International Journal of Advanced Research and Interdisciplinary Scientific Endeavours, Vol. 3(4), 2025
DOI: 10.61359/11.2206-2554

A Review of Fruit Disease Detection Using Deep Learning Models: Trends, Challenges, and Future Direction

D. Sujatha*, Dr. R. Sornakeerthi†, Dr.Sithishameem Fathima ‡

Email Correspondence*: ssujatha8476@gmail.com.

[1] Assistant Professor, Department of CSE, SRRCET.

[2] Assistant Professor, Department of ECE, UCE, Ramanathapuram.

[3] Associate Professor, Department of CSE, Syed Ammal Engineering College.

Abstract:

Fruits are the important nutrition in human life. Different diseases occur in the Fruit quality that affect the economic growth. Disease detection is important for ensuring crop health, yield, and food security. Traditional methods rely on manual inspection, which is time- consuming and error-prone. Deep learning (DL) models are the powerful tool for identifying disease in various fruits. Convolutional Neural Networks (CNNs) are highly effective for detecting and classifying fruit diseases using image data, offering automated, accurate, and scalable solutions for agricultural diagnostics. Fruit disease dataset such as Kaggle for classification and roboflow dataset for identifying the disease in fruits. There are so many Challenges that include restricted data diversity, poor generalization, and lack of interpretability. Future directions for identifying fruit diseases using deep learning include explainable AI, multimodal data fusion, and real-time mobile deployment. This review aims to guide future research toward robust, scalable, and interpretable solutions.

Keywords: Deep Learning, Fruit Disease, Convolution Neural Network, Agriculture.

1. Introduction

Fruit is an important crop of agriculture, providing significantly to food supply, nutrition, and economic stability. Fruit diseases are caused by fungi, bacteria, viruses, and environmental stressors. These diseases can lead to, reduced fruit quality, substantial yield losses and increased production costs, posing a serious threat to farmers and food security. Historically, fruit disease are inspected and detected by experts or farmers, which is time-consuming, labor-intensive, and often inaccurate due to human error and limited expertise. Laboratory- based diagnostic methods, while more precise, are expensive and not feasible for large-scale or real-time monitoring in the field. The dawn of deep learning (DL), a subset of artificial intelligence (AI), has revolutionized the field of computer vision and pattern recognition. Deep Learning models, particularly Convolutional Neural Networks (CNNs), have exceptional performance in image classification tasks, making them ideal for identifying the symptoms of fruit diseases from fruit images. This paper presents a comprehensive review of recent advancements in DL-based fruit disease detection. It explores the evolution of model architecture, the role of transfer learning, the availability and limitations of datasets, and the integration of DL into real-world agricultural systems. The review also identifies key

*Assistant Professor, Department of CSE, SRRCET.
†Assistant Professor, Department of ECE, UCE, Ramanathapuram.
‡Associate Professor, Department of CSE, Syed Ammal Engineering College.

Article Timeline: Received: Dec 09, 2025; **Revised:** Dec 11, 2025; **Accepted:** Dec 12, 2025; **Published:** Dec 12, 2025

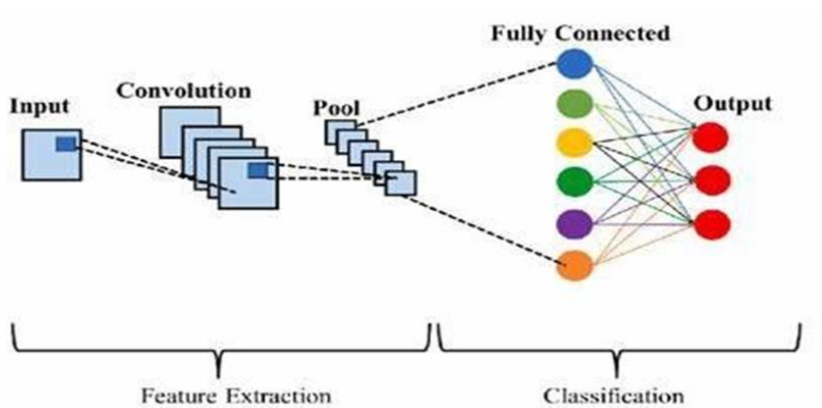
challenges, such as data scarcity, model generalizatpropose interpretability, and proposes future research directions to enhance the robustness, scalability, and usability of DL models in diverse farming environment. By synthesizing current research trends and highlighting gaps, this paper aims to support researchers, agronomists, and technologists in developing intelligent, accessible, and sustainable solutions for fruit disease management. The ultimate goal is to empower farmers with real-time, accurate tools that reduce crop loss, improve productivity, and promote resilient agricultural practices.

