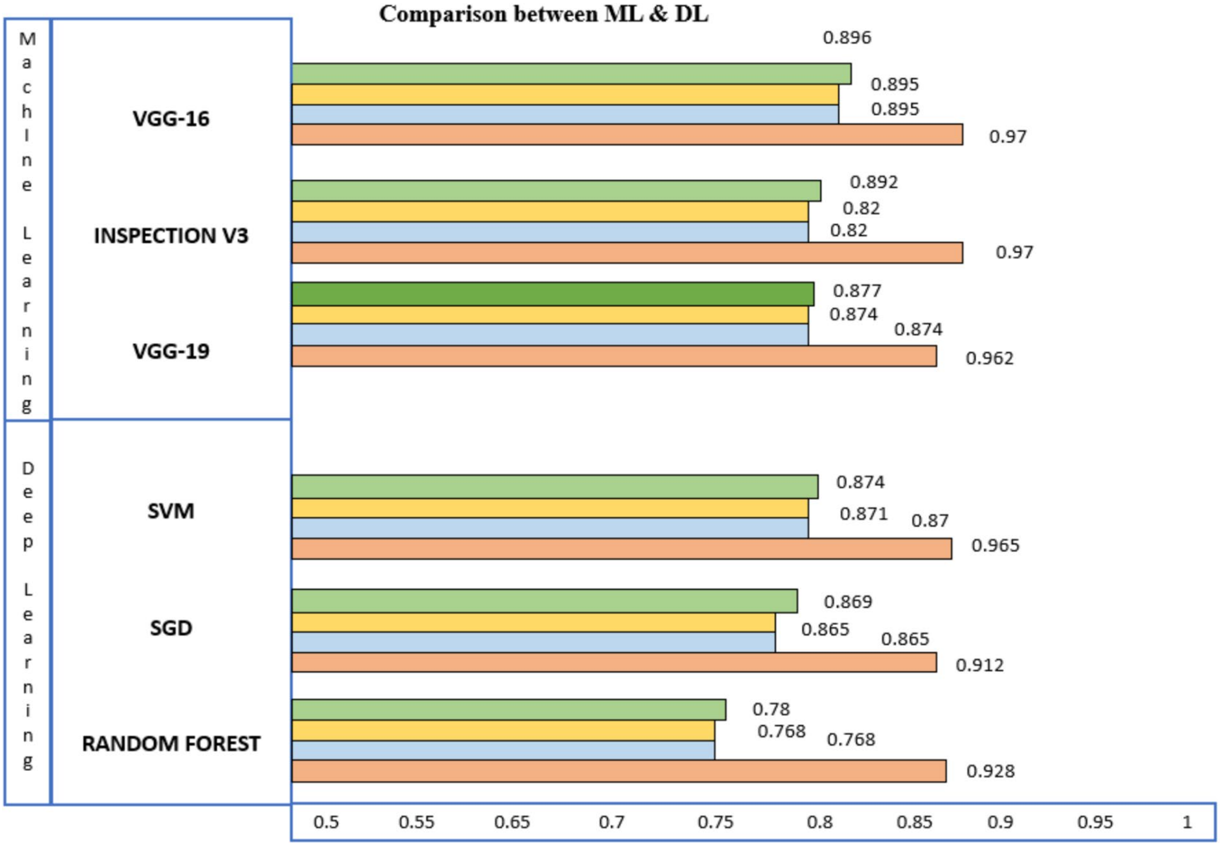


Fig. 21 Methods for detecting leaf diseases using DL



	Machine Learning			Deep Learning		
	Random Forest	SDG	SVM	VGG-19	INSPECTION V3	VGG-16
Precision	0.78	0.869	0.873	0.877	0.892	0.896
F1	0.767	0.865	0.871	0.874	0.89	0.895
CA	0.768	0865	0.87	0874	0.89	0.895

Fig. 22 Comparative review of ML and DL techniques

Another important mechanism named the normalized difference vegetation indicator (NDVI) is a widespread indicator used for plant growth evaluation using measuring the differences between infrared and red-light reflectance. The integration of this data along with ML and DL algorithms helps in water resource management, disease detection and identification, and yield prediction (Royimani et al. 2019). Satellite remote sensing technology assists farmers to execute focused and targeted initiatives, pest management, and accurate fertilization, thereby improving crop sustainability and productivity (Cavender-Bares et al. 2020; Lu et al. 2023; Royimani et al. 2019).

6.1.2 Unmanned aerial vehicles (UAVs)

Drones or UAVs are playing key roles in modern agriculture particularly in precision farming. Drone technology is equipped with state-of-the-art sensors which can provide accurate and highly up-to-date data on crop conditions at low altitudes (Lu et al. 2023). The usage of drone technology provides daily surveillance of specific regions and provides prompt information about plant health, nutritional levels, pest outbreaks, and water stress (Peña et al. 2015). Using this prompt information facilitates farmers in early diagnosis, avoiding crop losses, and maximizing resource utilization (Lu et al. 2023). UAVs are also helpful while reaching hard areas, non-invasive monitoring, large data monitoring, and in improved data analytics. Thermal sensors equipped with UAVs facilitate the evaluation of the surface temperature and soil moisture by tracking temperature fluctuations (Peña et al. 2015). It can also assist in surveying large areas and inaccessible regions than satellite data (Lu et al. 2023). The integration of ML and DL algorithms also increases the processing efficiency of data acquired using drone technologies. These algorithms are useful in identifying trends and anomalies, classifying plant

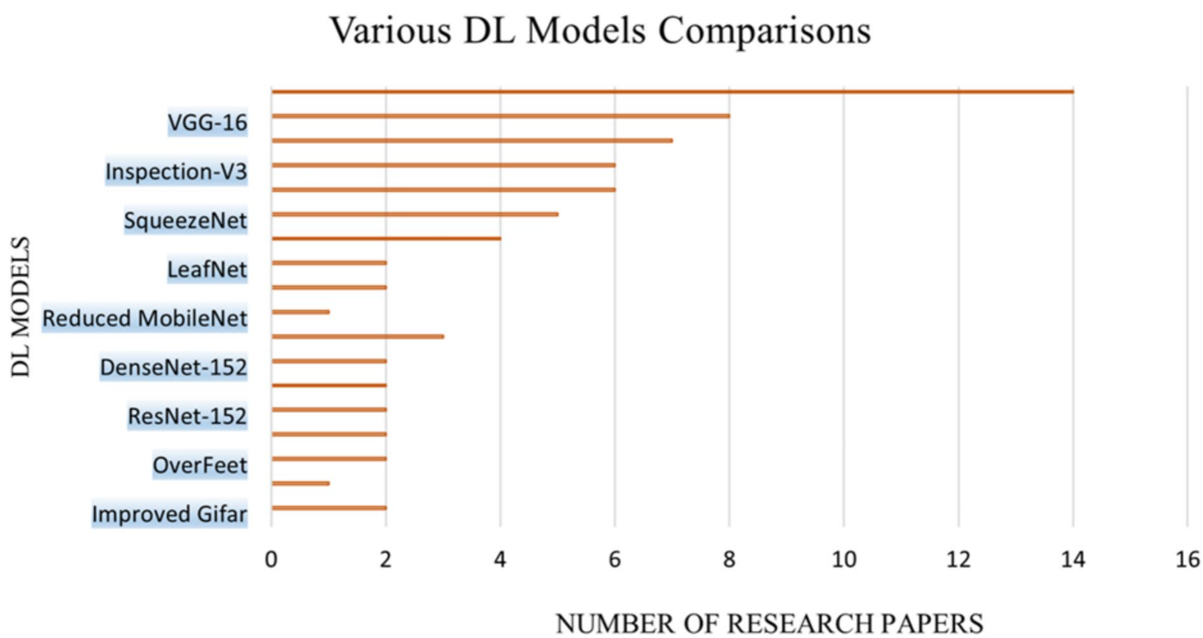


Fig. 23 Review of Different DL Techniques Used in Different Research Papers

growth conditions, and predicting probable crop outcomes (Royimani et al. 2019). It also facilitates precision agriculture by enabling data-driven solutions, optimizing crop management techniques, and improving overall production and sustainability.

