Crop Disease Prevention Through Soil Health Monitoring and AI-Based Detection: A Review Paper

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Abstract

Crop diseases and soil-related stresses significantly threaten global food security by reducing agricultural productivity and causing major economic losses. Manual disease identification is labour-intensive, time-consuming, and prone to human error, leading to the adoption of deep learning and smart sensing systems for automated crop monitoring. This review examines recent IEEE research contributions utilizing Convolutional Neural Networks, transfer learning approaches, lightweight models , semantic segmentation and real-time detection frameworks for potato, tomato, soybean, and black pepper disease diagnosis. Performance evaluations report accuracies ranging from 91% to 99.84%, while segmentation techniques achieve a Dice coefficient of 90.86%. Additionally, Decision Support Systems , IoT-enabled soil sensing, and quantum machine learning contribute to precision assessment of critical soil parameters such as pH, moisture, nutrient balance, and microbial activity. The review synthesizes datasets preprocessing methods, deployment strategies and real-world outcomes including a 23% yield improvement. Despite advancements, significant research gaps persist in real-time soil data integration, model scalability, and accessibility for small-scale farmers. Future directions highlight multimodal fusion, federated learning, and edge intelligence to develop robust, sustainable, and practical crop disease prevention systems. This review aims to support the development of an end-to-end intelligent agricultural framework combining soil health monitoring, leaf analysis, and automated irrigation for improved productivity and resilience.

Keywords

Crop disease detection, soil health monitoring, deep learning, IoT sensors, semantic segmentation, YOLOv5, CNN, precision agriculture, federated learning, smart irrigation.

I. INTRODUCTION

Crop diseases remain a major threat to global food production, contributing to approximately 20–40% loss in annual agricultural yield worldwide. Traditional detection techniques rely on manual visual inspection by farmers or agricultural specialists, which is labour-intensive, time-consuming, and prone to human error, achieving only 46.9–70% accuracy. Limited

access to trained experts in rural regions further delays diagnosis, leading to significant crop damage, drastic economic losses, and excessive fungicide usage that harms both soil and the environment.
Although most disease detection solutions focus on leaf-level symptoms, a substantial portion of crop diseases originate from soil-borne pathogens and imbalanced soil conditions. Critical soil health parameters such as moisture, temperature, pH, nutrient levels, and microbial activity play a significant role in crop immunity. Deviations from optimal soil conditions favor pathogenic growth, causing diseases such as late blight, damping-off, root rot, bacterial wilt, and Fusarium infections. Therefore, early soil monitoring is essential to prevent disease outbreaks before visible symptoms appear.

A. Technological Advancements in Smart Agriculture

Recent progress in Artificial Intelligence (AI) and deep learning has greatly improved the efficiency of disease detection and soil health monitoring. These technologies offer:

- Early disease prediction (3–7 days before visible symptoms)
- High multi-class classification accuracy (up to 99.84%)
- Real-time monitoring using IoT sensors and automated alerts
- Reduced human expertise dependency
- Scalable deployment via cloud, mobile, and web platforms

Deep learning models such as Convolutional Neural Networks (CNNs), MobileNetV2, Efficient Net, and Vision Transformers, paired with IoT-enabled smart irrigation and soil condition sensing, enable automated precision farming. Furthermore, emerging areas such as quantum machine learning and predictive decision-support systems enhance resilience against crop diseases.

B. Motivation and Scope of the Review

Crop disease detection and soil health management are often studied separately. However, an integrated approach can significantly minimize yield loss and improve farmer decision-making. This review consolidates insights from five peer-reviewed IEEE conference papers, covering:

- Potato disease detection using custom CNN and Efficient Net
- Tomato leaf disease classification using VGG-16 web-based deployment
- Black pepper disease recognition with transfer learning
- IoT-integrated decision support for tomato anthracnose prevention
- Real-time disease detection using YOLOv5 and Vision Transformers

C. Objective of the Study

This review aims to:

- Analyze deep learning-based methods for accurate crop disease detection
- Examine the role of soil parameters in disease prevention
- Explore IoT-enabled soil monitoring and smart irrigation technologies
- Highlight integrated frameworks for precision agriculture and sustainable farming

The synthesis of reviewed studies demonstrates how AI-driven detection, soil health analytics, and IoT-based automation collectively form an effective approach for early disease prevention, reduced chemical misuse, and improved agricultural productivity.

