Review

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Artificial Intelligence: A Promising Tool for Application in Phytopathology

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Abstract: Artificial intelligence (AI) is revolutionizing approaches in plant disease management and phytopathological research. This review analyzes current applications and future directions of AI in addressing evolving agricultural challenges. Plant diseases annually cause 10-16% yield losses in major crops, prompting urgent innovations. Artificial intelligence (AI) shows aptitude for automated disease detection and diagnosis utilizing image recognition techniques, with reported accuracies exceeding 95% and surpassing human visual assessment. Forecasting models integrating weather, soil, and crop data enable preemptive interventions by predicting spatial-temporal outbreak risks weeks in advance at 81-95% precision, minimizing pesticide usage. Precision agriculture powered by AI optimizes data-driven, tailored crop protection strategies boosting resilience. Real-time monitoring leveraging AI discerns pre-symptomatic anomalies from plant and environmental data for early alerts. These applications highlight AI's proficiency in illuminating opaque disease patterns within increasingly complex agricultural data. Machine learning techniques overcome human cognitive constraints by discovering multivariate correlations unnoticed before. AI is poised to transform in-field decision making around disease prevention and precision management. Overall, AI constitutes a strategic innovation pathway to strengthen ecological plant health management amidst climate change, globalization, and agricultural intensification pressures. With prudent and ethical implementation, AI-enabled tools promise to enable next-generation phytopathology, enhancing crop resilience worldwide.

Keywords: artificial intelligence; phytopathology**;** emerging disease; climate change; control diseases

1. Introduction

Plant diseases have plagued agricultural crops for centuries, presenting a persistent threat to global food security [1,2]. Annually, plant diseases account for an estimated 10-16% of global crop losses, translating into profound economic impacts [3,4]. With the global population projected to reach 9.8 billion by 2050, it is imperative to increase crop yields by 25-70% to meet escalating food demands [5], emphasizing the need for revolutionary advancements in managing plant diseases.

However, the dynamics of plant pathosystems are complex, influenced by genetic and environmental factors, and challenged by the evolution of host-pathogen interactions [6,7]. These interactions have been significantly altered in recent decades due to anthropogenic factors, particularly climate change and modern agricultural practices. Climate change has been a critical driver in the emergence and spread of new plant pathogens, altering the geographical distribution of existing diseases and creating favourable conditions for the emergence of novel pathogens [8,9]. Moreover, the intensification of agricultural practices, including the use of monocultures and high-input farming systems, has reduced crop diversity, making them more susceptible to widespread disease outbreaks [10–12].

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These evolving dynamics necessitate innovative solutions to expedite the discovery of knowledge in plant disease dynamics, enhance crop resilience, and understand plant-microbe interactions. Artificial Intelligence (AI) offers groundbreaking avenues for deciphering the complexity of plant pathosystems and deriving practical insights for disease management [13,14]. The capacity of AI to analyze large volumes of agricultural data enables the revelation of correlations beyond human cognitive abilities [15,16]. This capability positions AI as a formidable tool in more easily unraveling the nature of plant-disease interactions. These studies involve a substantial amount of data, and AI can identify behavioral patterns in ways that are not readily discernible through purely human analysis. Furthermore, machine learning algorithms can continually self-improve, progressively facilitating the interpretation of new data sets in similar studies, while discarding data that pertains to the inherent variability of the studies[17,18].

This review has three central aims: 1. Examine existing and emerging applications of AI supporting plant disease management; 2. Identify current challenges and gaps hindering adoption of AI-driven solutions; 3. Outline a roadmap for stakeholder alignment to mainstream AI in crop protection practices. By realizing these objectives through a detailed literature analysis, this review seeks to catalyse a strategic transition toward AI-enabled plant disease science and agriculture worldwide as a bridge to more sustainable food production, addressing these evolving challenges in plant pathosystems.

2. Overview of Phytopathology

Phytopathology, derived from the Greek words "phyton" (plant) and "pathos" (suffering), is the scientific discipline dedicated to the study of plant diseases. This field investigates the complex interactions between plants and pathogenic organisms, shedding light on the mechanisms underlying the onset and progression of diseases. The scope of phytopathology encompasses the etiology of diseases, their epidemiology, and the development of integrated strategies for managing them in agricultural and horticultural contexts [2]. It is estimated that over 50,000 species of plant pathogens cause damage to more than 30,000 plant species [1]. These pathogens comprise various taxa, including fungi, bacteria, viruses, viroids, protozoa, algae, and algae. Each pathogen type prompts unique disease manifestations and demands tailored investigative approaches. Furthermore, the effects of climate change, globalization, and crop intensification add complexity to deciphering modern plant disease epidemiology [8].

As a discipline so integral to food security and agricultural sustainability, the importance of phytopathology cannot be overstated. As mentioned earlier, plant diseases result in substantial economic losses in major staple crops worldwide, amounting to $220 billion in annual economic damages globally [3,4]. For instance, Fusarium wilt disease alone results in approximately $410 million in annual banana crop damages, while cassava brown streak disease incited over $100 million in crop damages across eastern Africa in the early 1990s [19,20]. By elucidating plant-pathogen interactions and disease epidemiology, phytopathology enables breeding disease-resistant varieties, optimizing cultural practices, and implementing integrated pest management interventions that minimize disease impacts and crop loss [6]. The development of resistant cultivars alone has saved certain crops from near extinction, as exemplified by saving papaya production in Hawaii from papaya ringspot virus in the mid-20th century [21]. A recent example of success in phytopathology is the management of coffee rust disease in Central America. Since 2012, coffee rust has significantly threatened coffee production, but the implementation of resistant varieties and improved agronomic practices has resulted in a notable recovery in affected regions [22]. Another case is the management of citrus tristeza virus in Florida, where the use of tolerant rootstocks and vector control has helped mitigate the impacts of the disease [23].

However, current disease management strategies often provide incomplete and temporary solutions in the face of an evolving pathogen landscape. In Figure 1, we present a conceptual framework that lists some of the major challenges in contemporary phytopathology, including: Emerging Diseases, Climate Change, Global Trade and Pathogen Dissemination, Breakdown of Resistance, and Data Analysis and Integration. In conclusion, phytopathology has played a crucial

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role in the management of emerging diseases, demonstrating its importance in the context of current agricultural challenges. The examples cited illustrate how phytopathological science has responded to specific diseases with innovations and adaptive strategies, highlighting its relevance in an ever-changing agricultural world.

