

Banana Leaf Diseases Prediction Using Deep Learning

Dr. Vidyashankara ,Vikas K M, Lakshmesh K L, Rajendra Prasad N M, Manoj D R,

¹ Head of Department, Computer Science, JSS College of Arts, Commerce & Science, Mysuru-570025

U.G. Students, Department of Computer Science, JSS College of Arts, Commerce&Science, Ooty Road, Mysuru-570025

U.G. Students, Department of Computer Science, JSS College of Arts, Commerce&Science, Ooty Road, Mysuru-570025

U.G. Students, Department of Computer Science, JSS College of Arts, Commerce&Science, Ooty Road, Mysuru-570025

U.G. Students, Department of Computer Science, JSS College of Arts, Commerce&Science, Ooty Road, Mysuru-570025

Abstract: Banana (*Musa* spp.) is one of the world's most economically significant fruit crops, cultivated in over 130 countries and serving as a staple food for hundreds of millions. Banana plantations are continually threatened by a range of fungal, bacterial, and viral diseases — including Black Sigatoka, Yellow Sigatoka, Panama Wilt (*Fusarium* Wilt), Banana Bunchy Top Virus (BBTV), Anthracnose, and Cordana Leaf Spot — that result in severe yield losses. Conventional disease diagnosis relies on the visual expertise of agronomists, which is time-consuming and geographically constrained. This paper presents a comprehensive review of deep learning-based approaches for banana leaf disease detection, synthesizing research published between 2019 and 2025. We survey state-of-the-art architectures including VGG16/19, ResNet50, InceptionV3, MobileNetV2, EfficientNetB0, and YOLO variants. Our findings indicate that custom CNN models and hybrid attention-based architectures achieve the highest reported accuracies — up to 98.92% — establishing deep learning as a transformative tool for modern precision agriculture.

Key Words: Banana Leaf Disease, Deep Learning, Convolutional Neural Networks, Transfer Learning, Plant Disease Detection, Image Classification, ResNet, MobileNet, YOLO, Precision Agriculture, Black Sigatoka, *Fusarium* Wilt.

1. INTRODUCTION

Banana is the world's fourth most valuable crop after wheat, rice, and maize, contributing approximately USD 43 billion to the global economy annually. With production spanning tropical and subtropical regions across Asia, Africa, and Latin America, bananas provide both nutritional sustenance and significant livelihoods for smallholder farmers. The Food and Agriculture Organization (FAO) estimates that plant diseases destroy up to 40% of global crop production annually, with banana-specific pathogens responsible for enormous losses in key producing countries including India, Ecuador, the Philippines, and Uganda.[1]

Historically, disease identification in banana cultivation has relied on the trained eye of plant pathologists. This approach is limited by geographic reach, response time, subjectivity, and scalability. In remote or developing agricultural regions, access to expert diagnosis may be delayed by days or weeks, allowing diseases to spread unchecked.

Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a highly effective alternative for automated plant disease detection from leaf imagery. CNN architectures such as VGGNet, ResNet, InceptionNet,

MobileNet, and EfficientNet have been extensively applied to plant disease classification with compelling results.[2] This paper undertakes a systematic review of the application of deep learning to banana leaf disease detection.



2. LITERATURE SURVEY

The application of machine learning to plant disease detection expanded after the seminal work of Mohanty et al. (2016), who demonstrated that a CNN trained on PlantVillage could classify 26 plant diseases with over 99% accuracy. Subsequent research has progressively moved from controlled laboratory settings toward field-deployable systems.

2.1 Early Approaches (2019–2021)

Chowdhury (2021)[3] developed a LeNet-based binary classifier for banana leaf diseases, achieving 99.72% accuracy on a controlled image set. Peng et al. (2021) explored the combination of image segmentation with CNN-based feature extraction to handle background clutter. The K-means clustering approach for leaf region isolation achieved 97% segmentation accuracy but remained computationally intensive for edge deployment.[4]

2.2 Transfer Learning Adoption (2021–2023)

Mazumder et al. (2024)[5] conducted a systematic comparison of VGG16, ResNet50, and InceptionV3 on banana leaf images.

