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REVIEW

Integrative approaches in modern agriculture: IoT, ML and AI for disease forecasting amidst climate change

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Abstract

Plant disease forecasting models, driven by concurrent data and advanced technologies, are reliable tools for accurate prediction of disease outbreaks in achieving sustainable and productive agricultural systems. Optimal integration of Internet of Things (IoTs), machine learning (ML) techniques and artificial intelligence (AI), further augment the capabilities of these models in empowering farmers with proactive disease control measures towards modern agriculture manifested by efficient resource management, reduced diseases and higher crop yields. This article summarizes the role of disease forecasting models in crop management, emphasizing the advancements and applications of AI and ML in disease prediction, challenges and future directions in the field via (a) The technological foundations and need for validation testing of models, (b) The advancements in disease forecasting with the importance of high-quality publicly available data and (c) The challenges and future directions for the development of transparent and interpretable open-source AI models. Further improvement of these models needs investment in continuous innovative research with collaboration and data sharing among agricultural stakeholders.

Introduction

The agriculture industry is expected to confront substantial problems in meeting the rising demand for food. The current agricultural production must be increased by 70% to supplement the food requirements of 9.6 billion inhabitants by 2050 (FAO, 2009), in spite of the diminishing availability of arable land, water, and the unprecedented events associated

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with climate change. Climate change has a major influence on agricultural productivity, and unprecedented weather changes adversely influence crop yields. Variation in weather events such as altered temperatures, frosts, precipitation events and drought can significantly lower agricultural production and quality. A rising trend of these climate extremes and their variability are ringing alarming bells for the future food security (Harkness et al., 2020). Atmospheric concentration of CO_2 crossed 400 ppm, which is could be attributed to deforestation and fossil fuel mining, eventually led to raise in atmospheric temperature, causing variation in intensity and duration of global winters and ultimately leading to alterations in phenologies and distributions of plant species (Matesanz et al., 2010; Pautasso et al., 2012; Quarles, 2007). In the face of these adversities, it becomes crucial to employ innovative approaches to enhance agricultural output (Pallathadka et al., 2022).

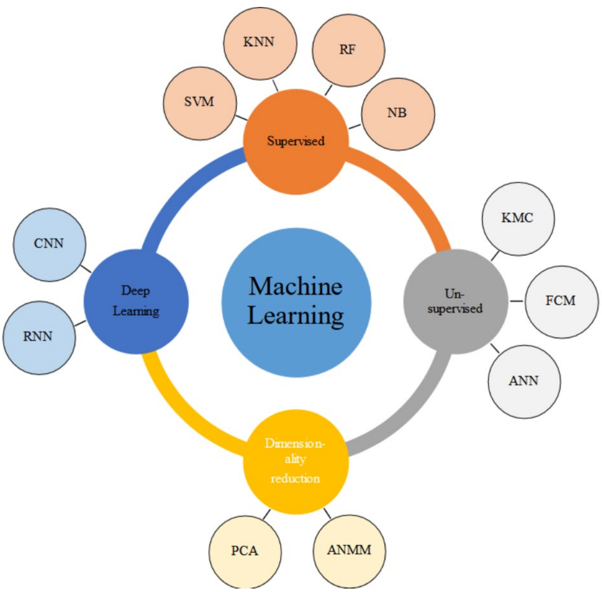
Agriculture's vital role in ensuring global food security is further complicated by significant challenges, including the impact of plant diseases on substantial yield reductions and crop quality loss (Oerke, 2006; Savary et al., 2012, 2019; Strange & Scott, 2005). Worldwide, severe crop post-harvest losses associated with pests and pathogens are evident, for instance, wheat being one of the staple food crops, was being reported with global yield losses of around 21.5% in 2019 (Savary et al., 2019). Climate change associated with variation in temperature, precipitation and CO_2 levels augment plant diseases and diminish the disease management practices through emergence/extinction of new disease complexes and variations in pathogen virulence with respect to geographical distribution (Coakley et al., 1999). Climate change is omnipresent, with potential of influencing plant pathosystems in a way to transform a troublesome disease in specified locality to a new agroecological region, and these climate alterations could also favour the pathogen for host-pathogen interactions, leading to increased vulnerability of crops to yield losses (Pautasso et al., 2012).Under projected scenarios, it is evident that climate change will affect plant diseases through complex interaction with the components of anthropogenic factors, thus making the un-raveling interaction among host, pathogen and environment.Efficient disease management is, thus, crucial for mitigating these losses, especially considering the growing global population (FAO, 2018). Increasing agricultural production through combating spectrum of challenges is attainable through technological improvements achieved in over a century for augmented production in agriculture. Emerging technologies like AI, ML, and IoT are revolutionizing agriculture by enhancing production efficiency and overcoming traditional farming challenges. The IoT has potentially grown in the past century through utilizing advanced sensor technology, reduced hardware size, and improved accuracy, supporting supply chains and ensuring high-quality, safe agricultural products. IoT-based systems in combination with ML algorithms are being implemented in optimizing crop fertilizer requirements through monitoring soil nutrient and moisture levels. (Sharma et al., 2020). Advancements in computing with ML, a facet of AI, is serving in accurate identification and recognition of diseases and pests of agricultural production. Deep learning (DL) as class of ML, in conjunction with image processing, enables accurate disease detection in paddy plants (Haridasan et al., 2023). Drones equipped with AI algorithms assist in field monitoring, pesticide spraying, and disease identification (Sharma et al., 2020). A computational framework built based on the existing realtime data with components of AI such as ML, DL and other algorithms to make useful assessments and predictions to improve human existence is considered as a model. Imbalances in climatic conditions are anticipated to be detrimental for plant health by different modes, of which favoring pathogen perpetuation with respect to incubation periods and reducing general tolerance of plant for stress (Pautasso et al., 2012; Sutherst et al., 2011). Gathering of data pertaining to the aforementioned factors for simulation models of ML and AI can support the better prediction of climate change associated effects on diseases. Hence, in the last five decades, majority of the models developed towards plant diseases dissemination has examined the impact of agricultural characteristics / environment on the development of pathogens/diseases in an effort to understand the systems better, whereas moderate number of studies dealt with the use of disease models for disease management techniques and very few models discussed the use of disease models for scenario analysis (Gonzalez-Dominguez et al., 2023). In this context, disease forecasting models, such as the interdisciplinary early warning system (EWS) for wheat rust in Ethiopia (Allen-Sader et al., 2019) and the ShIFT model for *Zymoseptoria tritici* (Beyer et al., 2022) play a pivotal role in efficient disease management strategies. Despite the promising outputs, technical challenges pertaining to data quality and integration are challenging the integral dependence (Pallathadka et al., 2022). However, the evolution of process-based models (Gonzalez-Dominguez et al., 2023) through extracting the advancements of AI and ML and implementation of intelligent irrigation systems (Sharma et al., 2020) are exhibiting tremendous potential for optimized consumption of resources to effectively detect and manage diseases for crop yield improvement.

