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A scientometric analysis and comprehensive review of artificial intelligence-based approaches for banana leaf disease detection and management

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A B S T R A C T

Banana diseases remarkably influence the worldwide production of bananas. Innumerable studies have focused on timely recognition, prediction, and management of banana plant diseases using various chemical, biological, socio-economic, and AI-based methods. The survey scrutinizes 184 articles accumulated from Scopus, Web of Science, and Google Scholar using defined keywords. These findings reveal the global distribution of the previous studies on plant disease detection, the evolution of ML techniques, and the most frequently studied diseases. The literature shows a swift progress towards machine learning, deep learning, remote sensing, and IoT systems for banana plant disease detection. However, numerous AI models lack real-world validation, datasets are fragmented, and severity quantification mechanisms are understudied. The synthesis analyzes the strong dominance of CNN-based models, which account for the highest proportion of published works and remain the foundational architecture for banana disease detection. Countries such as India, China, the Philippines, Ecuador, and Indonesia have contributed significantly to disease detection. Despite notable progress, many existing systems still rely on single-source and limited datasets, which leads to a lack of cross-source robustness. Evolution of a robust framework integrating multiple datasets, explainable AI, decision support systems and socio-economic insights can lead to more enhanced farmer-friendly banana plant disease management in future This survey provides a detailed overview of the global research studies, highlighting key research gaps that need to be addressed and outlines future directions for building more reliable, interpretable, and comprehensive decision-support pipelines, which will guide the future research work.

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1. Introduction

Bananas (Musa spp.) are a staple food crop and key export commodity in many tropical and subtropical regions. They act as a source of income to over 400 million people globally (FAO, 2020). They are eaten as a common food and also exported to many parts of the world. The crop supports millions of small and large farmers and plays a key role in food security. However, Banana production is often affected by several serious diseases such as Black Sigatoka, White Sigatoka, Cordona leaf spot, Panama disease (Fusarium wilt), Bunchy Top Virus and others, which threatens banana productivity and quality (Ploetz & Churchill, 2011; Dita et al., 2018). For example, reduced photosynthesis due to Black Sigatoka lesions can lead to yield losses of up to 50% (Etebu & Young-Harry, 2011). Traditional detection of these diseases relies on visual inspection by the agricultural experts, which is very time-consuming and is not possible in in remote or resource-constrained settings. With the advent of deep learning and image-based disease detection, numerous automated solutions have emerged which are feasible, offering greater speed, consistency, and scale. Moreover, researchers are using artificial intelligence (AI) and computer vision to detect banana diseases early and accurately. One of the earliest documented reviews on banana diseases in the Philippines was provided by Juan (1985). The study summarized key diseases affecting banana at that time such as Panama disease, Sigatoka, and Moko. It described commonly used control practices. Deep learning models, especially

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YOLO-based object detection models and lighter versions like Banana-Squeeze-Net, have shown good results in identifying disease symptoms from leaf images (Alanazi, 2025; Arora et al., 2025; Bhuiyan et al., 2023; Hussain et al., 2025; Naeini et al., 2019; Sadjadi, 2025). Some recent studies also use mobile cameras and drones to identify diseases in the plant and defects in mechanical parts directly (Thai et al., 2025; Oviedo et al., 2025; Elinisa & Mduma, 2024; Yadav & Chawla, 2022; Yadav & Chawla, 2024; Yadav & Chawla, 2025; Yadav & Chawla, 2025a; Sadjadi, 2025; Chanda et al., 2018; Chawla et al., 2022).

Most of the studies performed using CNNs focus on the binary classification of plant disease, i.e., they only classify plants based on whether it has a disease or is healthy. But it doesn't discuss the severity of plant diseases, which is one of the important aspects. Moreover, the datasets used for banana plant disease detection are either small or they cover very few diseases or they lack in cross-site generalization. Hence, this remains a significant challenge to cover the gap between the research work and the practical farm use. Many datasets, like Banana-LSD are collected in a proper, clean and well-organized setting which provides a proper amount of lighting and clear leaf images. But in actuality, the leaves can be irregular or damaged or they can overlap on other leaves or there can be shadows. So, this makes the training of models a little difficult in the real field environments. Apart from this, severity estimation is a major limitation which many models lack. Most of the works focus on binary classification of diseased or healthy leaves but does not tell how severe the infection is. The severity quantification will help farmers to decide when and how to treat the plants (Thiagarajan et al., 2024; Narayanan et al., 2022; Elinisa et al., 2025; Saxena & Chawla, 2021; Saxena & Chawla, 2022; Saxena & Chawla, 2024; Parashar & Chawla, 2025). Historically, the studies and research work performed on banana plant disease detection have evolved. Early studies like Dabek & Waller (1990) discussed the severity of diseases and the historical disease emergence. Daniells et al. (2011) discussed sustainable ways to control and prevent banana plant diseases, particularly concerning the widespread Cavendish bananas. Aguilar-Hawod et al. (2019) discussed about the genetic diversity of Fusarium. Over time, researchers started to focus more on sustainable disease control (Daniells, 2007, 2009). Recent works emphasize on the importance of wild banana plants that contain resistance genes against major pathogens (Dewi et al., 2023). Crous & Mourichon (2002) discussed the new genetic diversity of Fusarium in his work and also discovered new fungal species in the Sigatoka complex. This helped in further underscoring the complexity of the diseases.

