# RECENT ADVANCES IN DEEP LEARNING-BASED APPROACHES FOR PLANT DISEASE DETECTION

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***Plant diseases threaten global food security by causing substantial crop losses. Manual inspection is time-consuming and error-prone, motivating automated image-based diagnosis. Recent research has leveraged advanced ML/DL techniques – from traditional classifiers (SVM, RF, KNN) to deep models (CNNs, DBNs, RNNs) and modern architectures (transfer learning with ResNet/VGG/EfficientNet, Vision Transformers, attention-based networks) – to improve detection accuracy and speed. For example, deep CNNs fine-tuned on large leaf-image datasets often achieve ≥98% accuracy, far exceeding classical ML methods that rely on handcrafted features. Key findings include effective feature learning by CNNs and ViTs, and hybrid models that incorporate attention or RNN components for better localization. However, challenges remain: DL models require large, diverse datasets; they can overfit to background or lab conditions. Future directions emphasize lightweight edge deployment (e.g. on smartphones or drones), data-efficient learning (few-shot, self-supervised), multimodal sensing (RGB+NIR), federated model training for privacy, and explainable AI to assist farmers. This survey reviews recent ML/DL advances in plant disease detection, summarizing methodologies, datasets, evaluation criteria, and outlooks for practical deployment.***

***Keywords: Plant disease detection; Deep learning; Convolutional neural networks (CNNs); Vision Transformers (ViTs); Transfer learning; Edge computing; Explainable AI (XAI).***

## Introduction

Plant health is critical for agriculture and food security. Undetected diseases can devastate yields – current estimates attribute **30–40%** of crop losses to pathogens[1]. For example, one review notes that hundreds of millions face hunger partly due to such losses. Traditionally, disease diagnosis relies on expert inspection and lab tests, which are slow, costly, and impractical at scale. Automated image-based detection promises faster intervention and reduced yield loss. Advances in computer vision enable early disease spotting by analyzing leaf images for symptoms. Recent works have shown that ML and especially DL models can learn discriminative features from raw images, outperforming hand-crafted methods. This paper reviews these advances. We discuss how CNNs, RNNs, DBNs, transfer learning and transformers are applied to plant disease detection, compare traditional ML methods, survey public datasets, outline evaluation metrics, and analyze remaining challenges and future trends.

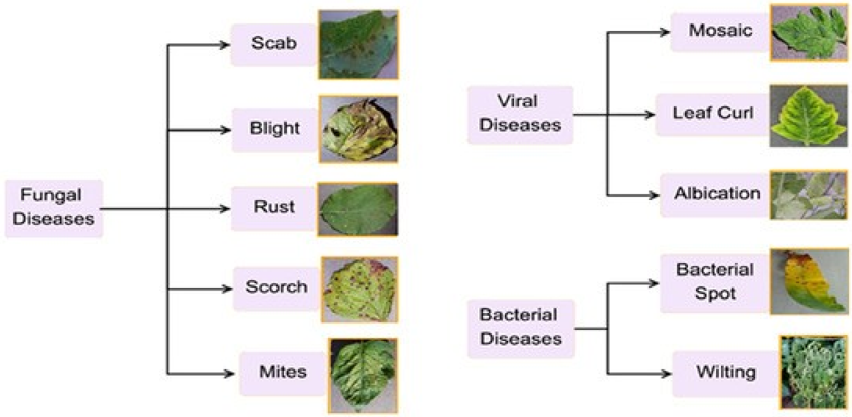

Figure 1. Representative Leaf Disease Categories Used in Deep Learning–Based Plant Disease Detection

## Machine Learning and Deep Learning Methods for Plant Disease Detection

Traditional ML classifiers (SVM, KNN, Decision Trees, Random Forests, etc.) were first used for leaf disease classification. These methods rely on extracted features (color histograms, textures, shape descriptors). They can perform well on small or lab datasets but struggle with real-world variability. Studies note that handcrafted features often fail to capture subtle lesions and are sensitive to

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[1] Nyawose, T.; Maswanganyi, R.C.; Khumalo, P. A Review on the Detection of Plant Disease Using Machine Learning and Deep Learning Approaches. J. Imaging 2025, 11, 326. https://doi.org/10.3390/jimaging11100326

lighting/background changes, limiting generalization. As a result, classical ML underperforms when images are high-resolution or taken in uncontrolled environments.

