REVIEW

Harnessing the future: cutting-edge technologies for plant disease control

Suborna Rani[1†], Kallol Das[2†*], F.M. Aminuzzaman[3], Benjamin Yaw Ayim[4], Natasza Borodynko-Filas[5]

[1] Faculty of Computer Science and Engineering, Patuakhali Science and Technology University, Patuakhali, Bangladesh
[2] College of Agriculture and Life Sciences, Kyungpook National University, Daegu, Republic of Korea
[3] Department of Plant Pathology, Sher-e-Bangla Agricultural University, Dhaka, Bangladesh
[4] Ministry of Food and Agriculture, Plant Protection and Regulatory Services Directorate, Ashanti, Ghana
[5] Plant Disease Clinic and Bank of Pathogens, Institute of Plant Protection – National Research Institute, Poznan, Poland
[†]These authors are contributed equally to this manuscript

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*Corresponding address:
kalloldas91@gmail.com

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Abstract
The world population is projected to reach 9.8 billion in 2050, and 11.2 billion in 2100 (United Nations) and people will need food, and decrease the farming land. Thus, the importance of Internet of Things (IoT) and Computer Science (CS) in plant disease management are increasing now-a-days. Mobile apps, remote sensing, spectral signature analysis, artificial neural networks (ANN), and deep learning monitors are commonly used in plant disease and pest management. IoT improves crop yield by fostering new farming methods along with the improvement of monitoring and management through cloud computing. In the quest for effective plant disease control, the future lies in cutting-edge technologies. The integration of IoT, artificial intelligence, and data analytics revolutionizes monitoring and diagnosis, enabling timely and precise interventions. Cloud computing facilitates real-time data sharing and analysis empower farmers to combat diseases with unprecedented efficiency. By harnessing these innovations, agriculture can embrace sustainable practices and safeguard crop health, ensuring a bountiful and secure future for the global food supply.

Keywords: agriculture, computer science, crop protection, IoT, plant diseases

Introduction

As plant diseases have a detrimental effect on agricultural productivity, experts are actively seeking novel and more efficacious ways to increase crop yields. Reducing economic losses is critically important, and early detection of plant diseases can aid in recommending a treatment strategy and substantially prevent the spread of diseases. In the past two decades, there has been much focus on automatically diagnosing plant diseases and estimating their severity using visible range images (Liang *et al.* 2019). Society has put forth stricter requirements for intelligent, precise, and automated disease and pest identification in response to growing interest in precision agriculture. Modern technology has therefore developed rapidly. Utilizing deep learning algorithms for identifying plant diseases can potentially alleviate challenges associated with the subjective process of disease selection, enhance the objectivity of feature extraction, and accelerate technological advancements by increasing research efficiency (Li *et al.* 2021). A decrease in crop yield is a direct result of plant diseases. Increased food insecurity could result from late detection of plant diseases. According to the FAO, each year, plant pests and diseases cause up to 40% crop loss (FAO 2021). Yet, the proliferation of IoT devices and the need for more decentralized processing power in sensor networks have introduced emerging challenges to the organization of the vast quantities of biomedical health data gathered by a wide range of healthcare monitoring sensors (Ma and Pang 2019; Kumar *et al.* 2021). An automated computational method for the identification and diagnosis of plant diseases would be extremely helpful for the experts who are tasked with making such diagnoses through optical observation of the leaves of diseased plants (Mohanty *et al.* 2016; Ghosh and Dasgupta 2022). Moreover, sensors, robots, models, and even AI are being increasingly used on today's farms. The growing human population necessitates a shift to digital farming to meet the demand for food while also minimizing negative impacts on the environment and the health of the soil (Walter *et al.* 2017). These tools can be used to detect, identify, monitor, predict, and/or manage plant pathogens and other biotic stressors. Improvements in computer vision technology have allowed for automatic diagnosis and tracking of plant diseases (Buja *et al.* 2021; Chouhan *et al.* 2020).

Due to the numerous varieties of cultivated plants and their preexisting phyto-pathological issues, even experienced agronomists and plant pathologists frequently fail to accurately diagnose specific diseases, leading to wrong recommendations and inappropriate treatments. Much work has been put into the development and application of sensing, imaging, and computational biology technologies for the purpose of managing plant diseases. Thus, the application of computer science (CS) and the Internet of Things (IoT) in agriculture is becoming increasingly important since it is employed for disease and insect control in crop production. The objective of this review is to ensure the empowerment of agriculture with cutting-edge technologies like IoT, AI, and data analytics to revolutionize plant disease monitoring and intervention to ensure timely and precise actions, safeguard crops, and secure a sustainable future for global food production.