2. Trends in Deep Learning for Fruit Disease Detection

Deep learning has rapidly transformed the landscape of fruit disease detection, offering scalable, accurate, and automated solutions. This section explores the key technological and methodological trends shaping the field.

A. Convolutional Neural Networks (CNNs)

CNNs are the backbone of image-based fruit disease detection. Their ability to extract hierarchical features from images makes them ideal for identifying disease symptoms such as spots, discoloration, and texture changes. The use of CNN algorithms facilitates the detection of the disease on fruits and aids in the classification of diseased versus healthy fruits. CNNs detect low-level features (edges, textures) in early layers and high-level features (spots, lesions, discoloration) in deeper layers. By preserving spatial relationships through convolution and pooling, CNNs can localize disease symptoms on fruit surfaces. CNNs handle variations in lighting, angle, and background, making them reliable across diverse image datasets.

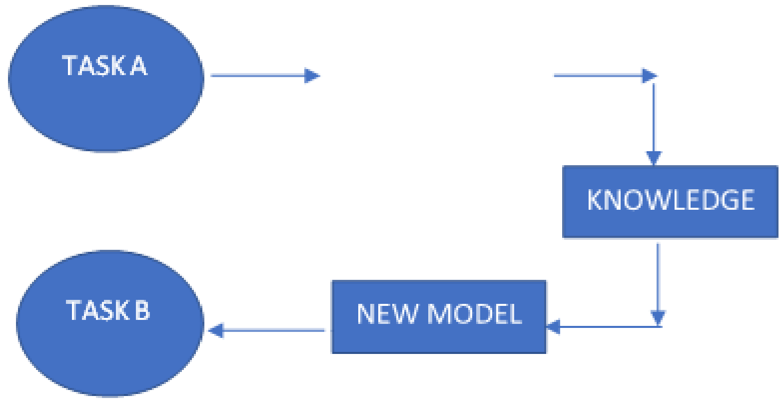


- **Input Layer**: Accepts fruit images, typically resized to a standard dimension (e.g., 128×128 or 224×224 pixels).
- **Convolutional Layers**: Apply filters to extract features like color changes, texture irregularities, and shape distortions.
- **Pooling Layers**: Reduce dimensionality while retaining essential features, improving computational efficiency.
- **Fully Connected Layers**: Interpret extracted features to classify the image into categories (e.g., healthy, anthracnose, powdery mildew).
- **Output Layer**: Uses softmax or sigmoid activation to predict the disease class.

CNN’s can identify a wide range of visual symptoms on fruits such as spots, discoloration and texture changes. It Processes thousands of images rapidly, enabling real-time disease monitoring. CNN achieves high classification accuracy (often above 90%) when trained on quality datasets.it can be deployed in mobile apps or drones for large-scale agricultural monitoring.

B. Transfer Learning

Transfer learning is a machine learning technique where a model trained on one task is repurposed as the foundation for a second task. This approach is beneficial when the second task is related to the first or when data for the second task is limited.



Transfer learning has become a powerful approach in fruit disease detection, especially when labeled data is limited. It involves using pre-trained deep learning models such as AlexNet, ResNet50, VGG16, InceptionV3, and MobileNetV2, which have been trained on large-scale datasets containing millions of images across thousands of categories. These models have already been learned to extract general features such as edges, textures, and shapes, which are transferable to new tasks. In the context of fruit disease detection, the early layers of these models are typically frozen to retain their learned features, while the final layers are replaced and fine- tuned using fruit-specific disease datasets. This process allows the model to adapt to identifying symptoms such as leaf spots, discoloration, mold, and surface lesions with high accuracy. ResNet50 is often favored for its deep architecture and skip connections that prevent vanishing gradients, while MobileNetV2 is ideal for mobile and edge deployment due to its lightweight design. InceptionV3 excels at multi-scale feature extraction, and VGG16 offers a straightforward yet effective baseline. By leveraging these models, researchers and developers can build efficient, accurate, and scalable solutions for automated fruit disease diagnosis, enabling real-time monitoring and decision-making in agricultural settings. Pre-trained models like ResNet50, VGG16, InceptionV3, and MobileNetV2 are widely adopted. These models, trained on large datasets like ImageNet, are fine-tuned on fruit disease datasets to achieve high accuracy with limited data.

