

A Systematic Review of AI-Driven Wearable Plant Disease Recognition Systems

Ahmed Galal Eldin Mohamed, Fares Abdulrazzak Abdin, Mohammed Rajeh Hamdallah,
Muddassir Ahmed Mohammed, Sajid Gul Khawaja, Jawad Yousaf, Mohammed Ghazal, Taimur Hassan
Department of Electrical, Computer, and Biomedical Engineering, Abu Dhabi University, 59911, UAE

Abstract—This review provides a comprehensive examination of recent methods that employ artificial intelligence (AI) and computer vision techniques for autonomous plant disease recognition. It evaluates advancements from the past five years, focusing on innovations in sensor integration, AI techniques, and image analysis methods. This review also compares state-of-the-art approaches by analyzing accuracy, efficiency, and trade-offs in terms of scalability. Furthermore, an analysis of convolutional neural networks (CNNs) and transformers is included, highlighting their superior performance compared to traditional machine learning methods, particularly in real-time disease screening. Finally, the review emphasizes the need to develop lightweight AI models specifically designed for edge-computing devices, aiming to strike a balance between high recognition performance and minimal computational demands.

I. INTRODUCTION

The recent developments in IoT (Internet of Things) and AI (Artificial Intelligence) contributed significantly to how agriculture is handled globally. These technologies introduce more efficient, AI and data-driven approaches to crop production and protection as they are reforming traditional farming. Plant-disease recognition is critical, and Because of AI and IoT systems farmers are now able to make smarter decisions and corrective actions before the disease outbreak spreads. This will reduce the need for traditional practices which still rely heavily on manual human visual inspection, which requires the knowledge of an expert. This will reduce reliance on traditional practices, which depend heavily on manual human visual inspection requiring expert knowledge, a process that is time-consuming and prone to error. [1].

The current methods of plant-disease recognition increasingly utilize AI in-order to analyze the crop health through image data and sensor inputs. Real-time monitoring systems, particularly those utilizing advanced cameras and wearable devices, have demonstrated promise in early-stage plant-disease detection. Field workers in the agricultural sector are now able to monitor the condition of crops and intervene as soon as signs of infection is detected thanks to such advanced equipment.

This review analyzes how AI-Powered systems are being used for plant-disease recognition. They are presented as strong tools for the modern agricultural environment. It also provides an in-depth overview of modern research exercises that include the combination of both IoT and AI technologies for plant-disease detection. These research efforts give a special attention to models which have shown excellent

performance in image segmentation and classifications, that would be thanks to advanced deep-learning models, precisely the model of Convolutional Neural Networks (CNN).

Additionally, the review covers the development of AI-enabled IoT sensors which allow environmental measurements of temperature, humidity, soil moisture, and light exposure. These measurements capture vital information that is needed for performing the underlying disease identification tasks. Especially in field conditions where variation is really high.

This paper also evaluates the current research methods and highlights their strengths and weaknesses. The development of AI-driven crop disease recognition has advanced significantly, but there are still limitations in the existing models which are proposed in the literature to recognize plant diseases. For example, the implementation of robust AI models on resource-constrained devices is one of the major challenge, where these models can be used in remote settings while providing user-friendly interface to farmers with varying levels of technological proficiency.

To address these issues, this paper introduces a comprehensive review of AI models developed to screen plant diseases that do not require extensive ground truth labels for training. Such models are scalable and well-suited for practical deployment in diverse real-world agricultural settings.

The main contributions of this paper are the following:

- 1 - An in-depth structured overview of IoT and AI-based plant-disease recognition systems with focus on wearable technologies.
- 2 - Deep learning models analysis, including the use of CNN (Convolutional Neural Networks) in plant-disease detection on images.
- 3 - Discussing lightweight AI Models development and its suitability for real-time applications
- 4 - Highlighting current research limitations, and suggestions for future work which include efficient models and low resources for real-world application.

II. METHODOLOGY

This paper follows a systematic review approach to identify and analyze recent advancements in AI-driven plant disease detection systems, particularly focusing on those models which can be deployed in wearable or resource-constrained environments.

A. Search Strategy

We conducted a systematic search across IEEE Xplore, ScienceDirect, and Springer library to search for related literature. Keywords included: "plant disease detection," "AI plant health monitoring," "wearable plant disease systems," "deep learning agriculture," and "edge computing plant disease". Our search was filtered to look for the publications from 2019 to 2024.