In contrast, [1]**Deep Learning** models automatically learn features from raw images, substantially improving performance. The most common approach is **Convolutional Neural Networks (CNNs)**. For example, Mohanty *et al.* (2016) trained AlexNet on 54,306 leaf images (14 crops, 26 diseases) and achieved 99.27% accuracy. Further comparisons have shown modern CNNs (VGG, ResNet, DenseNet, Inception) yielding similar ultra-high accuracies (DenseNet-121 reaching ~99.8% on PlantVillage)[2]. Table 1 (below) summarizes typical architectures used:

- **ResNet (e.g. ResNet50) –** deep residual networks for hierarchic features.
- **VGGNet –** simpler deep networks (VGG16/19) with very deep stacks of 3×3 conv layers.
- **Inception (GoogLeNet) –** mixed convolution kernels to capture multiple scales.
- **DenseNet** – dense connectivity for feature reuse.
- **EfficientNet –** compound scaling for lightweight yet accurate models.

CNNs can be used in two ways: training from scratch on a large plant-image dataset, or *transfer learning*, where an ImageNet-pretrained model is fine-tuned on leaf images. The latter is common, especially for smaller datasets. For instance, researchers have fine-tuned pre-trained MobileNet or EfficientNet models on tomato and other crop diseases, achieving strong results with limited data.

Hybrid CNNs incorporating attention or other modules have also emerged. Karthik *et al.* added residual links and attention gates in a custom CNN, reaching 98% accuracy on PlantVillage. Similarly, some works integrate channel/spatial attention (e.g. CBAM) into MobileViT (PMVT) networks to focus on infected regions.

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[1] Patterson, J.; Gibson, A. *Deep Learning: A Practitioner's Approach.* O'Reilly Media, 2017 p. 36

[2] Krishna, M.S.; Machado, P.; Otuka, R.I.; Yahaya, S.W.; Neves dos Santos, F.; Ihianle, I.K. Plant Leaf Disease Detection Using Deep Learning: A Multi-Dataset Approach. *J* 2025, *8*, 4. https://doi.org/10.3390/j8010004

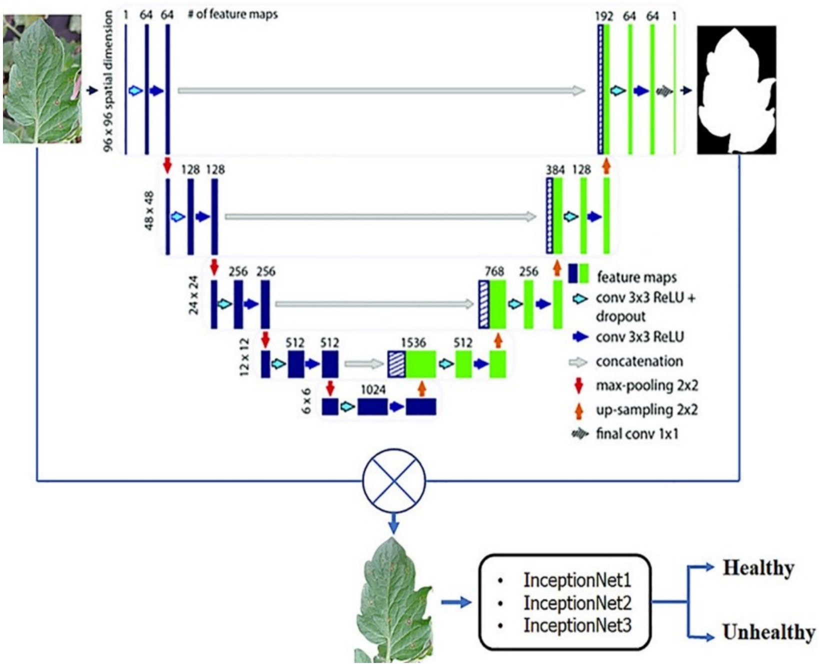

Figure 2. Deep Learning Architecture for Leaf Image Segmentation and Disease Classification Using Multi-Stage CNN and Inception Networks

Besides CNNs, **Recurrent Neural Networks (RNNs)** and attention mechanisms have been explored. RNNs are less common for static images, but one approach used an RNN with attention to sequentially focus on infected areas of a leaf. Lee *et al.* found that their attention-based RNN was more robust and generalized to unseen crop species than a vanilla CNN. They noted that plain CNNs often “learn” background or healthy parts, whereas their RNN helped localize lesions. Thus, RNN/attention modules can mitigate CNN biases.

