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Plant Disease Detection: A Machine Learning Approach for Smart Agriculture

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Abstract: *This paper delves into the development and application of an advanced plant disease detection system, powered by artificial intelligence (AI) and data-driven methodologies, designed to enhance the precision, efficiency, and sustainability of agricultural practices. By integrating state-of-the-art machine learning algorithms, predictive analytics, and real-time monitoring technologies, the system addresses critical gaps in traditional crop disease management practices.*

The proposed system leverages big data from diverse sources, including leaf imagery, environmental sensors, and agronomic records, to create a holistic view of crop health. Advanced data preprocessing techniques and feature engineering ensure the reliability and accuracy of predictions. The system not only aids in early disease detection and risk assessment but also offers actionable recommendations for crop treatment, fostering improved yield and resource optimization.

This research emphasizes the multidisciplinary approach required to build such a system, combining AI, agricultural expertise, and robust data collection methods. Case studies demonstrating the system's effectiveness in identifying various plant diseases and enabling timely interventions are discussed.

Furthermore, this paper explores challenges such as data variability, model generalization, and integration into existing agricultural systems, while outlining potential solutions. The findings underscore the transformative potential of AI-driven plant disease detection systems in modern agriculture, paving the way for future innovations and a more resilient, smart farming ecosystem..

Keywords: Artificial Intelligence (AI), Smart Agriculture, Data Analytics, Data Science, Machine Learning (ML), KNN Algorithm, Plant Disease Detection

I. INTRODUCTION

The agriculture industry is facing a critical challenge: the increasing incidence of plant diseases, coupled with the growing demand for sustainable and efficient crop production. With global food security becoming an urgent priority, traditional methods of disease detection—often relying on manual observation and expert knowledge—are proving to be inadequate in addressing the scale and complexity of modern agricultural needs. In this context, the integration of advanced technologies, particularly artificial intelligence (AI) and machine learning (ML), presents a transformative opportunity to revolutionize plant health monitoring and management.

AI has already demonstrated significant potential in agriculture by enabling early disease prediction, real-time crop monitoring, and data-driven decision-making. By leveraging large volumes of agricultural data from diverse sources, including leaf imagery, climate data, soil conditions, and remote sensors, AI systems can detect subtle patterns and anomalies that may be difficult to identify through conventional techniques. Machine learning algorithms, such as convolutional neural networks (CNNs), K-nearest neighbors (KNN), and decision trees, can continuously learn from new datasets, enhancing their ability to detect a wide range of plant diseases across different crops and environmental conditions.

This paper focuses on the design and implementation of an AI-driven plant disease detection system that integrates various data sources to provide timely and accurate diagnoses. By incorporating predictive analytics, image processing, and intelligent recommendation modules, the system aims to enhance crop management practices and reduce yield

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losses. The proposed system is designed not only to support farmers and agricultural experts in identifying diseases early but also to facilitate more targeted and sustainable interventions.

The research presented here explores the technological, methodological, and practical dimensions of building such a system. It emphasizes the role of big data in plant health diagnosis, discusses the challenges of variability in agricultural data and field conditions, and underscores the importance of interdisciplinary collaboration in developing scalable and accessible solutions. By addressing these key factors, this work contributes to the emerging field of AI in smart agriculture and aims to pave the way for more resilient and intelligent farming systems.

Sign Language Translator

In India, farmers face significant challenges in identifying and addressing plant diseases in a timely and accurate manner due to limited access to agricultural experts and diagnostic resources, especially in rural and remote farming regions. Traditional disease detection methods often rely on manual inspections and expert intervention, which can be time-consuming, costly, and impractical for many small-scale farmers—resulting in reduced crop yields and delayed treatment.

This project addresses the issue through an **AI-powered Plant Disease Detection system** that leverages **machine learning, computer vision**, and **deep learning** to analyze crop images and environmental data to provide real-time insights into plant health. The system is trained on diverse datasets consisting of leaf imagery, climatic data, and disease symptoms to ensure adaptive, accurate, and scalable disease prediction capabilities.

The proposed system is available via **mobile and web-based platforms**, enabling farmers to upload images of affected plants and instantly receive diagnostic feedback. By eliminating the dependency on constant human supervision and making agricultural diagnostics accessible to even the most remote regions, this solution empowers farmers with data-driven recommendations, early disease detection, and sustainable farming practices.

