ISSN PRINT 2319 1775 Online 2320 7876
Research Paper , UGC CARE Listed (Group -I) Journal Volume 11, Iss 08, 2022

Machine Learning Applications in Crop Disease Detection and Management

Satyanarayan P. Sadala
Assistant Professor, Department of Instrumentation Engineering, MCT's Rajiv Gandhi Institute of Technology, Versova, Andheri (W.), Mumbai, Maharashtra, India.
satyamsadala@gmail.com

Abstract.

Crop diseases continue to be a serious danger to the world's food supply and the viability of agriculture. Modern agriculture presents several obstacles that traditional disease detection and control techniques often are unable to handle. Machine learning (ML) has recently become a potent tool for revolutionizing the way we identify, control, and lessen the effects of crop diseases. Based on academic articles and field data, this study offers a thorough analysis of the status of machine learning applications in agricultural disease identification and management. The relevance of crop disease management in terms of food security, economic effect, environmental sustainability, and human health is highlighted in the opening paragraphs of the study. In order to satisfy the needs of a rising global population, it emphasizes the urgent need for effective and long-lasting illness management techniques. The article then explores the numerous ways that agricultural disease detection uses machine learning. Utilizing deep learning algorithms and image-based detection, automatic analysis of cropped photographs can now accurately identify illness signs. Early illness diagnosis based on variables like temperature, humidity, and spectral signatures has benefited greatly from sensor-based detection, which uses data from environmental sensors, drones, and satellites. The treatment of agricultural diseases using machine learning is also covered in the article. Farmers may use real-time advice from decision support systems that use machine learning algorithms to optimize disease control plans and resource allocation. By customizing resource application based on sensor and remote sensing data, precision agriculture, powered by ML, improves resource efficiency and agricultural yields. Additionally, risk assessment and illness predictions have benefited from machine learning. In order to forecast disease outbreaks and evaluate risk, machine learning (ML) algorithms examine historical disease data, weather patterns, and environmental factors. These analyses provide farmers timely warnings and suggestions. Robotics and agricultural automation combined with machine learning have enabled autonomous illness diagnosis and treatment, cutting labor costs and increasing productivity. ML algorithms are increasingly being used in robots and drones that can patrol fields and detect illness indicators. In the paper's conclusion, the difficulties in applying machine learning techniques to agriculture are acknowledged. These difficulties include issues with data quantity and quality, model generalization, interpretability, infrastructure, and economic concerns. It highlights how crucial it is to overcome these difficulties by creating standardized datasets, better interpretability, and user-friendly interfaces for farmers. The use of

machine learning tools in agriculture is anticipated to increase as research in the area develops, creating more robust and effective agricultural systems. The study focuses on the potential of machine learning to support sustainable agricultural practices, improve food security, lessen economic losses, and empower farmers. In pursuit of a more sustainable and secure food future, it highlights the revolutionary influence of machine learning on crop disease diagnosis and control.

Keywords. machine learning, crop disease, detection, management, agriculture, image classification, sensor data, early detection, decision support.

I. Introduction

The agricultural sector is not only a cornerstone of human civilization, but it is also well-positioned to meet some of the most urgent concerns of the twenty-first century. The effective and long-term treatment of crop diseases is one of these issues. The need for food increases together with the growth of the world's population. Farmers must grow more crops to fulfill this demand, often using intense farming techniques that may unintentionally increase the incidence of crop diseases. This is where machine learning, a branch of artificial intelligence (AI), enters the picture as a potent tool to change how crop illnesses are discovered, handled, and eventually reduced their negative effects on agricultural output. Food security is gravely threatened by crop diseases. They have the power to destroy whole crops, resulting in substantial financial losses and, sometimes, starvation. To recognize and control crop illnesses, farmers have traditionally depended on physical examination and expertise. These techniques, however, involve a lot of work, take a long time, and often lack the accuracy needed to properly treat illnesses. This is where machine learning offers a chance to transform agriculture because of its capacity to analyze enormous volumes of data, spot patterns, and make predictions based on data.