6.1.3 Ground-based sensing

Ground-based sensing is another useful method utilizing sensors positioned near the ground to collect complex and high-quality data about vegetation (Peña et al. 2015). This technique achieved the best results in plant disease detection and identification. It has the capability to provide localized and accurate data which is required for identifying plant growth, health, and disease (Zhang and Zhu 2023). Portable devices, including robots and automobiles, are merged with ground-based technology and equipped with different types of sensors, including cameras, LiDAR, and spectrometers (Jung et al. 2023). Moreover, this model reduces the impact of external factors which is vital in identifying and detecting specific features of different plants (Jung et al. 2023). It is widely used in greenhouses, research plots, and farms, where the actual engagement of farmers is essential to improving crop results.

6.1.4 1D and 2D data in remote sensing

- **1D Data:** This type of data is usually collected by sensors and corresponds to spectral data. It frequently derives from hyperspectral sensors. Hyperspectral sensors absorb light reflectance directly from pixels across various wavelengths. For example, temporal data and spectral signatures of plants obtained from environmental sensors. ML methods such as SVM, k-NN, and RF could directly process one-dimensional data by utilizing the time point as a feature. DL models such as RNNs, LSTMs, and CNNs utilize temporal dependencies when analyzing time-series data. For example, the 1D-CNN model employs ID filters to extract local features from spectral data, while its pooling layers facilitate dimensionality reduction.

  Architectural Modifications:
  1D-CNNs convolutional filtering systems have been developed for use on one specific dimension and RNNs models are specifically designed to process sequential data by maintaining an undetectable state that contains temporal dependencies.

- **2D Data:** Data obtained from thermal sensors or optical techniques is 2D data such as images recorded by drones or satellites. ML models require color, shape, and texture information from 2D data to transform them into 1D feature vectors. similarly, DL models such as 2D-CNNs, ResNet, and VGG utilize 2D convolutional filters (textures, colors) to capture spatial information, consequently utilizing pooling and fully connected layers to reduce spatial dimensions and classify the collected features.

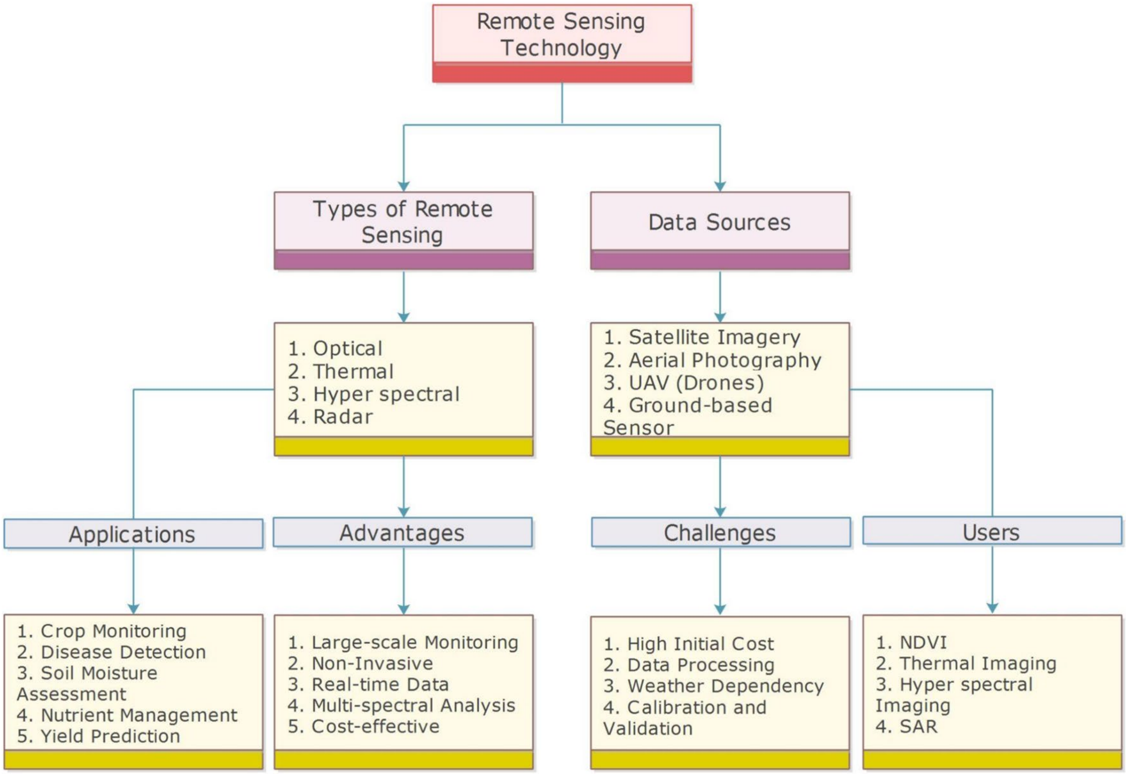


Fig. 24 Remote sensing technologies for plant disease detection

Architectural Modifications:
2D-CNNs convolutional filters are used to manipulate image data and attention methods such as ViTs) architecture can be applied to the region of interest to identify disease.

6.2 Importance of remote sensing in agriculture

The sustainability and productivity of modern farming were significantly improved by the utilization of UAVs and satellites technologies (Lu et al. 2023). Using these technologies, farmers may increase production, optimize the efficiency of the agriculture operations, and can make informed decisions. Real-time, recent, and comprehensive data related to crop growth, diseases, and environmental conditions may increase the resource efficiency (Jung et al. 2023). Using enhanced and high-quality images and spectral data, farmers can spot the disease symptoms earlier to their attack and can use alternate mechanisms such as chemical spraying to minimize the production loss. Sensing data can also be used to assess the water stress, plant growth, and nutritional levels of the plants (Jung et al. 2023). In addition, satellites and UAVs outfitted with multiple types of sensors can monitor soil moisture levels, hence enhance irrigation management. The integration of MI and DL algorithms with remote sensing technology enhances the efficacy of remote sensing technology in recognizing and identifying the presence of plant diseases and assist farmers in making timely decisions, managing supply chains, and in future planning (Cavender-Bares et al. 2020; Lu et al. 2023; Jung et al. 2023). It can also assist the implementation of sustainable agriculture methods that safeguard and keep the ecosystem safe (Abbas et al. 2023). By integrating advanced analytics, remote sensing data, and precisely using timely inputs such as herbicides, water, and fertilizers, farmers may increase crop productivity and minimize waste. Due to the involvement of remote sensing technologies in agriculture, it is becoming progressively more productive and environmentally sustainable (Abbas et al. 2023). Consequently, the importance of remote sensing in agriculture, especially in plant disease identification and detection, includes early disease detection, large area monitoring, continuous and real-time data acquisition, high-resolution images collection, non-invasive monitoring, cost-effectiveness, multiple stress factor detection, spatial and temporal analysis, resource optimization, and climate change adaptation. In summary, remote sensing assists farmers to make timely and informed decisions, minimize losses, and increase overall production while stimulating more sustainable farming practices.