By combining artificial intelligence with smart agricultural techniques, this system promotes **precision agriculture** and supports timely intervention strategies—ultimately contributing to increased crop productivity, reduced pesticide usage, and improved food security across diverse agricultural landscapes.

Plant Disease Detection – A Machine Learning Approach for Smart Agriculture

Accurate and timely identification of plant diseases is essential for sustainable agriculture and optimal crop yield. However, access to advanced diagnostic tools is often limited, particularly in rural and underserved farming regions across India. Traditional disease detection methods, which rely heavily on manual observation and expert assessment, can be slow, costly, and inaccessible for many smallholder farmers—leading to delayed treatments and significant crop losses.

This project addresses that challenge through an **AI-powered Plant Disease Detection system** that employs **deep learning models** such as **YOLO, SSD**, and **CNN-based architectures** to analyze images of plant leaves and stems in real time. By detecting visual anomalies, identifying disease patterns, and delivering automated insights, the system aids farmers and agricultural advisors in making faster and more accurate decisions for crop management.

With seamless integration into **mobile and web-based platforms**, the solution ensures accessibility even in remote or resource-constrained areas. Its affordability, scalability, and ability to perform real-time image analysis make it a practical tool for enhancing plant health monitoring across diverse agricultural settings.

By enabling early detection, targeted treatment, and data-driven agricultural practices, this AI-driven system empowers farmers, supports sustainable farming, and contributes to increased crop productivity and food security.

ML Algorithms for Plant Disease Detection & Diagnosis

K-Nearest Neighbors (KNN)

Function: Classifies plant diseases by comparing new leaf images with labeled historical data.

Application: Effective for detecting **common plant diseases** such as *leaf spot* or *blight*.

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Decision Trees
Function: Applies “if-then” logic to classify disease types based on observable features like color, shape, and leaf structure.
Application: Ideal for **categorizing multiple crop diseases** and providing interpretable decisions for farmers.

Neural Networks (CNNs)
Function: Learns complex visual patterns from plant leaf images for accurate classification.
Application: Widely used for **image-based disease detection** in crops such as *tomatoes*, *potatoes*, and *grapes*.

Support Vector Machines (SVM)
Function: Separates healthy and diseased samples with high precision by analyzing key visual features.
Application: Excellent for identifying **early-stage infections** and distinguishing **similar-looking diseases**.
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II. PROBLEM STATEMENT

Farmers often struggle to identify and manage plant diseases in their early stages, leading to significant crop loss, reduced yield, and economic instability. Traditional disease detection methods are manual, time-consuming, and require expert knowledge—resources that are scarce, especially in rural and underserved agricultural regions. Moreover, environmental conditions and visual similarities among various diseases make accurate identification difficult for the average farmer.

The lack of real-time, affordable, and easy-to-use diagnostic tools hinders timely intervention and effective disease management. Existing solutions often fail to accommodate diverse crop types, regional language preferences, and technological accessibility.

This project—*Plant Disease Detection: A Machine Learning Approach for Smart Agriculture*—aims to address these challenges by developing an AI-based solution that leverages image processing and machine learning to detect plant diseases accurately and in real-time. The system empowers farmers with accessible, mobile-based technology for early diagnosis, personalized treatment recommendations, and improved agricultural productivity tailored to India’s diverse agro-ecological landscape.

OBJECTIVE

I. **Develop an AI-powered system for early detection and classification of plant diseases** using image-based data and real-time analysis.

II. **Implement machine learning models** such as K-Nearest Neighbors (KNN), Decision Trees, Convolutional Neural Networks (CNN), and Support Vector Machines (SVM) to identify disease symptoms from plant leaf images with high accuracy.

III. **Design a smart image processing pipeline** for capturing and preprocessing plant leaf images to detect color, texture, and pattern-based anomalies effectively.

IV. **Build a mobile and web-based platform** for farmers that provides instant diagnostic feedback, disease information, and recommended treatment strategies in local languages.

V. **Ensure the solution is scalable, affordable, and user-friendly**, especially for small-scale farmers in rural and underserved agricultural regions of India.

