Artificial Intelligence in Phytopathology

Subjects: Environmental Sciences

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Plant diseases annually cause 10–16% yield losses in major crops, prompting urgent innovations. Artificial intelligence (AI) shows an 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.

artificial intelligence phytopathology emerging disease climate change control diseases

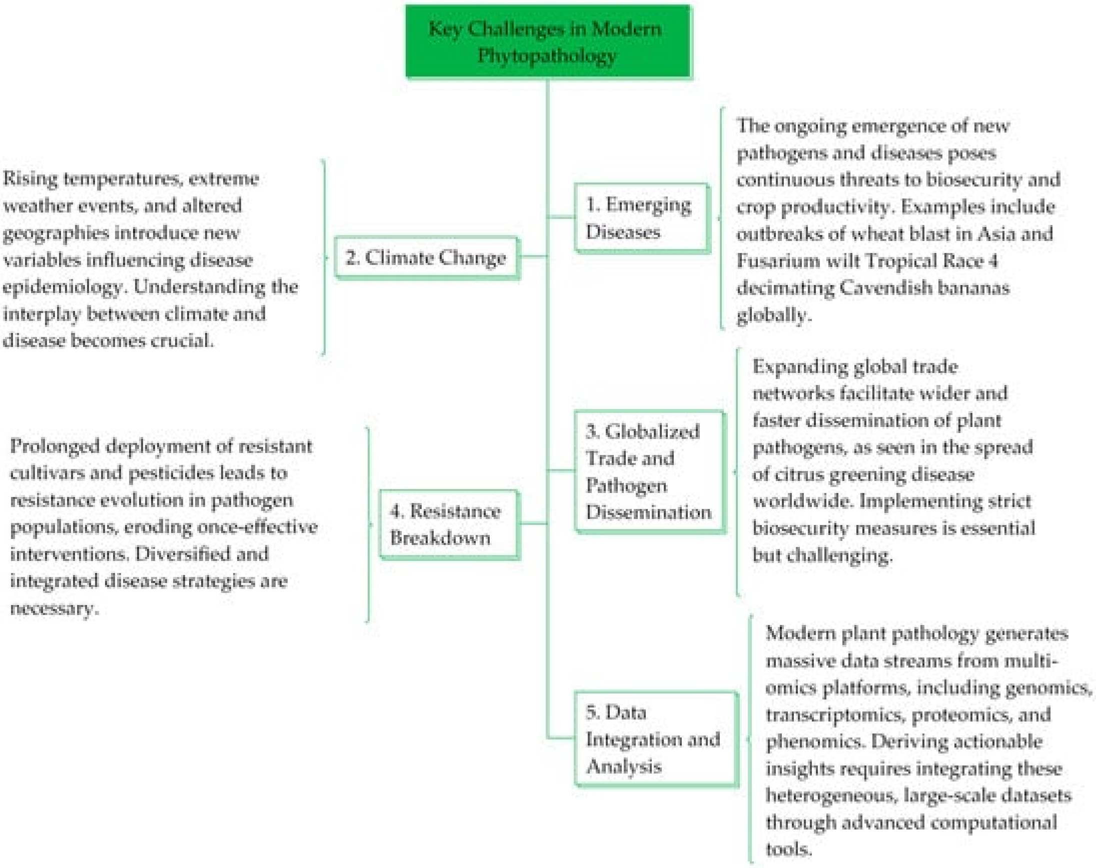
1. Overview of Phytopathology

Phytopathology 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 [1]. It is estimated that over 50,000 species of plant pathogens cause damage to more than 30,000 plant species [2]. These pathogens comprise various taxa, including fungi, bacteria, viruses, viroids, protozoa, 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 [3].

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 USD 220 billion in annual economic damages globally [4][5]. For instance, Fusarium wilt disease alone results in approximately USD 410 million in annual banana crop damages, while cassava brown streak disease incited over USD 100 million in crop damages across eastern Africa in the early 1990s [6][7]. 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 [8]. 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 [9]. 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 [10]. 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 [11].