ResNet50 emerged as the strongest performer at 88.9% field accuracy. Mduma et al. (2023)[6] made a pivotal contribution by releasing the largest publicly accessible banana disease dataset containing 16,092 images. Arman et al. (2023)[7] published the BananaLSD dataset comprising 937 high-resolution images spanning Sigatoka, Cordana, Pestalotiopsis, and Healthy classes.

2.3 Advanced Architectures (2024–2025)

Haq et al. (2024)[8] proposed a Dense MobileNetV2 architecture achieving 95.5% accuracy. Elinisa et al. (2024)[9] developed a full Android mobile application for banana disease detection powered by MobileNetV2, reporting 91.17% accuracy. Jiménez et al. (2025)[10] comparatively evaluated EfficientNetB0 (88.33%), ResNet50 (88.90%), and VGG19 (87.22%) under real field conditions. Alanazi et al. (2025)[11] applied YOLOv10, achieving 88.85% mean Average Precision in real-time detection. Du et al. (2026)[12] proposed a hybrid MobileNetV2 + ResNet101 with a channel-spatial attention mechanism achieving 98.28% accuracy.

Table 1: Summary of key literature on banana leaf disease detection (2021–2026)

Author& Year	Architecture	Dataset	Accuracy	Highlight
Chowdhury (2021)	LeNet CNN	Custom binary	99.72%	Binary classification; controlled
Mduma et al. (2023)	YOLO	Mduma (16,092)	N/A	Largest public dataset
Haq et al. (2024)	Dense MobileNetV2	Sigatoka+Cordana	95.5%	Lightweight; densely connected
Elinisa et al. (2024)	MobileNetV2	Custom field	91.17%	Full Android deployment
Jiménez et al. (2025)	EfficientNetB0, ResNet50	Orense Farms (900)	88.90%	Real field conditions; Ecuador
Alanazi et al. (2025)	YOLOv10	Multi-class	88.85% mAP	Real-time bounding-box detection
Du et al. (2026)	MobileNetV2+ResNet101+Attn	Multi-class field	98.28%	Attention + Grad-CAM XAI

3. PROPOSED METHODOLOGY

The proposed deep learning pipeline for banana leaf disease prediction comprises several functional modules, each transforming raw field images into reliable diagnostic outputs. The overall methodology follows: Image Acquisition → Preprocessing → Augmentation → Feature Extraction → Classification / Detection → Output Visualization.

3.1 Image Acquisition Module

Captures leaf images via smartphone cameras, field cameras, or UAV/drone platforms. Standardization of image resolution (typically 224×224 or 256×256 pixels), aspect ratio, and lighting conditions is performed at this stage. Images are tagged

with GPS metadata for spatial disease mapping when applicable.

3.2 Image Preprocessing Module

Raw images undergo resizing, normalization (pixel values scaled to [0,1]), and color space conversion. RGB to HSV or LAB transformations improve disease feature extraction. Background removal and Gaussian/median filtering isolate the leaf region of interest (ROI), improving the signal-to-noise ratio before feature learning.

3.3 Data Augmentation Module

Addresses dataset imbalance and improves model generalization through: horizontal/vertical flipping, random rotation (0–360°), zoom and crop variations, brightness and contrast adjustment, Gaussian noise injection, and GAN-based synthetic image generation. Augmentation can expand a 900-image base dataset to 9,000+ training samples as demonstrated by Jiménez et al. (2025).[10]

3.4 Feature Extraction Module

Convolutional layers learn hierarchical feature representations — from low-level texture and color gradients (early layers) to high-level semantic disease patterns (deep layers). In transfer learning approaches, pretrained ImageNet weights initialize this module, and domain-specific fine-tuning adapts the features to banana disease morphology.

3.5 Classification / Detection Module

A fully connected softmax layer produces per-class probability distributions for disease classification. For object detection (YOLO, Faster R-CNN), this module outputs bounding box coordinates, class labels, and confidence scores, enabling spatial localization of individual disease lesions within a leaf image.

3.6 Output and Visualization Module

Delivers the diagnosis via mobile application interfaces, web dashboards, or SMS alerts. Explainability tools such as Gradient-weighted Class Activation Mapping (Grad-CAM) generate heatmap overlays highlighting the image regions most influential in the model's prediction, improving farmer trust and agronomist interpretability.