II. LITERATURE REVIEW

1. **Black Pepper Leaf Disease Classification using Deep Learning Models (2024)** - This study applies Convolutional Neural Networks (CNN) and Inception-v3 architectures for the classification of black pepper leaf images. The research compared manual disease detection with automated approaches and found that deep learning significantly reduces manual errors. The automated classification supports timely preventive measures, enhancing disease management and minimizing crop damage.
   a. Uses CNN and Inception-v3 for accurate classification of black pepper leaf diseases.
   b. Achieves high accuracy, reduces manual errors, and enables timely preventive action.

2. **Detecting Plant Leaf Diseases with CNN and Deployment via Hugging Face (2024)** - This research developed a CNN-based model trained on tomato and potato leaf datasets, covering 13 different diseases. The model was deployed using Hugging Face, making it accessible for farmers as a scalable precision agriculture tool. It ensures reduced pesticide use by identifying diseases early, supporting sustainable farming practices.
   a. CNN model trained on multiple crop diseases with 91% accuracy.
   b. Deployed Deployed via Hugging Face for real-time farmer support and re- duced pesticide usage.

3. **Decision Support System for Anthracnose in Tomato Crops (2018)** - A Decision Support System (DSS) was designed using agroclimatic parameters such as temperature and humidity combined with supervised learning techniques. The system generated early preventive alerts, reducing fungicide usage while en- suring healthier tomato crops. The study highlights the potential of IoT and DSS integration in disease prevention.
   a. Employs agroclimatic data with supervised learning for anthracnose prediction.
   b. Provides preventive alerts, minimizing fungicide use and improving tomato crop yield.

4. **Optimized Crop Disease Segmentation using Efficient U-Net (2025)** - This work proposed EfficientUNet-B3, integrating EfficientNet as the backbone for accurate segmentation of potato leaf diseases. The model outperformed RS- UNet with higher Dice (90.86%) and MIoU (83.25%) scores, enabling precise lesion segmentation. It also supports severity scoring, which is essential for disease mon- itoring and crop management.
   a. Introduces EfficientUNet-B3 for accurate leaf lesion segmentation.
   b. Outperforms RS-UNet with high Dice and MIoU scores, enabling severity scoring.

5. **Potato Disease Detection using Deep Learning (2023)** - This study applied CNN-based classifiers on potato leaf datasetsfor early and late blight detection. Different architectures (DenseNet, ResNet, Inception, Efficient- Net) were compared, with

EfficientNet achieving the highest accuracy (99%). The combination of hyperspectral imaging with CNN models also showed promise for early disease detection.

a. Compares CNN architecturesfor potato disease detection.
b. Efficient Net achieved 99% accuracy; hyperspectral imaging shows potential for early detection.

6. **Potato Disease Prediction using Deep Learning (2025)** - A web-based prediction system was developed using Fast API and React, integrating CNN models like VGG16, ResNet50, and Google Net. The system provided farmers with real-time disease predictions and educational resources for prevention and management, making it highly practical for crop health support.
   a. Web-based system combining Fast API + React with CNN models.
   b. Provides real-time predictions and resources for farmers' disease management.

7. **Review of Soybean Crop Classification and Disease Identification using AI + IoT (2024)** - This review explored AI approaches such as CNN and ResCNN, alongside IoT- based robotic sensors, for soybean crop monitoring and disease detection. The study 4 emphasized the role of AI + IoT integration in germination monitoring, early alert systems, and optimizing farming cycles.
   a. Reviews AI (CNN/ResCNN) and IoT-based systems for soybean monitoring.
   b. Highlights improved germination monitoring, early alerts, and optimized farming cycles.

8. **Quantum Machine Learning in Crop Disease Monitoring (2025)** - This research investigated Quantum Machine Learning (QML) techniques for crop disease detection using spectral imaging, IoT, and remote sensing data. The results showed superior accuracy compared to classical ML approaches, though hardware limitations remain a challenge for real-world deployment.
   a. ExploresQML with IoT and spectral imaging for crop monitoring.
   b. Achieves higher accuracy than classical ML; hardware limitations noted.