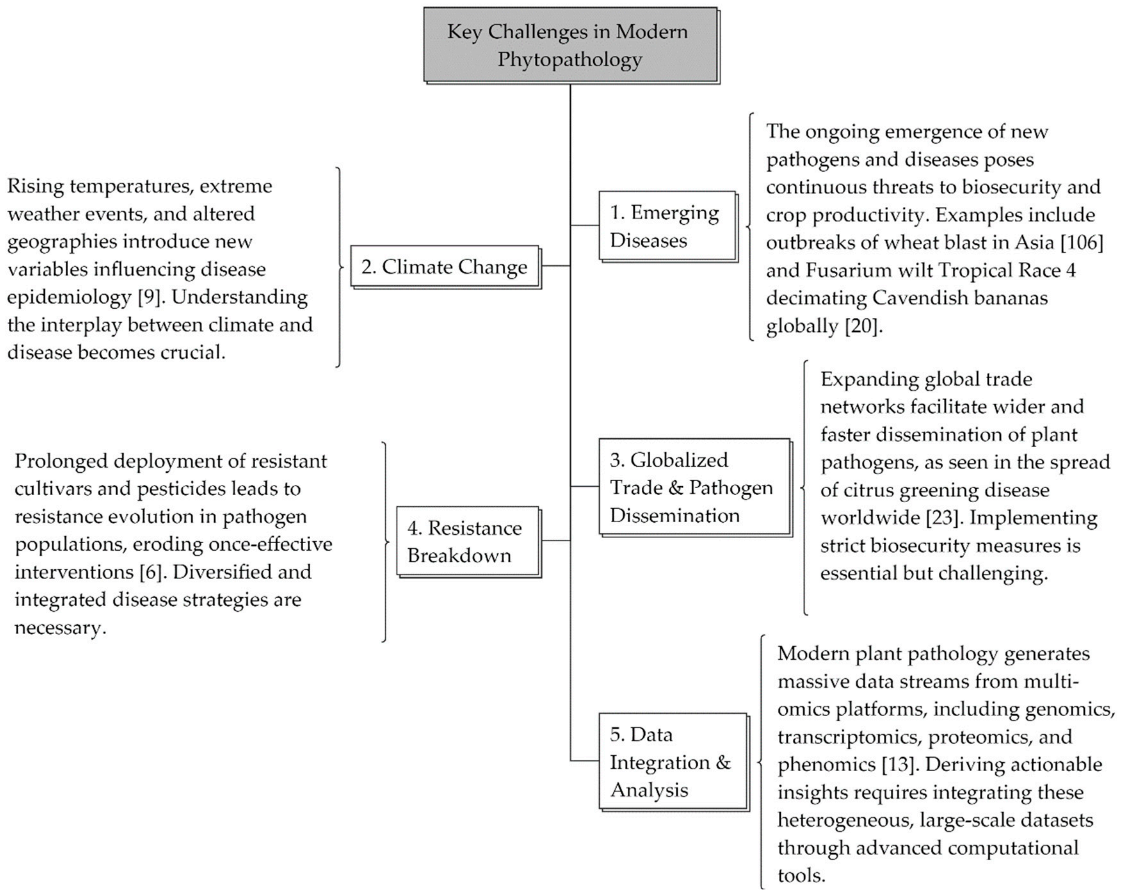

Figure 1. Several key challenges for innovation in modem phytopathology.

3. Role of Technology in Phytopathology

Historically, phytopathologists predominantly relied on conventional methods, such as visual inspection, symptomatology characterization, and pathogen isolation for plant disease diagnosis and management [2]. While these traditional techniques are valuable, they have inherent limitations, especially when considering the emerging agricultural challenges of the modern world. For instance, visual disease symptoms often do not manifest until infections are well-established, leading to delayed intervention and unchecked pathogen spread [24]. Reliance on visual symptoms alone also poses challenges in distinguishing between diseases with similar outward manifestations [25].

Traditional methods, such as pathogen isolation and culture, remain cornerstones in diagnostics. However, they require time-consuming processes and obtaining pure cultures can be technically challenging [26]. Furthermore, many phytopathogenic microbes exhibit complex life cycles, switching between morphological forms, which traditional techniques often fail to detect at low pathogen levels or in identifying novel strains [20,27]. This limits their reliability and applicability in the dynamic agricultural ecosystems of today.

3.1. Advent of Emerging Technologies in Agriculture

The advent of emerging technologies and advanced analytical tools has significantly altered the agricultural landscape. Next-Generation high-throughput DNA sequencing platforms, for instance, have revolutionized plant-microbiome studies, enabling rapid genomic characterization of plant-associated microbiota and pathogens [28,29]. Metagenomic approaches have elucidated complex plant-microbe interactions, identified novel pathogens, and assessed microbiome shifts correlating with health-disease transitions. Additionally, ultra-sensitive quantitative DNA and RNA diagnostic tests now facilitate detection of exceedingly low pathogen levels at early infection stages [25,30].

Remote sensing technologies and high-resolution spectral imaging through satellites, planes, and unmanned aerial vehicles offer large-scale capabilities in monitoring crop health and stress levels[31,32]. These tools enable real-time, non-invasive assessment of plant vigor and detection of disease outbreak locations in the field, facilitating timely and precise management interventions [33]. Recent advancements in nano-biosensors and lab-on-chip devices have allowed for the continuous monitoring of environmental parameters influencing disease development, such as temperature, humidity, soil water content, and microclimate conditions [34]. The integration of these sensors in agricultural ecosystems generates comprehensive datasets, shedding light on crop-climate-disease interplay [35].

Big data analytics, automation, robotics, and artificial intelligence (AI) are accelerating a paradigm shift towards data-driven precision agriculture systems [36–38]. Phytopathology, transitioning into a highly interdisciplinary and technology-intensive science, integrates diverse data streams. Advanced computational methods offer immense promise in deriving actionable insights from the wealth of agricultural big data for efficient disease management [39].