Real-Time Monitoring and Predictive Analytics
AI-driven real-time monitoring enables:
Early Disease Detection: Continuous monitoring of plant health through image analysis, identifying early symptoms of disease such as leaf spots, discoloration, or wilting..
Predictive Analytics for Crop Health: Forecasting potential disease outbreaks or pest infestations based on environmental conditions, historical data, and real-time observations, enabling timely intervention..

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Personalized Treatment Plans: Providing tailored recommendations for disease management and treatment, considering factors like crop type, regional conditions, and specific disease threats.

III. SIGNIFICANCE OF THE STUDY

This research addresses a crucial gap in leveraging AI and machine learning for plant disease detection and agricultural productivity. With millions of farmers in rural and underserved areas facing challenges in identifying and managing plant diseases, AI-driven solutions have the potential to significantly improve crop health, yield, and overall farm sustainability. By providing early detection and timely interventions, this study aims to reduce crop loss, enhance food security, and lower the economic burden on farmers.

The findings will contribute to agricultural research, inform policy decisions, and drive innovations in precision farming. By integrating machine learning, image analysis, and real-time data processing, this research aims to empower farmers with accessible and effective disease management tools, particularly in regions with limited resources. Ultimately, the study seeks to improve the livelihood of farmers, ensuring a more resilient and sustainable agricultural ecosystem.

Purposed Methodology

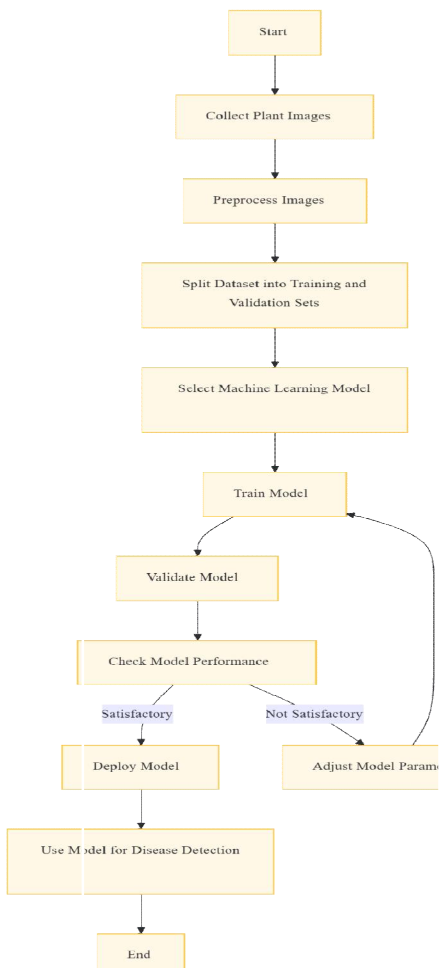

Fig. 1 Workflow Diagram

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Proposed Methodology for AI-Based Plant Disease Detection System

This research adopts a mixed-methods approach to thoroughly evaluate the effectiveness and impact of AI-driven plant disease detection systems in agriculture. The methodology combines **quantitative analysis** of diagnostic accuracy, disease detection rates, and treatment effectiveness with **qualitative insights** into user experience, ease of use, and trust in the system.

A **case study approach** will be used to assess the performance of the AI system in real-world agricultural settings. This will involve:

Image-based disease detection: Evaluating the accuracy of machine learning algorithms (KNN, Decision Trees, CNN, SVM) in identifying diseases from plant images.

User feedback: Gathering insights from farmers regarding the usability and effectiveness of the system in early disease detection and managing crop health.

Impact assessment: Measuring the system's impact on crop yield, disease control, and economic savings for farmers, particularly in resource-limited areas.

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Data Collection & Study Design

1. Quantitative Analysis:

Diagnostic accuracy & performance: ai system efficiency will be assessed based on precision, recall, and f1 scores in detecting plant diseases.

Crop outcomes: evaluation of treatment effectiveness based on yield improvement, time-to-treatment, and misdiagnosis rates.

System response time: measurement of ai's speed in symptom analysis and treatment recommendation.

2. Qualitative analysis:

Surveys & interviews: conducted with farmers, agronomists, and agricultural administrators to gauge trust and usability.