C. Hybrid and Ensemble Models

Researchers are increasingly combining CNNs with other architectures such as Recurrent Neural Networks (RNNs), attention mechanisms, and transformers to improve performance. Ensemble learning, which aggregates predictions from multiple models, enhances robustness and reduces overfitting. Hybrid and ensemble models are increasingly being adopted in fruit disease detection to enhance accuracy, robustness, and generalization. CNNs excel at extracting spatial features from fruit images, while RNNs are effective at modeling sequential dependencies, which can be useful in analyzing time-series data or image sequences. Attention mechanisms help the model focus on the most relevant regions of an image, such as diseased spots or lesions, improving interpretability and precision. Transformers, particularly Vision Transformers (ViTs), bring global context awareness and have shown promising results when integrated with CNNs. Ensemble learning, on the other hand, aggregates predictions from multiple models, such as different CNN architectures or hybrid models using techniques like bagging, boosting, or voting. This approach reduces overfitting and improves generalization by leveraging the strengths of diverse models. In practice, these advanced strategies have led to more reliable and scalable systems for automated fruit disease diagnosis, especially in real-world agricultural environments where data variability and noise are common.

3. Dataset Utilization

Public data set: There are several publicly available datasets that support fruit disease detection using deep learning. One widely used resource is the Fruits Diseases Classification Dataset on Kaggle, which includes images of apples, guavas, mangoes, and pomegranates categorized into 17 classes representing various diseases and healthy conditions. Another valuable dataset is the Fruit Disease Detection Dataset hosted on Roboflow, offering labeled images suitable for object detection tasks with 29 disease types such as anthracnose, rust, rot, scab, and mildew. These datasets are structured to facilitate training of CNNs, transfer learning models, and hybrid architectures for accurate classification and localization of fruit diseases. Additionally, GitHub repositories like the Fruit Infection Disease Dataset provide access to curated image collections focused on surface abnormalities, supporting experimentation with preprocessing techniques and custom model designs. These resources are instrumental for researchers and developers aiming to build robust, scalable solutions for automated fruit disease diagnosis in agricultural applications.

Custom and Field-Collected Datasets: Custom and field datasets play a crucial role in developing robust fruit disease detection models, especially when publicly available datasets are insufficient or lack specific regional relevance. These datasets are typically collected directly from orchards, farms, or agricultural research stations using cameras, smartphones, or drones under real-world conditions. They capture a wide range of environmental variations such as lighting, background clutter, and natural disease progression, which enhances the model's ability to generalize. Custom datasets are often annotated manually by agricultural experts to ensure accurate labeling of disease types and severity levels. Field data also allows for the inclusion of metadata like GPS coordinates, time of capture, and weather conditions, which can be valuable for context-aware disease prediction. By training models on such datasets, researchers can develop highly tailored solutions that reflect the actual challenges faced by farmers in specific regions or crop systems. To address real-world variability, researchers are creating custom datasets with images captured under diverse lighting, backgrounds, and environmental conditions. This helps improve model generalization.

4. Data Preprocessing and Augmentation

Data preprocessing and augmentation are critical steps in preparing fruit images for disease detection using deep learning models. Preprocessing involves resizing images to a consistent dimension, normalizing pixel values to a standard range, and removing noise to enhance visual clarity. Techniques such as color space conversion and segmentation help isolate the fruit from the background, allowing the model to focus on relevant features like spots, lesions, and discoloration. Augmentation, on the other hand, artificially expands the dataset by generating modified versions of existing images through rotation, flipping, zooming, cropping, and brightness adjustments. These transformations simulate real-world variations in lighting, orientation, and scale, helping the model generalize better and reducing the risk of overfitting. Together, preprocessing and augmentation improve the accuracy, robustness, and efficiency of CNN-based models, especially when working with limited or imbalanced datasets.

5. Deployment Platforms

Deployment platforms for fruit disease detection models are broadly categorized into mobile/edge devices and cloud-based systems, each serving distinct operational needs. Mobile and edge deployment leverages lightweight deep learning models such as MobileNet and EfficientNet, which are specifically optimized for low-power, resource-constrained environments like smartphones, tablets, and IoT devices. These models enable real-time disease detection directly in the field, allowing farmers to capture images of fruits and receive instant diagnostic feedback without needing internet connectivity. This on-device intelligence is crucial for remote or rural areas with limited network access. On the other hand, cloud-based systems provide scalable infrastructure for large-scale agricultural monitoring. These platforms can handle high volumes of image data, perform intensive computations, and integrate seamlessly with farm management systems for centralized decision-making. Cloud solutions also support continuous model updates, data analytics, and integration with satellite or drone imagery, making them ideal for commercial farms and agricultural research institutions. Together, these deployment strategies ensure that fruit disease detection tools are accessible, efficient, and adaptable across a wide range of agricultural contexts.