**Deep Belief Networks (DBNs)** – composed of stacked Restricted Boltzmann Machines – have also been applied. DBNs can be trained unsupervised to extract features and then fine-tuned for classification. Reported results include 96–97.5% accuracy on identifying leaf lesions and pests, illustrating that even older DL models can be effective if data permits.

Emerging architectures include **Vision Transformers (ViTs)** and hybrid CNN–ViT models. ViTs divide an image into patches and apply self-attention, capturing _global context. Light-weight ViT variants have been proposed for plant images; for example, the PMVT (Plant MobileViT) uses fewer parameters than traditional models but still “surpasses current leading lightweight and heavyweight networks” in accuracy. Hybrid models combine CNN backbones with transformer layers: e.g., a

ViT–CNN fused with near-infrared data achieved ~88.9% accuracy on field-collected images, outperforming a DenseNet baseline. These results suggest that incorporating attention (spatial or channel-wise) and transformer principles can improve detection under real-world variability.

In practice, the choice among these methods often balances accuracy vs. resource cost. CNNs like ResNet50 may achieve top accuracy but are heavy to train and deploy. EfficientNet or MobileNet variants offer a compact trade-off. YOLO-series object detectors are notable for real-time speed; one survey notes YOLOv3's effectiveness on edges. Hybrid approaches (e.g. CNN+RNN, CNN+Booster) further explore combining strengths. Overall, deep learning methods dramatically outperform classical ML in plant disease tasks[1].

A representative deep learning pipeline (Figure 3) for plant disease detection is illustrated, incorporating data augmentation techniques such as random cropping, flipping, color jittering, and the addition of noise to enhance model robustness. Multiple convolutional neural network (CNN) architectures, including ResNet, EfficientNet, and DenseNet, are employed with transfer learning.

Pretrained networks (e.g., ResNet50, EfficientNet-B3/B0) are fine-tuned on labeled leaf images to improve detection accuracy and generalization.

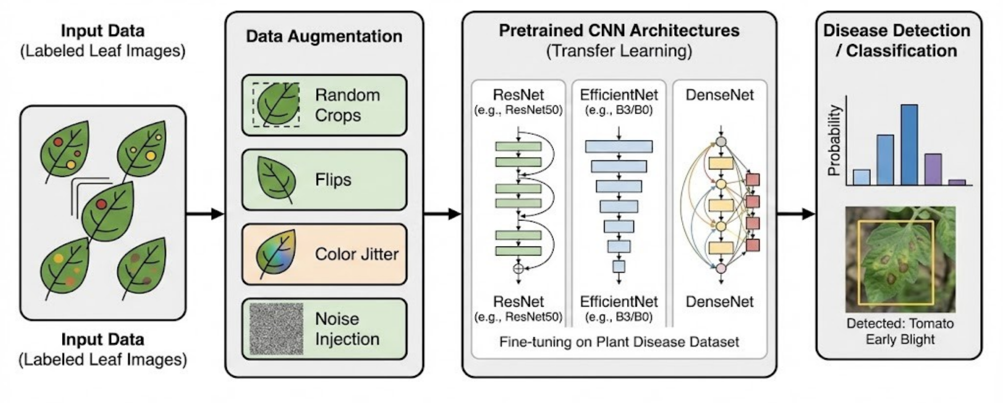

Figure 3. End-to-End Deep Learning Pipeline for Plant Leaf Disease Classification Using Data Augmentation and Transfer Learning