This comprehensive review aims to explore the intersection of IoT, ML, AI for disease forecasting models in precision agriculture under climate change, with a particular focus on wheat and other key crops. We analyzed various approaches, from traditional statistical models to advanced ML algorithms, discussing their performance, limitations, and potential for future enhancements. We also examined the integration of process-based models and insights from other crops into these technologies. Our objective was to provide a thorough understanding of how AI, ML, and cutting-edge forecasting models can be harnessed to effectively combat plant diseases, minimize yield losses, and ensure global food security. Through this review, we shed light on the potential of these technologies and stimulate further research and innovation in this field. However, it's important to recognize that several challenges, including data availability and model accuracy, still remain and need to be addressed to fully realize the potential of these technologies. The delineation for the integration of IoT, ML and AI for disease forecasting under climate change is outlined below.

IoT, ML, AI in modern agriculture, disease forecasting under climate change

The IoT represents a transformative paradigm in agriculture, connecting digitally enabled devices and machines over the internet. Known as the fourth industrial revolution (Industry 4.0) or the Industrial Internet of Things (IIoT), IoT's influence stems from its capacity to facilitate seamless communication between the physical and digital worlds. Remote sensors collect data from various agricultural processes, enhancing efficiency and decision-making and providing competitive advantages through actionable insights. These IoT sensors are connected through communication technologies for the data transfer to be implemented in AI based decision systems. Currently, various communication technologies viz., LoRa, RFM69, ZIGBEE, bluetooth, low-power wide Area Network technology, WiFi, WiMax, cellular technologies, are being used depending on the requirements of the number of nodes, distance of communication, data transmission speed and applicability (Qazi et al., 2022). The future of modern agriculture dealing with aerial monitoring systems like drones/unmanned aerial vehicles (UAVs) will rely much on cellular communication technologies for their large communication ranges and greater data transmission capability under field conditions (Qazi et al., 2015). AI and ML are at the forefront of agricultural innovation in utilizing amalgamated data from IoT, other sources for making decisions either through rule-based or data-driven approaches, that typically require human intelligence. ML, a subset of AI, utilizes algorithms to learn from data, providing valuable insights and automating critical steps. DL, an advanced form of ML, extracts complex information from large data sets, offering unprecedented opportunities for automation and intelligence in agriculture (Misra et al., 2020). IoT, ML and AI are distinct, despite of their interrelatedness in terms of application in computational intelligence to generate purposeful information from diverse data sets. In recent years, imaging techniques and computer vision approaches have become increasingly important for identifying and classifying plant diseases. Using computer vision in various electromagnetic spectrum areas, the visual features of plants that result from biotic stress-induced physiological changes viz., altered tissue colour, deformed leaves, or altered plant canopy, are evaluated. These technologies enable the early detection of diseases, helping to mitigate their impact on crop production. Image acquisition is the first step in the process, followed by pre-processing using segmentation techniques. Feature extraction and classification techniques are then applied to identify and classify the diseases present. The overall process of identification and segmentation of the input data/images into different classes is known as a classification problem in ML. Choosing the most apt classifier for the input data is crucial in AI decision-making. For the AI based decision making process, wide array of ML techniques are approached depending on the problem requirement, which are compartmentalized into supervised and unsupervised methods (Fig. 1) The optimal interplay of IoT, ML, and AI generate catalytic framework to facilitate the effective and precise utilization of inputs towards sustainable production.

Fig. 1 Various methods of ML for classification and segmentation; (SVM: Support vector machines, KNN: K-nearest neighbors, RF: Random forest, NB: Naive Bayes, KMC: K-means clustering, FCM: Fuzzy C-means, ANN: Artificial neural network, PCA: Principal component analysis, ANMM: Average neighborhood margin maximization, CNN: Convolutional neural network, RNN: Recurrent neural network)



The precision agriculture under climate change

Precision agriculture, also called precision farming, is a contemporary approach to sustainable agriculture to increase overall farmer profitability through streamlining and optimizing agricultural practices with cutting-edge technologies and data analysis. IoT in precision agriculture involves the use of sensors and wireless sensor networks (WSNs) to monitor and control agricultural systems remotely. Sensors collect data on parameters like soil moisture, temperature, and crop yield, which is then uploaded to an IoT cloud for analysis and decision-making. The integration of AI with WSNs enables real-time monitoring, intelligent data processing, and optimized power consumption. This combination of IoT, sensors, WSNs, and AI plays a crucial role in achieving higher crop yields and efficient resource management in precision agriculture. AI provides intelligent capabilities to machines, enabling them to analyze the data collected by IoT sensors. By leveraging AI-based algorithms in IoT data streams, farmers can make informed decisions regarding irrigation, fertilization, and pest control. This results in improved crop yield and resource efficiency. The integration of IoT, sensors, WSNs, and AI in precision agriculture holds great promise for enhancing crop productivity, optimizing resource management, and promoting sustainable farming practices (Sharma et al., 2020). Adopting new agricultural systems aligned with requirements in modern agricultural demands and new cultivars could potentially mitigate climate change impacts. One of the aspect of precision agriculture to mitigate climate change is through implementation of variable rate technology in the place of uniform rate technology towards site specific management and resource use efficiency, which further relies on the components of precision agriculture viz., sensor-based monitoring of inputs coupled with GPS and remote sensing (Roy & George K, 2020).

Plant health, along with the components of disease incidence such as plant pathogen survival and spread are deeply influenced by factors accompanying climate change. Variations in temperature and precipitation are transforming agricultural ecosystems, with temperature changes as the main factor impacting climate change, as highlighted by the need for advanced modelling approaches to understand and manage these changes (Garrett et al., 2022). This highlights the complex challenges climate change poses for agricultural practices and disease management. In response to these challenges, AI and ML technologies are playing an increasingly vital role, especially in disease forecasting models, not only as tools for managing these changes but also in adapting their functionalities and methodologies in response to specific targets of climate change. In the context of climate change and disease spread modelling, Hijmans et al. (2000) implemented the components of precision agriculture in estimating the global severity of potato late blight, highlighting areas of high and low severity across the globe. Dewdney et al. (2007) undertook a statistical comparison between two popular fire blight forecasters, MARYBLYT and Cougarblight, demonstrating that both predicted blossom blight infection more effectively than by chance alone. Meanwhile, Pinkard et al. (2010) utilized process-based models to estimate the impact of Mycosphaerella leaf disease on eucalypt plantation productivity under current and future climates. Their study emphasized the considerable variability in disease impact based on site productivity and environmental factors. Lastly, Juroszek and von Tiedemann (2015) provided a comprehensive review linking plant disease models to climate change scenarios, suggesting that while disease risk may decrease in some regions due to suboptimal conditions for pathogens, most pathogens' winter-time survival could be enhanced by future warmer temperatures. These studies collectively underline the significant potential, but also the complexities, of leveraging AI and ML for disease forecasting in a changing climate.

The disease forecasting for precision agriculture

Effective disease management and executing informed decisions by farmers and agronomists demand the investigation of reliable and timely data. Adequate investigation and curation of the available phenotypic indicators of disease are principal steps, executed through disease forecasting models for making informed decisions about resource allocation optimization, and minimizing the environmental impact of disease control measures. Environmental interaction with plants and pathogens plays a key role in the incidence, severity and spread of disease and understanding the interplay between plants, pathogens, and the environment leads to the implementation of better informed decisions into pathogen behavior and plant resistance mechanisms. The disease forecasting models predict the likelihood and severity of plant diseases by accounting for the variations in meteorite, edaphic factors of crop, pathogen and environment (Fenu & Malloci, 2021; Kaur et al., 2022) serve the purpose of disease management under changing climate scenario. AI and IoT are revolutionizing agriculture, particularly in the field of precision agriculture, which is a key component of sustainable farming in the 21st century, enabling improved farming practices through scientific framework of IoT, ML and AI for data driven decision making process.