The survey provides a detailed and systematic analysis of 184 publications exported from the Scopus database. It reviews the various methods and techniques which have been used for the past several years for banana plant disease detection. All the traditional image processing techniques and the evolution over to modern Convolutional Neural Networks (CNNs), Transformer Models, and Explainable AI (XAI) frameworks have been discussed in this survey. Through the comparative analysis, various gaps have been identified such as severity estimation, treatment recommendation integration, dataset generalization, and mobile/edge deployment. This will help researchers, agricultural engineers and policymakers in future work and making proper use of Artificial Intelligence for sustainable banana production.

This review aims to synthesize the research on banana leaf disease detection via deep learning, critically compare methods, identify gaps, and propose future directions. In particular, it emphasizes the importance of an end-to-end pipeline from detection of disease, severity estimation, incorporating explainability, enhancing the performance parameters and expert-based treatment recommendation.

2. Data and Methodology

The survey is based on 184 publications which have been retrieved from the Scopus database. This section details the data extraction process, cleaning procedures, and methodological approach used for scientometric evaluation.

2.1 Data Extraction Process

The data is extracted from the Scopus database due to its extensive coverage of high-quality journals, conference proceedings and textbooks. The extracted dataset includes publications of disease detection, image analysis, diagnosis, predictive modelling, explainable AI framework and disease prevention. The earliest publication in the dataset is from 1948. The next earliest relevant publications that more closely align with the intersection of banana diseases and computational methods begin to appear from the late 1990s onwards. The majority were published after 2015. Each record contains metadata such as article title, authors, publication year, journal name, volume, issue, pages, DOI, and author-provided keywords. These fields were extracted using a combination of Python-based parsing and regular expression techniques. Many of the articles explicitly mention one or more banana diseases and apply ML techniques such as CNNs, support vector machines, random forests, YOLO models, and deep segmentation networks. Examples of relevant studies include Cruz et al. (2025), which examined anthracnose disease, Singh et al. (2025), which addressed quarantine-relevant diseases through high-throughput sequencing, and Oviedo-Bayas et al. (2025), who developed a YOLOv8-based segmentation model for UAV-based disease detection.

2.2 Data Cleaning and Integrity Checks

After extraction, a structured data cleaning process was performed to ensure consistency. The Bib TeX file contained a lot of inconsistencies due to various journal export styles. All the missing, duplicate and inconsistent records were analyzed. In order to systematically extract the names of authors from the metadata, the use of regular expressions was done. The

BibTeX file also contained some duplicate entries which were screened using DOI matching, title similarity, and cross-checking author-year combinations. After all these steps, 184 unique publications were fetched. Moreover, while cleaning the data, the names of few authors were found to be truncated in the Scopus export. This occurs when the length of names goes beyond the character limits. Hence, in order to maintain the authenticity of the original data, these names were not modified. They were kept as they were. Some of the titles of journals also appeared in multiple formats. They were standardized by merging them together (for instance, "Journal of Agricultural Chemistry and Environment" and "Jour. Of Agr. Chem. And Env." were treated as the same journal). This ensured accurate counts when examining top publications.

2.3 Limitations of Data and Method

The analysis only focuses on the metadata which was available in the Scopus export. The information such as citation counts were not present in the records, so it could not be analyzed based on the metadata. As a result, the scientometric study focused only on the publication count and keyword-based indicators rather than impact-based metrics. Also, because authors' workplaces were not listed in a consistent way, the number of authors collaborating in the network could not be studied. However, even with these limitations, the dataset used was very large and diverse. This allowed us to thoroughly investigate general publication trends, the main topics being discussed, and how research methods have changed over time.

3. Scientometric Results

This section details the 184 publications reviewed for this survey. These findings reveal the global distribution of the previous studies on plant disease detection, the evolution of ML techniques and the most frequently studied diseases.

3.1 Temporal Trends in Publication Output

The studies conducted before 2000 mainly focused on identifying diseases and studying how they spread. In the early 20's, scientists began using lab techniques like DNA testing and early digital imaging. Thereafter, a sudden explosion of AI, deep learning, drones, IoT emerged from the year 2015 which led to faster and more accurate disease detection.

