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A Comprehensive Review of Machine Learning and Deep Learning Techniques for Banana Leaf Disease Detection

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ABSTRACT

Banana leaf diseases like Panama wilt, Banana Bunchy Top Disease (BBTD), and various fungal infections can seriously hurt crop yields and the farmers' bottom line. Lately, machine learning and deep learning have stepped up, giving us automated image-based tools that spot these diseases early and help farmers make smarter decisions. In this review, I dig into 29 research studies on banana leaf disease detection. I look at widely used datasets like BananaLSD [1], old-school image processing methods [17], convolutional neural networks (CNNs) [2], [4], hybrid deep learning models [7], [22], segmentation-based approaches [8], [23], and even YOLO for object detection [14].

When you stack them up, CNN-based and hybrid models leave traditional machine learning approaches in the dust. Still, there's a lot to tackle—things like limited datasets, changing environments, and the headaches that come with heavy computation and getting these systems up and running in the real world. Lightweight CNNs get a special spotlight here because they try to strike that tricky balance between accuracy and speed. This review points out where the research still falls short and sketches out where we need to head next if we want banana leaf disease detection to be scalable, efficient, and transparent.

KEYWORDS: Banana Leaf Disease Detection, Machine Learning, Deep Learning, Lightweight CNN, Image Classification, Segmentation, Object Detection

1. INTRODUCTION

Bananas are a big deal for food security and the economy worldwide. But here's the problem: banana crops get hit hard by fungal, viral, and bacterial diseases. When that

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happens, farmers lose a lot of their harvest. Right now, spotting these diseases usually means someone has to walk through the fields and check each plant by hand. It takes forever, it's really subjective, and honestly, it just doesn't work when you're dealing with huge plantations.

Machine learning and deep learning have completely changed how we spot plant diseases. Instead of doing everything by hand, now we can use image-based tools to diagnose problems. When researchers released the BananaLSD dataset [1], it really kicked off a wave of new work on classifying banana diseases. CNN-based models [2], [4] have pulled ahead of old-school image processing methods [17], showing much better results.

People report high classification accuracies, but a lot of current models chew up too much computing power and just aren't built for places where resources are tight—like on farms. That's why lightweight CNN architectures are getting more attention. They let you deploy models efficiently and at scale, without giving up on performance.

2. Related Work

Researchers have tackled banana leaf disease detection in a bunch of different ways. Some use classic image processing techniques—think old-school computer vision. Others go for deep learning, especially CNNs, to spot the problem. There are also hybrid setups that mix different methods, plus systems that focus on image segmentation or object detection to zero in on diseased areas.

2.1 Vision-Based Classical Image Processing Techniques

Back in the early days, researchers used pretty basic image processing and handcrafted features to spot diseases on banana leaves. Prabha and Kumar, for example, came up with a system in 2014 that used histogram-based segmentation and texture features, then ran those through a Support Vector Machine for classification. The system worked fast, but it struggled whenever the lighting changed or the background got noisy.

Ratna (2020) [26] discussed digital image processing approaches such as histogram equalization and threshold-based segmentation for disease identification. These methods were simple and easy to implement but lacked automatic feature learning capabilities.

Jadhaw and Bhandari (2024) [21] took a close look at different machine learning techniques for spotting diseases in banana leaves. They pointed out that while the older, classic methods are simple and pretty easy to understand, they just don't hold up well in real-world conditions.

You have to handcraft the features yourself, and honestly, these methods struggle when the environment gets tricky or changes a lot.

Paper	Approach / Technique	Advantages	Limitations
Prabha & Kumar (2014) [17]	Histogram + GLCM + SVM	Lightweight and interpretable	Sensitive to illumination changes
Ratna (2020) [26]	Histogram-based segmentation	Simple implementation	No automatic feature learning

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Jadhaw & Bhandari (2024) [21]	ML comparative analysis	Method comparison insights	Limited field robustness

2.2 CNN-Based Deep Learning Models

As deep learning kept moving forward, Convolutional Neural Networks (CNNs) basically took over banana leaf disease classification.