6.3 Integration of remote sensing with ML and DL models in plant disease detection systems

The integration of machine learning (ML) and deep learning (DL) with remote sensing technologies revolutionizes plant disease detection and identification, thereby improving efficiency, accuracy, and scalability (Cavender-Bares et al. 2020; Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023). This concept capitalizes on huge datasets acquired by remote sensing and the modern capabilities of ML and DL algorithms to provide a deep understanding of plant health and environmental conditions (Ojo and Zahid 2023). However, datasets annotations and preparation are vital while employing remote sensing technologies to integrate ML and DL into plant detection and identification systems (Ojo and Zahid 2023). These techniques ensure that the data is precise, accurate, and appropriate for the training and testing of robust models. UAVs and satellites that are equipped with multiple sensors can capture multispectral, hyperspectral, and thermal images to provide dependable and extensive coverage. UAVs also provide real-time, current, and high-resolution images acquired from different angles and heights to monitor specific areas (Peña et al. 2015).

Pre-processing of remote sensing data is essential to improve the performance of ML and DL algorithms, as unprocessed data frequently reveals noise and other artifacts such as fluctuations in lighting, radiometric correction, sensor features, and meteorological conditions (Zhang and Zhu 2023; Peña et al. 2015). Radiometric correction is widely used and a key step in data pre-processing. It can easily adjust data for atmospheric interference and sensor noise which ensure the reflectance values to precisely represent ground conditions (Cavender-Bares et al. 2020). Similarly, geometric correction modifies image alignment to a unified coordinate system to resolve motion errors resulting from sensor movement. Normalization is employed to improve the consistency among various images and sensors and to standardize data to a single scale. Moreover, segmentation and feature extraction methods are commonly used to isolate pertinent features, vegetation indices (e.g. NDVI), pertinent properties, and spectral signatures (Sridevy et al.2023). The pre-processing step also transforms raw data into an organized and consistent format to facilitate disease analysis processes and enhance decision-making in precision agriculture (Ojo and Zahid 2023; Sridevy et al. 2023).

6.4 Applications and case studies

This section discusses the applications of remote sensing technology in conjunction with ML and DL algorithms as detailed below.

6.4.1 Disease detection

Machine Learning and Deep Learning models have transformed plant disease diagnosis via remote sensing data, which provide previously unheard-of accuracy and efficiency (Zhang and Zhu 2023). These models easily recognize intricate patterns and abnormalities in plant images that point to illnesses like powdery mildew, wheat leaf rust, and other fungal infections (Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023). State-of-the-art ML and DL algorithms such as CNN and its family, Transformer-based models, and GAN's models are able to detect early indicators of disease that are not readily apparent to the human eye by analyzing high-resolution images (Mng'ombe et al. 2024; Dey et al. 2024). This capacity for early detection enables prompt treatments, greatly slowing the spread of diseases and reducing agricultural losses (Mng'ombe et al. 2024; Dey et al. 2024; Adekunle et al. 2024; Tiendrebeogo 2024; Kareem et al. 2024; Srivastava and Meena 2024; Paul Joshua et al. 2025; Barman et al. 2024; Sarkar et al. 2023; Zhang et al. 2019; Zhang and Zhu 2023; Peña et al. 2015; Cavender-Bares et al. 2020; Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023). These models facilitate farmers'implementation of targeted treatments, maximizing resource use and enhancing crop health by furnishing accurate and timely diagnoses. These models have the ability to identify plant diseases, increase agricultural output, and encourage sustainable farming methods by lowering the need for broad-spectrum herbicides (Mng'ombe et al. 2024; Dey et al. 2024; Adekunle et al. 2024; Tiendrebeogo 2024; Kareem et al. 2024; Srivastava and Meena 2024; Paul Joshua et al. 2025; Barman et al. 2024; Sarkar et al. 2023; Zhang et al. 2019; Zhang and Zhu 2023; Peña et al. 2015; Cavender-Bares et al. 2020; Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023).

6.4.2 Crop health monitoring

Remote sensing technology in integration with ML and DL models outclass the manual farming process. These technologies used spectral signatures, color, and texture information to efficiently detect crop health (Mng'ombe et al. 2024; Dey et al. 2024; Jung et al. 2023). These models used normalized difference vegetation indicator (NDVI), the most common indicator, as a botanical indicator among multiple indicators. NDVI can easily identify the gap between visible and near-infrared light reflected by plants that can assist in the detection of plant growth, disease, and stress factors (Mng'ombe et al. 2024; Dey et al. 2024). Remote sensing technologies such as satellites and UAVs acquired data across different spectra (hyperspectral, thermal), and ML and Dl algorithms are used to process this data to predict plant disease outbreaks, crop growth, and water level

(Dey et al. 2024). Farmers can get meaningful information from continuous tracking, which helps them to improve plant health and maximize production. The utilization of these modern technologies may improve precision agriculture, the sustainability of farming processes, and crop yields (Cavender-Bares et al. 2020).

6.4.3 Yield prediction

Crop production assessment is vital for future planning and supply chain management (Royimani et al. 2019). Remote sensing technologies, along with ML and DL algorithms, are playing an important role in crop production assessment by combining multiple features such as weather patterns, historical data, and current plant health (Cavender-Bares et al. 2020). Moreover, these algorithms consider multiple variables, including temperature, soil state, rainfall, and plant health. With the productive capabilities of these algorithms, farmers can improve the crop collection time and can predict product quantity, which helps in inventory management by minimizing waste and ensuring the consistency between supply and demand (Peña et al. 2015). It also assists farmers to efficiently plan market strategies and make them capable of setting competitive market pricing. In general, these technologies improve agriculture profitability and operational efficiency.

6.4.4 Water management

Water resource management is vital to agriculture's sustainability (Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023; Gogoi et al. 2018). ML and DL algorithms used soil moisture levels and crop water stress data acquired using thermal and multispectral sensors to assist farmers in proper management of water resources (Lu et al. 2023). These algorithms precisely predict proper plant hydration, assist in the assessment of water requirement capacity, and can help farmers in avoiding overwatering and irrigation expenses (Lu et al. 2023). Moreover, these models also help in various crop-related issues such as soil erosion, nutrient leaching, soil condition assessment, and raising crop quality overall (Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023; Gogoi et al. 2018). Therefore, ML and DL algorithms play a vital role in effective water planning, which promotes the overall profit as well as environmental sustainability.