6. Performance Metrics and Evaluation

Accuracy, Precision, Recall, F1-Score These metrics are standard for evaluating classification performance. Confusion matrices and ROC curves are also used for deeper analysis.

Accuracy Measures the proportion of correctly classified images out of the total samples.

Accuracy =(True Positives + True Negatives) / Total Samples

Precision Indicates how many predicted disease cases are actually correct. Precision= True Positives / (True Positives + False Positives)

Recall (Sensitivity) Measures how well the model identifies actual disease cases.

Recall =True Positives / (True Positives + False Negatives)

F1-Score Harmonic mean of precision and recall, balancing both metrics. F1-score= 2 × (Precision × Recall) / (Precision + Recall)

Confusion Matrix A confusion matrix for fruit disease detection provides a detailed breakdown of how well a model classifies each disease type, showing true positives, false positives, false negatives, and true negatives across all categories. It helps identify which diseases are often misclassified and guides model improvement.

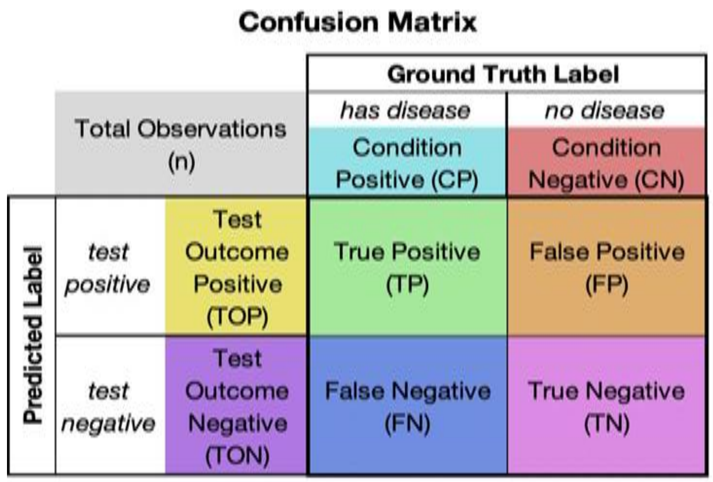


Figure 1: Basic colour coded confusion matrix with marginal sums

Performance Metrics For CNN

FRUIT DISEASE	PRECISION	RECALL	F1SCORE	SUPPORT	
Apple Scab	0.93	0.90	0.91	60	
Mango Anthracnose	0.95	0.96	0.96	210	
Banana Sigatoka	0.91	0.89	0.9 0	180	**Overall Accuracy 94.2%**
Grape Black Rot	0.88	0.86	0.87	70	
Orange Canker	0.92	0.93	0.93	110	
Tomato Early Blight	0.90	0.92	0.91	90	
Healthy Fruits	0.97	0.98	0.9 7	490	

Cross-validation and Real-world testing: Cross-validation and real-world testing are essential components in evaluating the reliability and practical effectiveness of fruit disease detection models. K-fold cross-validation is a statistical technique used to assess model performance by dividing the dataset into K equal parts, or "folds." The model is trained on K-1 folds and tested on the remaining fold, repeating this process K times so that each fold serves as a test set once. This method provides a more robust estimate of model accuracy, reduces bias, and ensures that the model generalizes well across different subsets of data. It is particularly useful when working with limited datasets, as it maximizes the use of available data for both training and validation. Real-world testing, on the other hand, involves deploying the trained model in actual agricultural environments to evaluate its performance under practical conditions. This includes assessing how well the model handles variations in lighting, background clutter, fruit orientation, and disease severity that are common in field settings. Field trials help identify limitations that may not be apparent during lab-based testing and provide insights into user experience, response time, and diagnostic accuracy. Together, cross-validation and real-world testing ensure that fruit disease detection models are not only statistically sound but also effective and reliable in real-world agricultural applications.

E-ISSN: 3048-7021 (Online)

7. Emerging Trends

A. Explainable AI (XAI)

Deep learning models are often criticized for being "black boxes," making it difficult to understand how they arrive at decisions. XAI tools like Grad-CAM (Gradient-weighted Class Activation Mapping) and LIME (Local Interpretable Model-agnostic Explanations) address this by visualizing which parts of an image influenced the model's prediction. For example, Grad-CAM highlights regions of a fruit image, such as spots or lesions, that the model considers important for classifying a disease. This not only builds trust among users but also helps researchers validate and refine model behavior. Recent studies like DBA-ViNet and multispecies frameworks have successfully integrated XAI to improve interpretability in fruit disease classification. Tools like Grad-CAM and LIME are used to visualize model decisions, making DL systems more transparent and trustworthy.