Rajalakshmi and her team (2025) rolled out a deep CNN model that spots diseases earlier and nails better accuracy than older approaches. Around the same time, Arifin (2025) used a GoogleNet-based CNN, which really stepped-up feature extraction and raised the bar for disease classification.

Singh and Guleria (2024) [11] introduced a fine-tuned CNN model using transfer learning to optimize performance.

Sangeetha and her team (2023) came up with a better deep learning model that zeroes in on detecting Panama wilt.

Then Jeyachandra and Vasumathi (2024) used CNNs to predict banana leaf diseases, which only adds more proof that deep learning works well for this kind of problem.

CNN models do a great job—they pick up on complex patterns in images and usually beat old-school machine learning methods. The catch? Most of these models need a lot of computing power and tons of training data

Paper	**Architecture**	**Key Contribution**	**Limitations**
Rajalakshmi et al. (2025) [2]	Deep CNN	Early detection model	Computational cost
Arifin (2025) [4]	GoogleNet CNN	Improved feature extraction	Model complexity
Singh & Guleria (2024) [11]	Fine-tuned CNN	Transfer learning optimization	Dataset dependency
Sangeetha et al. (2023) [7]	Agro DL Model	Panama wilt detection	High training overhead

2.3 Hybrid Deep Learning Frameworks

Hybrid models combine CNN architectures with additional layers or interpretability mechanisms to improve robustness and reliability.

Devi et al. (2022) [22] proposed an eight-layer deep CNN model for banana leaf disease prediction.

Murugesan et al. (2025) [12] introduced a hybrid deep learning model incorporating Grad-CAM interpretability to provide visual explanation of infected regions, increasing transparency in AI-based diagnostics.

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Hybrid approaches generally improve predictive accuracy and reliability but increase computational complexity and system overhead.

Paper	Techniques Combined	Advantages	Limitations
Devi et al. (2022) [22]	Multi-layer CNN	Improved prediction accuracy	Increased complexity
Murugesan et al. (2025) [12]	CNN + Grad-CAM	Interpretability enhancement	Higher computational demand

2.4 Segmentation-Based Detection Approaches

Segmentation helps zero in on infected spots before jumping into classification, which makes it easier to pinpoint exactly where the disease is.

Krishnan et al. (2022) built an automated system that handles both segmentation and classification for spotting diseases in banana leaves.

Elinisa et al. (2025) came up with a deep learning model that uses segmentation to catch banana diseases early.

Sure, segmentation makes it easier to find the problem areas and cuts down on background noise, but it does add extra steps and takes more computing power.

Paper	Technique	Advantage	Limitation
Krishnan et al. (2022) [8]	Segmentation + CNN	Improved localization	Increased complexity
Elinisa et al. (2025) [23]	DL-based segmentation	Early detection support	Training overhead

2.5 YOLO-Based Object Detection Approaches

Object detection models can spot diseased areas as they happen. Ibarra and his team (2023) used a YOLOv4 model to find Panama disease on banana leaves, drawing boxes around the affected spots in real time. These YOLO models work fast, which is great, but you'll probably need to tweak your hardware if you want to use them across big farms.

Paper	Model	Contribution	Limitation
Ibarra et al. (2023) [14]	YOLOv4	Real-time disease localization	Hardware requirement

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3. Popular Techniques in Banana Leaf Disease Detection Using Machine Learning and Deep Learning

Classical Image Processing and Machine Learning Techniques

Early systems for spotting banana leaf diseases depended on manually picking out features and then using basic classifiers. Prabha and Kumar (2014) used histogram-based segmentation and texture features, then ran those through an SVM to sort healthy from diseased leaves. Ratna (2020) focused on histogram equalization and thresholding to process digital images. Later, Jadhaw and Bhandari (2024) compared a bunch of machine learning methods to find the best way to identify diseases.

Most of these methods follow a similar pattern:

- they switch up the color space (like going from RGB to HSV),
- pull out texture features using GLCM,
- analyze shapes, and then classify the results with SVM or ANN.