## Datasets for Plant Disease Detection

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[1] Li, G.; Wang, Y.; Zhao, Q.; Yuan, P.; Chang, B. PMVT: a lightweight vision transformer for plant disease identification on mobile devices. *Front. Plant Sci.* 2023, *14*, 1256773. https://doi.org/10.3389/fpls.2023.1256773

High-quality, annotated image datasets are crucial. Popular public datasets include[2][3]:

- PlantVillage
- Rice Leaf Disease (Kaggle)
- PlantDoc

| **Dataset Name** | **Image Count** | **Crop Species** | **Classes** | **Environment / Type** | **Key Characteristics** |
|---|---|---|---|---|---|
| **PlantVillage** | ~54,303 | 14 | 38 | **Lab / Controlled** | High-quality images on plain backgrounds. A standard benchmark, though simple backgrounds can inflate model accuracy scores. |
| **Rice Leaf Disease (Kaggle)** | 2,627 | 1 (Rice) | 6 | **Field Conditions** | Focuses specifically on rice. Includes varying backgrounds, offering a different challenge compared to lab data. |

- Kaggle Plant Pathology

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[2] Xu, M.; Park, J.-E.; Lee, J.; Yang, J.; Yoon, S. Plant disease recognition datasets in the age of deep learning: challenges and opportunities. Front. Plant Sci. 2024, 15, 1452551. https://doi.org/10.3389/fpls.2024.1452551

[3] Singh, D.; Jain, N.; Jain, P.; Kayal, P.; Kumawat, S.; Batra, N. PlantDoc: A Dataset for Visual Plant Disease Detection. *GitHub repository*, 2020. https://github.com/pratikkayal/PlantDoc-Dataset

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|---|---|---|---|---|---|
| **PlantDoc** | 2,598 (Original)<br>~5,600 (Combined) | 13 | 17 to 27 | **Field / Real-world** | Images scraped from smartphones/web. High variation in lighting and occlusion. Later extended by Krishna et al. to include more classes. |
| **Kaggle Plant Pathology** | Varies<br>(e.g., ~23k in 2021) | 1 (Apple) | Various | **Field / Expert Labeled** | Annual challenge datasets (e.g., FGVC workshops). High volume with expert annotations. Focuses heavily on apple leaf diseases like scab and rust. |

Table 1. Plant Disease Datasets Overview

Each dataset has biases. PlantVillage's clean lab shots differ from field images, so models trained only on it may not generalize well. Classes are often imbalanced (some diseases much rarer), leading to skewed training. As an example, the combined PlantDoc/web dataset shows uneven class counts (see figure below), reflecting natural frequency differences and class selection choices.

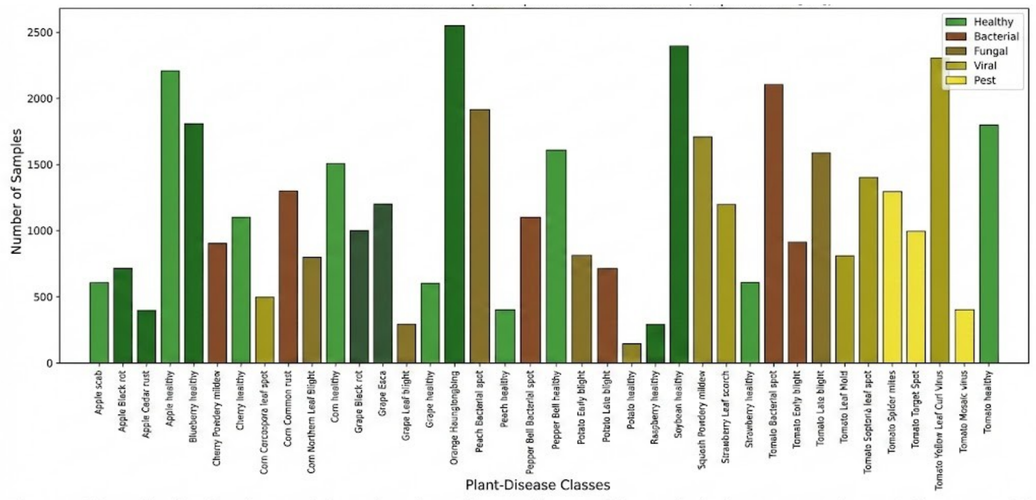

Figure 4: Class distribution in a multi-species plant disease dataset Classes include many species (apple, tomato, etc.) and diseases, with marked imbalance. Tomato-related classes (e.g., “Tomato Septoria” and “Tomato bacterial spot”) appear among others.