6.4.5 Pest detection

Remote sensing technologies, along with ML and DL algorithms, are quite effective in detecting and identifying pest early signs such as discoloured patches, damaged foliage, population, incursion, disease representatives, natural habitats, substantial damage to productivity, and biodiversity by analysing plant color and texture changes (Zhang and Zhu 2023; Peña et al. 2015; Cavender-Bares et al. 2020; Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023). These early symptoms help farmers take abrupt measures to minimize crop loss (Jung et al. 2023). This method improves pest management by minimizing the demand for chemicals and safeguarding plant health and yield (Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023). Consequently, these technologies facilitate farmers to handle their financial losses and increase production (Jung et al. 2023).

6.4.6 Crop mapping and classification

Accurate crop mapping and classification are vital to plan land utilization and managing agriculture (Lu et al. 2023). ML and DL algorithms perform efficiently to identify them using spectral and spatial features recorded by remote sensing technology (Zhang and Zhu 2023; Peña et al. 2015; Cavender-Bares et al. 2020; Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023; Gogoi et al. 2018). These algorithms use large volumes of data to accurately differentiate different plant disease types and provide a complete map of crop distribution (Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023; Gogoi et al. 2018). And using these maps, farmers can track plant health, growth, and soil conditions (Royimani et al. 2019). Moreover, these maps also provide useful information such as resource allocation, field management, and crop rotation. Agricultural operations may be improved by taking advantage of machine learning for crop mapping and categorization, resulting in improved crop management, increased yield, and better land use (Royimani et al. 2019).

7 Future trends and research directions

7.1 Emerging technologies

The remarkable improvement in ML and DL algorithms is set to considerably enhance plant detection and identification systems (Mng'ombe et al. 2024; Dey et al. 2024). These improvements are going to dramatically improve the precision and efficacy of wheat leaf rust detection, leading to more reliable and effective disease detection and control in agricultural contexts (Mng'ombe et al. 2024; Dey et al. 2024; Adekunle et al. 2024; Tiendrebeogo 2024; Kareem et al. 2024; Srivastava and Meena 2024; Paul Joshua et al. 2025; Barman et al. 2024; Sarkar et al. 2023; Zhang et al. 2019; Zhang and Zhu 2023; Peña et al. 2015; Cavender-Bares et al. 2020; Lu et al. 2023; Royimani et al. 2019;

Abdullah et al. 2023; Jung et al. 2023; Gogoi et al. 2018). Several state-of-the-art ML and DL algorithms are usable for effective plant disease detection and identification (Shafik et al. 2023; Demilie 2024). Transformer-based models are increasingly used in image recognition applications, often outclassing traditional CNNs (Barman et al. 2024). ViTs models are capable of capturing long-range relationships in images and can identify complex plant diseases (Barman et al. 2024). Similarly, in some cases where resources are limited, EficientNet family balances computational effectiveness and precision, making it suitable for precision farming (Nigam et al. 2024). GAN models have outclassed performance in utilizing synthetic datasets, as they can enhance training data and increase the possibility of handling limited labelled data for specific plant diseases such as leaf rust (Paul Joshua 2025). Transformer-based models such as ViTs are normally used for image classification tasks, while DETR is used for object detection. These models employ a self-attention approach to detect distant dependency in data, and they are incredibly successful in analyzing huge datasets. In ViTs, the primary layers (used for low-level patterns) can be locked to maintain general knowledge, and the last layers are adjusted for task-specific patterns. This mechanism reduces computational cost and overfitting problems especially when analyzing small datasets.

Recently, Explainable AI (XAI) models have proven significant results in providing transparency in ML and DL algorithms (Khalid and Karan 2024). In integration with the MI and DL algorithms, XAI fosters user confidence and increases the implementation of plant detection and identification systems by clarifying the decision-making processes of these algorithms (Khalid and Karan 2024). Additionally, Federated Learning AI models expedite the training process of ML and DL algorithms on various servers without requiring data sharing. This mechanism can simplify and improve the model generalization process by integrating data from multiple resources (Khalid and Karan 2024).

7.2 Research gaps

To fully exploit the opportunities of remote sensing technology, machine learning, and Deep Learning-based plant detection systems, regardless of significant developments, a number of research gaps persist as follows:

7.2.1 High-quality and diverse datasets

It is necessary to have appropriate datasets in order to develop algorithms and train machines to diagnose plant diseases from images. DL-based solutions require big datasets with thousands of images (Ahmad et al. 2023b). More comprehensive and varied datasets covering a range of crop sorts, climatic circumstances, and disease stages are required (Routis et al. 2024; Khalid and Karan 2024; Thivya Lakshmi et al. 2024; Pujari et al. 2024; Subbiah and Krishnaraj 2024; Mahadevan et al. 2024; Rani et al. 2024; Pawar et al. 2024; Dohare and Khan 2024; Gautam et al. 2024; Dubey and Choubey 2024; Bouacida et al. 2025; Kumar et al. 2024a; Usha Ruby et al. 2024; Raja and Nargunam 2024; Joseph et al. 2024; Jafar et al. 2024; Pavithra et al. 2023; Ahmad et al. 2023a; Madeira et al. 2024; Patil 2024; Chen et al. 2023; Bhola and Kumar 2025; Ramadan et al. 2024; Mandava et al. 2024; Cuenca-Romero et al. 2024; Zenkl et al. 2024; Reis and Turk 2024; Feng et al. 2024; Mao et al. 2024; Nigam et al. 2024; Sharma and Sethi 2024; Tolba and Talal 2024; Dixit et al. 2024; Saraswat et al. 2024; Abdelkrim 2024; Ali 2024; Jagadeeshan et al. 2024; Kumar et al. 2024b; Maqsood et al. 2024; Liu 2024; Subbiah and Nagappan 2024; Banerjee et al. 2024; Han et al. 2024; Kumar et al. 2024c; Sonmez et al. 2024; Tang et al. 2023; Khan et al. 2022; Mohapatra et al. 2021; Li et al. 2022; Nigam et al. 2023; Shafi et al. 2023; Singh et al. 2023; Nigus et al. 2024; Ahmad et al. 2023b). The ML and DL models will become more reliable and broadly applicable. From Fig. 12, it was discovered that the “PlantVillage” dataset is the most often used. However, several of the researchers in the examined studies chose to build unique datasets that are not publicly available.

7.2.2 Integration of multi-modal data

Integrating information from many sources (such as meteorological data, LiDAR, and hyperspectral imaging) may provide a fuller understanding of plant health (Lu et al. 2023). Using a multimodal dataset, researchers and farmers can develop new state-of-the-art models for early identification and detection of plant disease (Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023). This strategy helps in acquiring a more solid review of plant disease detection. The development of state-or-the-art techniques for efficiently integrating and evaluating multi-modal data requires future research.

7.2.3 Real-time data processing

Real-time data processing refers to analyze and interpret dataset within required time frame. Real-time data processing and analysis algorithms must be developed for rapid disease identification and detection (Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023; Gogoi et al. 2018). It can enhance decision-making processes and can minimize losses (Jung et al. 2023). The research's primary goals should be to enhance computing efficiency and cutting down on data processing delays.

7.2.4 Scalability and practical deployment

Many ML and DL models work well in controlled settings, but there are still issues with their scalability and usefulness when applied to actual agricultural systems (Royimani et al. 2019; Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023; Gogoi et al. 2018). A state-of-the-art ML and DL models are required to process large datasets in different conditions without losing their performance. A novel solution is also required that can be implemented in a real-world environment and provide tangible benefits. The development of these models for use in several kinds of dynamic field situations should be the subject of future research.