3.2. Need for Advanced Data-Driven Solutions

While emerging technologies provide promising avenues, significant challenges persist in effectively managing diseases within the highly complex and dynamic agricultural ecosystems of today. Globalization, climate change, and intensive farming systems facilitate increased emergence and faster evolution of plant pathogens [8,40]. Many conventional disease management approaches now face diminishing effectiveness due to rising pathogen resistance, alongside serious environmental and health concerns [11,12,41]

The complexity characterizing plant-pathogen interactions and disease epidemiology necessitates a paradigm shift towards sophisticated, integrated solutions. In this context, AI and advanced machine learning algorithms emerge as potentially transformative tools in modern data-driven phytopathology. Machine learning models can analyse vast, disparate datasets, including weather, soil, plant omics, microbiome, and pathogen genomic information [42]. These models discern subtle multivariate relationships, predict disease outbreak risks, and enable targeted intervention strategies undetectable via conventional approaches [13,14,42]. Continually learning from accumulating agricultural data streams, such AI-based systems progressively improve their predictive capabilities and decision support functionalities. Therefore, harnessing modern technology and computational innovation is imperative for developing dynamic, ecologically-balanced, and economically-viable plant disease management regimes, crucial in addressing the pressing food security challenges of the future [43].

4. Introduction to Artificial Intelligence (AI)

Artificial Intelligence (AI) represents a transformative paradigm in computing, revolutionizing how machines perform tasks that typically require human intelligence [44,45]. In this section, we delve into the fundamental aspects of AI, tracing its evolution, understanding its basic principles, and exploring its relevance to the field of phytopathology.

4.1. Definition and Basics of AI

Artificial intelligence (AI) encapsulates the capability of computer systems to perform tasks that typically demand human cognition, including learning, reasoning, perception, prediction and decision-making [46]. The essence of AI involves designing algorithms that enable machines to mimic facets of intelligence exuded by the human mind when perceiving surroundings, interpreting information, responding accordingly and even self-improving over time (Table 1).

The umbrella field of AI harbors a diverse range of sub-domains focused on replicating select aspects of natural intelligence. Machine learning enables statistical modeling to uncover hidden insights in data without explicit programming [47]. Computer vision seeks to provide machines the ability to identify, categorize and even generate visual imagery through deep neural networks [48]. Natural language processing focuses on empowering systems to comprehend human languages, engage in conversations and automate translations [49]. Expert systems attempt to encode structured rule-based human knowledge within defined domains as ontologies and inference engines [50]. Robotics integrates these various AI capabilities to instill physical machines with environmental perception, navigation and manipulation skills [51–53].

Two broad categories define AI systems – general AI, possessing multifaceted cognition skills similar to humans, and narrow AI, specialized for specific tasks [54]. While general AI remains an ongoing goal sought via integrated approaches, most current successes correspond to narrow AI tuned to perform singular high-level cognitive jobs. Common examples include smart assistants, recommendation engines, chatbots, fraud detection, supply chain optimizers and process automation. Remarkable feats have been achieved in select human mental capabilities through narrow AI, transforming diverse industries [55].

Central subfields within AI research are machine learning, computer vision and natural language processing. Machine learning explores pattern recognition in data to make predictions or decisions without explicit rule-based programming [47]. Deep learning constitutes a branch of machine learning built on neural networks with multiple layers. Diverse frameworks exist implementing supervised, unsupervised and reinforcement learning algorithms [56].

Table 1. Different Artificial Intelligence Models. Definition and Significant Date of development are included.

Artificial Intelligence Models	Definition and Significant Date	Reference
LLM - Large Language Model	These are systems that use large-scale neural networks to understand and generate human-like language. They excel in natural language processing tasks, such as text completion and language translation. Notable developments in large language models, especially the introduction of GPT-3, occurred around 2020-2021.	[57]
CNN - Convolutional Neural Network	A type of neural network designed for image processing and recognition. It uses convolutional layers to automatically and adaptively learn spatial hierarchies of features from input images. Proposed by Yann LeCun in the early 1990s, CNNs gained prominence in the mid-2010s with breakthroughs in image recognition tasks.	[58,59]
RNN - Recurrent Neural Network	A type of neural network architecture designed to recognize patterns in sequences of data. RNNs are well-suited for tasks involving sequential data, such as time series analysis and natural language processing. While the concept of RNNs dates back to the 1980s, their resurgence and success in various applications, especially in natural language processing, gained momentum in the mid-2010s.	[60]
GAN - Generative Adversarial Network	GANs consist of two neural networks, a generator, and a discriminator, which are trained simultaneously through adversarial training. GANs are used for generating new, realistic data instances, such as images. Introduced by Ian Goodfellow and his colleagues in 2014, GANs have since become a revolutionary concept in the generation of realistic data.	[61]

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SVM - Support Vector Machine	A supervised machine learning algorithm used for classification and regression analysis. SVMs are effective in high-dimensional spaces and are particularly useful in tasks like image classification and handwriting recognition. Proposed by Vladimir Vapnik and Corinna Cortes in the 1990s, SVMs gained popularity in the early 2000s and became a staple in machine learning applications.	[62,63]
KNN - k-Nearest Neighbors	A simple and effective algorithm used for classification and regression tasks. KNN makes predictions based on the majority class or average of the k-nearest data points in the feature space. KNN is a classical algorithm, and its principles have been known for decades. It is widely applied in various fields since the 1960s.	[64,65]
DNN - Deep Neural Network	A neural network with three or more layers, including an input layer, one or more hidden layers, and an output layer. Deep neural networks are capable of learning intricate representations and are used in various applications. While the concept of deep neural networks has roots in the 1960s, their resurgence and practical success came in the mid to late 2000s with advancements in training algorithms and hardware.	[66]
LSTM - Long Short-Term Memory	A type of recurrent neural network architecture designed to overcome the limitations of traditional RNNs in capturing long-term dependencies in sequential data. LSTMs are widely used in natural language processing and speech recognition. Proposed by Sepp Hochreiter and Jürgen Schmidhuber in 1997, LSTMs became popular in the mid-2010s, addressing challenges in capturing long-term dependencies.	[60,67]
RL - Reinforcement Learning	An area of machine learning where an agent learns to make decisions by interacting with an environment. The agent receives feedback in the form of rewards or penalties, allowing it to learn optimal strategies over time. RL has a history dating back to the 1950s and 1960s, but recent advancements, especially in deep reinforcement learning, have gained prominence since the mid-2010s.	[68,69]
BERT - Bidirectional Encoder Representations from Transformers	A pre-trained natural language processing model based on transformer architecture. BERT is particularly effective in understanding the context of words in a sentence and is used for various language-related tasks. Introduced by Google AI in 2018, BERT brought a breakthrough in natural language processing by capturing contextual information bidirectionally.	[70]