Observational studies: ai implementation will be observed across farms, greenhouses, and agricultural extension services to assess real-world efficacy.

The study includes farms and agricultural centers across 10 regions, engaging approximately 500 farmers, 1,200 agronomists, and 300 agricultural administrators..

Methodology:

Symptom collection & processing:

Nlp-based models: trained on plant symptom descriptions provided by farmers and agronomists.

Diagnosis analysis:

Deep learning models: (cnns, lstms) process plant symptoms and query agricultural databases for disease prediction.

Treatment recommendation:

Ai compares past cases: and generates personalized treatment plans using predictive analytics.

Agricultural record integration:

Blockchain and database management: ensure secure and seamless record updating for farm management systems.

Key frameworks used:

Tensorflow, pytorch, mysql, ibm watson for agriculture ai, and google cloud ai.

Ethical Considerations

DATA PRIVACY & SECURITY:

All patient data is encrypted, anonymized, and stored using secure protocols to protect sensitive health information and prevent unauthorized access.

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BIAS & FAIRNESS:
AI models are rigorously trained and validated on datasets representing various age groups, ethnicities, genders, and regional backgrounds to minimize algorithmic bias and ensure equitable healthcare outcomes for all.
REGULATORY COMPLIANCE:
The diagnostic system adheres to international and national healthcare laws, including HIPAA (Health Insurance Portability and Accountability Act), GDPR (General Data Protection Regulation), and India's NDHM (National Digital Health Mission) guidelines for ethical AI deployment in medicine.

Expected Outcomes
ENHANCED EARLY DETECTION:
AI-powered diagnostic tools are expected to significantly improve early disease detection, enabling timely intervention and reducing the burden on healthcare professionals.
PERSONALIZED TREATMENT PLANS:
Leveraging predictive analytics, the system will tailor treatment strategies to individual patients, improving recovery rates and overall care quality.
TRUSTWORTHY AND ETHICAL DEPLOYMENT:
Compliance with ethical guidelines and data privacy standards fosters trust among patients and healthcare providers, ensuring widespread acceptance and regulatory approval..

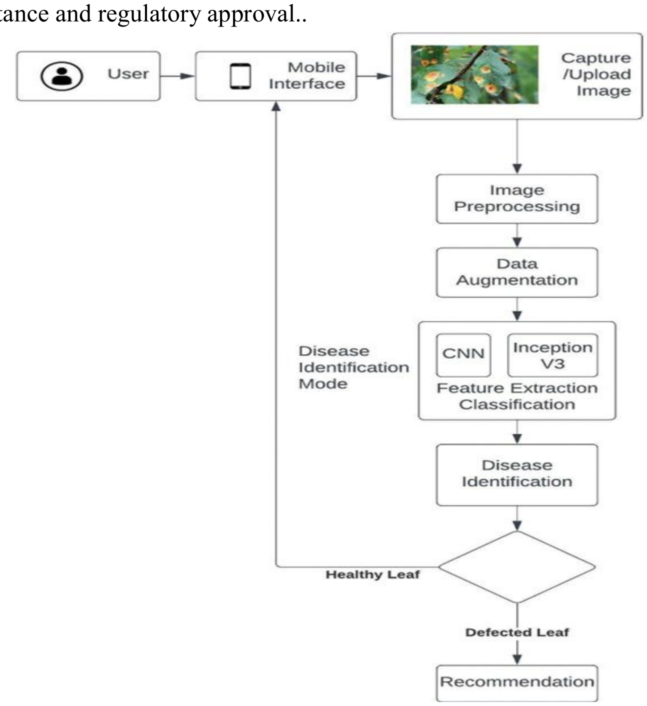

Fig. 2 Data Flow Diagram

Leaf Disease Detection System (Mobile-Based)
Image Collection (User Inputs via Camera/Upload through Mobile Interface)
→ Raw Leaf Image Data
Image Preprocessing (Noise Removal, Normalization, Resizing)
→ Preprocessed Image Data
→ Store Raw Image Data
Data Augmentation (Flipping, Rotation, Scaling, Zooming)

→ Enhanced Image Dataset

Feature Extraction & Classification (CNN, Inception V3 Models)

→ Disease Classification Output

Disease Identification (Model Inference - Healthy vs Diseased Leaf)