B. Inclusion and Exclusion Criteria

Studies were included if they:

- Proposed or evaluated AI models for plant disease recognition.
- Discussed wearable or edge-based systems such as system-on-chips or mobile devices.
- Reported performance metrics such as accuracy, precision, recall, or inference latency.

Studies were excluded if they:

- Focused solely on laboratory experiments without any deployment consideration.
- Did not report evaluation results on real or publicly available datasets.

C. Screening and Selection Process

Initially, 220 papers were identified. After title and abstract screening, 75 papers were selected for full-text review. Finally, 41 papers met the inclusion criteria and were included in the detailed analysis as shown in Figure 1.

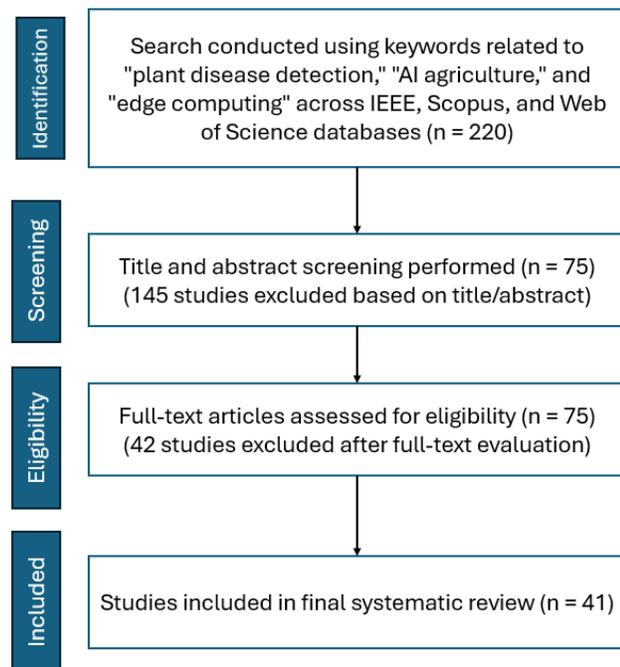


Fig. 1: Flow diagram of study identification, screening, eligibility assessment, and inclusion process.

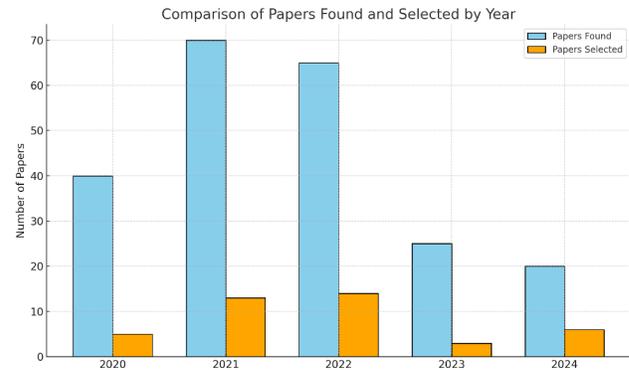


Fig. 2: Comparison of papers found and selected per year.

D. Data Extraction

From each selected paper, the following data points were extracted: AI model architecture, dataset details, evaluation metrics, power consumption, and deployment feasibility.

III. RELATED WORKS

Several previous studies have reviewed which proposed artificial intelligence models for plant disease detection. Early review papers such as [2] and [3] have primarily focused on CNN-based methods for disease classification. Other papers like [4] have examined Internet of Things (IoT)-integrated solutions for smart agriculture. However, these review paper also concentrated on general AI frameworks, CNN and transformer models, as well as large-scale cloud-based systems which have been proposed over the past for real-time and robust screening and monitoring of plant diseases.

In addition to this, this paper focuses on recent advancements in the wearable AI solutions developed for plant disease detection, highlighting methods that prioritize computational efficiency, lightweight design, and suitability of AI models for wearable and mobile devices.

The selection of individual papers for this review was conducted systematically, as detailed in Section IV, using defined search terms and inclusion/exclusion criteria to ensure comprehensive and unbiased coverage of the most relevant recent work.