4.2. Evolution of AI

The genesis of AI traces back to legends of intelligent automata and formal conjecturing of machine intelligence by mathematicians such as Ada Lovelace and Alan Turing in the 19th and early 20th century [46] (Figure 2). The field gained prominence in the 1950s when scientists and enthusiasts began earnest attempts at creating thinking machines. Early successes were symbolic reasoning engines designed using rules and semantic nets seeking to emulate the structured knowledge representation occurring in human minds. However, the inability of rule-based systems to handle uncertainty and noise eventually led to periods stagnation termed "AI winter" [71].

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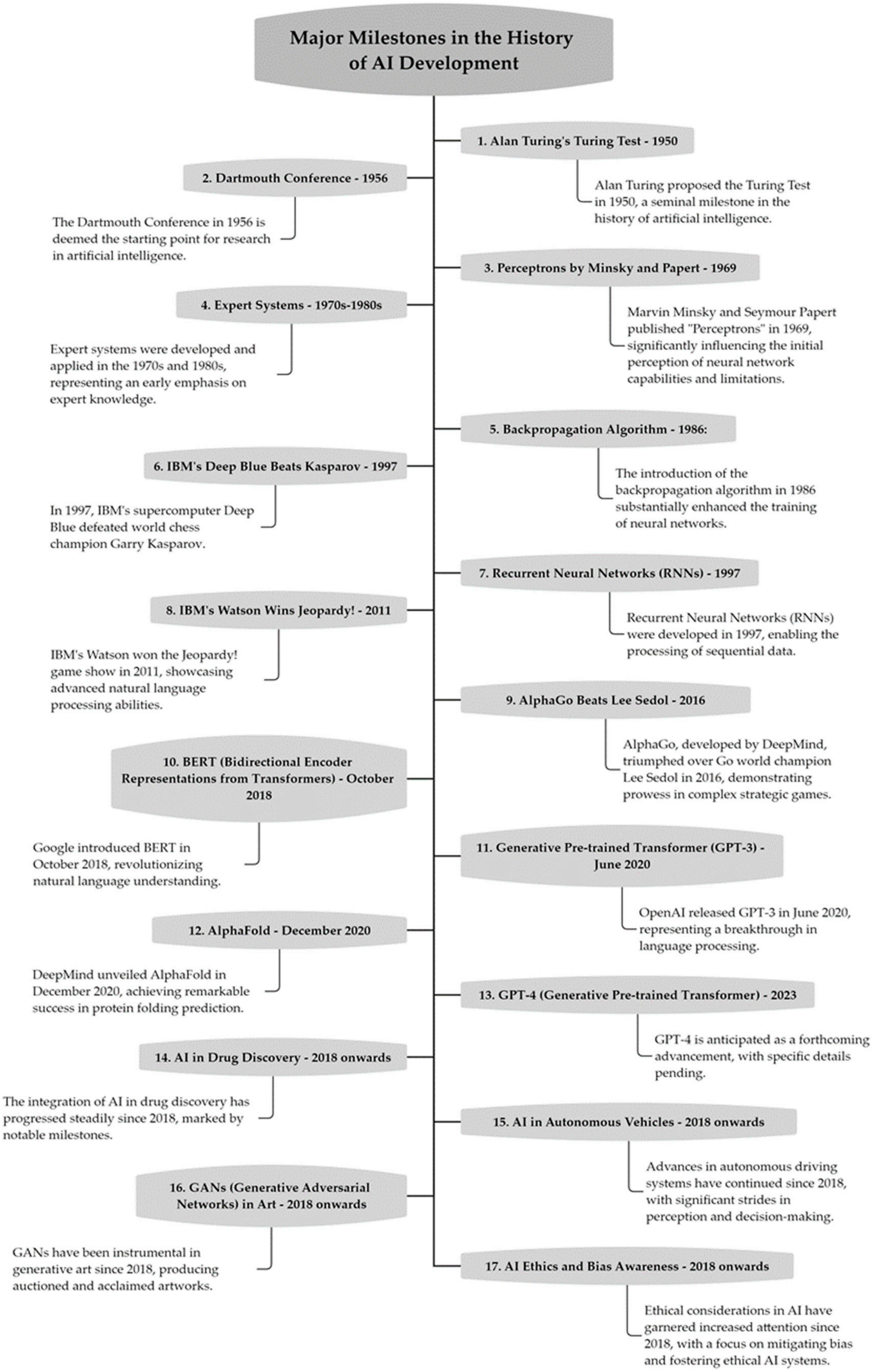

Figure 2. Major milestones in the history of AI development.

The resurgence and dramatic acceleration of AI progress began in the 21st century, catalyzed by exponential growth in computational power, data generation capacities and algorithmic advances especially in machine learning [47]. Improved statistical and mathematical understanding empowered data-driven modelling supplemented with increased storage and processing abilities to achieve remarkable predictive prowess. Particularly, the advent of deep neural networks led to breakthroughs across vision, speech and strategy games. Ongoing active research is directed toward developing human-like social and emotional capabilities [72].

Recent years have witnessed immense progress in natural language processing, enabling conversational AI through chatbots and voice assistants. A key limitation was the scope of their conversational capacity remaining narrow and brittle. This changed in 2022 with the arrival of chatbots like Anthropic's Claude and OpenAI's ChatGPT, which demonstrated human-like language mastery across diverse topics [73–75]. Built on foundation models leveraging massive datasets and computational scale, they signal a paradigm shift in AI's ability to perform complex language tasks once considered exclusively human [76]. Their flexible dialog abilities provide a glimpse into the possibilities of future communicative AI systems. Rapid innovation continues toward safer and more robust language models aligned with human values [77].

Understanding the basics of AI, its historical evolution, and its tailored applications to phytopathology sets the stage for exploring specific use cases and success stories, as detailed in subsequent sections (Figure 2). This comprehensive overview positions AI as a pivotal driver for advancing the field of phytopathology into a new era of data-driven and precision-oriented practices.