Sustainable development in agriculture

To meet the needs of the present and future generations of humans, sustainable development entails careful management and conservation of the planet's most fundamental natural resources (Fig. 1). Solutions based on sustainable development principles need to be developed and analyzed using an integrated and holistic approach. System dynamics is not only a suitable method for perceiving issues and providing solutions, but it also has the necessary tools for systemic analysis. One of the most critical areas of sustainable development in agriculture is widely recognized as a potentially fruitful strategy for ensuring the long-term financial health of the agricultural sectors.

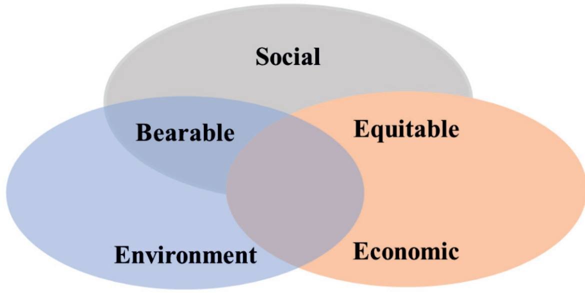

Fig. 1. The concept of sustainable development in agriculture

The growth in population has put a significant strain on the food supply chain, making it increasingly challenging to ensure that everyone has access to sufficient, safe, and nutritious food. The overharvesting of basic resources has had a negative influence on the land. Implementing contemporary farming practices that consider environmental concerns and economic turnover is essential if we are to achieve sustainable development, conserve basic resources, and introduce technological advancements (FAO 2017). An eco-agricultural approach emphasizes the need for a harmonious relationship between the environment and the agricultural economy to safeguard the long-term well-being of both. The Food and Agriculture Organization (FAO) defines sustainable development as progress that meets the demands of the present without compromising the ability of future generations to meet their own. This means managing and conserving natural resources while steering technological progress and institutional frameworks in a direction that ensures a steady stream of food for current and future generations. Soil, water, plant, and animal genetic resources must always be protected in tandem with agricultural and forestry progress toward sustainability.

Precision in agriculture

To manage farm operations, farmers are increasingly adopting the concept of Precision Agriculture (PA), which centers on the monitoring, analysis, and correction of crop variability both within and between fields. Research in precision agriculture is directed toward developing a Decision Support System (DSS) for farm-wide operations that can maximize profits from inputs while minimizing waste (McBratney *et al.* 2005). The most modern agriculture, known as precision farming (PF), is becoming increasingly popular among farmers. When compared to the conventional method of farming, average crop yields improve when the right amounts of inputs are used. As such, PF is an innovative system meant to boost agricultural output in several ways, including the use of technology, management, and information to boost output, quality, protect the environment, and save resources (Shibusawa 2001).

Advancements in agriculture have revolutionized farming practices with soil monitoring, sampling, and mapping enabling precise nutrient management. Crop monitoring and mapping using Global Satellite Positioning and remote sensing enhance decision-making for farmers. Detailed crop maps and plans optimize resource allocation, and are guided by input and irrigation maps. Soil fertility tests boost yield history and productivity. GIS-based agricultural mapping software aids financial analysis for better outcomes. Variable rate application and section control maximize efficiency. Agricultural robots complement this tech-driven approach, promising a sustainable future for farming (Table 1).

Remote sensing techniques based on IoT sensors play a crucial role in PF by tracking and collecting data on farmers' field crops and then delivering this information to them in processed form (Rehman *et al.* 2014). The current developments in PF that have taken place today will result in environmentally friendly agricultural technologies in the future. More specifically, PF will help small farmers in developing countries increase their yields while decreasing their labor and material costs. Ensuring sustainability and increasing profitability, while simultaneously minimizing negative impacts on the surrounding environment, are the primary objectives of precision agriculture (Fig. 2).