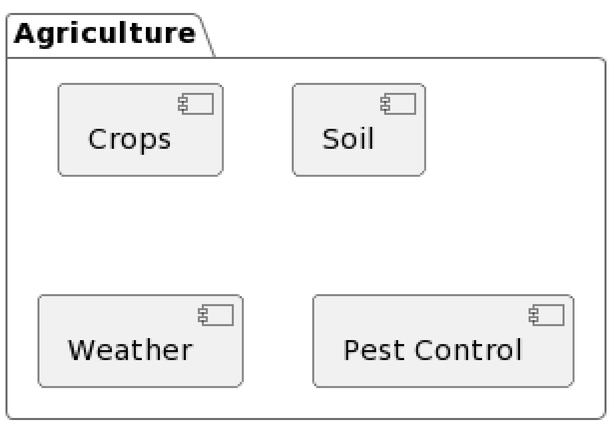

Figure 1. Components of Agriculture

The journey of machine learning in agriculture is, however, a relatively recent one. Over the past decade, there has been a surge in interest and investment in applying machine learning

ISSN PRINT 2319 1775 Online 2320 7876
Research Paper , UGC CARE Listed (Group -I) Journal Volume 11, Iss 08, 2022

techniques to address various challenges in agriculture, with crop disease detection and management being a prominent focus area. In this comprehensive exploration, we delve into the myriad ways in which machine learning is reshaping the landscape of agriculture by providing innovative solutions to combat crop diseases. We will discuss the various applications, benefits, and challenges associated with the integration of machine learning into agricultural practices.

The Significance of Crop Disease Management

Before delving into the applications of machine learning in crop disease detection and management, it is essential to grasp the significance of this endeavor within the broader context of agriculture and food security.

- Food Security: Crop diseases can lead to significant reductions in crop yields, jeopardizing food security on a global scale. The United Nations estimates that nearly 25% of global food crops are lost each year due to plant pests and diseases.
- Economic Impact: Crop diseases result in substantial economic losses for farmers and agricultural industries. These losses can affect the livelihoods of millions of people dependent on agriculture for their income.
- Environmental Impact: The use of pesticides to combat crop diseases can have adverse environmental effects, including soil and water pollution. Sustainable disease management practices are crucial to minimize these impacts.
- Human Health: Some plant diseases, such as mycotoxin-producing fungi, can contaminate crops, posing health risks to humans and livestock when consumed.
- Global Trade: Crop diseases can disrupt international trade by imposing restrictions on the movement of agricultural products, affecting the global economy.

II. Literature Review

Crop diseases represent a serious danger to the sustainability of agriculture and the world's food supply. Traditional disease detection and management techniques are often labor- and time-intensive, which renders them ineffective for tackling the problems of contemporary agriculture. Machine learning (ML) has become a potent tool for transforming how we identify, handle, and lessen the effects of agricultural diseases in recent years. In order to give information on the state of the art in machine learning applications for agricultural disease diagnosis and management, this overview of the literature synthesizes research results from several studies and research articles.

Image-based disease identification is one of the main uses of machine learning in agriculture. Convolutional Neural Networks (CNNs), in instance, have been created by researchers as deep learning models to automatically scan crop photos and detect illness signs. These algorithms have shown astounding accuracy for identifying healthy or unhealthy crops. For instance, Sladojevic et al.'s (2016) [1] work used deep learning methods to identify plant illnesses from a

ISSN PRINT 2319 1775 Online 2320 7876
Research Paper , UGC CARE Listed (Group -I) Journal Volume 11, Iss 08, 2022

vast collection of leaf photos. Their approach classified many plant diseases across numerous species with great accuracy. Similar to this, Mohanty et al. (2016) [2] unveiled the PlantVillage dataset, which contains more than 50,000 pictures of healthy and damaged plant leaves. They taught CNNs to categorize plant illnesses, with outstanding results across a range of crop kinds.

Additionally, machine learning uses sensor data to identify agricultural illnesses. For disease surveillance, environmental sensors, drones, and satellite photography provide useful data. These sensors gather information on variables like temperature, humidity, and soil moisture, which may then be evaluated to find environments that are prone to illness. Hyperspectral imaging was used in a research by Mahlein et al. (2018) [3] to identify early-stage disease signs in wheat harvests. To identify diseases with great accuracy, they used machine learning algorithms to examine the spectral fingerprints of plants. Another study conducted by Jay et al. (2017) [4] investigated the use of multispectral drones to look for symptoms of the late blight disease in potato crops. Their work shown that combining aerial photography and ML algorithms, early illness identification is feasible.