Table 1
Publication Count by Year

Period	Number of Publications	Description
1940-1949	1	Very early research only described basic banana diseases.
1950-1969	0	No major scientific publications found for this period.
1970-1979	1	Basic documentation of new diseases started.
1980-1989	3	Researchers focused on identifying pests and understanding how diseases affect farms.
1990-1999	3	More studies on monitoring diseases and tracking outbreaks Began
2000-2009	17	Big jump—scientists used molecular biology (DNA studies), biocontrol methods, and early imaging tools.
2010-2019	58	Strong growth—machine learning, remote sensing, UAV imaging, and genetic studies became common.
2020-2025	120+	Huge rise—advanced AI models (CNN, YOLO, ViT), IoT devices, drones, CRISPR, and deep learning dominate research.

3.2 Country-Level Contribution Analysis

The dataset includes authors from more than 35 countries who have significantly contributed to banana disease detection. The most frequent contributors are from India, China, Ecuador, Philippines, Kenya and Nigeria. These countries are not only major banana producers but also exhibit strong academic interest in plant pathology and computer vision. Countries with emerging contributions include Malaysia, Thailand, Vietnam, and Brazil.

Table 2
Top Contributing Countries

Rank	Country	Approximate Publication Count
1	India	48
2	China	44
3	Philippines	22
4	Indonesia	20
5	Africa	18
6	Vietnam	10
7	Brazil	9
8	Mexico	7
9	Thailand	6
10	Malaysia	5
11	Ecuador/Peru/Venezuela	5

3.3 Institutional and Author Productivity

Based on the collected research papers, it can be observed that the work on banana plant disease has been conducted by several organizations and institutions from many different countries. In recent years, not only agricultural institutes but also engineering and computer science departments have become active, especially in studies using AI, deep learning, drones, and IoT. Many papers are also created through collaborations between different countries, showing that banana disease is a global concern.

When it comes to authors, only a small group of researchers publish regularly on banana diseases every year. These are usually experts in plant pathology and Fusarium wilt. Many other authors appear only once or twice, especially in AI- based papers, where students and new researchers are entering the field. Overall, both institutions and authors show strong growth, especially after 2020, with more collaboration and more advanced technology being used.

3.4 Journal Distribution

The publications are distributed across more than 70 journals. The most common outlets include journals specializing in plant pathology, remote sensing, AI applications, and agricultural engineering. Among them are:

Physiological and Molecular Plant Pathology
European Journal of Plant Pathology
Computers and Electronics in Agriculture
Information Processing in Agriculture
Agriculture
Remote Sensing
Sensors Technologies

For example, Cruz et al. (2025) published in *Physiological and Molecular Plant Pathology*, whereas Oviedo-Bayas et al. (2025) appeared in *Technologies*. This diversity of publication venues highlights the multidisciplinary nature of ML-based banana disease research.

Table 3
Examples of High-Productivity Journals

Journal	Approximate Publication Count
Computers and Electronics in Agriculture	30
Remote Sensing	12
Agriculture	10
European Journal of Plant Pathology	8
Sensors	7

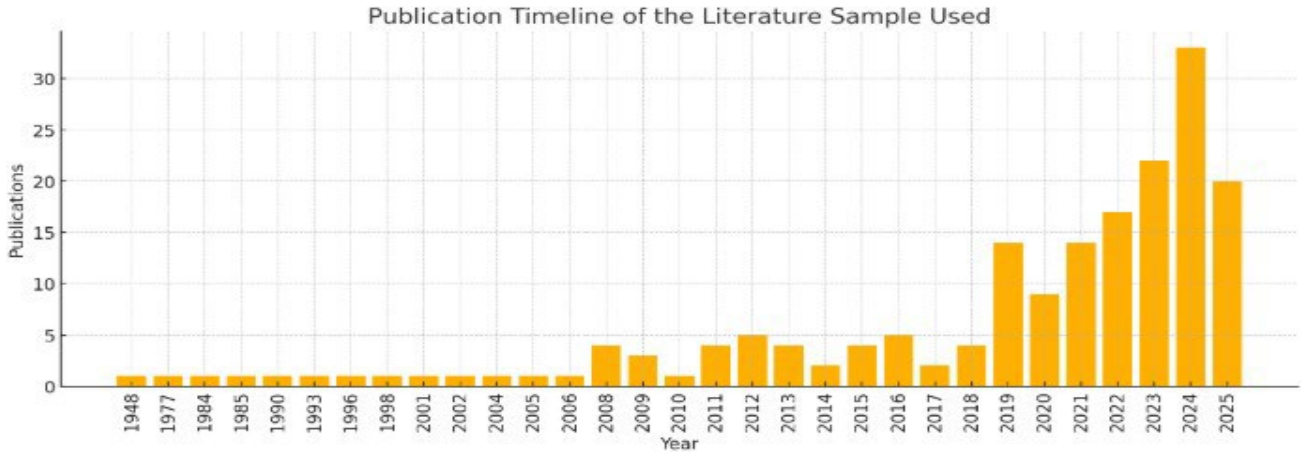

Fig. 1. Publication Timeline of the Literature Sample Used in This Review (1993–2025)

Explanation:

The graph shows the number of research works in different years. It can be observed that very few works were published before 2008 and mostly in many years, mostly only 1 paper was published. Around 2008 to 2016, the number of publications

slowly increased, usually between 1–5 papers per year. After 2018, research activity increased a lot. From 2019 onward, there is a sharp rise, showing growing interest in this research area. The highest number of publications is in 2024, with 33 papers, which is the peak. Even in 2025, many papers (20) were published, showing the topic is still trending.