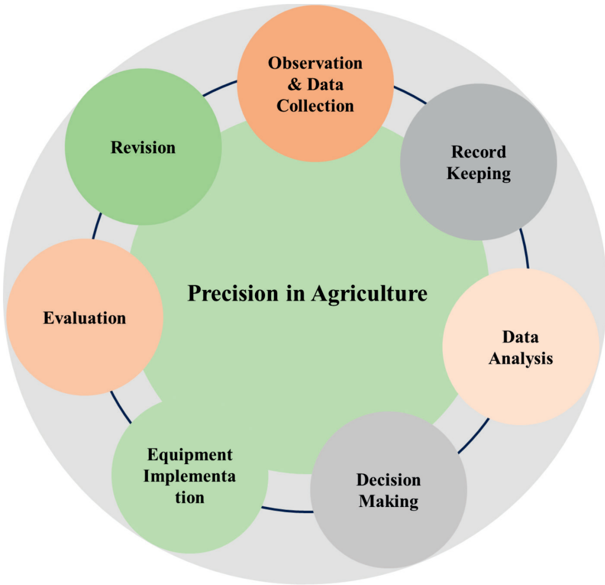

Fig. 2. Agricultural precision presented in a step-by-step diagram

Therefore, it is recommended that farmers invest in high-quality sensors and software that can accurately measure soil moisture, nutrient levels, and other important factors. Additionally, farmers should collaborate with agricultural researchers and extension agents to ensure that they are using the most up-to-date and effective precision agriculture techniques. By incorporating precision agriculture into their farming practices, farmers can increase yields, reduce costs, and improve sustainability.

Table 1. Precision agriculture and related technological platforms (Shakti 2021)

Stages	Task	Available technological platform
Observation and background data collection	• Soil monitoring, sampling, and mapping • Crop monitoring and mapping • Global Satellite Positioning (GNSS) Remote sensing Field/Crop scouting	Internet of Things Aerial photography
Data storage and decision-making	• Crop map or plan • Maps of inputs • Fertility, soil tests • Irrigation map • Yield history	Cloud computing Edge computing Fog computing Geographical Information System
Data analysis	• Better productivity • GIS based agricultural mapping software • Financial analysis	Big data Artificial intelligence Machine learning
Application technologies	• Variable rate application • Section control • Agricultural robots	Robotics Drones Autonomous tractors Automatic watering Seeding robots

Farming with computer vision and machine learning

Computer vision and machine learning (CVML) are very important in agriculture if we want to meet the growing demand for food (Bochtis *et al.* 2014; Liakos *et al.* 2018). Food demand has significantly increased due to population expansion and rapid urbanization (Hunter *et al.* 2017), which includes the effective food production rate with a finite number of arable lands and other resources in a sustainable method for precision agriculture (Aubert *et al.* 2012; Wu *et al.* 2018). In recent years agriculture has considerably improved its use of computer vision techniques by employing skilled machine learning algorithms to boost agricultural output in a more efficient and economical way (Gomes *et al.* 2012; Rehman *et al.* 2019). Numerous agricultural tasks have been completed using CVML techniques in the GPU environment, with the goal of achieving agricultural sustainability by analyzing a huge number of images captured by humans, robots, drones, and other distant sensors. Research is being done on developing and evaluating different types of monitoring and regulation systems for shifting temperature and moisture, CO_2 fixation, and other natural boundaries for IoT, and financial consequences (Elijah *et al.* 2018). In horticulture, the machine learning framework and IoT have been used to predict and enhance harvests, and the ML framework can be used for yield production (Maduranga and Abeysekera 2020). When diseases were accurately identified, appropriate pesticides applied and water system plans were provided, visibility and volume increased, and excessive pesticide usage decreased as well. Advanced IoT technologies, including NB-IoT, are used to manage and regulate massive amounts of data. IoT sensors are frequently used to develop ML systems that accurately identify ground limits such as soil moisture, soil temperature, and environmental variables as well as forecast relative outside humidity using similar information. Additionally, we can use hybrid machine learning and IoT frameworks to intelligently adjust water temperature to an ambient temperature.

Computer science and IoT in plant diseases

Phytopathology is a branch of agricultural sciences that requires fundamental knowledge of a wide range of disciplines, including botany, molecular biology, genetic engineering, meteorology, plant anatomy and physiology, virology, mycology, nematology, and virology (Vishnoi *et al.* 2021). Agricultural pests and diseases which can cause a wide range of symptoms and harm to plants, provide a foundation for their detection using remote sensing technology. This can be seen by examining the interactions between pathogens and the hosts (Zhang *et al.* 2019). The discovery of diseases in agricultural fields influences agricultural productivity, which necessitates the ongoing surveillance of agricultural goods for a variety of diseases in order to prevent crop failure. Computer vision and machine learning as well as IoT technologies have already achieved astonishing success in overcoming numerous automation issues pertaining to the processing of fruits and vegetables. Images of the exterior surfaces of fruits or vegetables are all that is needed for computer vision to identify them (Susovan *et al.* 2021). Monitoring plant diseases and managing pests needs a variety of approaches, each of which has its own advantages and disadvantages. IoT is a significant and upcoming factor for the agricultural industry in the age of the internet and connected devices. Technology connected to the IoT is important for agricultural sectors with real-time field monitoring enabled by IoT-based smart farming, and thus improving the entire agricultural system (Fig. 3).