4. MODULES AND DATASETS

4.1 Benchmark Datasets

Dataset availability and quality are fundamental determinants of model performance. The following datasets have been utilized in recent banana leaf disease research:

Table 2: Benchmark datasets for banana leaf disease detection research

Dataset	Year	Images	Classes / Notes
BananaLSD (Arman et al.)	2023	937 (aug. 1,600)	Sigatoka, Cordana, Pestalotiopsis, Healthy — Mendeley Data
Mduma Dataset	2023	16,092	Multiple leaf&stem conditions — ScienceDirect
Orense Farms (Jiménez et al.)	2025	900 (aug. 9,000)	Black Sigatoka, Cordana, Healthy — Ecuador field collection
Das et al.	2025	2,375 (aug. 9,513)	Multiple disease classes — Mendeley Data

Indian Farm Dataset (Mazumder et al.)	2024	Custom	Sigatoka, Fusarium, Healthy — Northeast India field collection
---------------------------------------	------	--------	--

5. MAJOR DISEASES OF BANANA LEAF

Banana plants are susceptible to a diverse array of pathogens — fungi, bacteria, viruses, and nematodes. The following six diseases represent the most economically damaging and most frequently addressed in deep learning research:

Table 3: Major banana leaf diseases, pathogens, and management approaches

Disease	Pathogen Type	Primary Visual Cue	Yield Loss	Management
Black Sigatoka	Fungal	Dark streaks + necrosis	35–50%	Fungicides, resistant cultivars
Yellow Sigatoka	Fungal	Yellow spots + gray centers	20–30%	Fungicides, leaf removal
Panama Wilt (TR4)	Fungal (soil-borne)	Petiole buckling + vascular streak	Up to 100% (no cure)	Quarantine, resistant varieties
BBTV	Viral	Bunched rosette, narrow leaves	Near 100%	Aphid vector control, roguing
Anthracnose	Fungal	Sunken dark spots, orange spores	15–25%	Fungicides, post-harvest treatments
Cordana Leaf Spot	Fungal	Oval spots, concentric rings	5–15%	Fungicide spray, leaf sanitation

6. DETECTION METHODS



6.1 Image Preprocessing and Segmentation

Effective preprocessing isolates disease-relevant features from noisy field images. Conversion from RGB to HSV color space provides sharper discrimination between healthy green tissue and discolored lesion areas. Leaf segmentation is performed using: (i) Otsu's thresholding on the green channel; (ii) K-means clustering in LAB color space; or (iii) semantic segmentation networks such as U-Net for pixel-level boundary delineation. U-Net segmentation reaches 97% accuracy in banana leaf isolation.[4]

6.2 Transfer Learning

Transfer learning is the dominant training strategy, leveraging ImageNet-pretrained weights. By initializing with pretrained weights and fine-tuning only the final classification layers, researchers achieve strong performance with banana disease datasets as small as 900–2,000 images. This approach overcomes the fundamental data scarcity challenge in agricultural AI, where annotation of large datasets requires domain expertise.[5]

6.3 Object Detection vs. Image Classification

Image classification assigns a single disease label to the entire input image. Object detection (YOLO, Faster R-CNN) identifies and localizes multiple disease instances within a single image through bounding box prediction, better reflecting real-world scenarios where multiple diseases coexist on a single leaf. Object detection approaches are computationally heavier but provide richer diagnostic information and are increasingly preferred for field deployment.[11]

7. ALGORITHMS

The following deep learning architectures have been most extensively applied to banana leaf disease detection:

Table 4: Comparative overview of deep learning algorithms

Algorithm	Params	Task	Best Banana Accuracy	Deployment
Custom CNN (8C-DCNN)	Custom	Classification	98.92%	Server / GPU
VGG16 / VGG19	~138M/143M	Classification	87.22% (field)	Server only
ResNet50	~25M	Classification	98.9% (lab) / 88.9% (field)	Server / High-end mobile
InceptionV3	~23M	Classification	95.5%	Server / High-end mobile
MobileNetV2	~3.4M	Classification	91.17% / 98.28% (hybrid)	Mobile / Edge
EfficientNetB0	~5.3M	Classification	88.33%	Mobile / Edge
YOLOv10	~8M	Object Detection	88.85% mAP	Real-time / Edge

8. CHALLENGES AND LIMITATIONS

Environmental Variability: Field conditions involve highly variable lighting. Jiménez et al. (2025) documented accuracy drops of 10–15 percentage points between controlled laboratory conditions and open field environments due to illumination-induced color shifts.