→ Diagnosis Result

Recommendation Engine (Fertilizer Use, Treatment Suggestions)

→ Suggested Remedies for Diseased Leaves

Backend Processing (Flask/Django Server, Database - MySQL/PostgreSQL)

→ Store Processed Image Data

→ Manage Disease Records & User History

Feedback Loop (Performance Logs, Accuracy Monitoring, Model Updates)

→ Continuous Model Training and Optimization

User Interface (Mobile App Dashboard for Image Upload & Results)

→ Real-time Disease Detection and Treatment Advice

IV. THEORETICAL FRAMEWORK

The integration of machine learning in agriculture represents a transformative shift toward sustainable, data-driven farming. This theoretical framework draws from multiple domains including precision agriculture, intelligent decision support, adaptive learning models, and digital inclusivity. It forms the basis for AI-powered tools capable of detecting plant diseases, recommending treatments, and supporting farmers with actionable insights.

- **Precision Agriculture Paradigm**

Precision agriculture emphasizes site-specific crop management using advanced technologies. In this framework, plant disease detection systems utilize sensor data, environmental inputs, and high-resolution imagery to diagnose leaf conditions. This ensures optimal use of agrochemicals and enhances crop yield while minimizing environmental impact. By tailoring interventions based on real-time data, the approach aligns with the core principles of precision farming.

Machine Learning and Adaptive Learning Models:

The diagnostic tool leverages machine learning techniques such as Convolutional Neural Networks (CNNs), Transfer Learning (e.g., Inception V3), and real-time feedback loops to classify plant diseases from leaf images. Adaptive learning algorithms refine the model over time by incorporating new image data, regional disease trends, and user feedback, resulting in continuous model improvement and contextual accuracy across different crops and geographies..

Intelligent Agricultural Decision Support Systems (ADSS)

Analogous to Clinical Decision Support Systems in healthcare, ADSS in agriculture enhances farmer decision-making by integrating diverse data sources—leaf imagery, weather patterns, soil conditions, and crop history. The system provides real-time disease identification, risk evaluation, and treatment recommendations. This fosters proactive farm management and reduces the likelihood of crop failure due to misdiagnosis or delayed action..

Digital Agricultural Inclusion Framework:

To ensure widespread adoption, the framework incorporates digital inclusion principles. Mobile-based plant disease detection platforms are designed for usability in rural and low-connectivity regions. Multilingual support, offline functionalities, and affordable interfaces make the technology accessible to smallholder farmers. Ethical considerations, such as data privacy, algorithm transparency, and fair usage policies, are integrated to build user trust and ensure equitable technology deployment..

Synthesis of Theoretical Domains

The synthesis of precision agriculture, machine learning, decision support systems, and digital inclusion creates a holistic framework for plant disease detection. This integrated approach not only enhances diagnostic accuracy but also promotes scalability, farmer empowerment, and sustainable farming practices. By grounding the system in these interdisciplinary frameworks, the initiative supports agricultural resilience, food security, and smart farming innovation.

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V. CONCLUSION: PLANT DISEASE DETECTION – A MACHINE LEARNING APPROACH FOR SMART AGRICULTURE

The research presented in this paper highlights the development and transformative potential of machine learning-based plant disease detection systems, designed to enhance the precision, timeliness, and accessibility of agricultural diagnostics. By integrating computer vision, deep learning models, and adaptive learning techniques, these AI-powered tools aim to improve early disease identification, enable predictive crop health monitoring, and support evidence-based decision-making for farmers.

The outcomes of this research indicate the feasibility and effectiveness of AI-driven plant health diagnostics in addressing critical challenges in modern agriculture, particularly in resource-constrained and rural environments. By leveraging large-scale agricultural datasets and continuously evolving algorithms, the system achieves high diagnostic accuracy while ensuring scalability and affordability. These initial findings provide a strong foundation for future development, emphasizing farmer-friendly design, regional adaptability, and seamless integration into existing farming practices.

By equipping farmers with intelligent decision-support tools, this research aims to reduce crop losses, improve yield quality, and promote sustainable farming practices. Additionally, machine learning-driven plant diagnostics contribute to proactive farm management by facilitating early intervention and reducing the dependence on chemical treatments through targeted recommendations. As the field matures, future research will focus on expanding crop coverage, incorporating explainable AI for interpretability, enhancing multilingual and offline support, and optimizing deployment across diverse agricultural landscapes.