4.3. Relevance of AI in Various Fields

In the realm of artificial intelligence (AI), its transformative impact extends far beyond theoretical frameworks, finding tangible applications in diverse fields. This section explores some of the pivotal areas where AI is making significant strides, revolutionizing industries and scientific endeavors.

4.3.1. Healthcare: Enhanced Diagnostics and Personalized Medicine

In healthcare, AI is revolutionizing clinical diagnostics through advanced medical imaging analytics and genomic pattern recognition. Enhanced diagnostics are now achievable through AI, with algorithms processing medical imagery to identify conditions undetectable by traditional methods, leading to earlier intervention [78]. AI's role in digital pathology has evolved, enabling the prediction of cancer metastasis risks well before clinical thresholds [79–81]. In drug discovery, AI techniques like deep learning are significantly reducing the time to generate novel medication candidates, marking a shift from years to days in drug development [82]. AI's impact in personalized medicine is profound, tailoring treatments to individual genetic profiles for optimized patient care [83]. The integration of AI in healthcare is advancing rapidly, promising transformative solutions in diagnostics, treatment, and drug development.

4.3.2. Engineering: Optimizing Complex Systems

In engineering, AI is increasingly integral in optimizing complex systems, leading to autonomous design improvements, predictive maintenance, and self-adaptive systems. Recent advancements have seen algorithms iteratively enhancing aerodynamic profiles, significantly reducing aircraft wing prototype development time [84]. Modern AI vision systems in the industrial sector now autonomously detect structural weaknesses, such as cracks in bridges, facilitating timely preventive repairs [85]. Furthermore, neural networks are enabling electronics to reconfigure circuitry in real-time, mirroring the adaptability of biological systems for resilient operations despite component damages [86,87]. AI's impact in engineering is profound, catalyzing innovation and enhancing efficiency across various domains.

4.3.3. Business: Data-Driven Decision Automation

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In business, AI is transforming decision-making by automating complex processes that previously relied heavily on human analysis. Advanced algorithms integrate a wide range of data, including historical records, product information, and macroeconomic trends, to guide critical business decisions such as risk management and process optimization [88]. Notably, in the financial sector, deep reinforcement learning is applied in stock trading, significantly outperforming human traders in terms of cumulative returns [89]. AI's capabilities extend to parsing complex legal documents swiftly using natural language processing, thereby assessing financial or compliance risks efficiently. The emergence of automated machine learning in business analytics further enhances AI-driven decision-making [90]. Moreover, AI's role in marketing decisions is becoming increasingly pivotal, offering data-driven strategies for more effective marketing campaigns [91]. These advancements in AI demonstrate its profound impact on business, enhancing decision-making efficiency and enabling organizations to navigate the complexities of modern data landscapes.

4.3.4. Transportation: Optimized Mobility

In transportation, AI is significantly advancing urban mobility and pioneering autonomous driving technologies. Modern adaptive traffic management systems, leveraging deep reinforcement learning, are effectively coordinating signals to alleviate congestion, with cities reporting improved travel times by 10-20% [92]. The advancement in self-driving vehicle technology, is based on the use of driving systems fuse sensor readings from multiple sensors, including cameras, LiDAR, radar, GPS, wheel odometry, and IMUs [93]. A key step of autonomous driving is the environmental perception, because the information received from the sensors influences core driving decision. However, perception requires processing a large amount of sensor data in real-time [94]. The integration of sensors, software, and AI computational power is indeed enhancing the safety of autonomous vehicles [95]. For instance, companies like Waymo have achieved over 20 million miles of autonomous driving on public roads, showcasing their ability to navigate diverse terrains with human-like environmental perception [96]. Recent studies indicate further developments in AI for self-driving technology, emphasizing the integration of AI in automotive manufacturing and vehicle navigation systems [97,98]. These innovations in AI are set to transform transportation, expanding access, reducing accidents, and paving the way for smarter, more efficient transportation solutions.

4.3.5. Space Exploration: Autonomous Exploration and Data Analysis

AI is increasingly crucial in space exploration, enhancing autonomous spacecraft operations and data analysis capabilities. Autonomous rovers and spacecraft are now equipped to make independent decisions on navigation and data collection, thanks to advancements in machine learning and artificial intelligence. For instance, NASA's Mars rovers, such as Curiosity and Perseverance, use AI to autonomously navigate the Martian terrain, adjusting their paths based on real-time data analysis. Recent research has further explored the applications of AI in space, including the development of AI for self-driving spacecraft technology and its role in space law [99,100]. Another study focuses on adapting AI frameworks to space mission autonomy, emphasizing the importance of trusted AI systems in space exploration [101]. These advancements in AI are paving the way for more efficient, autonomous, and intelligent space missions, promising significant improvements in space exploration and data analysis.

4.3.6. Education: Personalized Learning and Student Support

AI is revolutionizing the education sector by enabling personalized learning experiences and enhancing student support. Adaptive learning platforms powered by AI algorithms tailor educational content to each student's unique needs, optimizing their learning journey. AI-driven chatbots provide real-time assistance, answering queries and offering guidance. For instance, platforms like Duolingo use AI to customize language learning lessons based on user performance [102]. Recent studies in this field include bibliometric analysis of AI in personalized learning [103], exploring the implications of AI for personalized learning methodologies [104], and reviewing

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machine learning techniques for identifying learning styles [105]. Additionally, advancements in AI are transforming education management, providing personalized learning pathways [105]. AI's applications are vast and continuously evolving, reshaping industries like education by providing adaptive solutions for challenges, driving innovation for a more efficient and sustainable future.

5. Applications of AI in Phytopathology

Artificial intelligence (AI) is transforming approaches in phytopathology, catalyzing innovations in understanding, managing, and mitigating plant diseases. AI's capacity to analyze vast datasets reveals subtle correlations in plant-pathogen interactions, granting key insights for disease control [16]. This section surveys prominent applications of AI across major facets of phytopathology.