To address data issues, researchers employ augmentation and preprocessing. Images are typically resized (e.g. to 224×224), normalized, and augmented by random rotations, flips, color shifts, and noise injection. Advanced augmentations (GAN-based synthetic images) have been proposed to increase diversity. Annotation is another challenge: segmenting lesions or drawing bounding boxes is labor-intensive, so many methods assume only image-level labels. Overall, dataset quality (resolution, noise) and representativeness strongly affect detection performance.

## Performance Evaluation Criteria

Models are evaluated using standard classification and segmentation metrics. Common **classification metrics** (for leaf-level labels) include accuracy, precision, recall, and F1-score, defined in terms of true/false positives and negatives. For multi-class cases, averaged or per-class F1 is reported. Confusion matrices are also used to identify which diseases are frequently confused. Cross-validation (e.g. k-fold) is often employed to estimate generalization reliability, especially on limited data.

For **segmentation or localization** tasks (e.g. lesion area), overlap metrics are used. The **Intersection over Union (IoU)** measures the overlap between predicted and ground-truth masks, and the **Dice Similarity Coefficient (DSC)** is a related overlap metric ranging [0,1] (1 = perfect overlap). For instance, recent studies use IoU/DSC to quantify how well attention maps or segmentation masks align with actual diseased regions. For example, Zhang *et al.* measured IoU/DSC between model saliency maps and expert masks to assess interpretability[1]. Receiver Operating Characteristic (ROC) curves and Precision–Recall curves (with Area Under Curve, AUC) are also reported, especially in binary/class-imbalanced cases, to evaluate discrimination at various thresholds.

In summary, evaluation typically combines pixel-wise overlap (IoU, DSC) for localization accuracy and classification scores (accuracy, F1, AUC) for decision performance. A confusion matrix further reveals model bias (e.g. some diseases often mistaken). Cross-validation or repeated train-test splits ensure results are not due to lucky splits. Together, these metrics provide a comprehensive assessment of model effectiveness and robustness.

## Discussion

Current research shows a clear trend: deep models and transfer learning dominate, achieving near-perfect accuracy on benchmark sets. Lightweight and mobile-oriented architectures (e.g. PMVT, EfficientNet) are also explored for real-time applications. **Hybrid models** (e.g. CNN+ViT, CNN+booster, CNN+attention/RNN) have emerged to capture both local and global patterns; many have outperformed pure CNNs in field-like tests.

However, major challenges persist. A *lack of diverse, field-representative data* causes models to overfit to lab conditions. For example, models trained on PlantVillage often drop in accuracy on natural images. Similarly, two visually similar diseases (e.g. tomato early vs. late blight) can confuse CNNs if the background or symptoms overlap. Overfitting is common: as Zhang *et al.* quantify, many model “features” lie outside actual lesions, indicating reliance on irrelevant cues. Class imbalance (some diseases underrepresented) further biases training.

Deploying DL systems in real-world agriculture introduces practical hurdles. Large CNNs demand significant compute and memory; field devices (drones, smartphones) may not support them. For example, one group converted a trained model to ONNX and NCNN formats to run inference on a smartphone app. Even then, inference speed can be ~650ms per image on mobile, which is suboptimal for

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[1] Kondaveeti, H.K.; Simhadri, C.G. Evaluation of deep learning models using explainable AI with qualitative and quantitative analysis for rice leaf disease detection. Sci. Rep. 2025, 15, 31850. https://doi.org/10.1038/s41598-025-14306-3

real-time monitoring. Data privacy is also a concern: farmers may be unwilling to share images with cloud services.