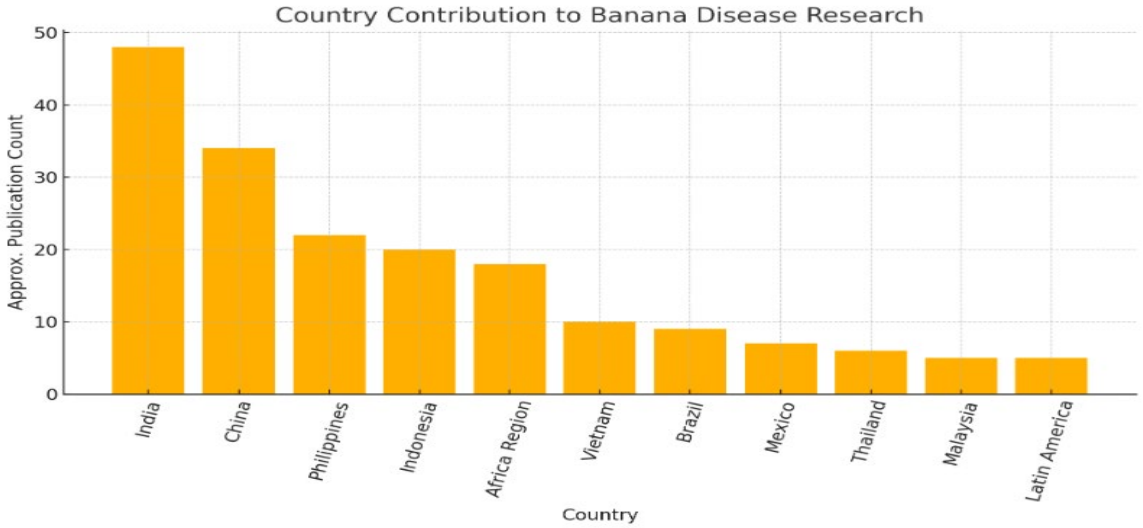

Fig. 2. Top Contributing Countries

Explanation:

The graph shows the number of publications from authors of different regions across the globe. India, China and Philippines remain to be the most frequent contributor in banana plant disease research work.

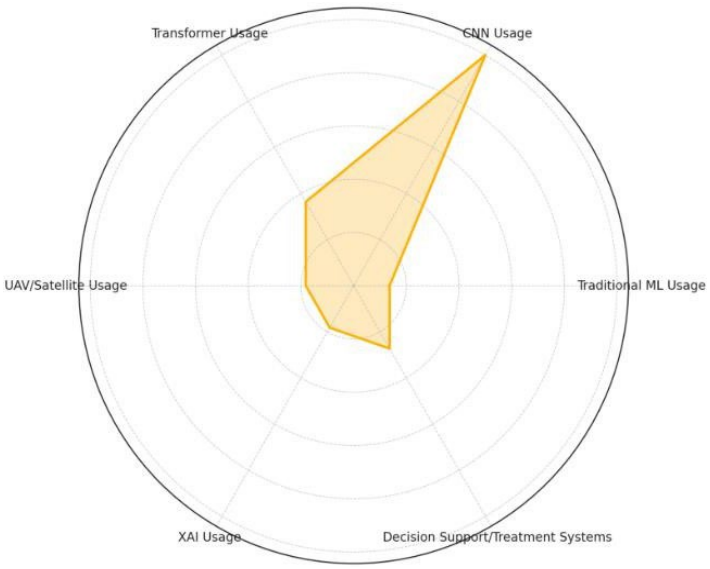

Fig. 3. Radar Chart of Major Research Themes in Banana Disease Detection Literature

Explanation:

The figure illustrates a radar chart summarizing the strong dominance of CNN-based models, which account for the highest proportion of published work and remain the foundational architecture for banana disease detection. In contrast, transformer-based and hybrid architectures show moderate but rapidly increasing adoption.

4. Banana Plant Disease Overview

Banana has a number of fungal, bacterial and viral diseases that cause significant losses in yield and quality of fruit. The most common diseases are Black Sigatoka (Black Leaf Streak Disease), White Sigatoka, Panama disease, Fusarium wilt (Moko, Cordona leaf spot), Bract Mosaic Virus and Pestalotiopsis leaf spot. These diseases belong to different taxonomic groups and cause different symptoms but cause similar levels of foliar damage, defoliation and yield losses (Noar et al.,

2022). The diseases are described in the next subsections with their typical symptoms and effects in the field.