In conclusion, computer science and IoT are increasingly being used to combat plant diseases. The combination of computer science techniques, such as machine learning and data analysis, with IoT devices has the potential to revolutionize the way we detect and prevent plant diseases. By continuously monitoring plant health, IoT devices can detect the early signs of diseases and alert farmers, enabling them to take swift action. Additionally, the use of big data analytics can help researchers identify patterns and develop predictive models, which can ultimately lead to more effective disease prevention and control strategies. As technology continues to advance, we can expect to see even more innovative solutions to plant disease management in the years to come.

Mobile application for pest and disease management

An alternate strategy involves making use of mobile applications for the early detection of diseases and pests. The only way for farmers to send a report to the app is to provide information indicating that a specific crop has been diseased. Along with displaying the location of the diseased crop on a map, the system will be synchronized to notify all the farmers that their crops need to be monitored and will offer a way of management to prevent the disease from spreading to other areas that are nearby. Most of the developed applications are centered on documenting diseases and pests

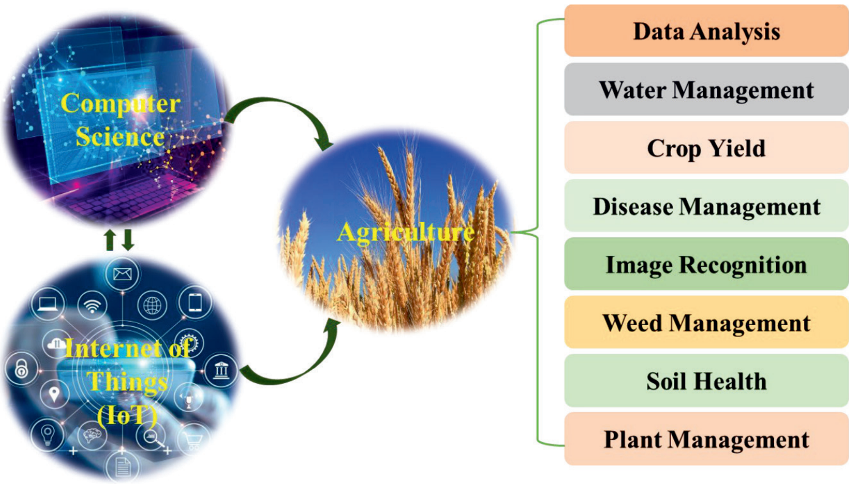

Fig. 3. Application of computer sciences and IoT in agriculture

together with their (i) underlying cause, (ii) symptoms, (iii) treatments for the infection and the outcomes of those treatments, and (iv) strategies for preventing the spread of the infection. State-of-the-art AIoT technology was fused with deep learning YOLOv3 to create effective pest detection tactics for mobile applications (Chen *et al.* 2020). *Tessaratoma papillosa*, a pest that appears on the undersides of leaves, was spotted in orchards with the help of this software and an unmanned aerial vehicle (UAV) (Chen *et al.* 2020). The affected plant component must be photographed for usage with mobile applications. During preprocessing, an in-built algorithm examines the image. Image color can be adjusted so that it is constant and homogeneous (Mendes *et al.* 2020). The contaminated tissue is then removed and compared to the picture model of the relevant insect or disease. In addition to the name of the pest and disease, the user will also learn what caused it, how it can be treated, how it can be prevented, and what preventative measures should be taken (Ouhami *et al.* 2021). Smartphone software also helps farmers identify the source of the diseases and continue with the process of application (Mrisho *et al.* 2020). An Android app was built that uses fuzzy entropy for disease detection in crops like paddy (Majid *et al.* 2013). The disease-extracting capabilities of fuzzy entropy make it a useful modeling tool for non-statistical imprecision. The outcome demonstrated that fuzzy entropy has an accuracy of over 90% in detecting disease in paddy, except for tungro disease, where it has an accuracy of only around 70%. This research identifies four different diseases that can affect paddy plants – bacterial leaf blight, tungro disease, brown spot, and leaf blast (Majid *et al.* 2013). By aiding in crop field monitoring, image processing methods hope to increase yields. Several studies in plant pathology have used computer vision in conjunction with computational intelligent approaches/soft computing methodologies (Sabrol and Kumar 2015).