However, current disease management strategies often provide incomplete and temporary solutions in the face of an evolving pathogen landscape. **Figure 1** presents 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. The examples cited illustrate how phytopathological science must respond to specific diseases with innovations and adaptive strategies, highlighting its relevance in an ever-changing agricultural world.



The ongoing emergence of new pathogens and diseases poses continuous threats to biosecurity and crop productivity. Examples include outbreaks of wheat blast in Asia and Fusarium wilt Tropical Race 4 decimating Cavendish bananas globally.

Rising temperatures, extreme weather events, and altered geographies introduce new variables influencing disease epidemiology. Understanding the interplay between climate and disease becomes crucial.

Expanding global trade networks facilitate wider and faster dissemination of plant pathogens, as seen in the spread of citrus greening disease worldwide. Implementing strict biosecurity measures is essential but challenging.

Prolonged deployment of resistant cultivars and pesticides leads to resistance evolution in pathogen populations, eroding once-effective interventions. Diversified and integrated disease strategies are necessary.

Modern plant pathology generates massive data streams from multi-omics platforms, including genomics, transcriptomics, proteomics, and phenomics. Deriving actionable insights requires integrating these heterogeneous, large-scale datasets through advanced computational tools.

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

2. 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 [1]. 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 [12]. Reliance on visual symptoms alone also poses challenges in distinguishing between diseases with similar outward manifestations [13].

Traditional methods, such as pathogen isolation and culture, remain cornerstones in diagnostics. They require time-consuming processes, and obtaining pure cultures can be technically challenging [14]. 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 [7][15]. This limits their reliability and applicability in the dynamic agricultural ecosystems of today.

2.1. 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 the rapid genomic characterization of plant-associated microbiota and pathogens [16][17]. 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 the detection of exceedingly low pathogen levels at early infection stages [13][18].

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 [19][20]. These tools enable the real-time, non-invasive assessment of plant vigor and the detection of disease outbreak locations in the field, facilitating timely and precise management interventions [21]. 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 [22]. The integration of these sensors in agricultural ecosystems generates comprehensive datasets, shedding light on the crop–climate–disease interplay [23].

Big data analytics, automation, robotics, and artificial intelligence (AI) are accelerating a paradigm shift towards data-driven precision agriculture systems [24][25][26]. 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 [27].

2.2. 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 the increased emergence and faster evolution of plant pathogens [3][28].

Many conventional disease management approaches now face diminishing effectiveness due to rising pathogen resistance, alongside serious environmental and health concerns [29][30][31].

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 analyze vast, disparate datasets, including weather, soil, plant omics, microbiome, and pathogen genomic information [32]. These models discern subtle multivariate relationships, predict disease outbreak risks, and enable targeted intervention strategies undetectable via conventional approaches [32][33][34]. 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 [35].

3. 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 [36]. This section surveys prominent applications of AI across major facets of phytopathology.

3.1. 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. [34] applied deep learning techniques for detecting and diagnosing cassava diseases through image analysis. Using a convolutional neural network, they achieved diagnostic accuracy above 90%, demonstrating deep learning's effectiveness in identifying various cassava diseases. This approach not only surpassed traditional methods in terms of accuracy and speed but also enabled the implementation of these models on mobile devices, facilitating diagnosis in the field.

Similarly, Fuentes et al. [37] implemented three artificial intelligence architectures—Faster R-CNN, SSD, and R-FCN—to detect and diagnose diseases and pests in tomato plants. These architectures fall within the broader context of convolutional neural networks (CNNs), which are particularly suited for image recognition tasks due to their ability to learn spatial hierarchies of features from input images. The application of these models in the study marked a significant advancement in the application of CNNs in image recognition tasks since their proposal in the 1990s. The authors of [37] used images captured by cameras at various resolutions, both of healthy plants and plants with symptoms. With these images, they trained the artificial processing models, which significantly improved the accuracy in disease and pest recognition and reduced false positives during the training phase. This systematic approach allowed the AI system to effectively recognize nine different types of diseases and pests in tomato plants, demonstrating the capability of these models to handle complex environmental variables present in a plant's surroundings. Following in the footsteps of these works, but not focused on a specific plant species, Sladojevic et al. [38] also used deep convolutional neural networks (CNNs), training the artificial model with an extensive database, which allowed it to distinguish between different types of diseases in the leaves of various genera and species. The novelty and advancement of the developed model lie in its simplicity, where healthy leaves and background images are aligned with other classes, allowing the model to distinguish between diseased and healthy leaves or their surroundings using deep CNNs. The experimental results showed an accuracy of between 91% and 99% in separate class tests and an overall accuracy of 95.8% in the trained model. These studies are a clear example of CNNs' ability to handle the complexity of visual data and improve the accuracy of automated diagnosis [38].