To address these, researchers propose several solutions. **Federated learning** could train global models without sharing raw images (farmers keep data local). **Data augmentation and GANs** are used to synthetically enrich datasets. **Multimodal sensing** (e.g. combining RGB with NIR or spectral data) can reveal features invisible in RGB; a ViT–CNN on multi-spectral rice images improved accuracy under field conditions. **Lightweight models** like YOLOv3 or MobileViT (PMVT) offer faster inference on edge devices. **Explainable AI (XAI)** techniques (Grad-CAM, LIME) are increasingly used to highlight diseased regions and justify predictions. For instance, one study integrated a text-based lesion-report module into a CNN, improving farmer trust despite slower speed. Self-supervised and few-shot learning methods are also promising for coping with limited labels, as some surveys note (though full solutions remain open).

In summary, the field is moving towards **robust, interpretable, and deployable** solutions. Trends include hybrid attention models, mobile/edge deployment, and leveraging unlabelled data. Future work must tackle dataset biases, create models that generalize across environments, and integrate AI detection into smart farming systems (drones, IoT sensors) for real-world monitoring.

## Conclusions and Future Work

Deep learning has markedly advanced plant disease detection. State-of-the-art CNN and transformer-based models consistently achieve very high accuracy on benchmark tasks (often >95%), greatly reducing manual effort[1]. Transfer learning (e.g. ResNet/EfficientNet pretrained on ImageNet) is standard, enabling quick adaptation to specific crops with limited new data. Vision Transformers and attention mechanisms have further improved localization of lesions and robustness to background variation.

Key takeaways include that DL-based systems can drastically improve detection speed and precision over traditional methods, but require careful handling of data diversity. Cross-dataset studies show models can fail when

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[1] Ihianle, I.K. Plant Leaf Disease Detection Using Deep Learning: A Multi-Dataset Approach. *J.* 2025, *8*(1), 4. https://doi.org/10.3390/j8010004

encountering new backgrounds or species not seen during training. Overfitting to non-disease cues remains a concern[1].

Looking ahead, several directions are ripe for research. **Edge AI and IoT integration** – deploying models on drones, robots, and handheld devices – will enable continuous real-time surveillance. For example, converting DL models to mobile-friendly formats (ONNX/NCNN) and running on smartphones or farm drones is under active development. **Federated and privacy-preserving learning** could let multiple farms collaboratively train models without sharing private images. **Multimodal approaches** (combining images with environmental sensors, weather data or hyperspectral imagery) may improve early detection. **Few-shot and self-supervised learning** are promising for scarce labels: by leveraging unlabelled images or one-shot examples, future models could learn new disease categories more efficiently. Lastly, continued emphasis on **explainability** and human–AI interfaces will help farmers trust and act on AI diagnoses.

In conclusion, ML/DL have revolutionized plant disease diagnosis, pushing accuracy to new heights. By addressing remaining gaps – diverse data, generalization, computational cost, and interpretability – future systems can achieve robust, scalable plant health monitoring, ultimately contributing to safer and more productive agriculture.

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***Բույսերի հիվանդությունները սպառնում են գլոբալ պարենային անվտանգությանը՝ առաջացնելով զգալի բերքի կորուստներ: Ձեռքով ստուգումը ժամանակատար և սխալների ենթակա է, ինչը դրդում է ավտոմատացված պատկերային ախտորոշման մշակմանը: Վերջին հետազոտությունները օգտագործել են մեքենայական ուսուցման/խորը ուսուցման***