Plant disease and pest remote sensing (RS)

Several RS systems exist that may be used to monitor plant health and identify diseases. Various RS systems have been applied to the task of recording infection symptoms (scabs, pustules, etc.), physiological responses (pigment content, water content, etc.), and structural changes (canopy structure, landscape structure, etc.) brought on by plant diseases and pests in order to more effectively detect and monitor these threats (Hahn 2009; Sankaran *et al.* 2010; Mahlein 2013). Visible and near infrared (VIS-SWIR) spectral systems, fluorescence and thermal systems, synthetic aperture radar (SAR), light detection and ranging equipment (Lidar) systems are the three main types of sensing systems for plant diseases and pest monitoring based on sensing principles. In general, sensors that detect wavelengths shorter than the visible spectrum (such as gamma rays, X rays, UV rays) are active, making them impractical for use in a mobile setting. These sensors are typically employed for indoor testing of plant diseases and pests, especially in edible (eaten raw) plants like vegetables and fruits. It is necessary to identify efficiently unique RS features to implement RS observations in plant disease and pest monitoring. Many other RS traits have been suggested or identified to use in identifying plant disease and pest symptoms and mapping plant distributions. Spectrum features in the visible and near-infrared range, fluorescence and thermal ranges, and the features in images and landscapes are the primary aspects of RS (Zhang *et al.* 2019).

Moreover, remote sensing offers a rapid, non-invasive, and reasonably economical approach for investigating the biophysical and biochemical characteristics of vegetation across extensive spatial regions (Ngie *et al*. 2014). It serves as a valuable resource, particularly in regions lacking detailed maps, by providing essential data for land-use and spatial planning (Leeuw *et al.* 2014). Additionally, remote sensing, including aerial photography, plays a crucial role as input for modeling various alternative land use scenarios (Leeuw *et al.* 2014).

In a study conducted by Tucker (1979), the capabilities of satellite remote sensing in assessing ecological conditions and predicting desert locust activity were showcased. Remote sensing data can effectively identify green vegetation, offering valuable guidance to ground survey teams. Subsequently, remote sensing imagery has been deployed in regions such as West Africa and the Red Sea area since the late 1980s to support these efforts (Cressman 1998). The utilization of remote sensing, specifically satellite data, shows great promise as a valuable tool for locust monitoring. Researchers have progressively employed satellite information to monitor and forecast two locust species: the desert locust and the Australian plague locust (Latchininsky 2013).

In conclusion, remote sensing offers a rapid, non-invasive, and cost-effective method to study vegetation across vast areas, aiding land-use planning where maps are scarce. It also plays a vital role for plant disease management as well as in modeling alternative land use options.

Techniques for monitoring plant diseases and pests

Various methods or combinations of algorithms are used to accomplish tasks such as distinguishing between diseases and pests, extracting the infection severity for making effective use of the RS features retrieved from various RS data formats for monitoring plant diseases and pests. Some statistical discriminant analysis methods show much more accurate data in very basic circumstances for detecting a single disease/pest or distinguishing between diseases and pests (Moshou *et al.* 2011; Yuan *et al.* 2014). Methods based on regression analysis are frequently used to grade the severity of plant pests and disease infections. Yellow rot in wheat was explored using linear regression (Huang *et al.* 2007). Artificial neural networks (ANN) and their descendant, deep learning methods, demonstrate a high capability in monitoring plant diseases and pests in some complex circumstances (Castro *et al.* 2015; Ferentinos 2018). Also, mapping using single phase and multi-phase RS pictures are two crucial methods for plant disease and pest monitoring. In cases where the disease symptom has a distinct spectral response, like cotton root rot, both hyperspectral and multispectral RS images were accurate for effective surveillance (Yang *et al.* 2010). Mapping with images from two phases, mapping images from many phases (typically 3–5 phases), and mapping based on a specified temporal trajectory are the three main ways to do multi-phase mapping. The two-stage monitoring method is typically implemented during a disease or pest outbreak. Here, it is important to capture two images: one before the breakout occurs, and another during or after the peak damage (Ji *et al.* 2004; Zhang *et al.* 2015).