5.1. Disease Detection and Diagnosis

Artificial intelligence (AI) enables rapid and precise disease detection and diagnosis, overcoming the limitations of techniques reliant on visual inspection. Numerous studies demonstrate the efficacy of AI in accurately diagnosing complex diseases. In an early example, Ramcharan et al. [14] developed a deep convolutional neural network capable of detecting four major cassava diseases from leaf images with over 90% accuracy. Similarly, Inoue et al. [106] employed machine learning to diagnose the devastating wheat blast fungus with 95% accuracy from lesion images.

Additionally, Fuentes et al. [107] implemented AI to tomato plant diseases. The authors presented a deep-learning-based approach to detect diseases and pests in tomato plants using images captured by camera devices with various resolutions. They proposed a method for local and global class annotation and data augmentation to increase accuracy and reduce false positives during training. The proposed system effectively recognizes nine different types of diseases and pests, with the ability to deal with complex scenarios from a plant's surrounding area. Sladojevic et al. [108] distinguished virus-infected grapevines from healthy vines using hyperspectral data and deep neural networks with 97% performance. The automated and enhanced disease diagnostics facilitated by these AI systems promises earlier intervention and treatment.

Recent studies have continued to demonstrate AI's potential in plant disease detection and diagnosis. For instance, Feng et al. [109]developed a convolutional neural network model for potato late blight detection method using deep learning, with high accuracy and fast inference speed, using a dataset of potato leaf disease images in single and complex backgrounds. The model was improved by introducing an attention module, reducing network depth, and reducing the number of convolutions, resulting in improved performance and reduced parameters. In the same line of work, Bracino et al. [110]carried out an study focus on the non-destructive classification of paddy rice leaf diseases using deep learning algorithms such as EfficientNet-b0, MobileNet-v2, and Places365-GoogLeNet. They aim to identify whether the rice paddy leaf is normal or infected with various diseases including bacterial leaf blight (BLB), bacterial leaf streaks (BLS), bacterial panicle blight (BPB), heart, downy mildew, hispa, or rice tungro disease (RTD). The study concludes that the best model for this classification task is EfficientNet-b0, which achieves an average accuracy of 97.74%. This research is significant as it provides a non-destructive method for accurately diagnosing rice diseases, which can help prevent product loss and improve crop quality [110].

A deep convolutional neural network model was developed by Jouini et al. [111] to detect wheat leaf rust using hyperspectral images, which achieved a testing accuracy of 94%. The method demonstrated the viability of real-time detection of wheat disease in resource-constrained environments, where prompt disease detection and management are essential for sustainable agriculture [111]. Zhou et al. [112] proposed a spectral feature pseudo-graph-based residual network (SFPGRN) for spectral analysis of plant diseases. The proposed method involves constructing a residual network model using a characteristic surface obtained via natural neighborhood interpolation based on preprocessed near-infrared spectral reflection signal and first-order differential spectral index. The SFPGRN method achieved a classification accuracy of 93.21% on a dataset of apple leaf diseases and insect pests [112]. Shi et al. [87] also proposed a fast Fourier Convolutional Neural Network (FFDNN) for accurate and explainable detection of plant stresses.

The FFDNN model used a fast Fourier convolutional block and a Capsule Feature Encoder to improve computing efficiency and interpretability [87].

AI, especially through deep learning techniques, is demonstrating immense potential to enable rapid, accurate, and automated detection and diagnosis of plant diseases from images. This promises to facilitate earlier interventions and specific real-time treatments. Continued progress in AI is expected to further augment disease diagnostic capabilities in phytopathology in the coming years.

5.2. Advancements in Plant Disease Propagation Modeling

The field of plant disease propagation modeling has witnessed transformative growth through the incorporation of artificial intelligence (AI) and machine learning techniques, opening new vistas in pathogen prediction and management. A pivotal approach in this arena is the application of machine learning models for disease prediction based on symptoms and environmental data. Prajapati et al. [113] have employed deep learning algorithms, including ResNet50, MobileNet, and Inception V3, for precise identification of diverse plant diseases. In Dagwale's work [114], a methodology using YOLOv5 model was introduced to predict leaf species and diseases across a spectrum of plant varieties. Both investigations underscore the efficacious implementation of AI-based systems for plant diseases prediction and identification.

Additionally, Garrett et al. [39] have applied sophisticated algorithms, such as Random Forest and Support Vector Machines, emphasizing the crucial interplay between climate change and pathogen emergence. These modeling approaches were similarly utilized by Oteros et al. [115], which delved into the creation of data-driven predictive models utilizing artificial intelligence to anticipate the occurrence of *Plasmopara Viticola* and *Uncinula Necator* in the viticultural regions of southern Europe. These models demonstrated a prediction accuracy exceeding 90% for infection risk and over 80% for treatment recommendations. Their research illuminates the potential of AI in synthesizing diverse data sets, thereby enriching our understanding and approach towards plant disease management [39,113,114].

In this context, the existing scientific literature encompasses a variety of meticulously developed strategies that significantly contribute to the advancement of predictive model development in the field of plant pathology. Notably, neural networks, especially convolutional neural networks (CNNs), are emerging as the predominant technique for classifying plant diseases, thanks to their inherent flexibility and automatic feature extraction capabilities [116]

In the realm of early disease detection in plants, technological advancements, particularly in Enhanced Data rates for GSM Evolution (EDGE) and deep learning, are playing a pivotal role. Marco-Detchart et al. [117] have innovatively implemented a multi-sensor consensus approach for plant disease detection, demonstrating efficacy surpassing traditional single-camera setups. Complementing this, Ojo and Zahid [118] have refined deep learning classifiers for plant disease detection by adeptly applying image preprocessing techniques and addressing class imbalance issues. These studies collectively highlight the critical role of cutting-edge technology in efficient disease management and resource optimization in agricultural sectors [117,118].

Vardhan, J. and Swetha, K. S. [119] developed a deep learning approach to detect plant diseases using images captured by drones. Their methodology involved gathering a database from the Internet, which was then separated and categorized to recognize various plant species and diseases. This database served as a test set to analyze the accuracy and reliability of their project. The core of their approach utilized a Convolutional Neural Network (CNN), composed of several layers, for predicting plant health. CNNs were chosen due to their superiority in handling complex categorization and detection challenges in crop disease, especially under difficult imaging conditions. Additionally, they implemented a prototype drone equipped with a high-resolution camera for live monitoring of large agricultural fields. The images captured by this drone were used to determine the health status of the plants, demonstrating the practical application of their methodology in real-world agricultural settings.

