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# A Review On Groundnut Diseases Detection

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## I. INTRODUCTION

Groundnut (Arachis hypogaea L.) is a globally significant oilseed crop cultivated extensively across Africa, Asia, and South America. Its agro-economic value extends beyond edible oil production to include protein-rich fodder, industrial uses, and revenue generation for smallholder farmers. However, groundnut productivity is severely constrained by a range of foliar and soil-borne diseases such as Early Leaf Spot (ELS) caused by Cercospora arachidicola, Late Leaf Spot (LLS) caused by Phaeoisariopsis personata, groundnut rust (Puccinia arachidis), stem rot (Sclerotium rolfsii), and Peanut Bud Necrosis Disease (PBND). These diseases pose a major threat, with global yield losses often reaching 50–70% in unmanaged conditions.

Traditional disease detection relies heavily on expert visual inspections, which suffer from several limitations:

• Subjectivity — Accuracy varies with agronomist expertise.

• Non-scalability — Manual scouting is slow and impractical for large fields.

• Environmental variability — Lighting, weather, and background clutter reduce reliability.

• Stage-dependence — Up to 40% of disease symptoms become visible only after significant crop damage.

To overcome these limitations, AI-based systems—particularly deep learning (DL) architectures—have been widely adopted due to their superior visual pattern-recognition capabilities. CNNs automatically extract hierarchical features, eliminating the need for handcrafted descriptors. Advanced techniques such as image fusion [1], hyperspectral imaging (HSI) [2], multimodal enhancement, few-shot learning [3], channel-attention networks [9], IoT-driven monitoring [4], UAV-based remote imaging, and ensemble CNNs [7] have further accelerated progress.

Although performance metrics in controlled experimental setups exceed 95–99%, real-world deployment remains limited due to dataset scarcity, environmental inconsistencies, overfitting, computational overhead, and lack of standardized benchmark datasets for groundnut. This review evaluates 15 state-of-the-art research works, analyzing their modeling strategies, imaging modalities, dataset properties, strengths, limitations, and applicability to real agricultural scenarios.

## II. REVIEW METHODOLOGY

To ensure a systematic and unbiased selection of research articles, a multi-stage review methodology was followed. A structured search was conducted across major scientific databases including MDPI, Elsevier, IEEE Xplore, Data in Brief, Sensors, Remote Sensing, and IJSDR. The search employed a combination of targeted keywords such as *"groundnut leaf disease detection," "plant disease CNN classification," "hyperspectral imaging agriculture," "image fusion deep learning crop," "multimodal plant disease detection," "few-shot learning agriculture,"* and *"IoT crop monitoring system."* These keyword sets were chosen to capture the widest possible range of studies related to computational plant pathology and advanced imaging-based disease detection. This strategy ensured the retrieval of highly relevant publications from both agricultural and machine learning domains.

Following the initial search, inclusion criteria were applied to filter appropriate studies. Only papers published between **2021 and 2025** were considered, with a focus on those employing deep learning, machine learning, hyperspectral imaging, IoT, or multimodal approaches. Articles were required to address plant leaf disease detection—preferably groundnut—while providing measurable performance metrics such as accuracy, F1-score, $R^2$ values, or spectral sensitivity. Additionally, papers needed to present well-defined datasets or clear methodological frameworks.

Studies were excluded if they lacked quantitative evaluation, focused solely on traditional agronomy without AI components, included duplicated content, or were preliminary preprints without substantial results. After applying these exclusion rules, only **15 research papers** met all the criteria. These selected works represent major advancements in image fusion, hyperspectral analysis, few-shot learning, ensemble CNNs, IoT-based diagnostics, dataset creation, and remote sensing for crop disease identification over the past five years.

## III. LITERATURE REVIEW

The following table provides a consolidated summary of the fifteen research papers reviewed (Ref. numbers correspond to the reference list).

| Ref No. | Author(s) | Year | Method | Dataset | Key Findings |
|---|---|---|---|---|---|
| [1] | Ma et al. | 2024 | Image Fusion + CNN | Multisource crop leaf images | Fusion improves multi-scale features; robust performance |
| [2] | García-Vera | 2024 | Hyperspectral + ML (Review) | HSI datasets | Spectral bands detect early stress conditions |
| [3] | Qureshi | 2024 | Few-shot + Multimodal DL | Groundnut RGB images | 98% accuracy with minimal data |
| [4] | Ouhami et al. | 2021 | IoT + Computer Vision | Remote sensing & sensor network | Real-time monitoring network for disease alerts |
| [5] | Asif et al. | 2025 | HSI + Deep Learning | Peanut hyperspectral signatures | Early disease detection via spectral variations |
| [6] | Renfroe-Becton et al. | 2022 | Regression + Imaging | Field peanut images | High $R^2$ disease progression modeling |
| [7] | Aishwarya & Reddy | 2023 | Ensemble CNN | Groundnut leaves | 97% classification accuracy using ensemble |
| [8] | Aishwarya (Dataset) | 2023 | Dataset Creation | 1800+ annotated images | Benchmark dataset for groundnut research |