Continued research is key to developing resilient crops and effective disease strategies (Sharma & Verma, 2019). For instance, despite the increased disease susceptibility due to the homogeneity of modern wheat varieties, advancements in early detection systems, forecasting techniques, and modern breeding practices have effectively contributed to decreased wheat yield losses due to rust (Tony Fischer, 2022). The interdisciplinary early warning system (EWS) developed by Allen-Sader et al., 2019 for wheat rust diseases in Ethiopia represents one such model. Additionally, the ShIFT model, developed for predicting the control threshold of the *Zymoseptoria tritici* fungal pathogen, has shown promising results (Beyer et al., 2022). Recent advancements in data analysis techniques and ML algorithms have significantly enhanced the efficacy of these models. For instance, Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) have been widely used due to their ability to learn representations from past events and predict future occurrences based on conducive conditions. However, these models are often seen as a “black box” due to the difficulty in explaining the relationship between input and output variables (Fenu & Malloci, 2021). The models can be categorized as empirical or fundamental, depending on whether they are based on historical records or experimental data (Kaur et al., 2022). Some models utilize binary and multi-class classification for disease occurrence estimation and disease severity forecasting, respectively. Others focus on predicting continuous numerical values, such as disease severity scores or the first date of disease occurrence (Fenu & Malloci, 2021).

A successful forecasting system must rely on reliable biological and environmental data, be cost-effective, and have multipurpose applicability. Recent advancements in data collection and analysis have made it possible to gather and process large amounts of data more efficiently, thereby improving the cost-effectiveness and applicability of these systems (Kaur et al., 2022). For instance, remote sensing data and hyperspectral images have been used to detect diseases at an early or pre-symptomatic stage, providing a wealth of information for the development of autonomous non-invasive systems for the prediction of biotic and abiotic stress in plants (Fenu & Malloci, 2021). However, relying solely on one type of data often falls short in developing models that effectively capture and predict the diverse nature of diseases in agricultural fields. Enhancing the robustness and broad applicability of these models, as noted by various researchers, can be achieved by combining different types of data sources. This approach includes incorporating detailed information like the age of the plants, their specific varieties, stages of growth, and characteristics of the soil (Fenu & Malloci, 2021).

In the context of modern agriculture, the evolution of modeling techniques from empiricism to a process-based approach has been driven by scientific knowledge about plant disease epidemics and their drivers. Recent work by Gonzalez-Dominguez et al. (2023) underscores the pivotal role of process-based models in understanding and predicting plant disease dynamics. Their work, which includes a discussion on *Venturia inaequalis*—the pathogen causing apple scab—exemplifies how knowledge from epidemiological studies can be integrated into process-based models. Two main process-based models for the dynamic simulation of *Venturia inaequalis* primary infections in apple, Rimpro and A-scab, highlight the importance of past research in the development of future disease modeling. As we progress, these models, driven by scientific knowledge, technological progress, and improved data analytical tools, will remain integral to Integrated Pest Management (IPM). The integration of plant disease models, plant growth models, and fungicide models in a multi-modeling approach is increasingly desirable, providing timely and reliable support for decision-making to growers and crop management advisors, thereby promoting sustainable control of plant diseases (Gonzalez-Dominguez et al., 2023).

The IoT, ML, AI development for disease forecasting

The role of AI, IoT, and ML in disease forecasting models for modern agriculture is multifaceted and continues to evolve. AI, IoT, and ML have enormous potential in enhancing the effectiveness of the models and optimizing resource allocation management through efficient integration of multiple data sources like plant characteristics, soil information, and environmental data. These models are crucial for disease management, providing accurate and timely data towards precision agriculture, including integrated pest management, sustainable farming practices, and plant disease control. AI, IoT, and ML technology have a significant impact on precision agriculture through enhanced monitoring and control of agricultural systems, which optimizes resource management and improves crop yield; this advancement, along with the evolution from databased to process-based models informed by scientific knowledge, pave to accurate predictability of disease, as highlighted under Fig. 2. The applicability of these technologies could stretch to automated disease detection by allowing AI algorithms to predict localized and global disease outbreaks. Garrett et al. (2022) discussed the importance of big data in plant disease management using AI, specifically highlighting the roles of climate projections and remotely sensed data. They emphasize the future potential of satellite systems like the Copernicus Hyperspectral Imaging Mission for the Environment (CHIME) and NASA's Surface Biology and Geology (SBG), which will enhance plant health monitoring by providing high-resolution hyperspectral imagery globally. This technological interaction between AI and advanced satellite data is essential for enhanced disease detection and climate change adaptation. Similarly, Leal Filho et al. (2022) present a comprehensive analysis of the integral role of AI in climate change

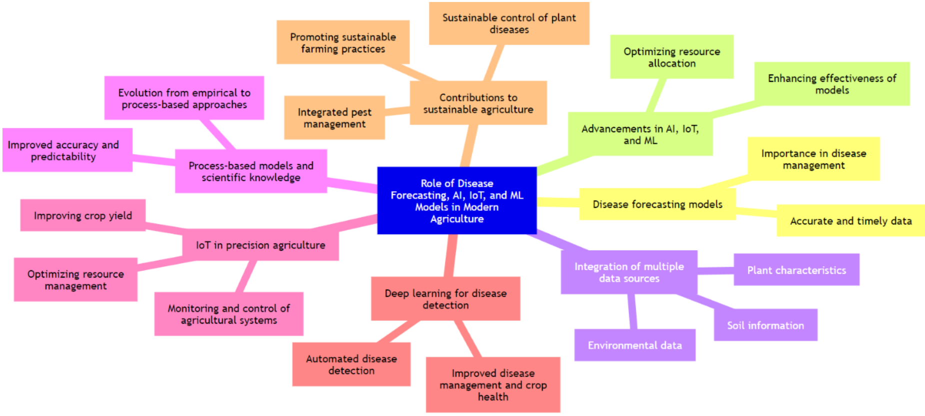


Fig. 2 Diagram overview of the role of disease forecasting, AI, IoT, and ML models in modern agriculture

adaptation, highlighting the extensive use of AI for climate change adaptation, primarily in monitoring climate dynamics and predicting climate change impacts in urban settings. The review emphasizes AI's capabilities in advanced modeling and forecasting, essential for assessing vulnerabilities due to direct environmental factor such as flood, drought or diseases across different regions. Additionally, it underlines the diverse applications of AI in areas ranging from water management and agriculture to wildfire control, also noting its contribution to disaster management and energy strategies is this production related aimed at reducing greenhouse gas emissions. Together, the insights from both papers paint a comprehensive picture of AI and ML's adaptability and their wide-ranging applications in agriculture and broader climate change adaptation efforts. These technologies are central in enhancing disease forecasting and management in agriculture and play a critical role in the overall global effort to adapt to and mitigate the impacts of climate change.