Recent studies have continued to demonstrate AI's potential in plant disease detection and diagnosis using more modern, precise, and powerful models thanks to the development of new AI capabilities. In 2022, Arinichev [39] explored the use of artificial intelligence technologies for diagnosing fungal diseases in cereals, specifically in wheat and rice, through methods of vision and automated recognition. This analysis revealed that artificial neural networks have the capability to detect and classify disease patterns, such as yellow spots, yellow and brown rust, and brown spots, with classification metrics ranging between 0.95 and 0.99. To advance in this line of research, Arinichev examined four well-established and relatively light convolutional neural network (CNN) architectures, namely, GoogleNet, ResNet-18, SqueezeNet-1.0, and DenseNet-121, with the DenseNet-121 model particularly standing out for its optimal combination of high precision and operational efficiency. Characterized by a relatively low number of parameters and a file size suitable for mobile devices, this model achieved exceptionally high classification accuracy, surpassing the other evaluated models. Similar to previous research, such as that of Ramcharan et al., the implementation of a light neural network like DenseNet-121 facilitated its application in the field on mobile devices, allowing for quick and accurate diagnostics [39].

In the case of the study carried out by Feng et al. [40], the authors 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. Feng et al. used the ShuffleNetV2 2× model, characterized by its high classification accuracy, while also having a larger parameter scale and memory space compared to other models with equal accuracy. The authors improved the model through strategies that included introducing an attention module, reducing network depth, and minimizing the number of 1×1 convolutions. This resulted in an enhancement of classification accuracy while simultaneously maintaining efficient inference speed on CPUs in the devices used for its application. In the same line of work, Bracino et al. [41] carried out a 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). Of the models used, EfficientNet-b0 was identified as the most effective, achieving an average accuracy of 97.74%. This model is distinguished by its focus on maximizing efficiency, optimally balancing network depth, width, and the resolution of input images through a compound scaling technique, resulting in superior performance with minimal memory requirements and floating-point operations per second (FLOPS). This efficiency and precision capability distinguish it from the model used by Feng et al., the ShuffleNetV2 2×, which, although highly precise, focuses on improving inference speed and reducing parameter size through the introduction of an attention module and the optimization of the network architecture. Bracino et al.'s significant contribution lies in providing a precise and non-destructive diagnostic method for rice diseases, thereby supporting the prevention of product loss and improving crop quality through the application of advanced and efficient AI technologies.

A deep convolutional neural network model was also developed by Jouini et al. [42] to detect wheat leaf rust. The authors advanced the application of a CNN by developing a model specifically designed for the detection of wheat leaf diseases using hyperspectral images, achieving an impressive testing accuracy of 94%. This study showed the feasibility of real-time disease detection in wheat, a critical advancement for resource-constrained environments where timely and effective disease management is vital [42]. In a related study, Zhou et al. [43] introduced a novel spectral feature pseudo-graph-based residual network (SFPGRN) for the spectral analysis of plant diseases. Their method innovatively constructs a residual network model using a characteristic surface derived from natural neighborhood interpolation based on preprocessed near-infrared spectral reflection signals and first-order differential spectral index, achieving a classification accuracy of 93.21% on a dataset of apple leaf diseases and insect pests [43]. Complementing these developments, Shi et al. [44] introduced a novel fast Fourier convolutional deep neural network (FFCDNN) designed for the accurate and interpretable detection of wheat yellow rust and nitrogen deficiency from Sentinel-2 time series data. The FFCDNN model stands out for its innovative use of a fast Fourier convolutional block and a capsule feature encoder, significantly enhancing computing efficiency and model interpretability. This approach not only achieves high classification accuracy but also provides insights into the host–stress interaction, marking a significant advancement over previous studies by integrating spatial-temporal information for global feature extraction [44].