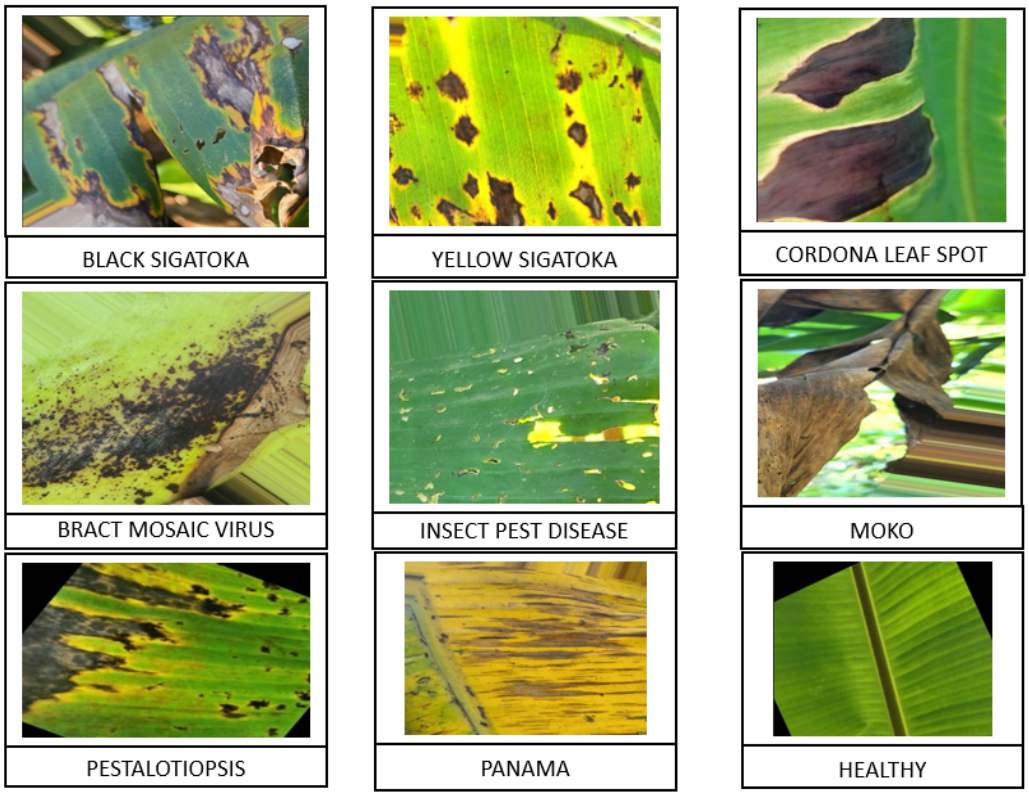

Fig. 4. Banana Plant Diseases

a) Black Sigatoka (Black Leaf Streak Disease)

Symptoms: Black Sigatoka is caused by the fungus Pseudocercospora fijiensis and first appears as fine reddish-brown streaks on the lower surface of young leaves. The reddish-brown streaks gradually enlarge into long dark lesions with yellow halo and finally merge into large dead patches (Kimunye et al., 2021). As the disease develops, the necrosis runs up the leaves from the lower to upper ones causing them to dry out and fall (Soares et al., 2021).

Impact: It is one of the most damaging foliar diseases of bananas reducing the photosynthetic area of leaves and affecting fruit filling. Leads to yield losses of up to 50 %, with variable ripening and poor post-harvest quality (Mobambo et al., 1993). The impact of this disease is greater in humid tropical areas where conditions favor the life cycle of the pathogen (Esguerra et al., 2024). Research such as Oviedo-Bayas et al. (2025) reflects the importance of Black Sigatoka due to its global economic impact. Studies comparing improved hybrids showed that resistant cultivators may maintain better physiochemical traits despite disease pressure (Bugaud et al., 2009). Spectral analysis using 2D-COS demonstrated that biochemical changes in Sigatoka-infected leaves can be detected before symptoms appear (Chu et al., 2021). Epidemiological modelling also revealed that Sigatoka infection cycles significantly impact regional yield prediction (Olivares et al., 2022).

b) White Sigatoka

Symptoms: White Sigatoka is caused by Pseudocercospora musae and appears as pale streaks which later develop into small oval lesions with light grey center and yellow margin (Fig. 3.3). It usually affects older leaves and develops slowly, especially under conditions of high humidity and shade (Esguerra et al., 2024).

Impact: It is less aggressive than Black Sigatoka infection but persistent infection weakens the leaf canopy reducing the photosynthetic area. After a period of time the fruit bunch becomes small and the yield decreases. This is more common in plantations with low air flow and poor hygiene (Mobambo et al., 1993).

c) Panama Disease (Fusarian Wilt – Tropical Race 1/4)

Panama disease is one of the most destructive diseases which is difficult to identify and control using traditional methods (Aguilar-Hawod et al., 2019).