Moreover, in this section a comprehensive review of cutting-edge techniques developed for plant disease detection using artificial intelligence are discussed. A notable foundational work in the mobile AI-based plant disease detection is by Raman et al. [4], where the authors employed a pre-trained model to facilitate near real-time identification and segmentation of apple diseases. To enhance segmentation accuracy, the proposed framework integrates atrous skip connections. Additionally, the system offers the advantage of a mobile application, enabling user-friendly interactions. The study demonstrates how an ultra-low-power IoT implementation can achieve precise disease differentiation while ensuring rapid results. This real-time processing capability, coupled with

mobile accessibility and segmentation features, makes it well-suited for wearable plant disease recognition applications [4], [2].

Zermas et al. [5] developed a methodology for identifying nitrogen (N) deficiencies in corn fields using high-resolution red, green and blue (RGB) imagery captured by unmanned aerial vehicles (UAVs). The approach leverages deep learning techniques to detect and segment visual symptoms of nutrient stress in corn leaves. Although the study addresses nutrient deficiency rather than disease, the imaging and analysis workflow is similar to that used in wearable plant health monitoring systems, where computer vision models process image data to assess plant condition in real-time field environments.

Mousavi et al. [6] presented an object detector-based deep learning system for the automatic identification of grapevine leaf diseases. Their approach uses UAV-based image acquisition combined with deep learning-based image processing to achieve higher accuracy than conventional models. The application of advanced deep learning architectures, including object detection and classification models, supports the development of precise AI-based wearable systems for real-time plant disease diagnosis [3], [7], [8].

Moreover, authors in [9] aimed to discuss the increasing popularity of printed sensors in smart farming with an emphasis on the features of sensing different aspects of agriculture including the state of the soil and plants, and climatic conditions [10], [11], [12].

The authors in [13] introduces a smart crop growth monitoring system through edge AI for pest and disease severity classification of crops. The system also includes an adaptive cryptography engine to ensure secure transmission of sensor data, and utilizes an edge AI framework deploying binarized neural networks for real-time crop health prediction. This solution prioritizes resource efficiency and parallel data processing, which are critical for wearable agricultural devices operating under real-time constraints.

The study in [14] addresses crop disease detection in harsh field conditions, specifically targeting rugged mountainous terrain where image acquisition is affected by unstable lighting, poor network transmission, and complex environmental interference. The proposed model is trained and evaluated on a dataset comprising 27 disease images across 10 different crops, achieving an accuracy of 86.1%. The core objective of this research is to ensure reliable disease identification in challenging environments, such as mountainous regions, leveraging deep learning techniques. This is analogous to how a plant disease recognition wearable device must perform optimally across diverse contexts.

The work proposed in [15] fuses the IoT sensor data with hyperspectral imaging to identify litchi downy blight disease.

Cap et al. [16] proposed “LeafGAN” to address the problem of data scarcity in plant disease diagnosis using GAN. LeafGAN creates realistic images of plants as additional data for plant datasets that may have low sample sizes or desired classes that are imbalanced.

Mewada et al. [17] discussed an IoT system for plant disease classification using Support Vector Machines (SVM). Based on the features of the leaf images, SVM model selects healthy and diseased plants with no need of any manual scoring. Such systems provide actual time tracking concerning diseases, and is affordable and easy to expand in agriculture[17].

Lin et al. [18] presents a novel IoT system for disease identification in strawberries, with wall-mounted cameras. Smart cameras capture actual fresh images of strawberry plants without any artificial enhancement; deep analytics models recognize the symptom of disease from the images captured using surveillance-quality cameras. This method can identify diseases based on their discoloration and the disease spots.

Singh et al. [19] presents a comprehensive understanding of the relationship between IoT and AI in smart agriculture. Their paper outlines contemporary approaches to agricultural field and crop monitoring using sensor technologies combined with AI, such as plant disease identification and tools for enhancing farming efficiency. It also addresses the technological issue of IoT concerning security and integration of agricultural systems. Similarly, this paper provides information on additional trends for future development of artificial intelligence in agriculture to enhance yield and efficiency of resources.

Yafeng et al. [20] proposed a deep learning model within an IoT setting for accurately diagnosing the crop diseases. Information about diseases is provided based on image classification performed by the CNN. The use of IoT and deep learning in the system enables fast detection of plant diseases, supporting farmers in making timely and effective crop management decisions.