***առաջադեմ տեխնիկաներ՝ ավանդական դասակարգիչներից (SVM, RF, KNN) մինչև խորը մոդելներ (CNN-ներ, DBN-ներ, RNN-ներ) և ժամանակակից ճարտարապետություններ (տրանսֆերային ուսուցում ResNet/VGG/EfficientNet-ի հետ, տեսողական տրանսֆորմերներ, ուշադրության վրա հիմնված ցանցեր)՝ հայտնաբերման ճշգրտությունն ու արագությունը բարելավելու համար: Օրինակ, խորը CNN-ները, որոնք նախապես ուսուցանված են տերևների պատկերների մեծ տվյալների բազաներով, հաճախ ձեռք են բերում ≥98% ճշգրտություն՝ զգալիորեն գերազանցելով դասական մեքենայական ուսուցման մեթոդներին, որոնք հիմնված են ձեռքով ստեղծված հատկանիշների վրա: Հիմնական նոր մեթոդները ներառում են CNN-ների և ViT-ների կողմից արդյունավետ հատկանիշների ուսուցումը, ինչպես նաև հիբրիդային մոդելներ, որոնք ներառում են ուշադրության կամ RNN բաղադրիչներ ավելի լավ տեղակայման համար: Այնուամենայնիվ, մնում են մարտահրավերներ՝ խորը ուսուցման մոդելներն ապահովում են մեծ, բազմազան տվյալների բազաներ. դրանք կարող են գերապատրաստվել ֆոնին կամ լաբորատոր պայմաններին: Ապագա ուղղությունները շեշտադրում են թեթև սարքերում տեղակայումը (օրինակ՝ հեռախոսներ կամ անօդաչուներ), տվյալների արդյունավետ ուսուցումը (սակավաթիվ օրինակներով, ինքնահսկողված), բազմամոդալ զգայացումը (RGB+NIR), ֆեդերացված մոդելների ուսուցումը գաղտնիության համար և բացատրելի արհեստական բանականությունը ֆերմերներին օգնելու համար: Հոդվածի շրջանակներում ուսումնասիրված և ամփոփված են բույսերի հիվանդությունների հայտնաբերման մեջ մեքենայական ուսուցման/խորը ուսուցման վերջին առաջընթացները՝ ամփոփելով մեթոդաբանությունները, տվյալների բազաները, գնահատման չափանիշները և գործնական տեղակայման հեռանկարները:***

***Բանալի բառեր՝*** *Բույսերի հիվանդությունների հայտնաբերում. Խորը ուսուցում. Կոնվոլյուցիոն նեյրոնային ցանցեր (CNN-ներ). Տեսողական տրանսֆորմերներ (ViT-ներ). Տրանսֆերային ուսուցում. Սահմանային հաշվարկներ. Բացատրելի արհեստական բանականություն (XAI):*

## ПОСЛЕДНИЕ ДОСТИЖЕНИЯ В ПОДХОДАХ К ВЫЯВЛЕНИЮ ЗАБОЛЕВАНИЙ РАСТЕНИЙ НА ОСНОВЕ ГЛУБОКОГО ОБУЧЕНИЯ

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***Болезни растений угрожают глобальной продовольственной безопасности, вызывая значительные потери урожая. Ручная инспекция является трудоёмким и подверженным ошибкам процессом, что стимулирует развитие автоматизированных систем диагностики на основе изображений. В последние годы исследования активно используют передовые методы машинного и глубокого обучения (ML/DL) — от традиционных классификаторов (SVM, RF, KNN) до глубоких моделей (CNN, DBN, RNN) и современных архитектур (трансферное обучение с использованием ResNet/VGG/EfficientNet, визуальные трансформеры, сети с механизмом внимания) — для повышения точности и скорости распознавания заболеваний. Например, глубокие сверточные нейронные сети (CNN), дообученные на больших наборах изображений листьев, часто достигают точности ≥98 %, что значительно превосходит классические методы машинного обучения, основанные на ручном извлечении признаков. Ключевые результаты включают эффективное обучение признаков с помощью CNN и Vision Transformers, а также гибридные модели, которые интегрируют механизмы внимания или рекуррентные компоненты (RNN) для улучшения локализации.Однако остаются определённые проблемы: модели глубокого обучения требуют больших и разнообразных наборов данных и могут переобучаться на фоне или лабораторных условиях. Перспективные направления развития включают разработку лёгких моделей для периферийных устройств (например, смартфонов или дронов), обучение с малым количеством данных (few-shot, самообучение), мультимодальные сенсорные системы (RGB+NIR), федеративное обучение для обеспечения конфиденциальности, а также объяснимый***

***искусственный интеллект (Explainable AI), призванный помогать фермерам. Настоящий обзор рассматривает последние достижения в области ML/DL для выявления заболеваний растений, обобщая методологии, используемые наборы данных, критерии оценки и перспективы практического внедрения.***

***Ключевые слова:***

*Выявление заболеваний растений; Глубокое обучение; Сверточные нейронные сети (CNN); Визуальные трансформеры (ViT); Трансферное обучение; Пограничные вычисления; Объяснимый искусственный интеллект (XAI).*