7.3 Potential for improvement

To ensure ML and DL models perform effectively across diverse regions, crop types, and disease variants, enhancing their generalization capabilities is crucial (Mng'ombe et al. 2024; Dey et al. 2024; Adekunle et al. 2024; Tiendrebeogo 2024; Kareem et al. 2024; Srivastava and Meena 2024; Paul Joshua et al. 2025; Barman et al. 2024; Sarkar et al. 2023; Zhang et al. 2019; Zhang and Zhu 2023; Peña et al. 2015; Cavender-Bares et al. 2020; Lu et al. 2023; Royimani et al. 2019; Abdullah et al. 2023; Jung et al. 2023; Gogoi et al. 2018; Abbas et al. 2023; Ojo and Zahid 2023; Sridevy et al. 2023; Shafik et al. 2023; Demilie 2024; Jackulin and Murugavalli 2022; Prasath et al. 2023; Ngongoma et al. 2023). Achieving this can be done through techniques like robust feature extraction and domain adaptation, which enable models to adapt to varying conditions and datasets without losing accuracy (Jung et al. 2023). Additionally, for these technologies to have a widespread impact, particularly among smallholder farmers, the development of cost-effective and accessible solutions is essential. This requires the creation of affordable sensors, simplified data collection methods, and lightweight computational models that can function efficiently in resource-constrained environments.

Collaboration between agronomists, computer scientists, and engineers is critical in addressing real-world agricultural challenges. Such interdisciplinary partnerships can drive the development of innovative solutions that bridge the gap between research, development, and practical field implementation (Demilie 2024; Jackulin and Murugavalli 2022). By integrating diverse expertise, it becomes possible to tailor technologies to meet the specific needs of farmers while ensuring scalability and sustainability (Demilie 2024).

Moreover, research into the most effective approaches for training users, providing ongoing support, and disseminating technology is also crucial. The success of any new agricultural technology hinges not only on its development but also on ensuring that farmers and agricultural workers are adequately trained and supported in its use (Demilie 2024). Comprehensive training programs, user-friendly interfaces, and accessible support systems are necessary to guarantee that new technologies are adopted efficiently and contribute meaningfully to improving agricultural productivity and sustainability (Abdullah et al. 2023; Jung et al. 2023; Gogoi et al. 2018; Abbas et al. 2023; Ojo and Zahid 2023; Sridevy et al. 2023; Shafik et al. 2023; Demilie 2024).

ML and DL models for plant disease identification and detection have revolutionized farming, achieving exceptional accuracy and scalability in identifying diseases such as wheat leaf rust. Cutting-edge algorithms like GANs and ViTs achieve superior accuracy and show significant effectiveness in analysing complex and spectral data, enabling early disease detection and quick management. Likewise, remote sensing technologies, coupled with IoT, enhance these features and bridge the gap between precision agriculture and field-level implementation. The implementation of these technologies poses significant challenges. The reliance on labelled datasets remains an unresolved challenge, as shown by the PlantVillage dataset, which frequently shows insufficient variability in environmental conditions and disease stages. similarly, class imbalance and dataset limitations limit model generalization. Coordination among researchers, data scientists, engineers, and farmers are essential for enhancing model interpretability, optimization, and developing solutions to meet farmers'demands. XAI models can elucidate decision-making processes and improve trust among farmers, while federated learning models can democratize access to diverse datasets while preserving data privacy. Cutting-edge models like ViTs and GANs utilize spectral, spatial, and temporal data integration techniques to enhance data precision. This integration could help in the understanding of diseases and their relationships with their surroundings. These innovations hold significant potential to enhance food security by minimizing yield losses, optimizing resource utilization, and implementing environmentally friendly procedures. However, fair resource management, including access to information, technology, and the environmental implications of sensor position, must be considered. In summary, models based on ML and DL have the potential to transform modern agriculture; yet, their effectiveness depends on overcoming technological barriers and aligning developments with the real requirements of farming communities.

8 Conclusion

The article provides a comprehensive overview of the current advancements in the technology for detection and identification of plant diseases used in agriculture. The initial goal was to assess recent plant disease detection and identification technologies that were employed with a focus to use remote sensing, ML and DL algorithms. The review commenced with the constraints and challenges as well as recent developments in plant disease detection and identification techniques were explained, specifically concerning wheat leaf rust detection. Subsequently, the existing listed and described datasets available for public access in the development of scientific research were also discussed in detail. Furthermore, an in-depth analysis of state-of-the-art studies in plant disease detection and identification, highlighting the strengths of existing works across different plants, and providing a detailed analysis of the utilization of MI and DL algorithms in this domain. The review then proceeded to discuss various remote sensing technologies used in the agricultural sector, along with their purpose and effectiveness in improving agricultural practices. Last but not the least, future scope and recent research developments and possibilities available in plant disease diagnosis and identification were discussed in detail to open new avenues for research in this specific area.

Acknowledgements This study is supported via funding from Prince Sattam bin Abdulaziz University project number (No. 01/2024/28439).

Author's Contribution [1]**Sajid Ullah Khan:** Being the first author of the paper, I wrote the first draft of the paper and designed the overall structure of the paper.

[2]**Anas Alsuhaibani:** Alsuhaibani works on the flow of the paper and wrote and analyzed Sect. 3 "Automated plant disease detection system".

[3]**AbdulRahman Alabduljabbar:** Performed proofreading and analytical review of the paper. Moreover, Visualization and validation are done by him.

[4]**Fahdah Almarshad:** She works on Sect. 5 "publicly available image dataset".

[5]**Youssef Altherwy:** Analyze the overall structure of the paper. Additionally, resources and administration of the project is done by him. He also works on Sect. 2.

[6]**Tallha Akram:** perform critical analysis and work on Sect. 6 of the paper.

Data availability All the data is publicly available.

Declarations

Conflict of Interest The authors have no conflict of interest.

References

Abbas A, Zhang Z, Zheng H, Alami MM, Alrefaei AF, Abbas Q, Naqvi SAH, Rao MJ, Mosa WF, Abbas Q (2023) Drones in plant disease assessment, efficient monitoring, and detection: a way forward to smart agriculture. Agronomy 13:1524

Abdelkrim O (2024) Hyperspectral imaging using deep learning in wheat diseases. In: 2024 8th international conference on image and signal processing and their applications (ISPA). IEEE, pp 1–8

Abdullah HM, Mohana NT, Khan BM, Ahmed SM, Hossain M, Islam KS,..., Ahamed T (2023) Present and future scopes and challenges of plant pest and disease (P&D) monitoring: Remote sensing, image processing, and artificial intelligence perspectives. Remote Sens Appl: Soc Environ 32:100996

Adekunle TS, Lawrence MO, Alabi OO, Afolorunso AA, Ebong GN, Oladipupo MA (2024) Deep learning technique for plant disease detection. Comput Sci Inf Technol 5:55–62

Ahmad A, El Gamal A, Saraswat D (2023a) Toward generalization of deep learning-based plant disease identification under controlled and field conditions. IEEE Access 11:9042–9057

Ahmad A, Saraswat D, El Gamal A (2023b) A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools. Smart Agric Technol 3:100083

Ali Z (2024) Yellow rust disease detection from wheat images. https://urn.fi/URN:NBN:fi:amk-2024052715871