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|---|---|---|---|---|---|
| [9] | Chen et al. | 2022 | Channel Attention CNN | Plant leaf datasets | 99% accuracy; lightweight model suitable for mobile |
| [10] | Hassan et al. | 2021 | Transfer Learning + CNN | Multi-crop datasets | 98% accuracy; strong generalization |
| [11] | Xu et al. | 2023 | Deep CNN | Peanut disease images | 97% accuracy with robust feature extraction |
| [12] | Sasmal et al. | 2024 | Dataset | Groundnut leaf dataset | High-resolution dataset for DL training |
| [13] | Anbumozhi & Shanthini | 2024 | GLDICCNN (CNN Classifier) | Groundnut images | High multiclass recognition accuracy |
| [14] | P. R. G. Reddy Lokesh et al. | 2025 | Hybrid Multistage DL | Groundnut images | Improved segmentation and classification |
| [15] | Yan et al. | 2025 | Prediction & Early Warning Models | Crop + environmental datasets | Disease forecasting and early warning |

**A. Image Fusion + Deep Learning Models**

Ma et al. [1] implemented multilevel wavelet-based image fusion to integrate texture, frequency, and spatial features from multiple imaging sources. Fusion enhances lesion boundaries, especially for diseases with overlapping color intensities (e.g., ELS vs LLS). Key contributions include feature redundancy elimination using fused wavelet coefficients, improved CNN discriminability under complex illumination, and robustness to background clutter and leaf vein variations. Image fusion is particularly valuable in real-field images where noise and shadows degrade CNN performance.

**B. Hyperspectral Imaging Systems (Deep Analysis)**

Hyperspectral imaging (HSI) captures reflectance across 100–300 spectral bands, enabling biochemical-level disease detection. García-Vera [2] highlighted HSI's ability to detect pre-symptomatic infections, identify pigment degradation and water loss, and differentiate fungal vs viral stress using vegetation indices such as

NDVI and PRI. Asif et al. [5] demonstrated using peanut spectral signatures that early disease stages show distinct absorption patterns in 550–650 nm (chlorophyll degradation), 700–750 nm (red-edge shift), and 900–1000 nm (water stress sensitivity). However, real deployment is constrained by high sensor costs, large data dimensionality requiring PCA, 3D-CNNs, or spectral attention networks, and the need for expertise in spectral calibration.

**C. Few-Shot Learning, Multimodal Enhancement (Expanded)**

Qureshi [3] addressed dataset scarcity—an issue affecting most groundnut datasets—through few-shot learning. Key innovations include a meta-learning framework enabling learning from 5–20 images per class, multimodal preprocessing for lighting equalization, and a prototype network formulation improving intra-class clustering. Few-shot models outperform traditional CNNs in low-data regimes, particularly when disease classes are visually similar or environmental variability is high, making them ideal for groundnut disease identification.

**D. IoT + Computer Vision + Remote Sensing (Expanded)**

Ouhami et al. [4] designed an integrated IoT-vision pipeline capturing real-time leaf images alongside environmental parameters such as temperature, humidity, and soil moisture. Data were processed via edge ML units, enabling on-field inferencing with minimal internet dependency. Yan et al. [15] extended this architecture by introducing disease forecasting models, spatiotemporal pattern recognition, and a risk-level alert system for farmers. IoT architectures are vital for scaling plant disease diagnosis across large agricultural landscapes.

**E. Ensemble CNNs & Transfer Learning Approaches (Expanded)**

Aishwarya & Reddy [7] proposed an ensemble of VGG19, InceptionV3, and ResNet50, combining low-level texture features, mid-level structural features, and high-level semantic features. Such ensembles reduce biases of single models and significantly improve generalization. Hassan et al. [10] demonstrated that transfer learning reduces training time, requires fewer samples, and achieves >98% accuracy across multi-crop datasets, making transfer learning ideal for resource-constrained agricultural applications.

## IV. IDENTIFIED RESEARCH GAPS

• Dataset limitations: Most datasets contain fewer than 2,000 labeled images and lack multi-season, multi-region diversity.

• Environmental sensitivity: DL models trained under controlled conditions fail when applied to outdoor images with shadows, soil, or overlapping leaves.

• Limited multimodal fusion: Few studies combine RGB + HSI + thermal + environmental analytics.

• High computational overhead: Many CNNs are too heavy for on-device inference on smartphones or IoT devices.

• Poor model explainability: Most models lack interpretable justification for predictions.

• Lack of field validation: Only a few studies conducted real-farm deployment tests.

## V. FUTURE SCOPE

• Hybrid Multimodal Imaging Systems: Integration of RGB, hyperspectral, thermal, and fluorescence imaging.

• UAV-Based Aerial Disease Mapping: Drone-based monitoring with multispectral sensors for large farms.

• Lightweight Edge-AI Architectures: Quantized CNNs (INT8), MobileNetV3, and attention-pruned networks for real-time analysis.

• Federated Learning: Privacy-preserving cross-farm model training without data sharing.

• Explainable AI (XAI): Tools like Grad-CAM, LIME, and SHAP to visualize disease-specific activation regions.

• Standardized Groundnut Dataset Creation: Multi-location, multi-season datasets with disease progression stages.

## VI. CONCLUSION

AI-driven groundnut disease detection has advanced rapidly with CNNs, HSI, multimodal enhancement, IoT monitoring, and ensemble models. However, dataset scarcity, environmental variations, sensor cost, and lack of real-field validation remain major challenges. Future systems will require multimodal imaging fusion, lightweight edge-AI deployment, UAV integration, and interpretable models to achieve reliable and scalable precision agriculture solutions.

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