They don't need a ton of computing power, and you can usually understand what's going on under the hood. But there's a catch—they're pretty sensitive to changes in lighting and rely heavily on manual feature selection. That makes it tough to scale these systems up.

Convolutional Neural Network (CNN)-Based Detection

CNNs really took over banana leaf disease classification because they can figure out features on their own—no handholding needed. Rajalakshmi and her team (2025) came up with a deep CNN model for catching diseases early. Then you've got Arifin (2025), who used GoogleNet-based CNN to push performance even further. Singh and Guleria (2024) took things up a notch with transfer learning, fine-tuning their CNN model for better results. Sangeetha and her group (2023) zeroed in on Panama wilt and built a smarter agro deep learning model just for that. Here's what CNNs bring to the table: they pull out complex features automatically, cut down on all the manual preprocessing, and usually beat old-school machine learning at accuracy. The catch? These deep models eat up a lot of computing power and need piles of data to really shine.

Hybrid Deep Learning Models

Hybrid models mix CNN architectures with ensemble methods or tools that make them easier to interpret. Devi et al. (2022) built an eight-layer deep CNN to predict banana leaf diseases. Murugesan et al. (2025) took things a step further—they combined CNN with Grad-CAM so you can actually see which parts of the leaf are infected.

These hybrid models bring a lot to the table. They predict better. They're tougher and less likely to break down when things get tricky. And you can actually understand what's going on inside. But there's a tradeoff. Training gets more complicated, and they need more computing power.

Segmentation-Based Detection Techniques

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Segmentation techniques pick out the infected parts of a leaf before running any classification, which helps the model zero in on the right spots. Krishnan and the team (2022) came up with an automated system that handles both segmentation and classification. Then Elinisa and colleagues (2025) built a deep learning model that uses segmentation to catch diseases early. Segmentation makes it easier to tell features apart and keeps the background from messing things up, but it also means extra steps and a more complex model.

YOLO-Based Object Detection Approaches

Object detection algorithms help spot diseased areas right away. Ibarra and his team (2023) used a YOLOv4 model to catch Panama disease on banana leaves. Their method draws bounding boxes around problem spots and works faster than older multi-stage models.

YOLO-based techniques handle real-time detection, pinpoint where issues are, and work well out in the field. But you'll need a GPU to get the best results, and you have to fine-tune the model if you want it to pick up on small lesions.

Lightweight CNN Architectures

Lately, researchers have been focusing on lightweight CNN architectures that strike a good balance between performance and speed. Mobile deep learning systems, for example, pull off real-time results without eating up a ton of processing power. When you tweak and fine-tune CNN models, you can squeeze out even more efficiency. The whole point of these lightweight methods is to shrink the number of model parameters, cut down inference time, make them work on devices with limited resources, and still keep classification accuracy high. This really matters in real-world agriculture, where you just don't have the luxury of powerful hardware.

Technique Category	**Key References**	**Strengths**	**Limitations**
Classical ML	[17], [21], [26]	Lightweight, interpretable	Low robustness
CNN-Based Models	[2], [4], [7], [11], [24]	High accuracy, automatic feature learning	High computational cost
Hybrid Models	[12], [22]	Improved robustness, interpretability	Increased complexity
Segmentation Models	[8], [23]	Better localization	Preprocessing overhead
YOLO Detection	[14]	Real-time detection	Hardware requirements
Lightweight CNN	[11], [15]	Efficient and scalable	May require performance trade-off