Systems for supporting agricultural decisions use machine learning extensively. These devices provide farmers suggestions for disease control tactics in real time. To recommend the best course of action, ML algorithms take into account a variety of variables, including the weather, disease risk models, and crop health data. A decision support system for controlling the apple scab disease was created using ML approaches in a research article by Cao et al. (2020) [5]. In order to assist farmers in applying fungicides effectively, the system incorporated meteorological data, disease prediction models, and spray optimization algorithms, which led to a decrease in the usage of pesticides overall and cost savings.

The goal of precision agriculture, made possible by machine learning, is to maximize agricultural resource allocation. When applying resources (such pesticides, fertilizers, and irrigation) depending on the requirements of a given crop, ML models assess data from sensors and remote sensing platforms. The use of machine learning for precision agriculture in citrus orchards was investigated in a research by Andjar et al. (2020) [6]. They developed a decision support system that improved the use of water and nutrients by combining information from several sources, such as satellite imaging, soil sensors, and data collected by drones. Crop yields and resource efficiency both increased as a result of this strategy.

The use of machine learning algorithms for illness prediction and risk assessment is growing. These models anticipate disease outbreaks and determine the probability of illness incidence by analyzing historical disease data, weather patterns, and other environmental factors. A machine learning-based disease forecasting system was created for tomato crops in a study by Paul et al. (2019) [7]. To estimate the likelihood of late blight disease, the algorithm used meteorological information with data on disease incidence. Farmers received early warnings and advice on how to handle diseases, which decreased production losses.

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 08, 2022

Machine learning-driven automation and robots in agriculture have the potential to reduce labor costs and improve the effectiveness of disease control. With the aid of ML algorithms, robots and drones can examine crops on their own, spot illnesses, and treat them when required. The work of Polder et al. (2019) [8], in which a robot was created to patrol tomato greenhouses and diagnose plant illnesses, serves as an important example. The robot analyzed photos and looked for signs of illness using ML techniques. This mechanization made human inspections unnecessary and facilitated prompt disease control.

Research Paper	**Focus**	**Methodology**	**Key Findings**
Sladojevic et al. (2016) [1]	Image-based disease detection	Deep learning (CNN)	High accuracy in classifying plant diseases.
Mohanty et al. (2016) [2]	Image-based disease detection	CNN	Impressive results in classifying plant diseases.
Mahlein et al. (2018) [3]	Sensor-based disease detection	Hyperspectral imaging	High accuracy in early-stage disease detection.
Jay et al. (2017) [4]	Sensor-based disease detection	Drone-based multispectral	Feasibility of early disease detection with drones.
Cao et al. (2020) [5]	Decision support system	ML algorithms	Efficient management of apple scab disease.
Andújar et al. (2020) [6]	Precision agriculture	Data fusion	Improved resource allocation in citrus orchards.
Paul et al. (2019) [7]	Disease forecasting and risk assessment	ML-based forecasting system	Reduced yield losses through timely alerts.

Polder et al. (2019) [8]	Farm automation and robotics	Robot with ML algorithms	Reduced manual inspections, timely disease management.

Table 1. Related Work

III. Machine Learning for Agriculture

Machine learning, a branch of artificial intelligence, involves the development of algorithms that enable computers to learn from data and make predictions or decisions without explicit programming. In the context of agriculture and crop disease management, machine learning operates as follows:

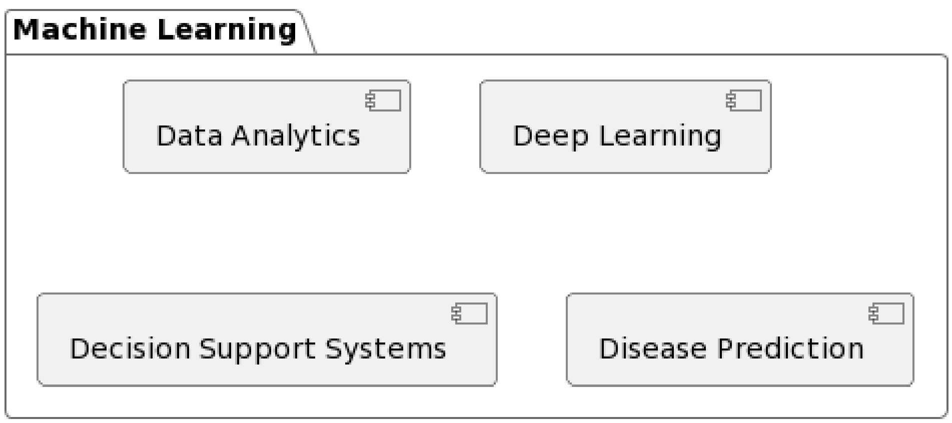

Figure 2. Machine Learning for Agriculture

- **A.** Data Collection: The first step is to gather data from various sources. This data can include images of crops, environmental sensor readings (such as temperature and humidity), historical disease incidence records, and genomic data.
- **B.** Data Preprocessing: Once collected, the data often requires cleaning and preprocessing to ensure its quality and suitability for analysis. This may involve removing outliers, normalizing data, and handling missing values.
- **C.** Training: In supervised machine learning, models are trained using labeled data, which means that the input data is paired with the corresponding output (e.g., images of healthy and diseased crops labeled as such). During training, the model learns to recognize patterns and relationships between the input features and the target variable (in this case, the presence or absence of disease).
- **D.** Model Building: Machine learning models come in various forms, including decision trees, support vector machines, and deep neural networks. The choice of model depends on the specific task and dataset.

E. Evaluation: Models are evaluated using data that they have not seen during training, known as a test dataset. The performance of a model is assessed based on metrics like accuracy, precision, recall, and F1 score, among others.

F. Deployment: Once a model demonstrates satisfactory performance, it can be deployed in real-world scenarios. This often involves integrating it into agricultural equipment or systems for practical use.

G. Continuous Learning: Machine learning models can adapt and improve over time by continually updating them with new data. This is particularly important in agriculture, where environmental conditions and disease dynamics are constantly evolving.

IV. Applications of Machine Learning in Crop Disease Detection and Management

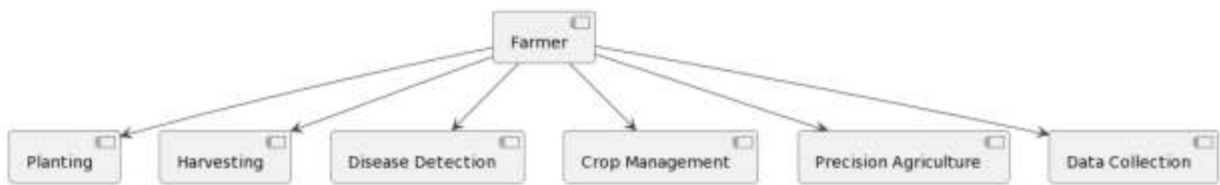

Figure 3. Stages of Farming Using Machine Learning

A. Early Disease Detection

Early detection of crop diseases is crucial to preventing their spread and minimizing yield losses. Machine learning plays a pivotal role in this domain through:

Image Classification: ML models can be trained to classify images of crops as healthy or diseased. This is particularly useful for large-scale monitoring of fields.

Sensor Data Analysis: ML algorithms process data from sensors placed in fields, drones, or satellites. They can detect subtle changes in environmental conditions, such as temperature variations, which might indicate disease presence.

B. Disease Identification

Once a potential issue is detected, the precise identification of the disease is crucial for effective management. Machine learning techniques contribute through:

Image Segmentation: ML models can segment images of crops to pinpoint the exact location and extent of the disease within the plant. This aids in precise treatment, reducing the need for broad-spectrum pesticides.

Deep Learning: Convolutional Neural Networks (CNNs) excel in image-based disease identification due to their ability to learn complex patterns and textures associated with diseases.