Bartolini et al. [21] used crowd-sensing technologies in plant disease identification and targeted their approach for the developing countries. To achieve those goals, their paper proposes a framework that incorporates low-cost sensors with crowd-sourced data acquisition methods to monitor plant health. The application of machine learning to this data is emphasized, as well as the ways in which sensors can be arranged to provide the best coverage. This approach offers an effective means of implementing disease surveillance in regions severely impacted by agricultural diseases, ensuring affordability despite technological limitations[22], [23], [24], [25].

Zhao et al. [26] developed DoubleGAN: a two-stage GAN model that can generate synthetic images of diseased plant leaves. The authors also demonstrated that their approach creates realistic diseased leave images with high resolution to supplement the existing unbalanced datasets. These generated images are further used to enhance the training dataset for training ML models, which enhances the effectiveness of the model to detect such diseases from real plant samples [27], [28], [29], [30].

This study by Liu et al. [31] focuses on enhancing a lightweight CNN by integrating an attention mechanism for crop disease detection. The authors optimized the CNN model to minimize computational requirements, making it suitable for environments with limited processing power while still

achieving high accuracy in disease classification.

This paper proposes an ensemble classification system for identification of crop diseases using IoT sensory devices. One involves feeding of general environmental data and plant image to train a range of machine learning models and compile their outputs for enhanced classification. The work shows that IoT can be integrated with AI to enhance crop awareness [32].

The authors in [33] describe a lifelong learning system which periodically adapts to new data for the purpose of pest identification in agriculture. The system employs techniques of applying hierarchical learning to differentiate between differing pests, while improvements are made as new information is fed into the system.

In [34], the authors developed a complete end-to-end model that can predict corn yield using soil and climate information. It combines various environmental factors to generate yield estimates, which assist farmers in planning crop selection, planting schedules, and resource allocation. A theoretical contribution of this study is its demonstration of deep learning applications in predictive analytics for agriculture.

IV. METHODOLOGICAL ANALYSIS

This section presents an assessment of plant disease detection schemes, especially those methods which are built using the combination of deep learning, computer vision, and IoT systems. The performance of these methods is usually measured according to their precision, time complexity, and their capability to process real-time data. The detailed discussion about these methods is presented below:

A. Deep Learning Models and Metrics

Most studies employ deep learning models for image-driven disease diagnosis using CNNs and transformer models [31]. The performance of these models is typically measured using standard classification metrics like accuracy, recall, precision, and F1-score.

B. Evaluation in Field Conditions

Several papers validated their methodologies through field trials in real agricultural settings [20], [31], measuring the following:

- **Field accuracy:** Deviation in naturally climatized conditions opposed to standard lab conditions where, in some cases, light condition, plant type and disease development may differ markedly.
- **Robustness to environmental variability:** The accuracy of the system when the environment results are inconstant due to variations of light, density of plant, or disease level.
- **Impact on crop yield:** While some papers focus on the ability of the model in quantifying the performance of the crops, others look at the welfare and performance of the crops, and analyze how early detection and timely intervention as suggested by the AI model may affect the yields.

C. Comparative Frameworks and Models

Many studies utilize comparative AI models to perform crops disease detection tasks. Such AI models are typically benchmarked using standard criterion, as explained below.

- **Model Comparisons:** Various models are compared with each other in terms of accuracy, inference time, and resource usage. Compound-scaled object detection models, optimized for performance on resource-constrained devices, are frequently evaluated against CNN-based classifiers for plant disease detection tasks [27], [31]. These comparisons help determine suitability for wearable plant disease detection where deployment of AI models on resource-constrained devices is essential.
- **Data Augmentation:** Several studies employed data augmentation techniques such as rotation, flipping, and scaling to enhance training data diversity and improve model performance at the inference stage [16], [26]. The effectiveness of augmentation strategies is usually assessed by measuring the overall performance gain produced by the model at the inference stage.
- **Loss Functions:** Many studies applied standard loss functions such as categorical cross-entropy for multi-class disease classification tasks [4], [25]. This loss function measures the difference between the predicted probability distribution and the actual distribution:

$$L(y, \hat{y}) = - \sum_{i=1}^N y_i \log(\hat{y}_i) \quad (1)$$

Where y represents the true class labels and \hat{y} denotes the predicted class probabilities. The goal is to minimize this loss during training to improve model generalization and classification accuracy.