In recent times, the research group of Hassan et al. [45] introduced a groundbreaking CNN architecture for plant disease identification, leveraging inception layers and residual connections to enhance feature extraction, while employing depth wise separable convolution to significantly reduce computational complexity. This model is distinct in its ability to achieve high accuracy across various plant disease datasets with a markedly lower parameter count, illustrating a significant advancement in AI's application to phytopathology. By optimizing the model to require fewer computational resources, this work facilitates the deployment of AI technologies on devices with limited processing capabilities, making sophisticated disease diagnosis tools more accessible to a broader range of users and applications [45].

A new evolution of CNN is the Siamese convolutional neural network (SNN). Narain et al. [46] introduced an enhanced approach to detection systems by implementing a SNN for identifying diseases in tomato leaves. Siamese neural networks stand out from conventional CNN models due to their unique structure, designed to learn to differentiate between pairs of inputs, making them exceptionally suitable for comparison and differentiation tasks. By evaluating similarities or differences between pairs of images, SNNs can offer notable accuracy in disease classification, often overcoming challenges faced by traditional CNNs in terms of intraclass variability and the scarcity of labeled data (**Figure 2**). In this work, Narain et al. developed a customized SNN by training with a specially collected dataset of 155 tomato leaf images, and the system demonstrated high efficacy, achieving an accuracy of 83.749% in training and 80.4% in testing. This improvement in disease classification represents a significant advancement over more classic CNN models. The implementation of Siamese networks signifies an optimization in the accuracy and efficiency of disease detection in crops, allowing for the application of appropriate management measures more quickly and accurately by providing a more robust and adaptable mechanism for recognizing complex patterns associated with various plant diseases [46].

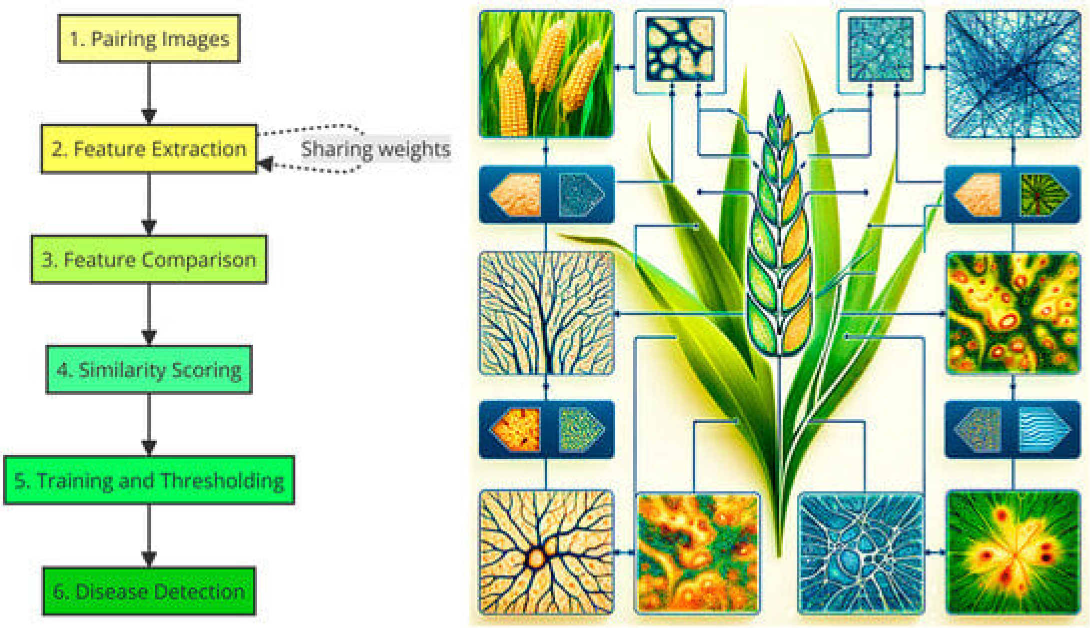


Figure 2. Graph diagram illustrating the operation of Siamese convolutional neural networks (SNNs) for detecting plant diseases from an image dataset.