9. **Agroinsights Chatbot: AI-Driven Precision Farming (2024)-**The study introduced an AI chatbot built using Flask, ML, and NLP techniques to assist farmers with yield prediction, disease detection, and fertilizer recommend- ations. The chatbot provided an interactive and easy-to-use interface, simplifying complex decision-making for farmers.
   a. AI chatbot integrates ML + NLP for disease detection and yield prediction.
   b. improves farmer engagement with simple conversational interfaces.

10. **Banana Crop Health: Deep Learning-Based Mode (2024)l**-This research implemented MobileNetV2 CNN for classification of banana diseases, including Panama, Black/Yellow Sigatoka, and Bacterial Soft Rot, using 3,012 images. Data augmentation improved performance, and the model proved efficient for Realtime disease monitoring on mobile devices.
    a. MobileNetV2 CNN applied for banana disease detection.
    b. Achieved high accuracy with augmentation; suitable for real-time mobile applications.

11. **Automatic Plant Watering and Disease Detection System (2025)** - An Arduino-based system was developed for automatic irrigation and disease detection. Soil moisture

sensors-controlled water pumps, while a Flask web app allowed real-time monitoring and leaf image uploads. A CNN model classified plant health and suggested treatments, providing a complete precision farming solution.

a. Combines IoT irrigation with CNN-based disease detection.
b. Provides real-time monitoring, reduced water wastage, and actionable recommendations.

12. **Advancing Tomato Leaf Hygiene with Machine Learning (2025)** - This study designed a CNN optimized with dropout and batch normalization, trained on thousands of annotated tomato leaf images. The model achieved 92.5% accuracy and outperformed traditional models, enabling continuous monitoring and proactive disease management.
    a. optimized for tomato leaf disease classification with 92.5% accuracy. Supports proactive intervention and reduces chemical usage.

13. **Vision Transformer-Based Framework for Soybean Leaf Diseases (2025)** - This study applied a pre-trained Vision Transformer (ViT) model for detecting soybean leaf diseases using multiple datasets (Auburn, Soybean Diseased Leaf, SoyNet). The model consistently achieved very high accuracy (97–99%), proving its effectiveness for precision agriculture.
    a. CNN Vision Transformer (ViT) applied to soybean leaf disease datasets.
    b. Achieved 97–99% accuracy; effective for precision farming and crop health monitoring.

14. **Crop Disease Detection and Monitoring System (2019)** - This uses image processing (K-means clustering) for disease area detection on soybean leaves. Integrates IoT sensors (soil moisture, temperature, humidity) for environmental monitoring. Employs automation via motors controlled by a microcontroller for irrigation and fertilizer application.
    a. Sends real-time alerts and updates wirelessly to farmers.
    b. Helps in early disease management, resource saving and crop yield improvement. monitoring.

III. COMPARATIVE ANALYSIS

Paper	Model /Technique	Crop / Focus Area	Task / Application	Accuracy / Metric	Strength
L-1	**Inception V3 / YOLOv5 / Vision Transformer**	Black Pepper	Leaf disease classification	99.84%	High accuracy, mobile deployment
L-2	**VGG-16**	Tomato / Potato	Multi-disease classification	91%	Large dataset, scalable web deployment

L-3	**J48 Decision Tree**	Tomato	DSS / Anthracnose	97.5%	Real-world field deployment, IoT integration
L-4	**EfficientUNet-B3**	Potato	Segmentation / Blight	90.86% Dice	Pixel-level localization, edge deployable
L-5	**Custom CNN**	Potato	Leaf disease classification	97.2%	Dataset diversity, practical baseline
L-6	**CNN**	Potato	Leaf disease detection	High	High accuracy in controlled environment
L-7	**AI + IoT Sensors**	Soybean	Disease detection & monitoring	NA	Real-time soil and environment data
L-8	**Quantum ML**	Various	Large-scale soil & disease modeling	NA	Fast multidimensional data analysis
L-9	**AgroInsights Chatbot**	Precision Farming	Farmer advisory / decision support	NA	Real-time guidance, user-friendly
L-10	**MobileNetV2, CNN**	Banana	Leaf disease detection	97%	Lightweight, mobile/edge deployment
L-11	**CNN + IoT**	Various	Automatic watering & disease detection	90%+	Integrates soil and leaf health monitoring
L-12	**CNN**	Tomato	Hygiene / early disease monitoring	92.5%	Real-time tracking and monitoring
L-13	**Vision Transformer**	Soybean	Disease	98.7%	High accuracy, robust to noisy field conditions
L-14	**K-means + IoT**	Various	General crop monitoring	NA	Low-cost IoT-based automatic detection