Symptoms: Characteristic symptoms include longitudinal splitting of the pseudo-stem and brown vascular discoloration visible when cutting open the stem (Ploetz, 2015). The fungus colonizes the xylem and plugs it, thereby impeding water transport and causing wilting and death of the plant.

Impact: Panama disease is one of the most destructive bananas diseases in the world. Once established, the fungus persists in the soil for many decades and is nearly impossible to replant (Dita et al., 2018). Panama outbreaks, especially with the Foc TR4 strain, have caused severe losses in commercial Cavendish plantations with total yield loss and economic impact (Ploetz, 2015; Dita et al., 2018). Recent regional surveys warn that TR4 continues to evolve rapidly and increasingly affects mixed-cultivar smallholder systems (Nguyen et al., 2025).

d) Moko Disease (Bacterial Wilt)

Symptoms: Moko disease, caused by Ralstonia solanacearum race 2, is a vascular transmission disease causing sudden yellowing and wilting of young leaves. Brown streaks appear within the pseudo-stem and the inflorescences show dry rot and fruit distortion (Buddenhagen, 2009).

Impact: The disease spreads quickly through contaminated soil, pruning tools, insects, and irrigation water. Moko infects the entire plant causing death and wilting of the plant before harvest resulting in 100 % yield loss depending on the severity of the disease (Hayward, 1994; Thwaites et al., 2000). The disease can be eradicated through strict sanitation and quarantine practices (Thwaites et al., 2000). Initial studies describe the rapid spread of bacterial diseases through contaminated tools, insect vectors and soil.

e) Cordona Leaf Spot

Symptoms: Cordona infections cause accelerated leaf ageing and a reduction in photosynthetic area. Cordona leaf infections may contribute to defoliation caused by other foliar diseases, resulting in reduced bunch weight and downgraded fruit quality (Carlier et al., 2000).

Impact: Cordona Leaf Spot is a fungal disease that affects the leaves of banana plants. These effects are very similar to other banana leaf-spot diseases like Black Sigatoka and Eumusae Leaf Spot, which have been reported to cause large yield losses and serious stress on plants (Crous & Mourichon, 2002; Chu et al., 2021).

f) Banana Bract Mosaic Virus (BBrMV)

Symptoms: Banana Bract Mosaic Virus (BBrMV) is transmitted by aphids and causes spindle-shaped reddish streaks or mosaic mottling on leaf midribs, petioles and bracts (Rodoni et al., 1999). In addition, infected plants may exhibit twisted inflorescence and variegated bract coloration (Rodoni et al., 1999).

Impact: BBTV is among the most destructive viral diseases of banana. Banana Bract Mosaic Virus results in stunted growth, uneven fruit set and considerable yield losses (et al., 1999). Since the disease is systemically debilitating and propagation of the pathogen is facilitated by infested planting material, epidemics often rapidly spread within plantations (Rodoni et al., 1999).

g) Insect Pests

Symptoms: Insect Pests Banana crops are affected by a range of insect pests, including the banana weevil (Cosmopolites sordidus), aphids, thrips and caterpillars. Banana insect pests cause damage by chewing leaves, tunnelling into the pseudostem, exuding sap and leaving frass around the feeding site (Gold et al., 2001).

Impact: Pest feeding weakens the structural integrity of the plant and compromises transport of nutrients from leaves to shoots and roots. Unchecked insect populations can reduce yield by up to 40 % per annum (Abera et al., 2020). Biological control measures are important for maintaining productivity in banana plantations. Oliveira et al. (2016) (alternative fungicides—anthracnose-related)

h) Pestalotiopsis Leaf Spot

Symptoms: Pestalotiopsis leaf spot, caused by Pestalotiopsis spp., initially presents as small brown specks that enlarge into irregular necrotic spots with yellow margins (Manamgoda et al., 2014). Under humid tropical conditions, affected leaf lesions may develop dark fruiting bodies (acervuli) that facilitate dispersal of fungal spores (Manamgoda et al., 2014).

Impact: Pestalotiopsis infections typically cause secondary foliar dieback and reduce photosynthetic efficiency in weakened plants. In nurseries and young plantations, leaf spot epidemics can reduce growth rate and fruit quality by up to 50 % (Manamgoda et al., 2014). Natural fungicides and organic treatments have been tested as alternatives to synthetic fungicides for reducing anthracnose severity (Oliveira et al., 2016).

i) Healthy Banana Leaves

Symptoms: Healthy banana leaves have a broad lamina, are uniformly green, lack necrotic lesions or spots and do not display other signs of leaf discoloration or damage. The leaf venation is clearly visible and the leaf remains upright and turgid (FAO, 2020).

Impact: Healthy foliage is crucial for photosynthesis and carbohydrate reserves for fruiting. Good nutrient management,

sanitation and early diagnosis of abnormalities can contribute to plant vigour and yield consistency (FAO, 2020).