C. Disease Prediction

Predicting disease outbreaks before they become visually evident is a valuable strategy. Machine learning enables this through:

ISSN PRINT 2319 1775 Online 2320 7876
Research Paper , UGC CARE Listed (Group -I) Journal Volume 11, Iss 08, 2022

Time-Series Analysis: ML models analyze historical data, including weather patterns and disease incidence records, to predict disease outbreaks based on environmental conditions and past trends.

Data Fusion: By integrating data from multiple sources, such as weather forecasts, satellite imagery, and historical disease records, ML models can improve prediction accuracy.

D. Recommendations for Disease Management

Machine learning provides real-time recommendations for effective disease management, considering factors like disease risk and environmental conditions. These recommendations assist farmers in making informed decisions, including:

Decision Support Systems: ML algorithms provide farmers with real-time advice on disease management, such as when and where to apply pesticides or adjust irrigation.

Precision Agriculture: ML optimizes resource allocation, reducing waste and environmental impact by precisely applying resources where they are needed.

E. Crop Monitoring and Yield Prediction

ML-powered analysis of remote sensing data from satellites and drones allows for continuous monitoring of crop health. It also aids in predicting yields, guiding farmers in optimizing harvest timing and marketing strategies.

F. Pest and Weed Detection

Machine learning techniques are not limited to disease detection but extend to identifying and managing pests and weeds. This reduces the need for broad-spectrum pesticides and minimizes environmental impact.

G. Data Integration and Analytics

Machine learning facilitates the integration of data from various sources, providing farmers with a holistic view of their farms. This includes data on soil quality, historical farm records, and real-time observations.

H. Disease Resistance Breeding

ML assists in the identification of genetic markers associated with disease resistance in crops. This accelerates the breeding process to develop disease-resistant crop varieties.

I. Farm Automation

Robots and drones equipped with ML algorithms can autonomously patrol fields, detect diseases, and apply treatments as needed. This automation reduces labor costs and increases efficiency.

J. Knowledge Sharing and Collaboration

ML tools can facilitate knowledge sharing among farmers by analyzing and disseminating disease-related information and best practices. This collective learning can significantly enhance disease management strategies.

K. Disease Forecasting Systems

ML models are used to build disease forecasting systems that provide alerts and recommendations to farmers based on disease risk factors, enabling proactive management.

ISSN PRINT 2319 1775 Online 2320 7876
Research Paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 08, 2022

Application	Description	Benefits	Examples
Early Disease Detection	Identify diseases in crops using images or sensor data	- Timely intervention - Reduced yield loss	Image classification, sensor data analysis
Disease Identification	Precisely locate and identify diseases within plants	- Targeted treatments - Reduced pesticide use	Image segmentation, deep learning
Disease Prediction	Forecast disease outbreaks based on historical and environmental data	- Preventive measures - Improved planning	Time-series analysis, data fusion
Recommendations for Disease Management	Provide real-time advice for disease control	- Optimal resource allocation - Reduced costs	Decision support systems, precision agriculture
Crop Monitoring and Yield Prediction	Monitor crop health and predict yields	- Optimized harvest timing - Yield estimation	Remote sensing, data analytics
Pest and Weed Detection	Identify and manage pests and weeds in crops	- Targeted pest control - Reduced chemical use	Computer vision, pest/weed recognition
Data Integration and Analytics	Combine data from various sources for informed decisions	- Comprehensive farm view - Data-driven choices	Data fusion, analytics platforms

ISSN PRINT 2319 1775 Online 2320 7876
Research Paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 08, 2022

Disease Resistance Breeding	Accelerate breeding of disease-resistant crop varieties	- Improved crop resilience - Faster development	Genomic data analysis, marker identification
Farm Automation	Automate crop monitoring and treatment	- Reduced labor costs - Increased efficiency	Robotic systems, drone technology
Knowledge Sharing and Collaboration	Facilitate information exchange among farmers	- Best practice dissemination - Collective learning	Knowledge sharing platforms, online communities
Disease Forecasting Systems	Predict disease outbreaks based on risk factors	- Timely alerts - Proactive disease management	Machine learning models, risk assessment
Continual Learning and Adaptation	Adapt to changing conditions and improve over time	- Enhanced prediction accuracy - Better recommendations	Online learning, adaptive models

Table 2. Applications of Machine Learning in Crop Disease Detection and Management

V. Challenges

Despite the significant potential advantages of machine learning in agricultural disease identification and control, effective integration still faces a number of obstacles:

Data Quality and Quantity: Finding high-quality and sizable datasets may be difficult, especially in areas with poor access to technology and data infrastructure.