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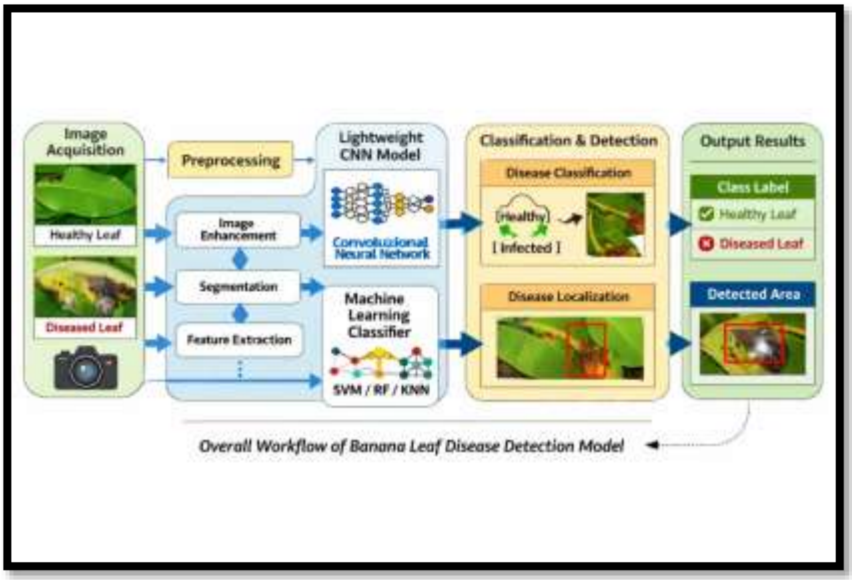

Fig. 1. Overall workflow of machine learning and lightweight CNN-based banana leaf disease detection model.

4. Existing Architecture of Machine Learning and Lightweight CNN-Based Banana Leaf Disease Detection Systems

Most banana leaf disease detection systems stick to a step-by-step process. First, they snap photos of the leaves. Then, they clean up those images, pull out important features, sort the results, and finally, show what they found. Looking at recent research, it's clear that most of these systems break things down into separate modules. This approach helps them work faster, stay reliable, and get more accurate results.

Basically, the whole setup falls into a few main layers:

4.1 Image Acquisition Layer

This part handles collecting banana leaf images for analysis. People use all sorts of tools—smartphones, digital cameras, field imaging systems, and even public datasets like BananaLSD [1]. Some researchers stick with controlled datasets, but others mix in real-field images to help the model handle a wider range of situations [7], [14]. The way these images are captured really matters. Good image quality, especially when lighting or backgrounds change, makes a big difference in how well the model works.

4.2 Preprocessing Layer

First, you need to clean up the images before you throw them into the model. Usually, that means things like resizing, normalizing, taking out noise, switching up the color space, boosting the contrast, or sometimes removing the background—especially if you're working with segmentation models. Traditional methods lean pretty hard on these steps. Deep learning models? Not so much. They can handle messier input, so you don't have to fuss as much with preprocessing.

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4.3 Feature Extraction Layer

In classical machine learning systems, handcrafted features such as texture (GLCM), color histograms, and shape descriptors are extracted manually [17], [26].

In deep learning systems, CNN architectures automatically learn hierarchical spatial features from input images [2], [4], [11]. Hybrid models combine convolutional layers with additional modules to enhance feature representation [22].

Lightweight CNN architectures optimize convolutional layers to reduce parameter size and computational cost while maintaining discriminative capability.

4.4 Classification and Detection Layer

Once the system pulls out features, it jumps right into figuring out what disease it's looking at—or where exactly the problem is. CNNs do most of the heavy lifting here, sorting images into healthy or diseased categories. Some researchers mix deep learning models to make predictions more reliable, while others use segmentation to pick out infected spots before making a call. Then there's YOLO, which works fast and boxes out diseased areas in real time. The classifier you pick really shapes how quick the system runs and how much computing power it needs.

4.5 Output and Visualization Layer

At the end, you see the detection results right on the screen. You get the predicted disease class, a confidence score, and a visual highlight of the infected areas using Grad-CAM. There are also bounding boxes from YOLO-based detection. These visuals don't just look good—they actually help you understand what's going on and make smarter decisions for managing crops.

4.6 Lightweight CNN Optimization Layer

These days, new architectures use clever tricks to make deployment easier. They prune models, cut down on parameters, and use more efficient convolution operations. There's also a lot of focus on fine-tuning and transfer learning [11], [15]. Lightweight CNNs try to strike a balance—they deliver solid predictive accuracy without gobbling up too many resources. That makes them a good fit for actual agricultural work, not just lab experiments.