IV. LIMITATIONS IDENTIFIED ACROSS STUDIES

Most models focus only on leaf images, not on soil health parameters.
Environmental variations (light, weather) reduce accuracy in field conditions.
Large dataset requirement for deep learning models.
Lack of integration between:

- Disease detection
- Soil moisture monitoring
- Automated prevention

IoT systems have latency and connectivity dependence in rural areas.
Transformer models, although accurate, require higher computational resources.

V. RESEARCH GAPS

A. Technical Challenges

Despite advances in deep learning and IoT-based crop monitoring, several technical challenges persist. Dataset bias limits generalization, as models trained on controlled datasets often underperform in real-field conditions, with accuracy drops of 5–15% [Paper 5]. Multi-disease and multi-crop integration is limited, and expanding class coverage reduces per-class accuracy. High-performing models such as VGG-16 and ViT-Base are computationally intensive, restricting edge deployment, while smaller models like YOLOv5 and EfficientNet-B3 offer mobility but may compromise accuracy. CNN-based models lack interpretability, suggesting the need for visualization techniques such as saliency maps and CAMs.

B. Agricultural Implementation Gaps

Adoption in real-world farming is hindered by limited accessibility for small-scale farmers, fragmented IoT integration, and high initial investment with uncertain ROI. Offline-capable applications, local language support, and standardized IoT protocols (MQTT, CoAP, REST APIs) are required to improve usability and interoperability.

C. Data-Related Gaps

Dataset diversity, geographic bias, and rare disease under sampling reduce model reliability. Single-year datasets fail to capture temporal and seasonal variations. Furthermore, there is a lack of unified platforms integrating leaf disease detection with soil health and environmental data, multimodal datasets, accurate low-cost soil sensors, and practical deployment of QML and AI chatbot systems. Soil nutrient deficiencies have not been linked to disease prediction, leaving a key gap for precision agriculture.

VI. CONCLUSION

Recent advances in deep learning and IoT have significantly improved crop disease detection, achieving 91–99.84% accuracy and enabling precise localization with models like EfficientUNet-B3. Field deployments, such as DSSAT, show 13–23% yield increases and reduced fungicide use, demonstrating practical benefits. However, challenges remain, including dataset bias, class imbalance, computational constraints, limited edge deployment, and low farmer adoption due to technical and economic barriers. Model interpretability is also limited, reducing trust in automated recommendations. Future research should focus on integrated systems combining leaf disease detection, soil health monitoring, and environmental sensing, with mobile-first deployment, federated learning, and standardized IoT protocols. Such approaches can enhance predictive disease management, improve sustainability, and support global food security by reducing crop losses and pesticide use while empowering farmers.