B. Few-Shot and Zero-Shot Learning

Traditional deep learning models require large amounts of labeled data, which is often unavailable for rare or emerging fruit diseases. Few-Shot Learning enables models to learn from just a handful of examples, while Zero-Shot Learning allows classification of diseases the model has never seen before by leveraging semantic relationships or textual descriptions. These approaches are particularly valuable in agricultural settings where new diseases may appear suddenly, and labeled data is scarce. They also reduce the cost and time required for dataset collection and annotation, making AI more accessible to small-scale farmers and researchers.

C. Multimodal Learning

Fruit disease detection is increasingly moving beyond image-only models. Multimodal learning combines visual data with other sources such as environmental sensor readings, weather conditions, and soil health metrics to provide a more holistic understanding of disease risk. For instance, a model might use leaf images along with humidity and temperature data to predict fungal infections more accurately. This integrated approach improves prediction accuracy and enables proactive disease management. A recent study published in Applied Fruit Science demonstrated the effectiveness of multimodal image fusion for early detection across multiple fruit species Combining image data with environmental sensors, weather data, and soil conditions for holistic disease prediction.

8. Challenges in Deep Learning for Fruit Disease Detection

Despite significant progress in deep learning (DL) for fruit disease detection, several critical challenges continue to hinder its widespread adoption and real-world effectiveness. One major issue is the limited availability of high-quality, annotated datasets for specific fruit species and diseases. Many existing datasets are small, synthetic, or collected under controlled conditions, lacking the diversity in lighting, background, fruit maturity, and environmental variability needed for robust model generalization. Class imbalance is another concern, as some diseases are overrepresented while others are rare, leading to biased models that struggle with underrepresented classes. DL models also face generalization and robustness issues, often performing well on training data but failing to adapt to unseen field conditions due to overfitting and environmental noise such as shadows, occlusions, and overlapping fruits. Cross-domain adaptability remains limited, with models trained in one fruit type or region requiring retraining to perform well elsewhere. Computational constraints further complicate deployment, as high-performing models like ResNet and DenseNet demand significant resources, making them unsuitable for low-power devices like smartphones or drones. Achieving real-time inference with high accuracy is especially challenging in remote or resource-limited settings. The lack of explainability in DL models, often perceived as black boxes, undermines user trust, particularly among farmers and agronomists who need transparent decision-making tools. Annotation and labeling also pose difficulties, requiring expert input that is time- consuming and costly, with potential subjectivity leading to noisy labels. Real-world deployment faces barriers such as poor internet connectivity in rural areas, the need for user-friendly interfaces for non-technical users, and ongoing maintenance to keep models updated with new disease patterns. Ethical and privacy concerns also arise, as farmers may be reluctant to share crop images due to fears of data misuse or lack of control, and models trained on region-specific data may inadvertently introduce bias, affecting fairness and inclusivity in agricultural AI solutions.

9. Future Direction

As deep learning continues to advance, its application in fruit disease detection holds transformative potential for agriculture. To move from experimental success to real-world impact, future research must address current limitations and embrace innovative strategies. Data-centric innovations such as synthetic data generation using Generative Adversarial Networks (GANs) can enrich training datasets with realistic disease images, especially for rare or emerging conditions. Few-shot and zero-shot learning approaches will empower models to recognize new diseases with minimal or no labeled examples, enhancing adaptability in dynamic environments. Multimodal data fusion integrating image data with environmental sensors, weather patterns, and satellite imagery can offer a comprehensive view of plant health and improve diagnostic precision. On the deployment front, lightweight architectures like MobileNet, EfficientNet, and TinyML variants will enable real-time disease detection on mobile and edge devices, while federated learning will allow decentralized model training across farms, preserving data privacy. Continual and lifelong learning will ensure models evolve with seasonal changes and emerging disease patterns. To foster trust, explainable AI techniques such as Grad-CAM, SHAP, and LIME will make model decisions transparent, and human-in-the-loop systems will refine predictions through expert feedback. Ecosystem integration is also vital, with DL-based disease detection becoming part of smart farming platforms that coordinate irrigation, fertilization, and pest control. Collaboration with agricultural extension services and policymakers will ensure these tools are accessible and aligned with local practices. Finally, sustainability and ethics must be prioritized through bias mitigation training models on diverse datasets and open-source collaboration to democratize access and accelerate innovation in agricultural AI.