Siamese convolutional neural networks operate into a sequence of steps illustrated in **Figure 2**: (a) Pairing Images: a set of image pairs of plants is created, where each pair consists of two images: it could be one of a healthy plant and one of a diseased plant, or two healthy plants, or two diseased plants. (b) Feature Extraction: each image in the pair is fed through a convolutional network that acts as a feature extractor. The key here is that both images go through the same network (sharing weights), ensuring that features are extracted uniformly. (c) Feature Comparison: the features extracted from each image are combined and fed into a layer that compares the two images. This comparison could be an absolute difference, a concatenation operation followed by dense layers, or even a more complex metric. (d) Similarity Scoring: the network produces a score that reflects the similarity between the two images. In the context of plant disease detection, a high score might indicate that both images are of plants in the same condition (both healthy or both diseased), while a low score might suggest one is healthy and the other is diseased. (e) Training and Thresholding: during training, the network learns what features are important for distinguishing between healthy and diseased plants. A similarity threshold is adjusted that best separates pairs of healthy plant images from pairs with at least one diseased plant. (f) Disease Detection: once trained, the network can take a pair of images, process them through the network to obtain the similarity score, and using the learned threshold, determine if the plants are healthy or diseased.

Other authors are making significant advances in developing models which are more advanced in capabilities and simpler in their handling, thanks to the evolution that vision systems and their conjunction with large language modeling systems are undergoing in recent months. In this line, Tabbakh and Barpanda [47] introduced an innovative hybrid model for the classification of plant diseases, through the integration of Transfer Learning with a Vision Transformer (TLMViT). This hybrid approach stands out for its unique ability to extract and analyze deep features of plant leaf images, achieving exceptionally high accuracy in the evaluated datasets. The TLMViT is a key innovation in this study, leveraging the architecture of transformers, which has revolutionized natural language processing, to apply it in the realm of computer vision. Vision transformers adapt the concept of attention, allowing the model to focus on the most relevant parts of the image for the classification task, significantly improving accuracy and efficiency in disease identification. Tabbakh and Barpanda used a dataset freely available in the PlantVillage project, as the authors comment. This dataset encompasses more than 54,000 images of more than 38 different crop species, with a particular focus on cassava, tomato, pepper, and potato. Each image within the dataset is labeled with the plant species and, if present, the disease. This resource is freely available for computer vision and deep learning tasks, such as image classification, object detection, and semantic segmentation. In the specific research of Tabbakh et al., three different crops from the PlantVillage dataset (pepper, potato, and tomato) were used, which include 20,638 images of diseased and healthy leaves. The application of their model managed to achieve identification accuracies above 98%. This hybrid model, combining transferred learning with the power of vision transformers, illustrates a qualitative leap in the detection and classification of plant diseases, offering new perspectives for precision agriculture and sustainable crop management [47].

The integration of advanced AI models, from deep convolutional neural networks to Siamese networks and vision transformers, underscores a transformative period in the field of phytopathology. These studies collectively represent a leap forward in precision phytopathology, offering not just higher accuracy in disease diagnosis but also a model for future research to build upon. Particularly, the adoption of vision transformers marks a novel approach, leveraging the strengths of AI to address complex agricultural challenges. This evolution of AI methodologies, characterized by increased model sophistication and adaptability, promises to significantly enhance disease detection capabilities, paving the way for more targeted and effective disease management strategies.

3.2. 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 field is the application of machine learning models for disease prediction based on symptoms and environmental data. 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.