Angamuthu T, Arunachalam AS (2023) A comprehensive survey on the revolution of plant disease detection and diagnosis through automated image processing techniques with CNN and RNN. Singaporean J Sci Res (SJSR) 15(1):1–8

Anju UV, Swaraj KP (2024) Real time iot enabled automated leaf disease identification using deep learning models–a review. In: AIP conference proceedings, vol 3037. AIP Publishing

Banerjee D, Kukreja V, Chandran N, Garg N (2024) Precision diagnosis of wheat powdery mildew using CNN and random forest. In: 2024 international conference on emerging smart computing and informatics (ESCI). IEEE, pp 1–6

Barbedo JGA, Koenigkan LV, Halfeld-Vieira BA, Costa RV, Nechet KL, Godoy CV, Junior ML, Patricio FRA, Talamini V, Chitarra LG (2018) Annotated plant pathology databases for image-based detection and recognition of diseases. IEEE Lat Am Trans 16:1749–1757

Barman U, Sarma P, Rahman M, Deka V, Lahkar S, Sharma V, Saikia MJ (2024) Vit-SmartAgri: vision transformer and smartphone-based plant disease detection for smart agriculture. Agronomy 14:327

Bhola A, Kumar P (2025) Deep feature-support vector machine based hybrid model for multi-crop leaf disease identification in Corn, Rice, and Wheat. Multimed Tools Appl 84(8):4751–4771

Bouacida I, Farou B, Djakhdjakha L, Seridi H, Kurulay M (2025) Innovative deep learning approach for cross-crop plant disease detection: A generalized method for identifying unhealthy leaves. Inf Process Agric 12(1):54–67

Cavender-Bares J, Gamon JA, Townsend PA (2020) Remote sensing of plant biodiversity. Springer Nature, p 581

Chelladurai K, Sujatha N (2024) A review of disease detection in leaves using image processing techniques based on thermal camera. Int J Intell Syst Appl Eng 12:175–184

Chen J, Zeb A, Nanehkaran YA, Zhang D (2023) Stacking ensemble model of deep learning for plant disease recognition. J Ambient Intell Humaniz Comput 14:12359–12372

Chen X, Liu T, Han K, Jin X, Yu J (2024) Semi-supervised learning for detection of sedges in sod farms. Crop Prot 179:106626

Ciobotari I, Príncipe A, Oliveira MA, Silva JN (2024) LiDAR data acquisition and processing for ecology applications. arXiv preprint arXiv:2401.05891

Cuenca-Romero C, Apolo-Apolo OE, Rodríguez Vázquez JN, Egea G, Perez-Ruiz M (2024) Tackling unbalanced datasets for yellow and brown rust detection in wheat. Front Plant Sci 15:1392409

Demilie WB (2024) Plant disease detection and classification techniques: a comparative study of the performances. J Big Data 11:5

Dey P, Mahmud T, Nahar SR, Hossain MS, Andersson K (2024) Plant disease detection in precision agriculture: deep learning approaches. In: 2024 2nd international conference on intelligent data communication technologies and internet of things (IDCIoT). IEEE, pp 661–667

Diker A, Elen A, Közkurt C, Kılıçarslan S, Dönmez E, Arslan K, Kuran EC (2024) An effective feature extraction method for olive peacock eye leaf disease classification. Eur Food Res Technol 250:287–299

Dixit N, Arora R, Gupta D (2024) Wheat crop disease detection and classification using machine learning. In: Infrastructure possibilities and human-centered approaches with industry 5.0. IGI Global Scientific Publishing, pp 267–280

Dohare AK, Khan AA (2024) Plant health monitoring system using machine learning. Int J Eng Manag Res 14:87–94

Dubey RK, Choubey DK (2024) Adaptive feature selection with deep learning MBi-LSTM model based paddy plant leaf disease classification. Multimed Tools Appl 83:25543–25571

Feng J, Zhang S, Zhai Z, Yu H, Xu H (2024) Dc2net: an asian soybean rust detection model based on hyperspectral imaging and deep learning. Plant Phenomics 6:0163

Gautam V, Ranjan RK, Dahiya P, Kumar A (2024) ESDNN: a novel ensembled stack deep neural network for mango leaf disease classification and detection. Multimed Tools Appl 83:10989–11015

Gogoi N, Deka B, Bora L (2018) Remote sensing and its use in detection and monitoring plant diseases: a review. Agric Rev 39:307–313

Han D, Wang P, Tansey K, Zhang Y, Li H (2024) A graph-based deep learning framework for field scale wheat yield estimation. Int J Appl Earth Obs Geoinf 129:103834

Houetohossou SCA, Ratheil Houndji V, Sikirou R, Glèlè Kakaï R (2024) Finding optimum climatic parameters for high tomato yield in Benin (West Africa) using frequent pattern growth algorithm. Plos One 19:e0297983

HR SK, KM P (2024) Deep convolutional neural networks fusion with support vector machines and K-nearest neighbors for precise crop leaf disease classification. IJACSA 15(3)

Jackulin C, Murugavalli S (2022) A comprehensive review on detection of plant disease using machine learning and deep learning approaches. Meas Sensors 24:100441

Jafar A, Bibi N, Naqvi RA, Sadeghi-Niaraki A, Jeong D (2024) Revolutionizing agriculture with artificial intelligence: plant disease detection methods, applications, and their limitations. Front Plant Sci 15:1356260

Jagadeeshan N, Nagendar Y, Swarnalatha K, Al-Attabi K, Ramachandra AC (2024) Three-dimensional convolutional neural network for wheat rust disease classification. In: 2024 international conference on distributed computing and optimization techniques (ICDCOT). IEEE, pp 1–4

Joseph DS, Pawar PM, Chakradeo K (2024) Real-time plant disease dataset development and detection of plant disease using deep learning. IEEE Access 12:16310–16333

Jung H, Tajima R, Ye R, Hashimoto N, Yang Y, Yamamoto S, Homma K (2023) Utilization of UAV remote sensing in plant-based field experiments: a case study of the evaluation of LAI in a small-scale sweetcorn experiment. Agriculture 13:561

Kamarianakis Z, Perdikakis S, Daliakopoulos IN, Papadimitriou DM, Panagiotakis S (2024) Design and Implementation of a low-cost, linear robotic camera system, targeting greenhouse plant growth monitoring. Futur Internet 16:145

Kareem MR (2024) Image analysis and detection of olive leaf diseases using recurrent neural networks. Al-Mustansiriyah J Sci 35:60–65

Karthickmanoj R, Sasilatha T, Singh NSS (2023) Plant disease detection using random forest classifier with novel segmentation and feature extraction strategy. J Eng Sci Technol 18(6):32–38

Khalid MM, Karan O (2024) Deep learning for plant disease detection. Int J Math Stat Comput Sci 2:75–84

Khan H, Haq IU, Munsif M, Mustaqeem, Khan SU, Lee MY (2022) Automated wheat diseases classification framework using advanced machine learning technique. Agriculture 12:1226

Kumar D, Kukreja V, Singh A (2024a) A novel hybrid segmentation technique for identification of wheat rust diseases. Multimed Tools Appl 83(29):72221–72251