Architectural Workflow Summary

The overall process flow can be represented as:

Image Acquisition → Preprocessing → Feature Extraction → Classification/Detection → Visualization

This structure provides flexibility and scalability along with the incorporation of lightweight deep learning models.

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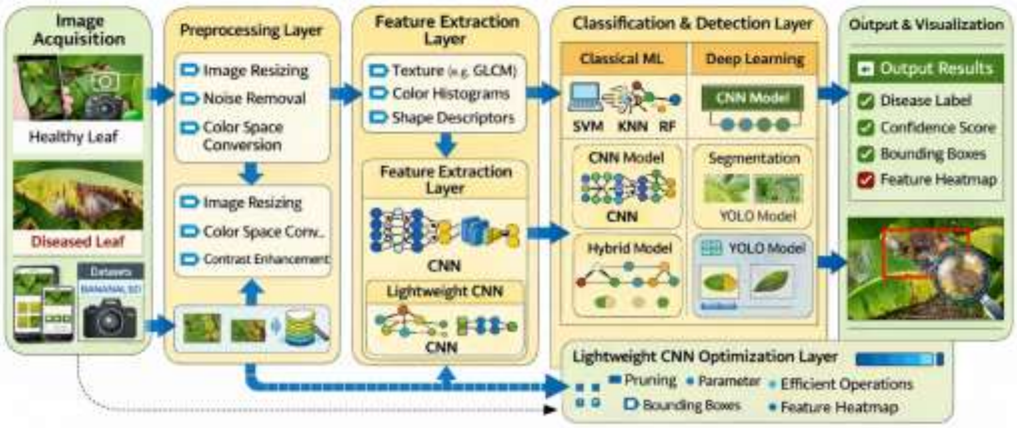

Fig. 2. Existing architecture of machine learning and lightweight CNN-based banana leaf disease detection

5. Challenges in Machine Learning and Lightweight CNN-Based Banana Leaf Disease Detection

Despite significant advancements in machine learning and deep learning techniques for banana leaf disease detection, several challenges limit large-scale deployment and practical agricultural adoption. Based on the reviewed studies, the key challenges are discussed below.

5.1 Limited and Imbalanced Datasets

Datasets like BananaLSD [1] have pushed supervised learning research forward, but honestly, a lot of studies still lean on small or carefully chosen datasets. You don't always see the real range—things like different stages of disease, leaf age, changing light, or messy backgrounds just aren't there. There's also the issue of class imbalance. Some disease categories show up way more than others, so models end up favoring those and miss the rest. When you train on these narrow or small datasets, models struggle to handle the messiness of real-world field conditions [7], [24].

5.2 Environmental Variability and Image Quality

Farming in the real world throws all sorts of curveballs—uneven lighting, messy backgrounds, stuff blocking the view, annoying shadows or reflections, and cameras pointing every which way. Old-school image processing methods really struggle when the lighting changes. Even deep CNN models, which usually do pretty well, start to stumble once you take them out of the lab. Making these systems tougher and more reliable in unpredictable conditions is still a big challenge.

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5.3 Computational Complexity of Deep Models

Deep CNNs, hybrid models, and segmentation frameworks usually demand a lot of computing power — both when you're training them and when you want to run them. Tons of parameters and layers slow down training, eat up memory, and tie you to high-end hardware. Sure, you get great accuracy, but these setups just don't work well if you're low on resources. That's why finding ways to make CNNs lighter and more efficient really matters.

5.4 Trade-Off Between Accuracy and Lightweight Design

Lightweight CNNs try to shrink model size and cut down on heavy computation. But when you trim down the number of parameters, you sometimes lose a bit of classification accuracy. The network might not dig as deep into features, so it can't represent data as richly. Finding the sweet spot between efficiency and strong predictions is still one of the toughest parts of building lightweight deep learning models.