DL techniques are applied by Haridasan et al., 2023 to automate accurate identification, classification and disease detection in paddy by integrating image processing, ML, and DL. It improves disease management, enables timely interventions, and enhances crop health and yield. Comparative studies of image processing techniques, including Otsu's thresholding method, further enhance disease detection and segmentation. The use of DL reduces reliance on conventional methods, providing an efficient and accurate solution for disease management in agriculture. This research highlights the potential of DL in revolutionizing disease management and complements the broader discussion on the role of AI, IoT, and ML models in modern agriculture. The past half-century has witnessed significant advancements in sensor technology, automatic environmental data collection, and the emergence of AI, IoT, and ML. These developments have profoundly influenced plant disease modelling, enabling more precise and timely predictions. Moreover, they have revolutionized numerous aspects of agriculture, from disease management to resource optimization. These technological advancements have enhanced our current agricultural practices and paved the way for future innovations in the field (Gonzalez-Dominguez et al., 2023; Sharma et al., 2020). In the realm of disease forecasting caused by pathogen variability, several key studies stand out. De Wolf and Francl (2000) employed neural networks to classify tan spot and Stagonospora blotch infections in wheat, achieving an accuracy of up to 84%, showcasing the potential of neural networks in plant disease prediction. Cowger et al. (2009) investigated the impact of post-anthesis moisture on Fusarium head blight (FHB) in wheat and concluded that predictive models must factor in post-anthesis environmental conditions for precise forecasting of FHB. Lastly, Sharma-Poudyal and Chen (2011) presented models that predict potential yield loss due to stripe rust in wheat, taking into account a wide range of weather variables for enhanced accuracy compared to older models. Collectively, these studies emphasize the evolving and increasingly important role of AI and ML in refining disease forecasting models across different pathogens and environmental conditions. Identification of a particular disease is the preliminary step for its management and employment of AI in innovative approaches to delineate disease is reported (Sharma et al., 2020). DenseNet model was developed by implementing dense CNN by Waheed et al. (Waheed et al., 2020), to detect diseases in corn leaves. Another model developed by combining deep NN with Jaya algorithm had efficiently identified and delineated various diseases in rice viz., bacterial blight, brown spot, sheath rot, and blast diseases (Ramesh & Vydeki, 2020). These approaches have shown great promise in improving disease management and crop health. However, there are still challenges to be addressed, such as the need for more accurate and robust algorithms and the integration of these technologies with other data sources for a more comprehensive approach to disease detection (Singh et al., 2020). An efficient system for automated detection of rice foliar diseases was built with ML techniques, including SVM, Naive Bayes, CNN on image data with enhanced quality by pre-processing through histogram equalization and feature extractions were performed with PCA (Pallathadka et al., 2022). This system aims to improve crop yield by making informed decisions on disease management, and also reduce the effort and time taken in sending samples to diagnostic labs/consulting experts. Experimental validation with rice foliar disease dataset with image pre-processing inferred the effectiveness of the systemin disease identification and classification, offering a reliable approach for efficient and accurate disease detection in modern agriculture, which can have a positive impact on crop productivity.

Overall, disease management strategies encompassing disease forecasting models have displayed significant effects in mitigating economic losses, reducing environmental impacts, and augmenting agricultural productivity through efficient decisions on disease predictions and optimal application of fungicides, thereby contributing to sustainable agriculture. The potential of the disease forecasting models for sustainable agriculture suggests a positive impact on food security, despite the lack of evident economic data in support. Nevertheless, the realization of these benefits often depends on the accuracy of the models and validation testing of high-resolution data for climate-derived parameters.

In the future, IPM will continue to guide the sustainable control of plant diseases, and disease models will continue to be a key component of IPM. In this context, plant disease models must be flexible and transparent, and be a component of a multi-modeling approach capable of providing timely and reliable support for decision-making to growers and crop management advisors (Gonzalez-Dominguez et al., 2023). The integration of AI and ML in disease forecasting models has significantly enhanced the ability to monitor and manage diseases in agriculture. These technologies enable farmers and agronomists to make informed decisions and implement appropriate disease control strategies, ultimately leading to more sustainable and productive agricultural systems (Sharma et al., 2020).

Advancements and applications of AI, ML, and disease forecasting models in crop management

Expansion of disease forecasting models through meaningful exploitation of genomic, phenotypic, and remote sensing data with AI, ML has been revolutionizing the crop disease management. The following section delves into the advancements and applications of AI, ML, and disease forecasting models in crop management. We will explore how these technologies and models have revolutionized the agricultural sector, from predicting and managing crop diseases to optimizing crop yield and resource utilization.

Evolution and applications of disease forecasting models

Significant progress has been made in developing disease forecasting models for wheat diseases such as rusts, foliar blights, smuts, bunts, Fusarium head blight, and Blast. These models have evolved over the time to meet the requirements of farmers to control the spread of these diseases, thereby minimizing yield losses. Botanical epidemiologists categorized disease forecasting models into two main groups viz., (a) data based/empirical/correlative models and (b) process based/mechanistic/explanatory/theoretical/analytical/fundamental models (Rossi et al., 2019), which vary in their approaches to understand and simulate systems (González-Domínguez et al., 2023). Both the data-based and process based models are used for making informed decisions for disease forecasting independently, as well as pragmatic combinations (Hybrid models) of these approaches (De Wolf & Isard, 2007). The evolution of modelling techniques from data-based (empirical) models to process-based (mechanistic) models over the past half-century has played a significant role in enhancing the accuracy and effectiveness of disease forecasting models. This shift has been driven by scientific knowledge about plant disease epidemics and their drivers, as exemplified by the wheat rusts and apple scab case studies (Gonzalez-Dominguez et al., 2023).

Data-based models

Data-based models are built upon mathematical or statistical frameworks and are designed to organize and standardize observed data, such as correlating disease patterns with environmental variables. These models typically do not delve into the biological mechanisms behind the diseases. They rely on extensive datasets that capture field variations, and their accuracy in predictions is confined to the scope of the input data used (Gonzalez-Dominguez et al., 2023). Examples of these models, listed chronologically, include the (Chester, 1943) model for Leaf Rust (LR), (Burleigh et al., 1972) model for LR, (Nagarajan & Singh, 1975, 1976) model for Stem Rust in India, EPIPRE model by (Rabbinge & Rijsdijk, 1983; Zadoks, 1981; Zadoks et al., 1984) initially used for stripe/yellow rust (YR) of wheat, (Statler & Helgeson, 1988) decision model for LR, (Rodríguez-Moreno et al., 2020) in Mexico for stripe and leaf rust of wheat using the classification and regression tree (CART), and more recently, ShIFT model by (Beyer et al., 2022) for *Zymoseptoria tritici*, and the Image processing model by (Wang et al., 2023) for stripe rust and leaf rust.