Kumar V, Banerjee D, Chauhan R, Thapliyal S, Sharma K, Gill KS (2024b) Unified methodology for wheat leaf disease identification: combining CNN and random forest approaches. In: 2024 3rd international conference for innovation in technology (INOCON). IEEE, pp 1–5

Kumar V, Gill KS, Chauhan R, Thapliyal S, Sharma K (2024c) Enhancing wheat disease classification: a hybrid approach combining CNN and random forest. In 2024 fourth international conference on advances in electrical, computing, communication and sustainable technologies (ICAECT). IEEE, pp 1–7

Li Y, Qiao T, Leng W, Jiao W, Luo J, Lv Y, Tong Y, Mei X, Li H, Hu Q (2022) Semantic segmentation of wheat stripe rust images using deep learning. Agronomy 12:2933

Liu H, Chen H, Du J, Xie C, Zhou Q, Wang R, Jiao L (2024) Auto-adjustment label assignment-based convolutional neural network for oriented wheat diseases detection. Comput Electron Agric 222:109029

Lu D, Ye J, Wang Y, Yu Z (2023) Plant detection and counting: enhancing precision agriculture in UAV and general scenes. IEEE Access 11:116196–116205

Macuácua JC, Centeno JAS, Amisse C, Jijón-Palma ME, Vestena KDM (2024) Automatic foliar spot detection from low-cost RGB digital images using a hybrid approach of convolutional neural network and random forest classifier. Boletim Ciên Geodésicas 30:e2024001

Madeira M, Porfírio RP, Santos PA, Madeira RN (2024) AI-powered solution for plant disease detection in viticulture. Procedia Comput Sci 238:468–475

Mahadevan K, Punitha A, Suresh J (2024) Automatic recognition of rice plant leaf diseases detection using deep neural network with improved threshold neural network. e-Prime-Adv Electr Eng Electron Energy 8:100534

Mandava M, Vinta SR, Ghosh H, Rahat IS (2024) Identification and categorization of yellow rust infection in wheat through deep learning techniques. EAI Endorsed Trans Internet Things 10

Mao R, Zhang Y, Wang Z, Hao X, Zhu T, Gao S, Hu X (2024) DAE-Mask: a novel deep-learning-based automatic detection model for in-field wheat diseases. Precis Agric 25:785–810

Maqsood Y, Usman SM, Alhussein M, Aurangzeb K, Khalid S, Zubair M (2024) Model agnostic meta-learning (MAML)-based ensemble model for accurate detection of wheat diseases using vision transformer and graph neural networks. Computers, Materials & Continua 79(2)

Mng'ombe M, Mtonga E, Chunga B, Chidya R, Malota M (2024) Comparative study for the performance of pure artificial intelligence software sensor and self-organizing map assisted software sensor in predicting 5-day biochemical oxygen demand for Kauma Sewage Treatment Plant effluent in Malawi. Front Environ Eng 3:1373881

Mohammad A, Eleyan D, Eleyan A, Bejaoui T (2024) IoT-based plant disease detection using machine learning: a systematic literature review. In: 2024 international conference on smart applications, communications and networking (SmartNets). IEEE, pp 1-7

Mohapatra SK, Prasad S, Nayak SC (2021) Wheat rust disease detection using deep learning. In: Data science and data analytics: opportunities and challenges. p 191

Mojaravscki D, Graziano Magalhães PS (2024) Comparative evaluation of color correction as image preprocessing for olive identification under natural light using cell phones. AgriEngineering 6:155–170

Morchid A, Marhoun M, El Alami R, Boukili B (2024) Intelligent detection for sustainable agriculture: A review of IoT-based embedded systems, cloud platforms, DL, and ML for plant disease detection. Multimed Tools Appl 1–40

Najafabadi MA, Kazemi I (2024) Systemic design of the very-high-resolution imaging payload of an optical remote sensing satellite for launch into the VLEO using an small launch vehicle. Heliyon 10(6)

Ngongoma MS, Kabeya M, Moloi K (2023) A review of plant disease detection systems for farming applications. Appl Sci 13(10):5982

Nigam S, Jain R, Marwaha S, Arora A, Haque MA, Dheeraj A, Singh VK (2023) Deep transfer learning model for disease identification in wheat crop. Eco Inform 75:102068

Nigam S, Jain R, Singh VK, Marwaha S, Arora A, Jain S (2024) EfficientNet architecture and attention mechanism-based wheat disease identification model. Procedia Comput Sci 235:383–393

Nigus EA, Taye GB, Girmaw DW, Salau AO (2024) Development of a model for detection and grading of stem rust in wheat using deep learning. Multimed Tools Appl 83(16):47649–47676

Ojo MO, Zahid A (2023) Improving deep learning classifiers performance via preprocessing and class imbalance approaches in a plant disease detection pipeline. Agronomy 13:887

Patil SL (2024) A high-accuracy deep learning approach for wheat disease detection. International conference on smart computing and communication. Springer Nature Singapore, Singapore, pp 277–291

Paul Joshua K, Alex SA, Mageswari M, Jothilakshmi R (2025) Enhanced conditional self-attention generative adversarial network for detecting cotton plant disease in IoT-enabled crop management. Wirel Netw 31(1):299–313

Pavithra A, Kalpana G, Vigneswaran T (2023) Deep learning-based automated disease detection and classification model for precision agriculture. Soft Comput 1–12

Pawar SE, Surana AV, Sharma P, Pujeri R (2024) Fruit disease detection and classification using machine learning and deep learning techniques. Int J Intell Syst Appl Eng 12:440–453

Peña JM, Torres-Sánchez J, Serrano-Pérez A, De Castro AI, López-Granados F (2015) Quantifying efficacy and limits of unmanned aerial vehicle (UAV) technology for weed seedling detection as affected by sensor resolution. Sensors 15:5609–5626

Prajapati HB, Shah JP, Dabhi VK (2017) Detection and classification of rice plant diseases. Intell Decis Technol 11:357–373

Prasath B, Akila M, Mohan M (2023) A comprehensive survey on IoT-aided pest detection and classification in agriculture using different image processing techniques. Int J Image Graph 2550040

Pujari P, Pujar P, Choudaki P, Kulkarni P, Doddamani P (2024) Improving plant health using machine learning for image based disease detection. 5(12):3701–3705

Rahman R, Indris C, Bramesfeld G, Zhang T, Li K, Chen X, Grijalva I, McCornack B, Flippo D, Sharda A (2024) A new dataset and comparative study for aphid cluster detection and segmentation in sorghum fields. J Imaging 10:114

Raja SN, Nargunam AS (2024) An optimal feature selection-based deep learning approach for wheat disease identification. Multimed Tools Appl 1–22

Ram BG, Oduor P, Igathinathane C, Howatt K, Sun X (2024) A systematic review of hyperspectral imaging in precision agriculture: analysis of its current state and future prospects. Comput Electron Agric 222:109037

Ramadan STY, Sakib T, Al Farid F, Islam MS, Abdullah J, Bhuiyan MR, Karim HA (2024) Improving wheat leaf disease classification: evaluating augmentation strategies and CNN-based models With limited dataset. IEEE Access 12:69853–69874

Rani L, Sarangi PK, Sahoo AK (2024) Image-feature based deep learning model for plant leaf disease detection. Macromol Symp 413(1):2200216

Reddy YA, Adimoolam M (2024) Efficient plant leaf disease detection using support vector machine algorithm and compare its features with Naive Bayes classification. In: AIP conference proceedings, vol 2729. AIP Publishing