Pest and disease management using spectral signatures

The amount of light, heat, or other electromagnetic radiation reflected from a surface is known as its reflectance. It is the fraction of incident energy that returns as reflected light and varies with wavelength. Different interactions affect leaf reflectance in different wavelength ranges, including the visible (400 to 700 nm), near-infrared (NIR, 700 to 1100 nm), and shortwave infrared (SWIR, 1100 to 2500 nm). Radiant energy absorption caused by the chemistry of the leaf, light scattering because of the surface and internal cellular structures of the leaves, and radiant energy absorption caused by the water, protein, or carbon content of the leaves are all factors that contribute to these interactions (Akbar 2020). Researchers have turned to correlation analyses to determine pathogen-specific spectral signatures, such as a spectral index and ratio with discriminant analyses. This is because of the constraints that were mentioned earlier (Eberlein *et al.* 2020; Furlanetto *et al.* 2021). However, these methods have not yielded definitive optimal spectral signatures. The same results show that abiotic and biotic characteristics like pigmentation correspond to the sensitivity of specific spectral zones with significant absorption (Golob *et al.* 2017). Changes in plant health can be detected using either hyperspectral imaging or non-imaging sensors (Guo *et al.* 2021). The biophysical and metabolic characteristics of plant tissue generate variations in reflectance. Plant stress causes changes in pigmentation, a hypersensitive response, and cell wall disintegration, all of which have an impact on visual qualities and the reflectivity of leaves (Mandi 2016). A mobile camera might be used for pest and disease identification by taking pictures of infected crops. The camera can take a picture, run an algorithm on it, and determine whether the plant is infected based on how it reflects light, within specified parameters. In a hyperspectral image, the reflectance (or transmittance) of each spectral band is measured independently for each pixel. A non-imaging hyperspectral sensor (i.e., point spectroscopy) records this information without any geographical context, yielding a spectral signature (or spectral profile) (Park *et al.* 2020). There are several steps in spectral signature analysis for plant health monitoring (Fig. 4).

Studies have shown that infestations of *Ips typographus* result in higher visible-light reflectance from damaged trees compared to healthy ones (Abdullah *et al.* 2019). Additionally, similar findings were observed using the red edge band to monitor early-stage bark beetle damage (Immitzer *et al.* 2014; Mullen 2016). Innovative technologies, such as automated image recognition methods, hold promise to revolutionize monitoring practices by enabling broader coverage. Consequently, these advancements can provide deeper insights into the population dynamics, distributions, and interactions of insect pests and diseases (van Klink *et al.* 2022).

Moreover, Carlos *et al.* (2019) detected spectral variation (relevant spectral wavelengths) in tomato plants infected with *Fusarium oxysporum*, allowing for early detection during the incubation period when symptoms are not visible. By employing reflectance

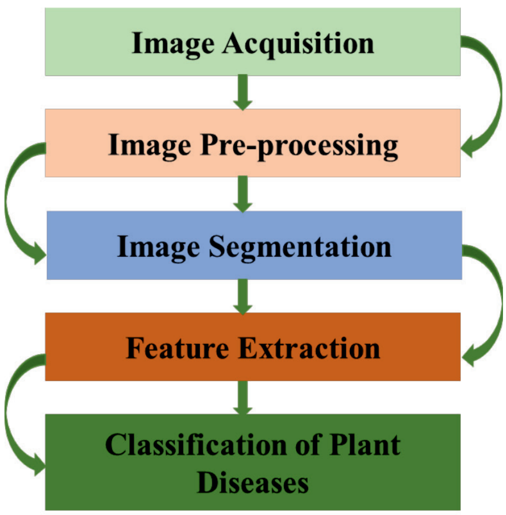

Fig. 4. Plant health monitoring using spectral signatures

spectroscopy and linear discriminant models, they achieved high accuracy (85–93%) in discriminating infected plants from healthy ones, based on changes in infrared reflectance of diseased leaves. Similarly, hyperspectral imaging was used to identify insect-infested maize plants, relying on detectable changes in specific spectral bands of leaf reflectance profiles (Prado Ribeiro *et al.* 2018). Smart sensor traps have been effectively employed in monitoring insect pests, including acoustic detection methods for stored pests (Eliopoulos *et al.* 2015), and light interruption for counting insect entries (Holguin *et al.* 2010). However, the predominant approach in the development of automatic pest monitoring devices involves imaging the trapped insects, often in conjunction with sticky traps or pheromone traps. Camera-based sensors utilize digital cameras for real-time visual inspection of trapped insects, and they are also integrated with artificial intelligence techniques to facilitate automatic detection and counting of insect pests (Ding and Taylor 2016).