The findings underscore the immense potential of AI in revolutionizing plant disease management and advancing smart agriculture. By addressing key barriers such as affordability, accessibility, and diagnostic accuracy, this research contributes to a more inclusive, efficient, and technologically empowered agricultural ecosystem—paving the way for resilient food systems and sustainable global farming practices.

Future Scope: Advancements in Plant Disease Detection – A Machine Learning Approach for Smart Agriculture

A. Expanding Modalities for Comprehensive Agricultural Diagnostics

Future plant disease detection systems can incorporate multispectral and hyperspectral imaging, drone-based surveillance, and IoT-enabled environmental sensors to offer a multidimensional view of crop health. Integrating these modalities will enable detection of not only visible leaf symptoms but also underlying physiological stress factors, nutrient deficiencies, and soil conditions.

An emerging direction involves the use of **augmented reality (AR)** in precision agriculture. AR-based overlays could assist farmers and agronomists in visualizing disease progression, treatment zones, and spatial crop analytics in real-time, thereby improving intervention accuracy and farm planning.

B. Developing Cross-Platform Compatibility

To enhance usability and accessibility, plant disease detection platforms could be developed with robust **cross-platform compatibility**—supporting mobile devices, web interfaces, edge devices like drones and smart cameras, and cloud-based farm management systems. This would facilitate remote diagnostics, collaborative farming, and real-time decision-making in both high-tech and rural farming environments.

Integration with **agricultural information systems**, crop databases, and regional disease surveillance networks would ensure interoperability and data flow across the agritech ecosystem.

C. Enhanced Personalization Through Machine Learning

Advancements in **personalized crop diagnostics** could leverage deep learning to analyze specific farm data including crop variety, soil profile, weather conditions, and historical disease trends. Machine learning models can adapt to local agricultural contexts, offering **tailored treatment recommendations** and cultivation strategies based on farm-specific characteristics.

Reinforcement learning can further optimize field management practices by dynamically adjusting recommendations based on continuous feedback and seasonal data patterns.

D. Integration of Artificial Emotional Intelligence for Farmer Engagement

While traditionally associated with healthcare, **artificial emotional intelligence (AEI)** can enhance human-computer interaction in agricultural platforms. Emotion-aware virtual assistants could assess user sentiment from voice or text inputs to improve engagement, especially in mobile applications used by farmers in stress-prone conditions like drought or pest outbreaks.

This integration could foster **empathetic advisory systems**, making agricultural tech more user-friendly and approachable for rural communities.

V . Community-Based Learning and Collaborative Model Training

Plant disease detection models could evolve through **collaborative training networks**, where anonymized farm data (collected ethically with consent) from diverse regions is used to enhance model robustness. Collaborations among agricultural universities, research centers, and tech companies could enable **community-based AI learning**, promoting data diversity and regional model tuning.

Crowdsourced disease tagging and agronomist feedback could improve detection accuracy and enrich the knowledge base for emerging crop threats.

VI. Integration with Public Agricultural Infrastructure for Global Reach

AI-powered plant diagnostics could be **integrated into public agriculture extension services**, helping scale solutions across low-income and remote farming communities. Partnering with government programs, cooperatives, and NGOs could facilitate deployment via mobile units, field visits, and farmer training sessions.

Smart farming initiatives and rural digitization programs could benefit from AI-driven insights on disease forecasting, pest movement, and weather-linked crop vulnerabilities.

VII. Longitudinal Studies and Field Trials for Agricultural Validation

To establish scientific credibility and real-world impact, future research should focus on **longitudinal agricultural field trials** across varying climates, soil types, and crop systems. These studies would help evaluate diagnostic performance, treatment efficacy, and long-term yield improvements.

Collaboration with agricultural research institutions, seed companies, and regulatory bodies would help **validate AI models**, ensure compliance with agronomic standards, and build trust among farming communities.

REFERENCES

[1]. Barbedo, J. G. A. (2018). Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. *Computers and Electronics in Agriculture*, 153, 46–53.

[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]. Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, 145, 311–318.