Process-based models

On the flip side, process-based models aim to capture the fundamental biological processes that drive disease dynamics. These models necessitate a deep understanding of the mechanisms at play and often model changes in host-pathogen interactions over time and space, influenced by various environmental factors (Gonzalez-Dominguez et al., 2023). Examples of these models, listed chronologically, include the RUSTDEP model by (Rossi et al., 1997) for LR, Model by (Rossi & Giosuè, 2003) for Powdery Mildew (PM) on winter wheat using infection chain, (Audsley et al., 2005) model for LR and YR, WHEATPEST model by (Willocquet et al., 2008) which includes simulations for various pests such as LR and YR, among others, PROCULTURE model developed in Belgium for Septoria leaf blotch on winter wheat in western Europe (El Jarroudi et al., 2009) and was later enhanced for improved disease prediction accuracy (El Jarroudi et al., 2017), EPIWHEAT model by (Savary et al., 2015) for simulating potential epidemics of wheat foliar diseases, including brown rust and Septoria tritici blotch, Model A and Model B by (Chaloner et al., 2019) for predicting the behavior of Z. tritici spores, a major pathogen affecting wheat leaves, EWS model by (Allen-Sader et al., 2019) for predicting and mitigating wheat rust diseases in Ethiopia, and (Salotti et al., 2022) model for Black Rust (BR), providing accurate predictions of stem rust epidemics in wheat through a weather-driven, mechanistic approach.

Table 1 provides an overview of different types of models, categorizing them based on their type (data-based, process-based, or hybrid), the diseases they target, and their developers and years of development. It includes examples of each type of model, offering a real-world perspective on how these theoretical concepts are applied in practice.

Hybrid-based models

In addition to these, the concept of using a multi-modeling (hybrid) approach has been discussed in recent literature. This approach could potentially integrate plant disease models, plant growth models, and fungicide models to provide a more comprehensive and flexible solution for decision-making tools in integrated pest management. This conceptual framework was initially discussed by Caffi and Rossi (2018) and further elaborated upon in a recent review (Gonzalez-Dominguez et al., 2023). An example of this approach is the EWS by (Allen-Sader et al., 2019) for wheat rust diseases in Ethiopia, which integrates diverse data sources and scientific expertise, including environmental data, biological data, and disease control measures, to provide a comprehensive tool for proactive disease management in wheat crops.

In the context of apple scab, two main process-based models, Rimpro (Trapman, 1993) and A-scab (Rossi et al., 2007), have been developed for simulating *Venturia inaequalis* primary infections. Rimpro is a commercial software that accounts for the dynamics of airborne ascospores and infection during the primary season, but it does not incorporate the ontogeny of pseudothecia. On the other hand, A-scab is fully published and transparent, incorporating all the biological processes described in the review by (Gonzalez-Dominguez et al., 2023). It uses hourly data of air temperature, rainfall, relative humidity, and leaf wetness to simulate pseudothecium development, the dynamics of ascospore maturation, ascospore discharge events, and infection establishment and severity.

Table 1 Summary of different types of disease forecasting models and their characteristics

Model type	Model name	Developers	Year	Diseases
Data-based	Chester's model	Chester	1943	Leaf Rust (LR)
	Burleigh et al.'s model	Burleigh et al.	1972	LR
	Nagarajan & Singh's model	Nagarajan & Singh	1975, 1976	Stem Rust
	EPIPRE	Rabbinge & Rijsdijk, Zadoks	1983, 1981, 1984	Stripe/Yellow Rust (YR)
	Statler & Helgeson's model	Statler & Helgeson	1988	LR
	Rodríguez-Moreno et al.'s model	Rodríguez-Moreno et al.	2020	Stripe and Leaf Rust
	ShIFT	Beyer et al.	2022	Zymoseptoria tritici
	Image processing model	Wang et al.	2023	Stripe Rust and Leaf Rust
Process-based	RUSTDEP	Rossi et al.	1997	LR
	Rossi & Giosuè's model	Rossi & Giosuè	2003	Powdery Mildew (PM)
	Audsley et al.'s model	Audsley et al.	2005	LR and YR
	WHEATPEST	Willocquet et al.	2008	Various pests including LR and YR
	PROCULTURE	El Jarroudi et al.	2009, 2017	Septoria leaf blotch
	EPIWHEAT	Savary et al.	2015	Multiple pest damage
	Model A and Model B	Chaloner et al.	2019	Z. tritici spores
	EWS	Allen-Sader et al.	2019	Wheat rust diseases in Ethiopia
	Salotti et al.'s model	Salotti et al.	2022	Black Rust (BR)
Hybrid	EWS	Allen-Sader et al.	2019	Wheat rust diseases in Ethiopia

Detailed study of popular models for disease forecasting

Some of the earlier models, such as those developed by Chester (1943), Burleigh et al. (1972), and Nagarajan and Singh (1975, 1976), among others, have played pivotal roles in the historical development of disease forecasting. Their detailed descriptions and analyses can be found in other dedicated resources. While these models continue to hold relevance, this overview focuses more on recent models and those with significant potential for current and future applications in disease forecasting and management, reflecting the ongoing advancements in this field. As mentioned earlier, a diverse range of disease forecasting models have been developed to tackle wheat diseases, each with its unique set of data requirements and complexities. In the following sections, we will explore some of these models in greater detail.

EPIPRE (EPidemics PREdiction and PREvention) Initiated in 1978, is a cooperative project involving farmers, the State Extension Service, the Research Institute for Plant Protection (IPO), the Agricultural University, and various other institutions in the Netherlands and Belgium (Rabbinge & Rijsdijk, 1983; Zadoks, 1981). It is a field-specific simulation model developed to manage wheat diseases, initially in response to severe yellow/stripe rust epidemics (Rabbinge & Rijsdijk, 1983). The system operates on a field-by-field basis, providing specific recommendations for each registered field. Farmers contribute data, including field characteristics, crop stage, disease/pest information, sowing time, cultivar, soil characteristics, herbicide and growth-regulator application, and nitrogen fertilization. These field observations and data are then stored in a central data bank within the EPIPRE system. EPIPRE utilizes this comprehensive dataset from the databank to calculate expected damage and losses, which forms the basis for crucial decision-making, including the determination of whether to apply fungicides for effective disease and pest management (Rabbinge & Rijsdijk, 1983).

EPIPRE's primary objective is to minimize biocide usage and maximize the value added to the crop by biocide application, within the legal limits. The system's philosophy is that the farmer is the master of their own field. EPIPRE provides field-specific advice, which is more precise than the more general advice provided by the Extension Service. The farmer then uses or disregards the advice at their discretion (Zadoks et al., 1984). Performance evaluations of EPIPRE have shown that it recommends significantly fewer treatments than other sources, but the net yield is similar or slightly higher. Farmers with lower yield levels are more inclined to follow EPIPRE recommendations than those with higher yield levels. The system also contributes to a reduction in pesticide use and a decrease in the risk of fungi and insects developing resistance to pesticides (Rabbinge & Rijsdijk, 1983). Originally used for stripe rust, EPIPRE has been expanded to manage other diseases and pests, including eyespot, powdery mildew, brown rust, septoria leaf spot, glume blotch, and aphids (Smeets et al., 1994). The system's adaptability and effectiveness underscore its value in sustainable crop management.

The RUSTDEP (RUST Development of EPidemics) Model is a sophisticated simulation tool that has been meticulously engineered to forecast the severity of rust diseases in winter wheat. This model harnesses weather data and factors integral to disease development, such as the length of the infectious period. The model's robustness has been tested against a comprehensive spectrum of disease severity, from light to severe epidemics. The validation process involved visual comparison between actual and simulated data, the Kolmogorov-Smirnov test, and regression analysis. In 80% of the cases, based on visual comparison, the simulated disease severity consistently fell within the 95% confidence interval for the mean of actual data, demonstrating the model's high accuracy. In the remaining 20% of cases, the simulations only deviated from the confidence limits at a low level of disease severity, likely due to the inherent challenges in assessing disease severity during the early stages of an epidemic. The Kolmogorov-Smirnov test further confirmed that the simulations were statistically similar to field observations, with the maximum distance between the distribution of field data being lower than the critical values at both 99% and 95% probability levels. The study concluded that the RUSTDEP model is a statistically accurate simulator of the field data, and its robustness and accuracy suggest that it could be used as a reliable tool for long-term forecasting of rust diseases in winter wheat. These results underscore the model's reliability and precision in predicting disease severity, making it a valuable tool in the field of plant pathology (Rossi et al., 1997).