5.5 Lack of Cross-Dataset Generalization

Most studies just test models on one dataset. Hardly anyone checks how well they work across different datasets. Here's what happens: models get too comfortable with the data they know, their performance drops when you move to a new region, and they miss how diseases can look different in other places. If we want these models to actually work out in the real world—on different farms, in different climates—we need to make sure they can handle all kinds of conditions. That's the only way they'll be ready to scale up.

5.6 Limited Interpretability and Explainability

Grad-CAM approaches [12] make things a bit clearer by actually pointing out which regions are infected, but honestly, most CNN models still feel like black boxes. In agriculture, farmers and experts want more than just a prediction. They need to see why the model made its call, get confidence scores, and know exactly where the infection is. Pushing explainable AI further is still a big deal for research.

5.7 Localization and Small Lesion Detection

Segmentation models and YOLO-based detectors do a better job at finding where things are. But small lesions often slip through the cracks. Early disease signs can be really subtle, and bounding boxes just don't catch those tiny infection patterns. So, catching diseases early is still tough.

5.8 Standardization and Benchmarking Issues

Right now, studies don't follow a standard way to measure how well models perform. Some report accuracy, others mention precision or recall, and a few add F1-score, but it's all over the place. Because of this, you can't really compare one model to another in a fair way. It's tough to reproduce results, too, and nobody can say for sure if a model is actually ready to use out in the real world. If we want to move forward, we need to agree on a common evaluation framework. It's as simple as that.

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6. Future Research Directions

Although considerable improvements have been made in the techniques of machine learning and deep learning in the detection of banana leaf diseases, some challenges act as a barrier to the deployment of the techniques in the field. Based on the research studies, the challenges in the detection of banana leaf diseases are discussed below.

6.1. Emerging Technologies:

The upcoming systems for banana leaf disease detection are expected to utilize advanced lightweight deep learning models, transformer models for computer vision, and attention mechanisms for improving feature representations. By incorporating Vision Transformers, lightweight CNN-Transformer hybrids, and explainable AI models, it is expected to improve the accuracy of disease detection even in complex environmental conditions. In addition, the usage of digital agriculture and intelligent image systems could help to implement predictive crop health monitoring by continuously tracking the disease.

6.2. Improvement Areas:

We need better ways to handle tricky lighting, messy backgrounds, and all the unpredictable stuff you find in real banana fields. Speed matters too. It’s tough to keep accuracy high while making CNNs light enough to run smoothly. Smarter data augmentation, sharper domain adaptation, and testing across different datasets all help the model handle new situations. Plus, if everyone used the same benchmarks and evaluation rules, it’d be a lot easier to compare results from different studies.

6.3. New Models and Approaches:

Down the road, we’ll probably see systems that mix lightweight CNNs with attention modules, segmentation networks, and multi-task learning. So you get classification, localization, and severity estimation all at once. Transfer learning and knowledge distillation help shrink model size without losing accuracy. There’s also a lot of potential in combining image data with info about the environment or crop conditions—that tends to make detection more reliable. And don’t forget federated learning; it lets different farms train models together without having to share their data.

6.4. Integration Possibilities:

You can hook banana leaf disease detection systems right into mobile apps, smart advisory tools, and precision farming gear, giving farmers instant help when they need it. When these systems connect to automated crop monitors and digital dashboards, it gets way easier to track disease outbreaks on a big scale and make better decisions fast. But for any of this to actually work in the real world, researchers, AI developers, and farmers need to work together. That’s the only way these tools will make a real, lasting difference in agriculture.

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References:

[1] S. E. Arman, M. A. B. Bhuiyan, H. M. Abdullah, S. Islam, T. T. Chowdhury, and M. A. Hossain, "BananaLSD: A banana leaf images dataset for classification of banana leaf diseases using machine learning," *Data in Brief*, vol. 50, p. 109608, Oct. 2023, doi: 10.1016/j.dib.2023.109608.