Reis HC, Turk V (2024) Integrated deep learning and ensemble learning model for deep feature-based wheat disease detection. Microchem J 197:109790

Routis G, Michailidis M, Roussaki I (2024) Plant disease identification using machine learning algorithms on single-board computers in IoT environments. Electronics 13:1010

Royimani L, Mutanga O, Odindi J, Dube T, Matongera TN (2019) Advancements in satellite remote sensing for mapping and monitoring of alien invasive plant species (AIPs). Phys Chem Earth Parts A/B/C 112:237–245

Sajitha P, Andrushia AD, Anand N, Naser MZ (2024) A review on machine learning and deep learning image-based plant disease classification for industrial farming systems. J Ind Inf Integr 38:100572

Saraswat S, Batra S, Neog PP, Sharma EL, Kumar PP, Pandey AK (2024) An efficient diagnostic approach for multi-class classification of wheat leaf disease using deep transfer and ensemble learning. In: 2024 2nd international conference on intelligent data communication technologies and internet of things (IDCIoT). IEEE, pp 544–551

Saraswathi E, Faritha Banu J (2024) A novel probabilistic intermittent neural network (PINN) and artificial jelly fish optimization (AJFO)-based plant leaf disease detection system. J Plant Dis Prot 131(2):587–600

Sarkar C, Gupta D, Gupta U, Hazarika BB (2023) Leaf disease detection using machine learning and deep learning: review and challenges. Appl Soft Comput 145:110534

Saxena V, Singh M, Saxena P, Singh M, Srivastava AP, Kumar N, Deepak A, Shrivastava A (2024) Utilizing support vector machines for early detection of crop diseases in precision agriculture a data mining perspective. Int J Intell Syst Appl Eng 12:281–288

Segarra J (2024) Satellite imagery in precision agriculture. In: Digital agriculture: a solution for sustainable food and nutritional security. Springer International Publishing, Cham, pp 325–340

Shafi U, Mumtaz R, Qureshi MDM, Mahmood Z, Tanveer SK, Haq IU, Zaidi SMH (2023) Embedded AI for wheat yellow rust infection type classification. IEEE Access 11:23726–23738

Shafik W, Tufail A, Namoun A, De Silva LC, Apong RAAHM (2023) A systematic literature review on plant disease detection: motivations, classification techniques, datasets, challenges, and future trends. Ieee Access 11:59174–59203

Sharma T, Sethi GK (2024) Improving wheat leaf disease image classification with point rend segmentation technique. SN Comput Sci 5:1–12

Sharma G, Kumar A, Gour N, Saini AK, Upadhyay A, Kumar A (2024) Cognitive framework and learning paradigms of plant leaf classification using artificial neural network and support vector machine. J Exp Theor Artif Intell 36:585–610

Singh D, Jain N, Jain P, Kayal P, Kumawat S, Batra N (2020) PlantDoc: a dataset for visual plant disease detection. In: Proceedings of the 7th ACM IKDD CoDS and 25th COMAD. pp 249–253

Singh R, Krishnan P, Singh VK, Das B (2023) Estimation of yellow rust severity in wheat using visible and thermal imaging coupled with machine learning models. Geocarto Int 38:2160831
Sonmez ME, Sabanci K, Aydin N (2024) Convolutional neural network-support vector machine-based approach for identification of wheat hybrids. Eur Food Res Technol 250(5):1353–1362
Sridevy S, Devi MN, Sankar M, Moorthi NR (2023) Image pre-processing techniques utilized for the plant identification: A review. Pharma Innovation 12(6):320–324
Srivastava M, Meena J (2024) Plant leaf disease detection and classification using modified transfer learning models. Multimed Tools Appl 83:38411–38441
Stamford J, Aciksoz SB, Lawson T (2024) Remote sensing techniques: hyperspectral imaging and data analysis. In: Photosynthesis: methods and protocols. Springer, New York, NY, pp 373–390
Stephen A, Arumugam P, Arumugam C (2024) An efficient deep learning with a big data-based cotton plant monitoring system. Int J Inf Technol 16:145–151
Subbiah P, Krishnaraj N (2024) Automated plant disease detection systems for the smart farming sector. In: Agriculture and aquaculture applications of biosensors and bioelectronics; IGI global, pp 296–309
Subbiah P, Nagappan K (2024) Plant leaf disease detection using metaheuristic optimization algorithms and deep learning. Rev Intell Artif 38(2)
Tang Z, Wang M, Schirrmann M, Dammer K-H, Li X, Brueggeman R, Sankaran S, Carter AH, Pumphrey MO, Hu Y (2023) Affordable high throughput field detection of wheat stripe rust using deep learning with semi-automated image labeling. Comput Electron Agric 207:107709
Thakur D, Srinivasan S (2024) AI-PUCMDL: artificial intelligence assisted plant counting through unmanned aerial vehicles in India's mountainous regions. Environ Monit Assess 196:1–26
Thivya Lakshmi R, Katiravan J, Visu P (2024) CoDet: a novel deep learning pipeline for cotton plant detection and disease identification. Automatika 65:662–674
Tiendrebeogo A (2024) Identification of plants from the convolutional neural network. Multimed Tools Appl 83(23):63121–63131
Tolba A, Talal N (2024) An interpretable deep learning for early detection and diagnosis of wheat leaf diseases. Optim Agric 1:81–93
Usha Ruby A, George Chellin Chandran J, Chaithanya BN, Swasthika Jain TJ, Patil R (2024) Wheat leaf disease classification using modified ResNet50 convolutional neural network model. Multimed Tools Appl 83(23):62875–62893
Walsh JJ, Mangina E, Negrão S (2024) Advancements in imaging sensors and ai for plant stress detection: a systematic literature review. Plant Phenomics 6:0153
Wiesner-Hanks T, Stewart EL, Kaczmar N, DeChant C, Wu H, Nelson RJ, Lipson H, Gore MA (2018) Image set for deep learning: field images of maize annotated with disease symptoms. BMC Res Notes 11:1–3
Xue J, Qian X, Kang DH, Hunter JG (2024) Plant density and health evaluation in green stormwater infrastructure using unmanned-aerial-vehicle-based imagery. Appl Sci 14:4118
Zenkl R, McDonald BA, Walter A, Anderegg J (2024) Towards high throughput in-field detection and quantification of wheat foliar diseases with deep learning. bioRxiv, 2024-05
Zhang Z, Zhu L (2023) A review on unmanned aerial vehicle remote sensing: platforms, sensors, data processing methods, and applications. Drones 7:398
Zhang J, Huang Y, Pu R, Gonzalez-Moreno P, Yuan L, Wu K, Huang W (2019) Monitoring plant diseases and pests through remote sensing technology: a review. Comput Electron Agric 165:104943
Zhang S, Liu Y, Xiong K, Tian Y, Du Y, Zhu Z, Du M, Zhai Z (2024) A review of vision-based crop row detection method: focusing on field ground autonomous navigation operations. Comput Electron Agric 222:109086
Zhao S, Duan Y, Roy N, Zhang B (2024) A deep learning methodology based on adaptive multiscale CNN and enhanced highway LSTM for industrial process fault diagnosis. Reliab Eng Syst Saf 249:110208