The EPIWHEAT model As described by (Savary et al., 2015), is a robust and adaptable simulation tool designed to forecast potential epidemics of wheat diseases. Its unique feature is its ability to make predictions based solely on physical environmental conditions, without incorporating any disease management actions, whether direct or indirect. The model's structure is rooted in the key stages of disease progression, including the transition of sites from healthy to latent, infectious, and finally, removed. It also considers lesion expansion, a feature not accounted for in its predecessor, EPIRICE. EPIWHEAT simplifies the simulation of host dynamics such as growth and senescence by employing a minimal set of parameters and a select few driving functions. For the study, the model was populated with processes and parameters specific to two critical wheat diseases: brown rust (leaf rust; *Puccinia triticina*) and Septoria tritici blotch (*Zymoseptoria tritici*). The researchers conducted a comprehensive evaluation of the model, comparing the simulated epidemics with observed data at various scales, ranging from individual fields to the national level in France, and even extending to the European scale. The results underscored EPIWHEAT's capacity to provide robust estimates of potential wheat disease epidemics at spatial scales beyond the individual field, thereby establishing it as a reliable platform for predicting potential epidemics of wheat foliar diseases at large scales. Despite its strengths, the authors acknowledged the need for further development and refinement of the model. They highlighted the model's implicit assumption of random distribution of diseased sites and uniform vulnerability of healthy sites, which may not always hold true in real-world scenarios. Nevertheless, the EPIWHEAT model stands as a significant contribution to the field of disease modelling, with the potential for wide-ranging applications in any environment where wheat is grown globally.

The early warning system (EWS) model In recent years, the development of disease forecasting models has made significant strides, particularly with the implementation of the Early Warning System (EWS) for wheat rust diseases in Ethiopia (Allen-Sader et al., 2019). This system, one of the first of its kind in a developing country, has been instrumental in mitigating the impact of wheat diseases. The EWS leverages a multitude of data sources and scientific expertise, providing a comprehensive toolset for proactive disease management in wheat crops. The system operates by integrating real-time field survey observations, advanced numerical weather prediction data, spore dispersion forecasts, and environmental suitability model forecasts. This information is then analyzed and interpreted by experts in Ethiopia to assess current and future disease risks. The EWS also disseminates this information to key stakeholders, including policy makers, research institutes, and farmers, providing them with actionable insights for disease management. Moreover, the EWS has been successful in providing timely information to assist policy makers in allocating limited fungicide stocks during the wheat seasons. The EWS not only provides early warning systems but also informs decision-making processes, enabling farmers to take timely and informed actions to prevent or minimize the impact of diseases. This innovative system, with its underpinning technologies, is transferable to forecast wheat rusts in other regions and can be readily adapted for other wind-dispersed pests and diseases of major agricultural crops.

The ShIFT (SeptorIa ForecasT) model Developed by (Beyer et al., 2022), is a significant advancement in disease forecasting. This weather-based model is specifically designed to predict the optimal timing for the application of a systemic fungicide to control *Zymoseptoria tritici*. The model's unique strength lies in its ability to accurately quantify the temporal distance between critical rainfall periods and the breaking of the control threshold of Z. *tritici* on winter wheat, using data from field experiments conducted in Luxembourg. The ShIFT model has undergone rigorous validation using external data from 2017 to 2019, demonstrating a high accuracy rate of 84.6% within the efficacy period of current commercial fungicides. The average deviation between the observed and predicted dates of epidemic outbreaks was a mere 0.62 ± 2.4 days, with a maximum deviation of 19 days, indicating the model's precision. Unlike previous models, ShIFT directly forecasts the time for fungicide application, eliminating the need for users to interpret epidemiological outputs. This data-driven approach, combined with an understanding of pathogen dynamics, empowers farmers to make informed decisions and implement effective control strategies. However, it's important to note that the model should not be used in regions without local validation, particularly where fungal plant pathogens other than Z. *tritici* are dominant.

The 'Wang Model' In recent advancements, a notable predictive model has been developed by (Wang et al., 2023), which leverages image processing technology to detect stripe rust and leaf rust in various wheat varieties under both field and laboratory conditions. This model utilizes ML algorithms, namely Support Vector Machine (SVM), Back Propagation Neural Network (BPNN), and Random Forest (RF), to construct disease identification models for individual wheat varieties. When tested under identical environmental conditions and wheat varieties as those used for training, the model exhibited impressive identification accuracies. However, its performance fluctuated when applied to different wheat varieties or under varying environmental conditions. Despite these variations, the model demonstrated its potential in disease identification, delivering satisfactory performance when disease images of different varieties captured under diverse conditions were used for modelling. This research highlights the potential of image-based disease identification across various wheat varieties and under different environmental conditions, thereby paving the way for more comprehensive and adaptable disease forecasting models in wheat.

Disease forecasting for biocontrol and resistance

Recent advancements in AI and ML have significantly contributed to disease forecasting for biocontrol and resistance, improving forecasting accuracy and operational efficiency. Notable studies in this area include the work of Kennelly et al. (2007), who employed basic weather and phenological thresholds to forecast grapevine downy mildew outbreaks in multiple locations accurately. In a similar vein, Pavan et al. (2011) developed a web-based system for strawberry disease forecasting that optimized fungicide applications and reduced unnecessary sprays by 50%. Probert et al. (2018) highlighted the efficacy of real-time decision-making models during emergency disease outbreaks like foot-and-mouth disease, emphasizing the importance of state-dependent interventions. Most recently, Motisi et al. (2022) designed ExpeRoya, a qualitative model for forecasting coffee leaf rust, which successfully integrates a multitude of interactions within the disease-coffee pathosystem based on easily obtainable field data. These studies exemplify the promising advances AI and ML are bringing to the field, including improved forecasting accuracy and operational efficiency.

Spatial and temporal modelling of disease

The spatial and temporal modelling of disease is a critical aspect of disease management as environmental factors play a crucial role in determining the fate of the crop disease status. The importance of temperature in Stewart's disease incidence in corn was evaluated using three models to forecast the prevalence through temperature variations (Esker et al., 2006). A web based AI decision system to improve fungicide efficiency for potato and tomato late blight was built by Small et al. (2015) by linking meteorological data to AI models. Meno et al. (2022) focused on demonstrating the efficacy of early blight forecasting models for potato crops in NW Spain by focusing on plant features. Skelsey (2021) employed anomaly detection algorithms for greater forecasting accuracy (up to 97%) of potato late blight in Great Britain. Along with disease forecasting, Lecerf et al. (2019) tested the MARS-Crop Yield Forecasting System, revealing its capability to predict yields of major crops in the EU and emphasizing the system's consistency compared to meteorological predictors. The models involving the multitude of climatic factors for disease forecasting require cautious collective evaluation of data features by AI and ML techniques, which are not only becoming increasingly accurate but also more comprehensive in incorporating spatial and temporal variables.