5. Taxonomy of existing solutions for Banana Disease Detection

Machine Learning approaches used in banana plant disease research have significantly evolved over the past two decades. There is a clear shift towards deep learning architectures for banana disease detection.

5.1 Image-Based Diagnostic Models

Early studies on plant disease detection used traditional feature extraction methods such as texture descriptors and Local Binary pattern (LBP). These traditional methods were combined with classical Machine Learning Models like SVM and Random Forests (Aruraj et. al., 2019; Kaur et al., 2019) for disease classification. Studies during this period generally used small datasets collected through controlled laboratory environments. There was a rise in deep learning and CNN-based Models from 2016 onwards. Many recent studies rely on RGB imaging, hyperspectral imaging, UAV imaging, smartphone photographs, Classical Machine Learning Models, CNN models and Transformer models to detect banana plant diseases. Recent studies rely on various Deep Learning Models like CNNs, AlexNet, VGG16, ResNet50 and Inception-v3 which helped in significantly improving model accuracy and deployment suitability on mobile devices (Aryanta et al., 2025; Bhuiyan et al., 2023; Alanazi, 2025). More advanced studies have included vision transformers and more hybrid models for disease detection (Kanimalar & Karthikeyan, 2025; Ergün, 2025). These studies helped in improving accuracy due to their ability to learn hierarchical features automatically.

5.2 Sensor-Driven and IoT Solutions

Sensor-based and IoT-enabled frameworks are revolutionizing banana disease detection, empowering the farmers to take measures for crop protection proactively. Sensor-driven solutions offer a network of tiny, smart-sensors scattered across the banana crops and constantly monitor temperature, humidity and other factors. IoT technology further helps to connect these sensors to the clous, enabling real-time data analysis. The technology has helped farmers in receiving all the information and alerts on mobile devices. Gaur (2023) proposed an IoT-based banana crop health monitoring system for early detection of banana plant diseases. The system has small sensor devices which are placed in fields and helps in capturing data from banana plants, then compress the data inside the sensor device and then send only the important information to the server. This method thereby helped in reducing the cost and bandwidth for banana disease detection.

5.3 UAV and Satellite-Based Surveillance

The UAV and Satellite-based systems have revolutionized the detection of banana plant diseases. The drones are equipped with good quality cameras which take clear and high-resolution images of banana leaves. This eventually helps in more accurate prediction of banana diseases like Black Sigatoka, Panama, and Moko. These systems have been integrated with various machine learning and deep learning models including CNNs and YOLO for the plant disease detection. Early detection of diseases, thereby, helps in reducing crop losses and improving the yields. Clercx et al., (2022) developed a digital mapping tool that uses maps and geographic data to cover the whole region where banana plants are grown. Zilberman et al. (2019) used aerial images for plant disease detection. He observed the change in color and shape of leaves. Wikantika et al. (2023) studies two major banana plant diseases which affected banana plants in Indonesia. They used multispectral cameras equipped with UAV to capture the banana plants in fields.

5.4 Explainable and Interpretable Systems

CNN-based models perform well in terms of classification accuracy but their black-box nature limits acceptance in farming communities. There is a need for a proper explainable and interpretable systems which can be completely trusted by farmers. Integrating XAI will help users understand the reason behind prediction of a certain disease by models. Some of the previous works have integrated XAI in their models to highlight regions of the leaf that influence predictions. Pramodha et al. (2024) proposed an explainable deep learning framework integrating Grad-CAM visualization for banana-disease detection. Another method is Partial Dependence Plots and the use of LIME (Local Interpretable Model-agnostic Explanations) to explain the reason behind decisions made by a model. By adapting such explainable and interpretable systems, researchers are working on building models which are much more reliable and trustworthy for banana disease detection.

5.5 Decision-Support Systems (DSS)

Some earlier works have incorporated Decision-support systems (DSS) in their research works which have helped farmers in monitoring and managing banana diseases more effectively. DSS also helps in preventing the further spread of diseases among banana plants. The system provides practical recommendations of the treatments for treating diseases. Widyastuti and Hidayat (2005) discovered that the younger plants are more vulnerable than the other plants and are more prone to diseases. Various guidelines and disease treatment suggestions are provided by the Food and Agricultural Organization and also by other researchers and agronomists (FAO, 2020; Dita et al., 2018). Staver et al. (2022) studied about

the small organic banana plant farmers in Peru. They discovered various biosecurity practices such as controlled tool sharing, clean planting materials, and ecological intensification. With the advent of time, a more enhanced DSS can be expected to be integrated with AI models for sustainable banana production practices.