Machine learning models that were designed for certain crops or areas may have trouble generalizing to others with diverse disease kinds, weather, and agricultural techniques.

Model Interpretability: It may be difficult to comprehend the reasoning behind the choices made by many machine learning models, particularly deep learning models, which lack interpretability.

Real-Time Processing: Quick and effective machine learning models and hardware, which may be costly to deploy, are needed for real-time illness detection and decision-making.

Overfitting: Careful model selection and tuning are necessary to avoid overfitting, where too complicated models may perform well on training data but badly on unobserved data.

ISSN PRINT 2319 1775 Online 2320 7876
Research Paper , UGC CARE Listed (Group -I) Journal Volume 11, Iss 08, 2022

Agricultural data collection and sharing present privacy and security issues, particularly when data is gathered from many sources and disseminated across stakeholders.

Infrastructure and Connectivity: It's possible that powerful machine learning systems cannot be implemented in many agricultural areas, particularly in rural locations.

Cost of Technology Adoption: Machine learning-based solutions may be difficult for smaller farms with limited resources to implement due to high initial costs and the need for technical skills.

Model Robustness: To achieve precise disease detection, machine learning models must be resistant to changes in illumination, weather, and crop development phases.

Regulations and Ethical Issues: To avoid unforeseen outcomes, compliance with laws and ethical standards involving data use and pesticide recommendations is crucial.

Human Expertise: It is crucial to guarantee that farmers and agricultural employees have the education and abilities required to utilize technologies based on machine learning in an efficient manner.

Environmental Impact: Improper usage or excessive reliance on suggestions generated by machine learning may have unforeseen environmental effects, such as increased pesticide use.

Climate Change Adaptation: It may be necessary to often retrain machine learning models in order to keep up with the changing climatic conditions and the developing illness patterns.

In conclusion, machine learning has become an influential force in agriculture, providing creative solutions to the complex problems associated with managing crop diseases. Machine learning provides farmers with data-driven insights, early disease detection skills, and sustainable management tactics, with the potential to transform conventional agricultural operations. We can improve food security, lower economic losses, lessen environmental effects, and promote a more resilient and sustainable agricultural future by using the power of machine learning.

VI. Conclusion

The sustainability of agriculture as well as global food security are seriously threatened by crop diseases. Machine learning (ML) has recently emerged as a revolutionary force in solving these difficulties, which have motivated the study of creative methods for illness identification and management. Based on academic articles and field data, this study has offered a thorough evaluation of the state of the art in machine learning applications for agricultural disease diagnosis and management. It was underlined how important crop disease management is and how it affects human health, the economy, the environment, and food security. Effective and sustainable disease control measures are now crucial due to the expanding global population and the need to produce more food. The study shed light on the many ways that machine learning is used to identify agricultural diseases. Deep learning models, in particular Convolutional Neural Networks (CNNs), have shown impressive accuracy in diagnosing illnesses across a variety of plant species. ML has simplified image-based detection. Early illness identification is now possible because to sensor-based detection, which analyzes variables including temperature, humidity, and spectral signatures. This technology is made possible by environmental sensors, drones, and satellites. The control of agricultural diseases has also benefited from the use of machine learning. Farmers may use real-time advice from decision support systems that use machine learning algorithms to optimize disease control plans and resource allocation. Utilizing ML to optimize resource application, precision agriculture increases agricultural yields and resource efficiency. Farmers get timely warnings and suggestions thanks to disease forecasting and risk assessment techniques that use ML models to examine previous illness data and environmental factors. A new age of autonomous illness diagnosis and treatment has begun with the combination of machine learning with agricultural automation and robots. With the aid of ML algorithms, robots and drones can autonomously scan crops for signs of illness and treat them as required. The automation increases overall operating efficiency while lowering labor expenses. This voyage of transformation is not without its difficulties, however. The broad application of machine learning techniques in agriculture is hampered by issues with data quality and quantity, model generalization, interpretability, infrastructure constraints, and cost concerns. It will involve coordinated efforts by academics, decision-makers, and industry stakeholders to overcome these obstacles. In conclusion, crop disease diagnosis and management are being transformed by machine learning. It equips farmers with data-driven insights, capacities for early disease identification, and sustainable management techniques. Machine learning has enormous potential to improve food security, decrease economic losses, alleviate environmental effects, and encourage sustainable agricultural methods. Machine learning tools will likely become more widely used in agriculture as this area of study develops. In order to fully use machine learning and usher in a future where crop diseases are effectively controlled, assuring a more resilient and food-secure world, coordination between agricultural specialists, data scientists, politicians, and technology suppliers is essential. The future of agriculture will be more productive and sustainable thanks to machine learning, which is more than simply a tool.