Extended applications of ML, AI

Application of AI and ML can be extended towards managing various aspects of agricultural production, viz., crop yield prediction, intelligent harvesting and improved irrigation systems, accounting for augmented accuracy and efficiency of modern farming systems. For instance, sharmal et al. provided various examples of dynamic decision making by AI applications with data across different regions for crop yield prediction in wheat, silage maize, corn, rice, wheat, and barley (Sharma et al., 2020). One of the studies mentioned is by Kamir et al. (2020), who used ML models to identify yield gap hotspots in wheat production. They generated very high-resolution yield maps using data from various sources, including Normalized Difference Vegetation Index (NDVI) time-series data, rainfall and temperature data, and observed grain yield maps collected using intelligent harvesting machines. In another study, (Feng et al., 2020) proposed a hybrid approach for wheat yield prediction in New South Wales, Australia. They utilized multiple growth-specific indicators, such as agricultural production system simulators (APSIM), NDVI, and SPEI (Standardized Precipitation and Evapotranspiration Index), before predicting wheat yield using regression models. Similarly, (Cai et al., 2019) integrated climate and satellite data over fourteen years to predict wheat yield in Australia using ML algorithms such as SVM, RF, and Neural

Networks (NN). They found that climate data provided distinctive information compared to satellite data for yield prediction. Intelligent harvesting techniques with AI generated 3X faster robot harvesting methods to help with the labor shortage problem of Japanese farmers in harvesting asparagus crop (Sakai et al., 2013). Intelligent harvesting was made possible through the amalgamation of AI with laser sensors to collect 3D distance information of Asparagus to efficiently identify and harvest asparagus without relying solely on color properties.

Predicting appropriate planting dates in wheat by considering the meteorological parameters in Turkey is successfully executed by Gümüşçü et al. (2020) with supervised ML algorithms, including K-Nearest Neighbor (kNN), SVM, decision trees. (Gümüşçü et al., 2020). Data for their training the model included meteorological parameters from the past 300 days in Turkey with generic algorithm for feature selection and they concluded that the kNN classification algorithm performed robustly and provided the most accurate predictions for wheat crop planting dates in Turkey. Aghighi et al. (2018) conducted another comparative study with advanced regression algorithms such as Gaussian process regression, support vector regression (SVR), boosted regression tree, and random forest to forecast yield of silage maize in Iran (Aghighi et al., 2018), with the superior performance of boosted regression tree among the evaluated models.

Switching to DL models, corn yield was predicted with SVR model by employing five year moving average corn yield, enhanced vegetation index from satellite data, and historical climatic data (Kuwata & Shibasaki, 2015). They incorporated a 5-year,. Similarly, the efficiency of DL models such as RNN in integrating numerous features of soil properties, rainfall data, nutrient measurements over 31 years for forecasting rice yield was witnessed (Kulkarni et al., 2018). Another DL approach was employed by (Nevavuori et al., 2019) to predict wheat and barley yield prediction in Pori, Finland with convolutional neural network (Nevavuori et al., 2019). convolutional neural network for wheat and barley yield prediction in Pori, Finland. Another study in the Guangxi Zhuang Autonomous Region, China demonstrated the application of AI and ML in predicting summer and winter rice yield by building an end to end model (Chu & Yu, 2020).

Challenges and future directions

The visual representation in Fig. 3 depicts an overview of the challenges, future directions, and conclusions in the applications of AI models in the field of plant disease forecasting models through illustrating the progress, interconnectedness of the concepts, and potential benefits of integrating AI into agriculture. This figure serves as a visual representation for the following detailed discussion, where each of these elements is explored in depth.

Future of ML, AI in precision agriculture

Employing advanced technologies such as AI and the IoT into agriculture is promising yet requires addressing many challenges that are hindering the transition from traditional farming methods to more technologically advanced ones, such as low farmer literacy rates, resistance to digital skill acquisition, limited internet connectivity, predictive accuracy issues, high initial investments, and high energy consumption. Data transmission issues associated with the implementation of technologies like IoT can be particularly challenging in areas

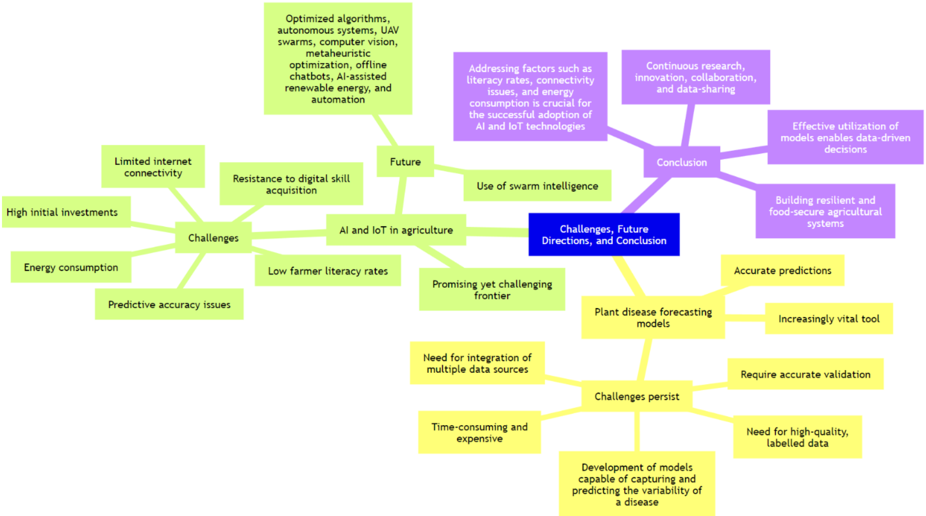


Fig. 3 A diagram summarizing the challenges, future directions, and conclusions in plant disease forecasting models and AI applications in agriculture

with poor internet connectivity, besides poor accessibility of cloud services for data storage and analysis (Sharma et al., 2020). In addition to missing information, duplication, outliers, and integrity breaches of data, the application of AI and ML techniques in plant disease detection presents further issues with computer vision, image processing and availability of sufficient enough clean data for model training (Pallathadka et al., 2022).

However, despite these challenges, the future of AI and the IoT in precision agriculture is promising. (Sharma et al., 2020) highlight the use of swarm intelligence as the future of precision agriculture, where robust and adaptive ML and DL algorithms inspired by swarm intelligence can effectively predict and monitor various parameters in agriculture. This includes real-time field and livestock monitoring, spraying of pesticides and fertilizers, and efficient automation of tasks such as harvesting and weed elimination. Additionally, the integration of AI and IoT technologies in precision agriculture involves optimized algorithms, autonomous systems, UAV swarms, computer vision, metaheuristic optimization, offline chatbots, AI-assisted renewable energy, and automation from seed sowing to harvesting. These advancements empower farmers with technology for optimal outputs, enhancing efficiency through smart irrigation, drones, and robots. Future work in this field includes further development of generative AI and exploration of sustainable resource management. Overall, the combination of AI and IoT technologies is revolutionizing the agricultural industry, with ML and DL algorithms playing a vital role in soil and crop prediction, paving the way for more efficient and productive farming practices (Sharma et al., 2020).