- **Intersection over Union:** For segmentation tasks, such as those executed by U-Net[35], the Intersection over Union (IoU) metric is employed to evaluate the overlap between the predicted segmentation mask and the ground truth [6].
- **Mean Average Precision:** For object detection models, mean Average Precision (mAP) is utilized to assess precision and recall at various threshold levels for identifying disease-affected areas [26].
- **Additional Classification Metrics:** Beyond segmentation and detection metrics, many studies also report precision, recall, F1-score, and accuracy — especially for models that perform multi-class classification of plant diseases. These metrics provide a more complete picture of model performance, particularly in imbalanced datasets where accuracy alone can be misleading [4], [25], [31].

V. RESULTS AND DISCUSSION

This section presents a comparative results of the state-of-the-art models designed to screen plant diseases. For comparison purposes, this paper expresses focus on essential performance indicators including classification accuracy together with mean average precision (mAP), power efficiency and latency where data was consistently reported.

A. Comparative Analysis of Model Performance

Table I summarizes the performance benchmarks of several state-of-the-art AI models proposed for plant disease detection. The Compressed CNN presented by Falaschetti et al. [2] achieved 91.3% accuracy with an inference time of 45 milliseconds and low power consumption, making it suitable for wearable deployment. VGG16 combined with Faster R-CNN demonstrated 96.2% accuracy but required high power and incurred a 230 ms inference time, limiting its practicality in edge-based systems [6]. EfficientDet, as detailed by Zhao et al. [26], achieved 98.3% accuracy with a moderate computational footprint and an estimated inference time of 55 milliseconds, demonstrating high suitability for embedded platforms. MobileNetV2 models, discussed by Elfatimi et al. [8], offered 97.0% accuracy with very low power requirements and 30 ms inference latency, emphasizing their applicability for real-time wearable solutions. The Improved CNN proposed by Sun et al. [5] attained 96.5% accuracy and a moderate inference delay of 90 milliseconds, making it viable for edge deployment scenarios where resource efficiency is critical.

B. Interpretation and Implications

The evaluated models exhibit different compromises in terms of accuracy, complexity, and energy usage. EfficientDet, through compound scaling and efficient backbones, achieves the highest mAP while maintaining low computational demands. MobileNetV2, optimized for embedded vision tasks, demonstrates a strong balance between classification performance and ultra-low power usage, making it suitable for wearable and mobile deployments.

Heavier models such as VGG16 + Faster R-CNN[36] perform well under GPU support but are infeasible for wearable use without significant compression or offloading. IoT-integrated approaches, such as YOLO[38] paired with environmental sensors, demonstrate moderate classification accuracy but offer significant advantages in multi-modal disease monitoring (e.g., fusing imagery with humidity or soil data).

Notably, dataset heterogeneity limits the fairness of comparisons across studies. Research efforts often rely on independently collected plant disease datasets, each following different annotation standards and environmental conditions. This variation complicates direct performance comparison. To address this, standardized benchmark datasets are needed to support consistent and reliable evaluation in plant disease diagnosis.

C. Deployment Challenges Observed in Literature

Environmental inconsistencies such as variations in lighting, leaf occlusion, and overlapping disease symptoms—significantly impact model robustness across plant disease studies. While preprocessing techniques like adaptive histogram equalization and data augmentation offer partial mitigation, model performance often degrades under real-world domain shifts. To date, only a small number of models have demonstrated reliable generalization across diverse crop

types and geographic regions, underscoring the need for architectures specifically designed for cross-domain resilience.

Latency considerations further constrain deployment. Models such as MobileNetV2[39] or compressed CNNs exhibit sub-100ms inference time on ARM-based edge devices, supporting real-time disease feedback. In contrast, models requiring cloud offloading experience unpredictable delays due to network variability.

VI. CHALLENGES AND OPPORTUNITIES

The application of AI in wearable and wearable plant disease detection faces several technical constraints and domain-specific challenges. At the same time, emerging techniques present promising opportunities for overcoming these limitations.