During 2022 several studies were published to apply different algorithms and predictive models using AI. For example, a very interesting work is that published by Garrett et al. [27] in which the authors utilized Random Forest and Support Vector Machines (SVMs) to analyze the complex interplay between climate change and pathogen emergence. Random Forest is an ensemble learning method for classification, regression, and other tasks. It operates by constructing a multitude of decision trees during training for more accurate and robust predictions (**Figure 3**). SVMs, in contrast, are powerful supervised machine learning models used for classification and regression challenges, effectively handling high-dimensional spaces and complex datasets. Employing these algorithms, Garrett et al. aimed to capture and model the nuanced relationships between environmental factors and the likelihood of pathogen spread, underscoring the potential of AI to offer predictive insights into plant disease dynamics influenced by climate variables. Their methodology showcases the strengths of combining multiple AI approaches to enhance predictive accuracy and provide actionable insights into pathogen management strategies [27]. These modeling approaches were similarly utilized by Otero et al. [48], who 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. Otero et al. employed a variety of machine and deep learning algorithms, including Logistic Regression, Decision Trees, Random Forest, Gradient Boosting, K-Nearest Neighbors, Naïve Bayes, Support Vector Machines, and Deep Neural Networks. Logistic Regression provides a probabilistic approach for binary outcomes, making it suitable for disease presence predictions. Decision Trees offer clear, interpretable decisions. Random Forest improves on Decision Trees by combining multiple trees to reduce overfitting. Gradient Boosting sequentially corrects errors, enhancing model performance. K-Nearest Neighbors classifies based on the majority vote of nearest data points, offering simplicity and effectiveness. Naïve Bayes, based on Bayes' theorem, excels in classification with an assumption of feature independence. Support Vector Machines efficiently handle high-dimensional data, optimizing margins between classes for clear decision boundaries. Notably, the models employed by Otero et al. achieved over 90% accuracy for infection risk and over 80% for treatment recommendations, highlighting the potential of AI in enhancing disease management strategies in vineyards across Southern Europe [48].