Challenges in implementation of computer science and IoT

The performance of big data technologies can be negatively impacted by the possibility of spoofing, data hacking, manipulation, and cyber-attack on personal information. Therefore, ensuring the safety of this data is a significant difficulty when deploying IoT (Asghari *et al.* 2019). Important issues include the veracity and diversity of data as well as its quality, accuracy, and application. There should not be any erroneous information in the data and it is challenging to organize the data since it might be organized, semi-structured, or unstructured (Ardagna *et al.* 2018). It is also important to pick a suitable method of data visualization, like a graph or chart, to highlight the conclusions obtained from the data. The quantity of data that must be analyzed is another factor that determines whether the process of data extraction for decision-making is cost-effective. Engineers and researchers from all over the world have developed various frameworks and architectures for deploying IoT and big data computing technologies in the area of agriculture in anticipation of a global food shortage. There are a number of open-source IoT systems available, but there is still a high demand for improvement in terms of data privacy, ownership, liability, and security (Alam *et al.* 2017). Prior to deployment, there are several issues that must be resolved, including backwards compatibility with existing systems, enhanced interoperability of smart devices from different manufacturers, and protection against data leakage. The interaction between the physical layer and the service layer is enabled through the communication layers. Depending on their defining features, wireless networking technologies including Bluetooth, Zigbee, LoRA, SigFox, and WiMax all have different capacities for covering large areas and transferring large amounts of data quickly. It is also difficult to determine which communication technology is the most effective in terms of low power consumption, broad coverage, and stable connection (Zhang *et al.* 2019). Even for the monitoring and control of a relatively modest agricultural field, the initial investment in IoT technology with WSN is substantial, and IoT--based smart farming necessitates trained technicians/

professionals to hone features, alter codes, and provide the needed data. Image analysis and hyperspectral imaging-based systems outperformed visual disease severity ratings, but there are still some skillful and straightforward solutions as well as objectives to reach (Mahlein *et al.* 2018). More accurate methods of plant protection and disease rating are desperately needed to meet the impending difficulties. So, for early identification and prevention, plant protection requires the development of trustworthy data analysis systems to handle picture annotations and pre-labeling of plant data (Kuska and Mahlein 2018). Some obstacles still exist that prevent the strategies from being put into effect, despite the significant progress that has been made in the monitoring of plant diseases and pests over the last few decades. The first problem is finding and eliminating plant pests and diseases before they cause too much damage. Reliable RS monitoring of plant diseases and pests is typically achieved after symptoms are completely manifested, which may be too late to prevent further damage (Li *et al.* 2015). The second problem is finding the source of a specific disease or pest in the context of real-world field settings, when multiple types of crop stress may be present at the same time (Yuan *et al.* 2014).

Germany, Denmark, Finland, the United States of America, Australia, New Zealand, India, and many other countries have already developed commercial agricultural robots with various localization systems including GPS, vision, laser, sensor-based navigation, etc. (Roldán *et al.* 2018). Though agricultural robotics has come a long way, it still faces significant obstacles. With respect to automated decision making and prediction for digital farming, there are still several technical hurdles that farmers must face when deploying autonomous agricultural vehicles. Another major problem is that farmers typically cannot afford robots due to their high initial cost and ongoing maintenance costs. Drones have been used for crop monitoring, early weed and pest detection, and pesticide and herbicide spraying, however these applications still need more refinement to be reliable and accurate.