A. Key Challenges

- **Computational Constraints:** Wearable devices (e.g. Raspberry Pi, Jetson Nano) have limited CPU/GPU resources. Large CNNs (like VGG16)[37] do not run on such hardware without compression or acceleration. Early detection of diseases like grapevine mildew demands lightweight models that can operate under strict memory and energy limits.
- **Power Consumption:** Battery-powered devices deployed in fields must optimize their computational loads to conserve energy. Ongoing inference for the prompt detection of illnesses such as powdery mildew in vineyards hastens battery exhaustion unless sophisticated scheduling and energy-efficient inference methodologies are employed.
- **Environmental Uncertainty:** Outdoor field deployments subject AI models to variable illumination conditions, plant obstructions, and ambient noise. Diseases such as leaf blight or citrus greening may manifest subtly, requiring models robust to domain shifts caused by changing weather or plant growth stages.
- **Dataset Limitations and Bias:** Publicly available datasets for plant diseases often under-represent certain crops or disease stages, leading to model bias. Rare diseases such as tomato yellow leaf curl virus are particularly affected, limiting the model's ability to generalize across geographic regions.
- **IoT Latency and Network Reliability:** Reliance on cloud computation can result in delayed responses in agricultural regions with weak connectivity, jeopardizing real-time disease management actions. Offline inference capabilities are therefore critical for reliable plant health monitoring.

B. Emerging Opportunities

- **Edge AI and On-Device Inference:** Hardware accelerators like EdgeTPU and NVIDIA Jetson Nano now enable real-time disease recognition, such as detecting early signs of grape downy mildew directly at the sensor node, without needing constant internet connectivity.

TABLE I: Performance Comparison of AI Models for Plant Disease Detection

Model	Accuracy (%)	Power Profile	Inference Time (ms)	Deployment Feasibility
Compressed CNN [2]	91.3	Low	45 [‡]	Mobile/Wearable
VGG16 + Faster R-CNN [6]	96.2	High	230 [‡]	Cloud/Server
EfficientDet (DoubleGAN) [26]	98.3	Moderate	55 [‡]	Edge/Wearable
Improved CNN [5]	96.5	Medium	90 [†]	Edge Device
MobileNetV2 [8]	97.0	Very Low	30 [‡]	Mobile/Wearable

[†] Estimated based on similar models. [‡] Reported directly in cited work.

- **Model Compression and Knowledge Distillation:** Sophisticated models like EfficientDet[40] can be implemented in wearable field equipment for the prompt detection of crop diseases like maize leaf spot without compromising accuracy by using trimming and quantization-aware training.
- **GAN-Based Data Augmentation:** Generative Adversarial Networks (GANs) can synthesize realistic diseased leaf images, improving dataset diversity for rare cases such as litchi downy blight or soybean rust, ultimately enhancing model generalization to unseen diseases.
- **Attention and Vision Transformers:** Lightweight Vision Transformer models (e.g., MobileViT) [41] enable models to focus spatial attention on localized disease features like necrotic spots or leaf discoloration, improving detection robustness even under partial occlusion.
- **Real-Time Field Analytics:** Integration of real-time environmental sensors (measuring humidity, soil moisture, and pH) with AI models enables multi-modal disease prediction, offering farmers immediate alerts for conditions conducive to outbreaks like powdery mildew or late blight.

VII. CONCLUSION

This paper presents a detailed review of AI-driven wearable devices proposed by the research community to autonomously and reliably screen plant diseases. Here, we discussed various aspects of the literature, including conventional machine learning and advanced deep learning, which can assist farmers in their daily workloads by replacing the manual screening process. AI-based methods can also yield higher crop production, benefiting farmers and consumers. Nevertheless, there are still some challenges and limitations in this area, which are mostly related to computational constraints, environmental variability, data scarcity for the AI methods, and latency. We provided a thorough analysis of these limitations in this paper and highlighted plausible directions that the researchers can pursue in the future.