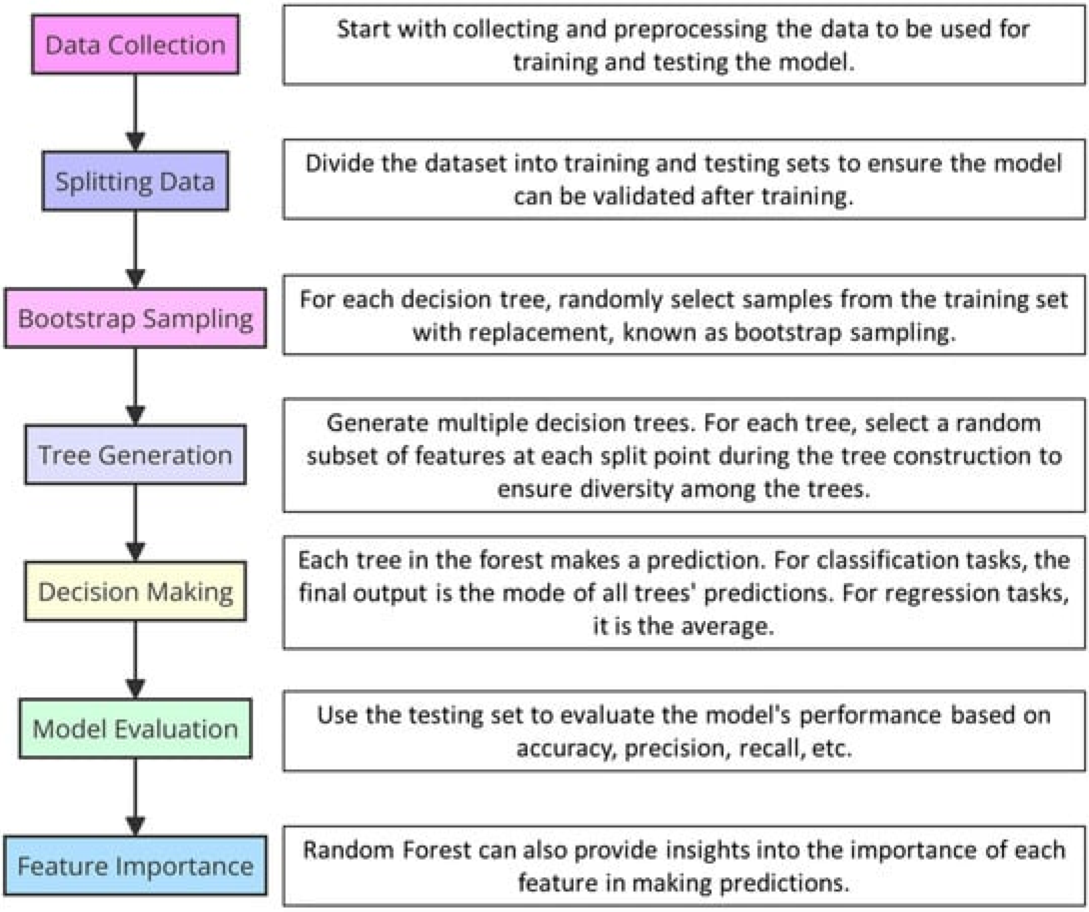


Figure 3. Graph diagram illustrating how Random Forest system works.

Collaboration and innovation in AI and cloud-based platforms are charting new paths in the monitoring and forecasting of plant diseases. The study published by Lavanya and Krishna [49] has developed a 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. [48] and Zen et al. [50]. The study by Zen et al. focuses on developing an AI-based mobile application for detecting plant diseases with high accuracy, utilizing CNN and RNN with TensorFlow.js. TensorFlow.js is an open-source library developed by Google for machine learning in JavaScript. It enables the training and deployment of machine learning models directly in the browser or on Node.js. TensorFlow.js provides a flexible and efficient platform for building and executing machine learning algorithms on web-based applications, allowing for interactive and real-time applications of AI technologies without the need for backend servers. The application in this study was tested on tomato plant diseases, achieving prediction accuracies of 100% for early blight, 90% for bacterial spot, and 100% for both healthy and late blight conditions. This research showcases the application’s capability to recommend treatment options based on image analysis, offering a significant tool for farmers to identify and manage plant diseases effectively [48][49][50].

During 2023, in the realm of early disease detection and prediction in plants, technological advancements, particularly in Enhanced Data rates for GSM Evolution (EDGE) and deep learning, have played a pivotal role. Marco-Detchart et al. [51] focuses on the development of a robust, multi-sensor consensus approach for plant disease detection using the Choquet Integral. The Choquet Integral is a mathematical concept used in decision-making and information aggregation integrated in an Edge-AI device. Edge-AI refers to the deployment of AI applications directly on devices located at the “edge” of the network, rather than relying on centralized cloud services. This means that computations are performed close to where data are generated, such as in smartphones, surveillance cameras, or IoT devices, which allows for faster processing times, reduced bandwidth costs, and improved data privacy. This device was designed to improve disease classification by capturing multiple images of plant leaves and applying data fusion techniques. The system demonstrated increased robustness in classification responses to potential plant diseases, leveraging deep learning models for better analysis and classification. This innovatively implemented a multi-sensor consensus approach for plant disease detection, monitoring and prediction demonstrating efficacy surpassing traditional single-camera setups. Complementing this, Ojo and Zahid [52] have refined deep learning classifiers for plant disease detection by adeptly applying image preprocessing techniques and addressing class imbalance issues. Ojo and Zahid focused on enhancing deep learning classifiers for plant disease detection by addressing data imbalances and applying image preprocessing techniques. They used techniques like Adaptive Histogram Equalization (AHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), and image sharpening to improve image quality. They tackled class imbalance with methods like Synthetic Minority Oversampling Technique (SMOTE), Major-to-Minor Translation (M2m), and Generative Adversarial Networks (GANs). These studies collectively highlight the critical role of cutting-edge technology in efficient disease management and resource optimization in agricultural sectors [51][52].