Collaboration and innovation in AI and cloud-based platforms are charting new courses in the monitoring and forecasting of plant diseases. Lavanya and Krishna [120] have developed a

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collaborative AI and cloud-based platform for plant disease identification, tracking, and forecasting. This innovative approach merges a mobile application with AI algorithms, providing real-time disease diagnostics and disease density mapping. This collaborative and technology-driven approach reflects a shift towards more integrated and interconnected systems for plant disease management, akin to the initiatives by Otero et al. [115] and Zen et al. [121] in developing predictive models for vineyards and AI-based mobile applications for plant disease detection, respectively [115,120,121].

These developments mark a milestone at the confluence of advanced technology and agronomy, heralding a new era in plant disease management. The fusion of machine learning techniques with cloud-based collaborative platforms is redefining the approach of farmers and scientists to plant disease challenges. These advancements not only enhance accuracy in disease detection and management but also facilitate a prompter and effective response, crucial for global sustainability and food security.

5.3. Precision Agriculture and Management

The advent of artificial intelligence (AI) in agriculture marks a significant milestone in the evolution of precision farming, offering a promising avenue for enhancing yields while minimizing ecological impacts. Groundbreaking developments in AI, such as advanced robotic weeders equipped with computer vision, have substantially reduced herbicide usage, exemplifying a move towards more sustainable farming practices [122]. Machine learning models that integrate weather, soil, and crop data have become increasingly sophisticated, aiding farmers in making well-informed decisions about irrigation, fertilization, and harvesting [123]. The democratization of AI through affordable solutions is further expanding the accessibility and effectiveness of precision farming [124].

The role of AI in plant pathology, as outlined by Buja et al. [125] emphasizes the importance of early detection and rapid, accurate diagnostics for managing phytopathological challenges. This progress, marked by the application of nanotechnologies and the integration of the Internet of Things (IoT), is revolutionizing preventive strategies in combatting phytopathogens. Liakos et al. [15] provide a comprehensive review of machine learning applications in agriculture, demonstrating how AI, combined with sensor data, is transforming farm management systems into real-time, intelligent platforms. These platforms offer insightful recommendations, significantly aiding in farmer decision-making across various aspects of agriculture, including crop, livestock, water, and soil management.

Kumar et al. [126] introduced DeepMC, a deep learning-based microclimate prediction framework utilizing IoT data, which exemplifies the potential of AI in enhancing precision agriculture. DeepMC's innovative approach to predicting a range of climatic parameters, including soil moisture, humidity, and temperature, offers accurate forecasts crucial for agricultural decision-making. The integration of AI in image processing has made significant contributions to precision agriculture. Studies by G S. & Rajamohan [127] and Sasikala D. & Sharma K. [128] demonstrate how AI-driven image processing technologies improve crop monitoring and management, further bolstering the efficiency and accuracy of agricultural practices.

Furthermore, the work of Joseph R.B. et al. [129] and Arokia Raj V.H. & Xavier de Carvalho C. [130] highlight the integration of AI in agricultural automation and agrometeorology, respectively. These studies underscore AI's potential in enhancing the efficiency of agricultural products and in offering model-based decision support systems that unite AI with precision agriculture.

Lastly, Williams et al. [131] developed the AI2Farm model, a machine learning-based approach that analyzes the impact of global and domestic events on agricultural production, consumption, and pricing. This model represents a significant advancement in precision agriculture by providing farmers with tools to adapt to both conventional and unconventional challenges in agriculture.

In summary, the integration of AI into precision agriculture and management marks a transformative shift in modern farming encompassing sustainable practices, advanced diagnostics, data-driven decisions, and innovative technologies. These developments are crucial to meet escalating food demands while maintaining ecological balance. Concurrently, manifold AI applications in detection, forecasting, precision management, and monitoring are transforming

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phytopathology. As these techniques mature, AI-enabled tools promise to strengthen global food security and agricultural sustainability amidst evolving plant disease challenges. Taken together, the advent of precision agriculture powered by AI constitutes a strategic innovation pathway for next-generation phytopathology and plant protection practices worldwide. With prudent and ethical implementation, data-driven smart farming technologies can enable sustainable intensification of crop productivity to feed rising populations in the face of climate change and agricultural pressures.

6. Integration Challenges and Ethical Considerations

6.1. Technical Barriers to AI Implementation

While artificial intelligence promises transformative phytopathology innovations, prudent precautions are necessary for its successful integration into agricultural systems. Technical barriers persist in developing robust, reliable AI solutions for real-world plant disease environments [47]. A key limitation of many current machine learning models is their narrow focus on specific crops, pathogens, and controlled settings [132]. Algorithms trained on limited datasets often fail to generalize across diverse agricultural contexts. The myriad variations in crop cultivars, growth stages, climates, soil conditions, and pathogen strains pose challenges in creating AI tools with sufficient flexibility for in-situ usage [13,133].

Progress is also impeded by lack of coordination across data collection efforts and unwillingness to openly share datasets between research groups and private entities. Most available plant disease datasets remain relatively small-scale and sparse [14]. Such fragmented data restricts the training and performance scope of AI systems. While emerging sensor, imagery and genomic technologies offer copious agricultural data streams, integrating such disparate formats for AI utilization is non-trivial and requires dedicated preprocessing pipelines [15].

Researchers have outlined frameworks to methodically address these technical barriers through good data practices and coordinated action [132,134]. Recommendations include collaborative open-access data platforms, standardized collection protocols, and emphasis on creating shareable datasets with diversity. Transfer learning methods that leverage models pre-trained on large natural image repositories are also being explored to improve generalization despite limited domain-specific agricultural data [135].

In additions, while AI holds the potential to drive sustainable agricultural practices, such as optimizing resource use and minimizing chemical inputs, it is also essential to consider the environmental footprint of the AI technology itself. This includes the carbon footprint associated with data centers powering AI applications and the environmental impact of manufacturing AI hardware. Sustainable AI in agriculture should strive for a balance where the ecological benefits of its application significantly outweigh its environmental costs [136].