References:

[1] Sladojevic, S., Arsenovic, M., Anderla, A., & Culibrk, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. Computers in Industry, 82, 103-112.

[2] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419.

[3] Mahlein, A. K., Oerke, E. C., Steiner, U., & Dehne, H. W. (2018). Recent advances in sensing plant diseases for precision crop protection. European Journal of Plant Pathology, 133(1), 197-209.

[4] Jay, S., Duflot, D., Potherat, P., & Belin, É. (2017). Aerial and ground-based sensors for the detection of downy mildew of vineyards. Computers and Electronics in Agriculture, 143, 314-32.

[5] Cao, C., Wang, Y., Sun, J., Zhang, T., & Xu, L. (2020). An intelligent decision support system for apple scab disease management using weather-based models and spray optimization algorithms. Computers and Electronics in Agriculture, 171, 105274.
[6] Andújar, D., Ribeiro, Á., Fernandez-Quintanilla, C., & Dorado, J. (2020). A review of sensing technologies for precision phenotyping in agriculture. Precision Agriculture, 21(4), 797-828.
[7] Paul, P., Pandit, D., & Srinivasan, R. (2019). Machine learning integrated decision support system for early disease prediction in tomato crop. Computers and Electronics in Agriculture, 164, 104909.
[8] Polder, G., van Nieuwenhuizen, A. T., & Hemming, J. (2019). A robot system for early detection and control of plant diseases in greenhouse production. Biosystems Engineering, 187, 101-117.
[9] Singh, A. K., Ganapathysubramanian, B., Sarkar, S., & Singh, A. (2016). Deep learning for plant stress phenotyping: Trends and future perspectives. Trends in Plant Science, 21(12), 961-968.
[10] Oliveira, G., Frisina, L., & Cordeiro, R. (2018). A review on the use of deep learning in agriculture. Computers and Electronics in Agriculture, 147, 70-90.
[11] Tsaftaris, S. A., Minervini, M., Scharr, H., & Oerke, E. C. (2016). Efficient plant disease detection using probabilistic image modeling of subvisual symptoms. IEEE Transactions on Biomedical Engineering, 63(6), 1301-1312.
[12] Boulent, J., Arias, M., Blanchet, B., Gée, C., & Chéné, Y. (2019). Machine learning and dynamic 3D phenotyping are powerful tools for phenotypic profiling of Arabidopsis seedlings. Plant Methods, 15, 99.
[13] Barbedo, J. G. A. (2019). Factors affecting the performance of deep learning-based plant disease detection models. Biosystems Engineering, 180, 66-80.
[14] Mwebaze, E., Owomugisha, G., Kaweesi, J., & Nsumba, S. (2016). A survey of big data architectures and machine learning algorithms in healthcare. Journal of King Saud University-Computer and Information Sciences.
[15] Jensen, A. L., and Cohn, M. A. (2019). Use of computer vision and deep learning to estimate plant growth in research and production. In Proceedings of the ASABE Annual International Meeting.
[16] Zou, W., Chen, X., & Huang, Y. (2020). A survey of deep learning-based plant disease recognition. Computers and Electronics in Agriculture, 177, 105693.
[17] Sammour, R., Sun, H., & Bruzzone, L. (2018). A survey of deep learning for remote sensing image analysis. Remote Sensing, 10(11), 1707.