The study by Vardhan et al. [53] takes an innovative approach to plant disease detection and monitoring using drone-captured imagery. They developed a comprehensive database from online sources, categorizing various plant species and diseases for analysis. This database was crucial for testing the accuracy and reliability of their CNN-based model. Their methodology emphasizes the use of CNNs due to their effectiveness in complex categorization and detection challenges, especially under varied imaging conditions. Additionally, they introduced a prototype drone equipped with a high-resolution camera for live field monitoring, showcasing the practical application of their research in real agricultural settings. This integration of advanced imaging techniques and AI algorithms represents a significant step forward in agricultural technology, offering a more efficient and accurate method for plant health assessment and disease management. In relation, the study published by Dagwale et al. [54] showed the YOLOv5 model, an advanced neural network architecture for real-time object detection, to accurately predict leaf species and diseases across various plant types using the PlantDoc dataset. YOLOv5 (You Only Look Once version 5) is designed for rapid image processing, identifying, and classifying multiple objects simultaneously with high precision. This integration showcases the potential of leveraging cutting-edge AI technologies like YOLOv5 to enhance disease detection accuracy in agriculture, marking a significant advancement in plant pathology diagnostics and disease spread and monitoring [54].

It is notably how 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 [50][53]. The developments shown in this subsection 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.

3.3. Comprehensive Evaluation and Prospects of AI Technologies in Phytopathological Applications

In the rapidly evolving domain of AI-assisted plant disease management, the integration of pretrained models, such as ResNet-18 and ResNet-50, marks a significant leap towards refining disease detection and diagnostic accuracy. These models, part of the Residual Networks (ResNets) introduced to mitigate the vanishing gradient problem in deep convolutional neural networks (CNNs), incorporate “shortcut connections” that allow gradients to flow through the network without undergoing non-linear transformations, thereby facilitating the training of much deeper networks. ResNet-50, a 50-layer CNN comprising 48 convolutional layers, one MaxPool layer, and one average pool layer, employs a “bottleneck” design in each residual block to reduce the number of parameters and accelerate layer training. This bottleneck design, featuring a stack of three layers instead of two, utilizes 1 × 1 convolutions to compress and then expand the number of channels, significantly lowering computational complexity while maintaining or enhancing model performance [55].

Originally trained on the expansive ImageNet dataset, these models exhibit exceptional prowess in feature recognition, offering tailored solutions for the nuanced challenges of phytopathology. Their capability to discern complex image characteristics with remarkable precision positions them as indispensable tools for identifying plant pathologies, often surpassing traditional visual inspection methods with accuracies ranging between 95% and 97%. Furthermore, the application of these pretrained models extends beyond disease identification to encompass broader spatial analyses, as evidenced by their deployment within the ArcGIS ecosystem for tasks like land cover classification and aerial feature extraction, underscoring their potential to revolutionize the monitoring and management of plant health on a large scale [56].

The comparative analysis of AI models, including CNNs, YOLOv5, and MobileNet, illuminates the diverse applicability and efficacy of these technologies in phytopathology. Each model, with its unique strengths (be it CNNs for their image processing capabilities, YOLOv5 for its rapid processing speed facilitating timely interventions, or MobileNet for offering an efficient solution on low-power devices), advances our capacity to manage plant disease spread through predictive analyses that integrate environmental and symptomatic data. This synthesis not only augments diagnostic precision but also enhances proactive disease management strategies. Nevertheless, the practical application of these models encounters challenges such as the need for image preprocessing and handling unbalanced datasets, propelling the pursuit of technological innovations, especially in the realm of Edge-AI devices. These advancements promise a transformative impact on disease monitoring, enabling more accurate and accessible diagnostics.

As AI technologies continue to evolve, alongside breakthroughs in sensor technologies, we are ushered towards a new era of integrated and automated plant disease management. This journey is not without its hurdles, necessitating innovative approaches like transfer learning and the development of multisensorial detection systems to overcome current limitations. The ongoing exploration and refinement of AI models in phytopathology not only pave the way for future research directions but also highlight the pivotal role of AI in crafting sustainable, precision-based solutions for global agricultural challenges.

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