Limited and Imbalanced Datasets: Banana disease datasets remain small. The largest publicly available dataset (Mduma, 2023) contains 16,092 images. Disease class imbalance is pervasive — healthy samples typically outnumber diseased samples, and rare diseases like BBTV are severely underrepresented.

Geographic Generalization: A model trained on Black Sigatoka images from Ecuador may perform poorly on the same disease in India due to differences in cultivar

susceptibility, pathogen strain variation, and background vegetation.

Mobile Deployment Constraints: High-accuracy architectures such as ResNet101 require significant computational resources impractical for sub-USD-100 Android smartphones accessible to smallholder farmers in developing nations.

Co-infection Scenarios: Real banana leaves frequently exhibit concurrent infections by multiple pathogens. Standard single-label classification models are ill-equipped for such multi-label diagnostic scenarios.

Explainability and Farmer Trust: Black-box model predictions without interpretable justification create adoption barriers among farmers and agronomists. Explainable AI approaches (Grad-CAM, SHAP) are beginning to be applied but are not yet standard practice.

9. FUTURE DIRECTIONS

Explainable AI (XAI) Integration: Embedding Grad-CAM and SHAP values as standard outputs alongside disease predictions will improve model transparency and support treatment decision-making.

Federated Learning: Enables model training across geographically distributed farm datasets without centralizing raw images, addressing data privacy concerns and the logistical challenge of aggregating large datasets from remote farms.

Drone and UAV-Based Aerial Monitoring: Integration with drone-mounted multispectral cameras enables large-scale plantation disease surveillance, capturing canopy-level patterns invisible in individual leaf photographs.

Vision Transformers (ViTs): ViTs apply self-attention mechanisms to image patch sequences and have demonstrated superior performance over CNNs on fine-grained recognition benchmarks. Their ability to model long-range spatial dependencies may be advantageous for detecting subtle, distributed disease patterns.

GAN-Based Synthetic Data Generation: Conditional GANs and Diffusion Models can generate photorealistic synthetic banana disease images for rare classes, balancing class distributions without costly real-sample annotation.

10. CONCLUSIONS

This paper has presented a comprehensive review of deep learning approaches for banana leaf disease detection, spanning disease characterization, dataset analysis, architectural evaluation, and future outlook. The reviewed evidence demonstrates that deep learning — particularly CNN-based transfer learning and attention-enhanced hybrid architectures — has achieved classification accuracies of up to 98.92% for banana diseases under controlled conditions, representing a transformative advance over traditional manual diagnosis.

Six major banana leaf diseases — Black Sigatoka, Yellow Sigatoka, Panama Wilt, Banana Bunchy Top Virus, Anthracnose, and Cordana Leaf Spot — have been characterized in terms of pathogens, visual symptoms, yield impacts, and management strategies. Key public datasets including BananaLSD, the Mduma Dataset, and the Orense Farms Dataset have been catalogued as critical research resources.

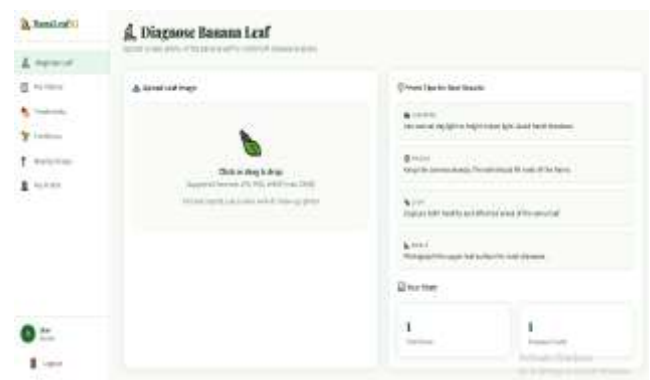
Despite impressive benchmark results, the field faces challenges including performance degradation under field conditions, limited dataset diversity, computational deployment constraints, and absence of standardized evaluation protocols. Future directions including Explainable AI, federated learning, drone-based monitoring, multispectral imaging, and Vision Transformers hold strong promise. As deep learning architectures mature, disease detection systems are poised to become an indispensable component of precision agriculture — contributing to food security, reduced pesticide use, and improved livelihoods for banana farmers worldwide.