REFERENCES

1. D. Sasi, A. P, J. Jinso, J. Paul, and D. V, "Black Pepper Leaf Disease Classification using Deep Learning Models," in Proc. Recent Advances in Intelligent Computational Systems (RAICS), 2024, pp. 1–6. [Online]. Available: https://doi.org/10.1109/RAICS61201.2024.10690146
2. T. P. G. James, A. K. M. S, P. J, D. R, V. G, and A. K. J, "Detecting Plant Leaf Diseases with Convolutional Neural Networks (CNN) and Deployment via Hugging Face," in Proc. Int. Conf. Power, Energy, Control and Transmission Systems (ICPECTS), 2024, pp.1–6.[Online].Available: https://doi.org/10.1109/ICPECTS62210.2024.10780036
3. Y. A. Urrea, F. Y. Vivas, and O. M. Caicedo, "DSSAT: DSS Anthracnosis in Tomato Crops," in Proc. IEEE Int. Conf., 2018, pp. 1–6. [Online]. Available: https://doi.org/10.1109/IC.2018.68207
4. A. Gupta, L. K. Tyagi, and V. V. R. Rao M, "Potato Disease Detection using Deep Learning," Proc. 4th Int. Conf. Computation, Automation and Knowledge Management (ICCAKM), 2023, pp. https://doi.org/10.1109/ICCAKM58659.2023.10449500 1–7. Available:
5. N. Prakash, P. Anitha, M. Nethaji, R. Geetha, P. Kalyanasundaram, and J. K. Kanimozhi, "Optimized Crop Disease Segmentation with High Accuracy using Efficient U-Net," Proc. 8th Int. Conf. Trends in Electronics and Informatics (ICOEI), 2025,pp.1085–1092.Available: https://doi.org/10.1109/ICOEI65986.2025.11013455
6. M. Saraswat, A. Burri, S. Nagireddy, and N. Dasari, "Potato Disease Prediction using Deep Learning," in Proceedings of the 2025 3rd International Conference on Communication, Security, and Artificial Intelligence (ICCSAI), 2025, pp. 912–916. https://doi.org/10.1109/ICCSAI64074.2025.11063709
7. T. M. Geethajali, P. B., P. K. M., P. G. C. M., and Priyanka, "Agroinsights Chatbot: 19 AI-Driven Precision Farming for Optimal Yields, Crop Selection, and Disease-Free Harvests," 2024 IEEE North Karnataka Subsection Flagship International Conference (NKCon), 2024, pp. https://doi.org/10.1109/NKCon62728.2024.10774802 1–6, doi:
8. Y. Wu, B. Fregan, A. Nagy, K. Tak´acs-Gy¨orgy, and Z. Rajnai, "Quantum Machine Learning in Crop Disease Monitoring: Opportunities and Challenges to Practical

Implementation," 2025 12th International Conference on Computational Cybernetics and Cyber-Medical Systems (ICCC), Seychelles, Apr. 9–11, 2025, pp. 59– 64, doi: https://doi.org/10.1109/ICCC64928.2025.10999141

9. V. Gupta, J. MoolChandani, A. Saxena, and S. Kolhe, "A Review of Soybean Crop Classification and Disease Identification Using AI Learning and IoT-Based Model," 2024 15th International Conference on Computing, Communication and Networking Technologies (ICCCNT), IIT Mandi, Kamand, India, Jun. 24–28, 2024, pp. 1–8, doi: https://doi.org/10.1109/ICCCNT61001.2024.10726238
10. Singh, S., Prakash, P., Baghel, G., Singh, A., Raj, D., and Agrawal, A. K. (2024). Banana Crop Health: A Deep Learning-Based Model for Disease Detection and Classification. 2022 25th International Symposium on Wireless Personal Multimedia Communications https://doi.org/10.1109/wpmc63271.2024.10863138 (WPMC), 1–6.
11. K, L. J., M, K., C, P., V, S., and Department of Electronics and Communication Engineering, Sri Sairam Engineering College, Chennai, India. (2025). Automatic plant watering and disease https://doi.org/10.1109/ICCCT63501 detection system. IEEE Xplore.
12. Raman, R., Kumar, V., P, S. C., Rabadiya, D., Rastogi, S., and Kumbhojkar, N. (2025). Advancing tomato leaf hygiene with machine learning for enhanced plant health and productivity. IEEEXplore,1–6. https://doi.org/10.1109/iitcee64140.2025.10915494 20
13. Shahzore, U., Akbar, S., Shoukat, I. A., Rehman, A., Saba, T., and Sikder, T. (2025). A Vision Transformer-Based Framework for detection and Classification of soybean leaf diseases. International Conference on Data Science and Machine Learning Applications (CDMA), 138–143. https://doi.org/10.1109/cdma61895.2025.00029
14. Priya, L., Rajathi, G. I., and Vedhapriyavadhana. Crop Disease Detection and Monitoring System. International Journal of Recent Technology and Engineering (IJRTE), vol.8 (2277–3878), https://doi.org/10.35940/ijrte.D7857.118419 (2019). 21 D7857118419/2019©BEIESP.