10. Conclusion

The future of fruit disease detection through deep learning is set to revolutionize precision agriculture by addressing current limitations and embracing innovative solutions. Data-centric advancements such as synthetic data generation using GANs will enrich training datasets, especially for rare diseases, while few-shot and zero-shot learning will enable models to recognize unfamiliar diseases with minimal labeled data. Multimodal fusion of image data with environmental sensors and satellite imagery will provide a holistic view of plant health, enhancing diagnostic accuracy. Model optimization through lightweight architectures like MobileNet and EfficientNet will support real-time deployment on mobile and edge devices, and federated learning will allow decentralized training across farms while preserving data privacy. Continual learning frameworks will ensure models adapt over time to seasonal changes and evolving disease patterns. Explainable AI techniques like Grad-CAM, SHAP, and LIME will make model decisions transparent, fostering trust among users, while human-in-the-loop systems will integrate expert feedback to refine predictions. Integration into smart farming platforms will link disease detection with broader farm management systems, and collaboration with policymakers will ensure accessibility and alignment with local practices.

Ethical considerations such as bias mitigation and open-source collaboration will promote fairness and accelerate innovation, ultimately leading to intelligent, inclusive, and sustainable agricultural ecosystems.

6. References

[1] Dasari Savith, Adusumalli Sai Lochan, & Kandula Shivani. (2025). Detection and classification of fruit diseases by using deep learning algorithm. Vol. 8(3).

[2] Saravanan Srinivasan, Lalitha Somasundaram, Sukumar Rajendran, Virendra Paul Singh, Sandeep Kumar Mathivannan, & Usha Moorthy. (2025). DBA-ViNet: An effective deep learning framework for fruit disease detection using explainable AI. BMC Plant Biology, 25(1), 965. https://doi.org/10.1186/s12870-025-07015-6

[3] Parmar, P. J., & Shrimali, M. (2024). Identification of fruit severity and disease detection using deep learning. Vol. 12(12S), 288–295.

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

[5] Tan, M., & Le, Q. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. In Proceedings of ICML (pp. 6105–6114).

[6] Naveen, J., & Bhat, M. S. P. (2025). AI in agriculture: A review of deep learning-based crop disease detection. Vol. 14(8). https://doi.org/10.17148/IJARCCE.2025.14829

[7] Upadhyay, A., Chandel, N. S., Singh, K. P., & Rani, P. (2025). Deep learning and computer vision in plant disease detection: A comprehensive review of techniques, models, and trends in precision agriculture. Artificial Intelligence Review.

[8] Kale, D. R., Mane, T. S., Buchade, A., Patel, P. B., Wadhwa, L. K., & Pawar, R. G. (2025). Federated learning for privacy-preserving fruit disease detection. IEEE Xplore.

[9] Rani, R., & Kumar, G. R. (2025). Automated guava disease detection using fine-tuned MobileNet for improved agricultural productivity. IEEE Xplore.

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

[11] Liu, J., & Wang, X. (2021). Plant diseases and pests detection based on deep learning: A review. Plant Methods, 17(1), 22.

[12] Fuentes, A., Yoon, J., Park, S., & Lee, D. (2019). A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Computers and Electronics in Agriculture, 161, 9–24.

[13] Li, G., Zhang, F., Zhang, C., & Huang, Q. (2023). PMVT: A lightweight vision transformer for plant disease identification on mobile devices. Frontiers in Plant Science, 14, 1256773.

[14] Khan, F., Muhammad, A., & Ali, M. (2023). A mobile-based system for maize plant leaf disease detection and classification using deep learning. Frontiers in Plant Science, 14, 1079366.

[15] Khattak, A., Asghar, M. U., Batool, U., Asghar, M. Z., Ullah, H., Al-Rakhami, M., & Gumae, A. (2021). Automatic detection of citrus fruit and leaves diseases using deep neural network model. IEEE Access, 9.

[16] Rehman, M. Z. U., Ahmed, F., Khan, M. A., Tariq, U., Jamal, S. S., Ahmad, J., & Hussain, I. (2022). Classification of citrus fruit diseases using deep transfer learning. Computers, Materials & Continua. https://doi.org/10.32604/cmc.2022.019046

7.Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

8.Funding

No external funding was received to support or conduct this study.