Optimal data collection with appropriate sensors for the suitable AI model

The advancements in data collection and analysis techniques, coupled with the growing understanding of plant disease dynamics, are paving the way for more efficient, cost-effective, and applicable forecasting systems, thereby contributing to the prevention and mitigation of the impact of crop and plant diseases on food production. This is particularly crucial for those crops that serve as staple foods for millions of people residing in the least developed countries. Furthermore, the need for high-quality, labelled data, integrating multiple data sources, and developing models capable of capturing and predicting the variability of disease in the field were reported (Fenu & Malloci, 2021; Kaur et al., 2022). Which emphasizes the importance of training datasets for the generation of effective of AI and ML applications for sustainable and modern agriculture (Sharma et al., 2020). Stringent regulations and caution need to be followed in data selection, as there is a high risk that models developed with incomplete or inaccurate data could lead to erroneous projections, causing financial losses to farmers.

Data based automation in agriculture is deeply evolving and transforming agriculture from conventional to modern digital agriculture, in this scenario it is imperative to understand the synergies between various technological components. Modern digital agriculture is built with a broad spectrum of sensors, and diverse ML models forming together as AI models for predicting complex dynamics of crop-disease interactions. Figure 4 brief overview of various sensors, AI Models, and crop-disease combo states.

Sensors are employed for accurate data collection at the base level, serving as the foundation for building AI models. They range from cellular level sensors to satellite based sensors, providing detailed insights into plant health, chemical compositions, and abiotic /biotic stress. The selection of appropriate sensors is dependent on the unique requirements of each crop and the type of diseases under evaluation. Integrating different sensors with ML models can give insights about crop´s basic details (RGB sensors), temperature (thermal sensors), water & nutrient status (thermal and multispectral sensors), photosynthetic efficiency (fluorescence, multispectral, hyperspectral sensors) and disease resistance or the performance of herbicides (hyperspectral sensors), enabling real-time observation with data transmission. It is imperative to choose appropriate sensor and ML model combinations for efficient conversion of raw data from sensors to actionable AI for addressing the specific needs of each crop. Selecting the right AI model is determined by the nature of data and models capabilities. Decision trees offer good baseline models and are easily interpretable for RGB data, while more complex models like Random Forests, Support Vector Machines (SVM), and Convo-

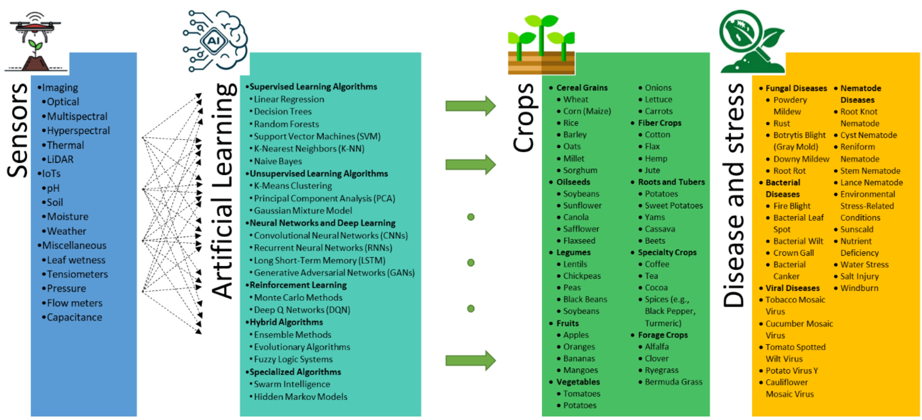


Fig. 4 Integrated overview of sensor technologies, AI models, and crop-disease combo states in modern agriculture

lutional Neural Networks (CNNs) provide efficient classification and interpretation of complex hyperspectral sensor data, whereas Recurrent Neural Networks (RNNs) are particularly effective in modelling with time-series data. It is inferred that proper alignment of sensors with AI models and its adaptation to specific crop-disease combinations is vital in building a strong AI model. In conclusion, precision agriculture is not about the isolated adoption of advanced technologies but about their careful and informed combination. Through cautious integration of relevant sensor technologies and AI modelswith crop-disease dynamics, we can pave efficient and sustainable agriculture system.

Despite of the superior advancements in this field, hurdles such as accurate data validation for the models need to be addressed for reliable predictions in different contexts of model development. Although this validation process is costly and time-consuming, but it is vital for the models' utility and ethical implementation. The models should also be evaluated for their potential to assist users and enhance illness management. By addressing these issues, agronomists and farmers will be better equipped to make judgment calls and implement disease management plans.(Gonzalez-Dominguez et al., 2023). The interactions of pathogens with G X E represent complex aspects under changing climate, which led to the shift of plant disease modeling from empirical to process-based methods (Gonzalez-Dominguez et al., 2023). Shifting from data-based models to process-based models is advantageous in terms of augmented model efficiency by collecting detailed information about pathogen x genotype x environment interactions to produce a thorough grasp of disease forecasting. Implementing these models in Integrated Pest Management (IPM) potentially paves the way for sustainable agriculture, particularly in light of the European Union's goal to reduce pesticide use by 50% by 2030. Furthermore, Gonzalez-Dominguez et al. indicated that future research the future research should emphasize more on improving model validation and incorporating these models into decision support systems, taking into account both the technical maintenance and socioeconomic factors, which is a vital approach for unraveling the benefits of plant disease models in effective disease management for achieving sustainable crop production. In the end, it is evident that the generation of improved disease forecasting models requires ongoing research activities that necessitate continuous innovative research, collaboration, and data-sharing among stakeholders in agriculture research, considering the immense promise of plant disease forecasting models in the agricultural sector. Implementation of these models can help farmers and agronomists make well-informed decisions to establish resilient and food-secure farming systems.

Summary and conclusion

In summary, this article has explored the potential of AI, IoT, and ML in addressing climate change, plant disease forecasting and crop management strategies and inferred that disease forecasting models play crucial role in crop management and further advancements in contributions from AI and ML could strengthen disease prediction in agriculture. The current study also delineated significance of validation testing of the models to guarantee the reliability on these models for future crop production, which is challenged by availability of high-quality publicly available data. The complexity of advanced ML models, and the lack of open data present hurdles that require strategies to enhance transparency and interpretability without compromising predictive power. To address this, future research should focus on improving the usability and accessibility of process-based models and integrating them into decision support systems for disease management, efficient resource use with precision agriculture. Moreover, interdisciplinary collaboration between researchers, farmers, and policymakers is essential to advance the field of plant disease forecasting. By fostering data-sharing and innovation, stakeholders can collectively work towards making data-driven decisions and implementing effective disease control strategies. The success of future advancements in IoT, ML, AI based disease forecasting relies on continued research and advances in AI and IoT technologies, making it more efficient, sustainable, and productive. However, its adoption requires addressing factors like low farmer literacy rates, limited internet connectivity, and efficient management of energy consumption in the field.

In conclusion, the practical application of plant disease forecasting models in conjunction with IoT, ML and AI technologies, continuous research and collaborative efforts, has the potential to empower farmers and agronomists to make informed decisions about resource and disease management, transforming towards sustainable modern agriculture, and contributing to resilient and productive agricultural systems with enhanced food security for future.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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