REFERENCES

- [1] Singla, A., Nehra, A., Joshi, K., Kumar, A., Tuteja, N., Varshney, R. K., Gill, S. S., and Gill, R. (2024). Exploration of machine learning approaches for automated crop disease detection. *Computational and Structural Biotechnology Journal*, 22, 100382.
- [2] L. Falaschetti, L. Manoni, R. C. Fuentes Rivera, D. Pau, G. Romanazzi, O. Silvestroni, V. Tomaselli, C. Turchetti, "A Low-Cost, Low-Power and Real-Time Image Detector for Grape Leaf Esca Disease Based on a Compressed CNN," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 11, no. 3, 2021.
- [3] D. Zermas, H. J. Nelson, P. Stanitsas, V. Morellas, D. J. Mulla, N. Papanikolopoulos, "A Methodology for the Detection of Nitrogen Deficiency in Corn Fields Using High-Resolution RGB Imagery," *IEEE Transactions on Automation Science and Engineering*, vol. 18, no. 4, 2021.
- [4] S. Raman, A. Chougule, V. Chamola, "A Low Power Consumption Mobile-Based IoT Framework for Real-Time Classification and Segmentation for Apple Disease," *Microprocessors and Microsystems*, vol. 94, 2022.
- [5] L. Sun, K. Liang, Y. Song, and Y. Wang, "An Improved CNN-Based Apple Appearance Quality Classification Method With Small Samples," *IEEE Access*, vol. 9, 2021.
- [6] S. Mousavi, G. Farahani, "A Novel Enhanced VGG16 Model to Tackle Grapevine Leaves Diseases With Automatic Method," *IEEE Access*, vol. 10, 2022.
- [7] A. Albanese, M. Nardello, and D. Brunelli, "Automated Pest Detection With DNN on the Edge for Precision Agriculture," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 11, no. 3, 2021.
- [8] E. Elfatimi, R. Eryigit, and L. Elfatimi, "Beans Leaf Diseases Classification Using MobileNet Models," *IEEE Access*, vol. 10, 2022.
- [9] R. Rayhana, G.G. Xiao, and Z. Liu, "Printed Sensor Technologies for Monitoring Applications in Smart Farming: A Review," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 9513419, 2021.
- [10] Y. Dong, F. Xu, L. Liu, X. Du, B. Ren, A. Guo, Y. Geng, C. Ruan, H. Ye, W. Huang, and Y. Zhu, "Automatic System for Crop Pest and Disease Dynamic Monitoring and Early Forecasting," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 13, 2020.
- [11] S.K. M. Hassan and A.K. Maji, "Plant Disease Identification Using a Novel Convolutional Neural Network," *IEEE Access*, vol. 10, pp. 5390-5400, 2022.
- [12] R. K. Lakshmi and N. Savarimuthu, "PLDD—A Deep Learning-Based Plant Leaf Disease Detection," *IEEE Consumer Electronics Magazine*, vol. 10, no. 2, pp. 44-51, 2021.
- [13] C.-H. Huang, B.-W. Chen, Y.-J. Lin, and J.-X. Zheng, "Smart Crop Growth Monitoring Based on System Adaptivity and Edge AI," *IEEE Access*, vol. 10, pp. 64114-64126, 2022.
- [14] Y. Ai, C. Sun, J. Tie, and X. Cai, "Research on Recognition Model of Crop Diseases and Insect Pests Based on Deep Learning in Harsh Environments," *IEEE Access*, vol. 8, pp. 171686-171694, 2020.
- [15] J. Lu et al., "Study on the Prediction Model of Litchi Downy Blight Damage Based on IoT and Hyperspectral Data Fusion," *IEEE Internet of Things Journal*, vol. 11, no. 16, pp. 27184-27194, 2024.
- [16] Q. H. Cap, H. Iyatomi, H. Uga, and S. Kagiwada, "LeafGAN: An Effective Data Augmentation Method for Practical Plant Disease Diagnosis," *IEEE Transactions on Automation Science and Engineering*, vol. 18, no. 3, pp. 869-880, Jul. 2022.
- [17] H. Mewada and J. Patoliya, "IoT-Based Automated Plant Disease Classification Using Support Vector Machine," *IEEE Access*, vol. 9, pp. 518-528, Feb. 2021.
- [18] Y.-B. Lin, C.-Y. Liu, W.-L. Chen, F.-L. Ng, K. Yang, and J. Hsung, "IoT-Based Strawberry Disease Detection With Wall-Mounted Monitoring