Future opportunities and prospects of computer science and IoT

Crops are highly vulnerable to the effects of disease and disease control is essential for optimizing crop productivity. The health of plants can be negatively impacted by a wide range of pathogens, including bacteria, viruses, fungi, nematodes, and others. Farmers can prevent disease and subsequent losses by implementing the best practices for managing crop diseases. However, these procedures could be more expensive and time-consuming. Presently the application of tools such as the computer vision system (CVS), genetic algorithm (GA), and artificial neural network (ANN) show better performance and versatility in the field of agriculture. Using a rule-based engine, a new system has been built to aid in disease diagnosis and recommend effective treatments. An appropriate preprocessing of the images is necessary for correct dissemination of this data, whether through cameras or other methods, allowing for an accurate treatment of numerous applications to boost crop yields and field conditions (Kuchumov *et al.* 2019). With a global population projected to hit 9.6 billion by 2050, the agricultural sector must expand to meet its demands despite environmental problems including unfavorable weather and climate change. IoT enables smart farming and precision applications which will help the agricultural industry increase productivity, decrease expenses, minimize waste, and enhance the harvest quality (Fantin *et al.* 2021). At the moment, IT and CS AI are the most studied topics. Agriculture can benefit from the rapid technical advancement and variety of applications, which can make it more precise and cost-effective than ever before. Significant problems in conventional farming include incorrect chemical use, pest and disease infestation, poor irrigation and drainage, inaccurate production projection, weed control, and so on. This is where artificial intelligence comes in to help traditional farming overcome its shortcomings and aids with precision agriculture (Fantin *et al.* 2021).

Smart farming is an approach to farming that makes use of numerous technological innovations (such as IoT and wireless sensing networks) to increase productivity at every step (Farooq *et al.* 2019). Researchers across the world are trying to find ways to lower the price of the hardware and software used in IoT applications for farming, with the end goal of increasing crop yield. For smart devices to use less power and perhaps extend their lifespan, it is necessary to combine IoT with green computing technology. The number of fault tolerance in a system should be maintained with utmost care if it is to produce error-free results (Supriya and Gopal 2021). Predicting the development of a disease helps farmers take effective measures to manage it before it causes irreparable damage. Different researchers use different types of sensors to record imagery data, such as fluorescence imagery sensors, spectral sensors, thermal sensors, and RGB sensors (Lee *et al.* 2017). It has become a common practice to use image processing techniques for virtual data analysis in the diagnosis of plant diseases. In a specific study, an IoT system strategy was applied for pest and plant disease prediction to avoid the excessive application of different fungicides and pesticides (Lee *et al.* 2017). Improvements in data processing made possible by PA's burgeoning computer industry have given farmers greater leeway in their choices. Most agricultural countries have accepted the use of computer systems to boost the productivity and production of farming areas (Saddik *et al.* 2022). The scientific world has been captivated by the simplicity, effectiveness, and versatility of CRISPR and its associated proteins, derived from the adaptive immune system of prokaryotes. This innovative approach has piqued interest in genetically enhancing plant disease resistance for the sake of sustainable agriculture (Das *et al.* 2023).

Conclusions

Over the past three decades, agricultural modernization has made significant changes, thanks to the growth of the information technology sector in industry. The incorporation of industrial developments into a sustainable agriculture production system has been particularly helpful in agricultural research. When a nation has a sizable agricultural base, it is seen as socially and economically developed. The flexibility, promotion, and lower costs of machine learning can be helpful in evaluating the complex link between the inputs and outputs of agricultural systems. These analytical approaches are characterized by non-linearity, time-varying characteristics, and many unknown factors. One of the most difficult undertakings, namely, automating agriculture with intelligent robotic systems has already captured the interest of researchers due to the wide range of potential and commercial applications. One possible landmark for the agricultural industry is the introduction of artificial intelligence which means that the necessity for labor, duration and other inputs is diminished. The use of AI, drones and other aerial devices have already ushered in a revolutionary new era in digital farming, expanding opportunities for precision agriculture techniques including crop scouting, crop monitoring, weed, disease, and insect control, spraying, and selective harvesting. It is crucial for plant protection assessment and management to have dependable, timely, and effective monitoring of diseases and pests across large areas. A few RS techniques have been established during the past few decades to supplement traditional, labor-intensive examination of plants against diseases and pests. Extending genomics from models to crops will be the primary problem facing the plant science community in the future. Integrating genomic and agronomic data is particularly significant for improving agricultural yield per acre because of its implications for disease management.

In conclusion, the convergence of IoT, AI, and data analytics marks a transformative era in plant disease control. These cutting-edge technologies empower farmers with real-time monitoring, precise interventions, and data-driven insights, fortifying crop health and boosting food production. To fully harness their potential, collaborative efforts among policymakers, researchers, and farmers are imperative. Prioritizing investment in research and training programs will equip the agricultural sector with the necessary tools to combat diseases effectively, ensuring a resilient and prosperous future for global food security.

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