6.2. Ethical Issues in AI-Driven Phytopathology

The integration of AI into agriculture also raises pressing ethical concerns regarding data privacy, accountability, labor impacts and environmental sustainability that warrant scrutiny [137,138]. Critics caution that AI-enabled crop management regimes could reinforce unsustainable industrial farming at the cost of rural livelihoods, localized knowledge and food sovereignty of smallholder farmers [139,140]. Therefore, phytopathology AI systems must be designed through inclusive stakeholder participation, centering human needs and values.

There are apprehensions surrounding the data privacy and consent procedures involved in collecting large agricultural datasets for training AI models, which could include farmer proprietary information alongside field images or soil data [36]. The onus is on researchers to implement ethical data management practices that protect farmer interests and anonymity. Moreover, the proprietary black-box nature of some commercial AI technologies obscures model biases and prevents oversight into decision-making rationales [141] (Ribeiro et al., 2016). Such opacity becomes ethically problematic for AI systems deployed in social realms including agriculture [142].

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Broader concerns also exist around delegating data-driven farming fully to AI, potentially marginalizing rural communities and eroding farmers' autonomy, knowledge and Sense of Place [139]. Hence human-centered design considerations must shape responsible AI integration in phytopathology, serving to augment not replace agricultural expertise and intuition. Ongoing farmer education and upskilling initiatives are imperative to democratize AI access, allowing rural communities to reap the benefits equitably and partake in co-developing solutions attuned to local needs [43,143].

6.3. Regulatory Frameworks and Standards

Realizing ethical AI for agriculture requires establishing regulatory frameworks and technological standards guiding development and deployment [144]. At present, there is lack of governance surrounding creation, sales and monitoring of AI phytopathology technologies. Policy interventions are required at national and global levels to regulate quality control, risk assessments and liability attribution of agricultural AI systems. Such oversight can mitigate dangers of hastily implemented tools with unreliable real-world performances or unexamined biases causing harm [145,146].

Global agreements are also needed to align technological approaches, architecture choices, data formats, curation protocols, and performance benchmarks across the emerging field of AI phytopathology [147]. Common technology standards will support collaboration, open data sharing, and interoperability, accelerating innovation. Furthermore, voluntary professional codes of ethics around topics such as model transparency, auditability, and farmer privacy could guide institutional research and industry product design [148]. Overall, multi-tiered governance combining binding regulations and soft-law ethics codes can steer agricultural AI progress along responsible trajectories.

In summary, realizing AI's promise in transforming 21st century phytopathology necessitates prudently navigating accompanying integration barriers and ethical tensions. Only through holistic frameworks considering all stakeholder needs can AI technologies serve humanity in enabling sustainable plant disease management worldwide. The path forward lies in inclusive and values-based co-development of agricultural AI tools, supported by emergent policy regimes governing these evolving technologies for societal benefit.

7. Conclusions

7.1. Summary of Key Findings

This comprehensive review highlights the immense potential of artificial intelligence (AI) to transform modern approaches in plant disease management and phytopathological research. Through an extensive analysis of existing literature, manifold AI applications across major facets of phytopathology have been delineated.

Notable successes have been demonstrated in employing AI for automated disease detection and diagnosis using image recognition techniques like convolutional neural networks. Studies indicate AI can identify plant diseases, often with 95-97% accuracy, exceeding human visual inspection. AI also shows aptitude for data-driven disease spread forecasting, integrating weather, soil, and crop parameters to predict outbreak risks up to 3 weeks prior at 81-95% precision. This enables preemptive and targeted protection strategies minimizing pesticide usage.

Furthermore, AI is optimizing precision agriculture through site-specific interventions tailored to local conditions based on integrated crop data analysis. This holds promise to boost yields while protecting ecosystems. AI monitoring of plant and environmental cues also facilitates pre-symptomatic disease alerts for early action. Ongoing research on explainable and transparent AI can mitigate issues surrounding model opacity.

Overall, real-world evidence affirms that AI-enabled tools can strengthen disease control, enhance crop resilience, and unlock novel phytopathological insights from increasingly complex agricultural data streams. AI's self-improving and generalizable capabilities make it well-suited to

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address evolving plant health challenges amidst climate change, globalization, and intensified farming systems.

7.2. Implications for the Future of Phytopathology

The integration of AI portends a paradigm shift in phytopathology and plant protection strategies worldwide. As algorithms become more robust and tailored for agricultural settings, AI's role is poised to expand from assisting tasks to autonomous in-field decision making around disease management. With sufficient training data encompassing diverse cropping contexts, AI systems can attain the flexibility and adaptiveness required for broad deployment.

Advances in sensors, automation, and robotics will enable expansive data generation on crop status, disease progression, and environmental influences. AI's capacity to assimilate such big data and discern correlations can illuminate plant-microbe interactions, evolutionary dynamics, and epidemiology at unprecedented resolution. These insights promise to accelerate knowledge discovery and innovation in phytopathology, seeding 21st century breakthroughs.

Overall, the advent of data-driven smart farming powered by AI algorithms marks a historic juncture in tackling plant disease burdens. As phytopathology transitions into an interdisciplinary, technology-intensive science, AI will catalyze a strategic shift towards precision and sustainable agriculture. This new paradigm seeks ecological disease prevention over chemical controls, supporting global food security and environmental objectives.

7.3. Call to Action for Researchers and Stakeholders

Realizing the immense promise of AI in enabling next-generation phytopathology necessitates focused efforts by researchers worldwide alongside multi-stakeholder participation. Key priorities include assembling diverse open-access datasets, advancing collaborative models, strengthening farmer education, and developing supportive policies.

Researchers must coordinate shared protocols and create expansive training datasets encompassing various crops, cultivars, pathogens, and agricultural environments. This will improve AI model robustness, avoiding dataset limitations. Committing to open data access and developing regional repositories is critical to accelerated innovation.

Advancing participatory models where farmers help co-design context-specific AI tools is vital to democratize benefits equitably. Capacity building to equip farming communities in adopting smart technologies responsibly is imperative. Policymakers must also implement updated regulations governing agricultural AI development and deployment for the public good.

In summary, the promising future of AI in plant disease management calls for collective action by stakeholders worldwide. Through ethically aligned, inclusive efforts that put farmers first, AI can help secure the productivity and sustainability of agricultural systems globally in the face of rising pressures. This necessitates bridging disciplinary divides and steering agricultural AI progress along humanistic trajectories.

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