[2] N. R. Rajalakshmi et al., "Early Detection of Banana Leaf Disease Using Novel Deep Convolutional Neural Network," *Journal of Data Science 10.58982/krisnadana.v4i2.749 (*https://ejournal.sidyanusa.org/index.php/jkdn/article/view/749) *and Intelligent Systems*, vol. 3, no. 3, pp. 192–199, 2025, doi: 10.47852/bonview.JDSIS42021530 (https://doi.org/10.47852/bonviewJDSIS42021530).

[3] H.-T. Vo, L.-D. Quach, and H. T. Ngoc, "Ensemble of Deep Learning Models for Multi-plant Disease Classification in Smart Farming," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 5, pp. 1045–1052, 2023.

[4] N. Arifin, "Classification of Banana Leaf Diseases Using a GoogleNet-Based Convolutional Neural Network Architecture," *Jurnal Krisnadana*, vol. 4, no. 2, pp. 95–102, Jan. 2025, doi: 10.58982/krisnadana.v4i2.749 (https://ejournal.sidyanusa.org/index.php/jkdn/article/view/749).

[5] S. Pujari, J. Patil, and S. Patil, "A CNN-Enabled Context-Aware Wireless Sensor Network for Smart Banana Cultivation," *Informatica*, vol. 49, pp. 247–256, 2025, doi: 10.31449/inf.v49i37.10490.

[6] M. Sandhya, P. M. Dayana Sherine, and S. Pradhan, "Smart Crops Management Principles for Smarter Models: Survey of Deep Learning and Machine Learning Approaches for Leaf Disease Detection," *International Journal for Multidisciplinary Research*, vol. 8, no. 1, Jan.–Feb. 2026.

[7] R. Sangeetha, J. Logeshwaran, J. Rocher, and J. Lloret, "An Improved Agro Deep Learning Model for Detection of Panama Wilts Disease in Banana Leaves," *AgriEngineering*, vol. 5, no. 2, pp. 660–679, 2023, doi: 10.3390/agriengineering5020042.

[8] V. G. Krishnan, J. Deepa, P. V. Rao, V. Divya, and S. Kaviarasan, "An automated segmentation and classification model for banana leaf disease detection," *Journal of Applied Biology & Biotechnology*, vol. 10, no. 1, pp. 213–220, Jan. 2022, doi: 10.7324/JABB.2021.100126.

[9] S. A. Nandhini, R. Hemalatha, S. Radha, S. Gaur, and R. Selvarajan, "A Smart Agriculturing IoT System for Banana Plants Disease Detection through

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/8jepza22

Inbuilt Compressed Sensing Devices," *Research Square*, Nov. 2022, doi: 10.21203/rs.3.rs-2182006/v1.

[10] R. Priyadarshini and A. Vinothini, "Disease diagnosis in banana leaves: a review on AI powered techniques," *PeerJ Computer Science*, vol. 11, p. e3310, Dec. 2025, doi: 10.7717/peerj-cs.3310.

[11] G. Singh and K. Guleria, "A Fine-Tuned Convolutional Neural Network Model for Banana Leaf Disease Detection," in *Proc. 11th Int. Conf. Reliability, Infocom Technol. Optim. (Trends Future Directions) (ICRITO)*, Noida, India, 2024, pp. 1–6, doi: 10.1109/ICRITO61523.2024.10522296.

[12] S. Murugesan et al., "Robust multiclass classification of crop leaf diseases using hybrid deep learning and Grad-CAM interpretability," *Scientific Reports*, vol. 15, no. 29955, 2025, doi: 10.1038/s41598-025-14847-7.

[13] M. G. Selvaraj et al., "AI-powered banana diseases and pest detection," *Plant Methods*, vol. 15, no. 92, 2019, doi: 10.1186/s13007-019-0475-z.

[14] N. C. Ibarra, M. P. Rivera, and C. O. Manlises, "Detection of Panama Disease on Banana Leaves Using the YOLOv4 Algorithm," in Proc. 15th Int. Conf. Computer and Automation Engineering (ICCAE), 2023, pp. 263–267, doi: 10.1109/ICCAE56788.2023.10111416.