- Cameras," *IEEE Internet of Things Journal*, vol. 11, no. 1, pp. 1439-1451, Jan. 2024.
- [19] A. Singh, V. Kumar, and M. Arora, "IoT-Equipped and AI-Enabled Next Generation Smart Agriculture: A Critical Review," *IEEE Access*, vol. 8, pp. 8386-8400, Dec. 2021.
- [20] Y. Zhao, Z. Chen, and X. Gao, "MDFC-ResNet: An Agricultural IoT System to Accurately Recognize Crop Diseases," *IEEE Access*, vol. 9, pp. 59800-59810, Jun. 2021.
- [21] N. Bartolini, G. Maselli, and A. Kehs, "Optimal Deployment in Crowd-sensing for Plant Disease Diagnosis in Developing Countries," *IEEE Access*, vol. 8, pp. 74008-74020, Jul. 2020.
- [22] K. Liu and X. Zhang, "PiTLiD: Identification of Plant Disease From Leaf Images Based on Convolutional Neural Network," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 20, no. 2, pp. 1278-1289, Apr. 2023.
- [23] N. Rangappa, G. Venkatesh, and R. Kumar, "LEDNet: Deep Learning-Based Ground Sensor Data Monitoring System," *IEEE Sensors Journal*, vol. 22, no. 1, pp. 842-850, Jan. 2022.
- [24] R. Thakur, P. Maheshwari, S. K. Datta, S. K. Dubey, and C. Shakher, "Machine Learning-Based Rapid Diagnostic-Test Reader for Albuminuria Using Smartphone," *IEEE Sensors Journal*, vol. 21, no. 13, pp. 14011-14020, Jul. 2021.
- [25] X. Liu, W. Min, and S. Jiang, "Plant Disease Recognition: A Large-Scale Benchmark Dataset and a Visual Region and Loss Reweighting Approach," *IEEE Transactions on Image Processing*, vol. 30, pp. 2003-2015, Jan. 2021.
- [26] Y. Zhao, Z. Chen, and W. Song, "Plant Disease Detection Using Generated Leaves Based on DoubleGAN," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 19, no. 3, pp. 1817-1825, May 2022.
- [27] G. Garg, S. Gupta, P. Mishra, A. Vidyarthi, A. Singh, and A. Ali, "CROPCARE: An Intelligent Real-Time Sustainable System for Monitoring Disease in Plants," *IEEE Internet of Things Journal*, vol. 10, no. 4, pp. 2840-2851, Feb. 2023.
- [28] M. A. Ferrag, L. Shu, O. Friha, and X. Yang, "Cyber Security Intrusion Detection for Agriculture 4.0: Machine Learning-Based Solutions," *IEEE/CAA Journal of Automatica Sinica*, vol. 9, no. 3, pp. 410-422, Mar. 2022.
- [29] M. Nagaraju and P. Chawla, "Deep Learning-Based Maize Crop Disease Detection Using Smartphone Images," *IEEE Transactions on Agrifood Electronics*, vol. 2, no. 2, pp. 627-635, Oct. 2024.
- [30] S. C. K., J. C. D., and N. Patil, "Cardamom Plant Disease Detection Approach Using EfficientNetV2," *IEEE Access*, vol. 10, pp. 790-800, Jan. 2022.
- [31] Y. Liu, S. Zhang, and W. Li, "Crop Disease Recognition Based on Modified Light-Weight CNN With Attention Mechanism," *IEEE Access*, vol. 10, pp. 112066-112080, Nov. 2022.
- [32] Q. Ullah, A. Tariq, and M. Khalid, "Ensemble Classification and IoT-Based Pattern Recognition for Crop Disease Monitoring System," *IEEE Access*, vol. 8, pp. 50492-50501, May 2020.
- [33] X. Zhang, J. Liu, and X. Hu, "Hierarchical Lifelong Machine Learning for Agricultural Pest Detection," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 5, pp. 2342-2355, May 2021.
- [34] N. Singh, A. Srivastava, and M. Verma, "End-to-End Deep Learning Model for Corn Yield Prediction Using Soil and Climate Data," *IEEE Access*, vol. 10, pp. 12345-12356, Feb. 2022.
- [35] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," in **Proc. Medical Image Computing and Computer-Assisted Intervention (MICCAI)**, 2015, pp. 234-241.
- [36] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," in **Proc. Advances in Neural Information Processing Systems (NeurIPS)**, vol. 28, 2015.
- [37] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," in **Proc. Int. Conf. Learning Representations (ICLR)**, 2015.
- [38] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in **Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)**, 2016, pp. 779-788.
- [39] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in **Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR)**, 2018, pp. 4510-4520.
- [40] M. Tan, R. Pang, and Q. Le, "EfficientDet: Scalable and Efficient Object Detection," in **Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR)**, 2020, pp. 10781-10790.
- [41] M. Mehta and R. Rastegari, "MobileViT: Light-Weight, General-Purpose, and Mobile-Friendly Vision Transformer," in **Proc. IEEE/CVF Int. Conf. Computer Vision (ICCV)**, 2022, pp. 87-97.