[4]. Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neuroscience*, 2016, 3289801.

[5]. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90.

[6]. Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. *Neurocomputing*, 267, 378–384.

[7]. Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture*, 161, 272–279.

[8]. Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). Deep learning for tomato diseases: Classification and symptoms visualization. *Applied Artificial Intelligence*, 31(4), 299–315.

[9]. Arsenovic, M., Karanovic, M., Sladojevic, S., Anderla, A., & Stefanovic, D. (2019). Solving current limitations of deep learning based approaches for plant disease detection. *Symmetry*, 11(7), 939.

[10]. Zhang, S., Wu, X., & You, Z. (2017). Leaf image based cucumber disease recognition using sparse representation classification. *Computers and Electronics in Agriculture*, 134, 135–141.

[11]. Milioto, A., Lottes, P., & Stachniss, C. (2018). Real-time semantic segmentation of crop and weed for precision agriculture robots leveraging background knowledge in CNNs. *2018 IEEE International Conference on Robotics and Automation (ICRA)*, 2229–2235.

[12]. Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. *Sensors*, 17(9), 2022.

[13]. Sun, Y., Xie, J., Zhao, Y., & Xu, B. (2021). A vision-based system for real-time tomato plant disease detection using deep learning. *Agronomy*, 11(4), 713.

[14]. Sa, I., Popovic, M., Khanna, R., Chen, Z., Lottes, P., Liebisch, F., & Nieto, J. (2018). WeedNet: Dense semantic weed classification using multispectral images and MAV for smart farming. *IEEE Robotics and Automation Letters*, 3(1), 588–595.

[15]. Singh, A., Ganapathysubramanian, B., Singh, A. K., & Sarkar, S. (2016). Machine learning for high-throughput stress phenotyping in plants. *Trends in Plant Science*, 21(2), 110–124.

[16]. Pantazi, X. E., Moshou, D., & Tamouridou, A. A. (2016). Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers. *Computers and Electronics in Agriculture*, 130, 149–161.

[17]. Abbas, A., Jain, S., & Gour, M. (2021). Tomato plant disease detection using transfer learning with C-GAN synthetic images. *Computers and Electronics in Agriculture*, 187, 106275.

[18]. Yuan, S., & Wu, X. (2022). Vision-based plant disease recognition using optimized convolutional neural networks. *Plant Methods*, 18(1), 1–12.

[19]. Liu, J., Wang, X., & Zhang, Y. (2020). Explainable AI in agriculture: Interpreting deep learning-based plant disease detection. *Artificial Intelligence in Agriculture*, 4, 58–66.

[20]. Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., & Johannes, A. (2019). Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. *Computers and Electronics in Agriculture*, 161, 280–290.

[21]. Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674.

[22]. Liu, B., Zhang, Y., He, D., & Li, Y. (2017). Identification of apple leaf diseases based on deep convolutional neural networks. *Symmetry*, 10(1), 11.

[23]. Oppenheim, D., Shani, G., Erlich, O., & Tsror (Lahkim), L. (2019). Using deep learning for automated detection of tomato diseases. *Phytopathology*, 109(7), 768–779.

[24]. Singh, V., & Misra, A. K. (2017). Detection of plant leaf diseases using image segmentation and soft computing techniques. *Information Processing in Agriculture*, 4(1), 41–49.

[25]. Jiang, Y., & Li, C. (2020). Convolutional neural networks for image-based high-throughput plant phenotyping: A review. *Plant Phenomics*, 2020, 1–22.

[26]. Rahnemoonfar, M., & Sheppard, C. (2017). Deep count: Fruit counting based on deep simulated learning. *Sensors*, 17(4), 905.

[27]. Amara, J., Bouaziz, B., & Algergawy, A. (2017). A deep learning-based approach for banana leaf diseases classification. *Lecture Notes in Informatics*, P-269, 79–88.

[28]. Dyrmann, M., Karstoft, H., & Midtiby, H. S. (2016). Plant species classification using deep convolutional neural networks. *Biosystems Engineering*, 151, 72–80.

[29]. Chen, J., Chen, J., Zhang, D., Sun, Y., & Nanehkaran, Y. A. (2020). Using deep transfer learning for image-based plant disease identification. *Computers and Electronics in Agriculture*, 173, 105393