[15] A. A. Ahmed and G. H. Reddy, "A Mobile-Based System for Detecting Plant Leaf Diseases Using Deep Learning," *AgriEngineering*, vol. 3, pp. 478–493, 2021, doi: 10.3390/agriengineering3030032.

[16] M. N. Hasan, M. Mustavi, M. A. Jubaer, M. T. Shahriar, and T. Ahmed, "Plant Leaf Disease Detection Using Image Processing: A Comprehensive Review," *Malaysian Journal of Science and Advanced Technology*, vol. 2, no. 4, pp. 174–182, 2022.

[17] D. S. Prabha and J. S. Kumar, "Study on Banana Leaf Disease Identification Using Image Processing Methods," *International Journal of Research in Computer Science and Information Technology*, vol. 2, no. 2(A), pp. 88–92, Mar. 2014.

[18] K. Seetharaman and T. Mahendran, "Leaf Disease Detection in Banana Plant using Gabor Extraction and Region-Based Convolution Neural Network (RCNN)," *Journal of the Institution of Engineers (India): Series A*, 2022, doi: 10.1007/s40030-022-00628-2.

[19] P. Siricharoen, B. Scotney, P. Morrow, and G. Parr, "A Lightweight Mobile System for Crop Disease Diagnosis," in *International Conference on Image Analysis and Recognition*, pp. 456-464, 2015.

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/8jepza22

[20] T. Wiesner-Hanks et al., "Image set for deep learning: field images of maize annotated with disease symptoms," *BMC Research Notes*, vol. 11, no. 440, 2018, doi: 10.1186/s13104-018-3548-6.

[21] A. Jadhaw and R. Bhandari, "Detection of Banana Leaf Disease and its Analysis Using Different Techniques," *Research and Reviews: Journal of Agriculture and Allied Sciences*, vol. 13, no. 1, pp. 18–26, Apr. 2024.

[22] M. S. Devi, B. Vamshikrishna, J. A. Pandian, P. V. Rao, and S. R. Yaseen, "Eight Convolutional Layered Deep Convolutional Neural Network based Banana Leaf Disease Prediction," in *Proc. Int. Conf. Comput., Commun., and Intell. Syst. (ICCCIS)*, Noida, India, 2022, pp. 313–318.

[23] C. A. Elinisa, C. W. Maina, A. Vodacek, and N. Mduma, "Image Segmentation Deep Learning Model for Early Detection of Banana Diseases," *Applied Artificial Intelligence*, vol. 39, no. 1, p. e2440837, 2025.

[24] R. Jeyachandra and D. Vasumathi, "Banana Leaf Disease Prediction Using Convolutional Neural Networks," *Journal of Computational Analysis and Applications*, vol. 33, no. 8, pp. 1881–1894, 2024.

[25] H. Bouwmeester, G. Blomme, A. B. Omondi, and W. Ocimati, "Banana bunchy top disease in Africa—Predicting continent-wide disease risks by combining survey data and expert knowledge," *Plant Pathology*, vol. 72, no. 8, pp. 1476–1490, 2023.

[26] S. Ratna, "Digital Image Processing And Histogram With Python And Pycharm Text Editor," *Technologia: Jurnal Ilmiah*, vol. 11, no. 3, p. 181, 2020.

[27] J. V. Anchitaalagammai et al., "NexGen AgriCare: Advancing Crop Resilience via Real-Time Disease Detection and IoT-Driven Results for Banana Crop," in *Proc. IEEE ic-ETITE*, pp. 1–8, 2024.

[28] C. Keerthana, M. V. S. Rao, P. Yalla, P. Tejasree, and R. S. Sai, "Strategic Implementation of Disease Management in Banana Plants Through Soil Mineral Deficiency Correction," *International Journal of Electrical and Electronics Engineering*, vol. 12, no. 17s, pp. 254–260, 2024.

[29] M. Islam and G. K. Dey, "Precision Agriculture: Renewable Energy Based Smart Crop Field Monitoring and Management System Using WSN via IoT," in *Proc. IEEE ST147673*, 2019.