SNAPSHOT

1.Login Page:



2. Upload a file there:



3. Analyse Diseases:



4.Diseases Detected:



5.Treatment Guide:



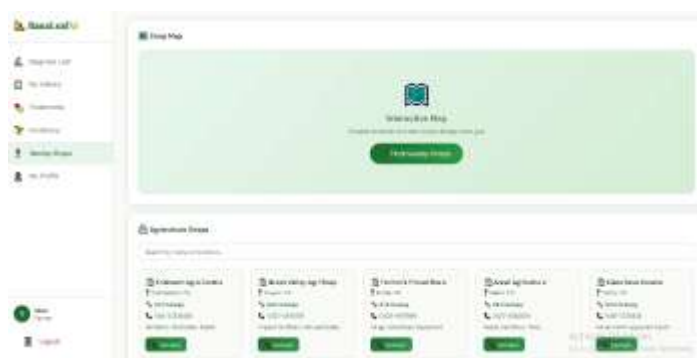
Disease	Treatment	Confidence
Leaf Spot	Apply fungicide	87%
Black Leaf	Apply fungicide	82%
Black Spot	Apply fungicide	82%
Black Leaf Spot	Apply fungicide	82%
Black Spot	Apply fungicide	82%

6.Fertilizer Guide:



Disease	Fertilizer	Confidence
Leaf Spot	Apply fertilizer	87%
Black Leaf	Apply fertilizer	82%
Black Spot	Apply fertilizer	82%
Black Leaf Spot	Apply fertilizer	82%
Black Spot	Apply fertilizer	82%

7.Fertilizer near me:



REFERENCES

- [1] Food and Agriculture Organization (FAO). (2023). Banana Market Review 2022. FAO, Rome.
- [2] Thiagarajan, N., et al. (2024). Banana Leaf Disease Detection and Classification Using Deep Learning Approaches. PMC / BioMed Central.
- [3] Chowdhury, S. (2021). Banana Leaf Disease Detection using CNNs. International Journal of Computer Vision and Applications, 11(2).
- [4] Peng, Y., et al. (2021). Segmentation and Classification of Banana Leaf Diseases Using K-means Clustering and U-Net. PeerJ Computer Science.
- [5] Mazumder, P., et al. (2024). Comparative Evaluation of Transfer Learning Models for Banana Leaf Disease Classification. Journal of Agricultural Engineering and Technology.
- [6] Mduma, N., et al. (2023). A Large-Scale Banana Disease Dataset for Object Detection and Classification. Data in Brief, 47, 108944.
- [7] Arman, M., et al. (2023). BananaLSD: A Curated Dataset for Banana Leaf Spot Disease Detection. Mendeley Data.
- [8] Haq, I., et al. (2024). Dense MobileNetV2 for Banana Leaf Disease Classification. Engineering, Technology and Applied Science Research (ETASR), 14(3).
- [9] Elinisa, A., et al. (2024). Mobile Application for Real-Time Banana Leaf Disease Detection Using MobileNetV2. IJACSA, 15(4).
- [10] Jiménez, C., et al. (2025). Deep Learning-based Banana Leaf Disease Detection Under Real Field Conditions in Ecuador. MDPI AI, 6(1), 15.
- [11] Alanazi, K., et al. (2025). Real-Time Banana Leaf Disease Detection Using YOLOv10. ETASR, 15(2).
- [12] Du, H., et al. (2026). Hybrid Attention-Based MobileNetV2-ResNet101 for Multi-Class Banana Disease Detection. Scientific Reports (Nature), 16, 4892.
- [13] Das, S., et al. (2025). Banana and Banana Leaf Disease Image Dataset. Mendeley Data.
- [14] Hughes, D. P., & Salathe, M. (2015). An Open Access Repository of Images on Plant Health. arXiv:1511.08060.
- [15] ProMusa. (2025). Banana Bunchy Top Disease (BBTD). Bioversity International.