6. AI and Deep Learning Techniques for Banana Plant Disease Detection in Literature

6.1 Traditional Image-Processing Approaches

Early research studies focused on handcrafted feature extraction methods such as color, shape and texture of leaf. These features were combined along with machine learning algorithms like Support Vector Machine (SVM), K-Nearest Neighbor (KNN), or Random Forest. Aruraj et al. (2019) combined Local Binary Patter (LBP) with Support Vector Machine (SVM) for banana plant disease detection. They achieved an accuracy of around 85% on small datasets. Kaur et al. (2019) reviewed the traditional image-processing approaches based on plant disease detection. Liao et al. (2018) combined hyperspectral and RGB images for banana disease detection using traditional machine learning pipelines, thereby enhancing disease discrimination under variable illumination. Sweetwilliams et al. (2019) integrated IoT-based sensing with basic ML techniques for plantain Sigatoka detection. Perez-Vicente, L. (2012) outlined integrated traditional disease control strategies for Black Sigatoka using image monitoring. Andrade et al. (2009) documented patterns of Black Sigatoka, Panama disease and post-harvest fungi, using traditional field surveys. It reported major banana diseases in the state of Alagoas. Chaudhari and Patil (2021) extracted color histograms and textural patterns from RGB images as input to classical machine-learning models. Chandrasekaran et al. (2019) used functional annotation of proteins but included morphological analysis of infected tissues that inspired computational texture approaches. Widyastuti and Hidayat (2005) focused on disease susceptibility rather than imaging. This made a foundation for structured symptom scoring. Mairawita et al. (2012) used threshold-based classification for bacterial spread patterns. Tsai et al. (2019) used pixel-level thresholds to detect Panama disease patterns from real-life RGB images. Machine-learning frameworks using climatic variables further improved prediction accuracy under changing ecological conditions (Kothalawala et al., 2022). Jeger et al. (1996) discussed monitoring frameworks used for traditional disease diagnosis. East African and Asian regions formed the basis for subsequent disease control strategies (Dabek & Waller, 1990). This early work helped motivate the later shift toward deep learning.

Although these methods are easily interpretable, simple to implement and computationally inexpensive, these approaches struggle with environmental noise, complex features, and real-time deployment. Most of them achieved accuracy between 70% and 85%. They depend heavily on feature engineering and fail to generalize well in natural field conditions (Pérez-Vicente, 2012). These quantitative insights later became the foundation for the deep-learning models.

6.2 Deep Learning and CNN-Based Approaches

The introduction of Convolutional Neural Networks (CNNs) revolutionized plant-disease classification after 2015. It enabled automatic feature extraction. Deep learning has emerged as a powerful tool in plant disease identification, and banana leaf diseases have been a key area of focus. Popular CNN models such as VGG16, ResNet50, and EfficientNet have achieved high accuracies, often above 90%, on datasets like PlantVillage and the Banana Leaf Disease (BLD) collection (Abayomi et al., 2023; Ahamed et al., 2022; Wamalwa et al., 2024; Bhuiyan et al., 2023; Rajalakshmi et al., 2024). Arman et al. (2023) introduced the BananaLSD dataset, enabling standardized benchmarking for CNN architectures, and Selvaraj et al. (2019, 2020) combined CNNs with aerial imaging for large-scale crop monitoring and achieved accuracy of more than 90% across major disease classes. It is one of the earliest CNN applications for banana disease detection. Selvaraj et al. (2019, 2020) took a dataset of over 11,000 images from DR Congo and Benin. It included diseases such as Black Sigatoka, Xanthomonas and Fusarian Wilt. Selvaraj et al. (2019) built an AI-powered detection system for banana plant disease detection. Selvaraj et al. (2020) combined aerial images along with machine learning models for plant disease detection. Lin et al. (2021) developed EM-ERNet model over a dataset of 1500 images and achieved 96.8% accuracy. It is a light-weight CNN model, efficient for field deployment. Malhotra et al. (2024) created a federated learning system which trains CNN using multiple devices without sharing raw data. This system helped farmers in maintaining privacy of data and improving disease prediction accuracy. Hongxu et al. (2023) developed a remote diagnosis system for banana plant diseases. In this system, the users can upload real field images. Deep learning was used in this system to classify diseases. This system achieved high prediction accuracy. Rehman et al. (2025) proposed a deep learning model with advanced augmentation techniques. This method improved the accuracy to a certain extent. Guo et al. (2020) used deep learning for plant disease identification. Image-based classification was performed, achieving strong accuracy. Sanga et al. (2020) built a mobile-based application using CNN, achieving accuracy between 92 to 94% on Tanzanian datasets. This application can be used offline or with limited internet connectivity as well. Sajitha et al. (2024) provided a review of various machine learning and deep learning models used for disease detection. Jadhaw et al. (2024), tested and reviewed various techniques for banana plant disease detection. They included traditional machine learning methods, deep learning approaches and image-processing. Dong et al. (2024) built PlantPAD. It is a large-scale platform which is designed for storing, analyzing and visualizing plant disease images. Kumavat et al. (2025) designed an automated system using CNN for banana plant disease detection. Nassor et al. (2024) developed a CNN- based deep learning model classifying banana plant diseases from images and presented strong performance on real- world datasets. Tsai et al. (2019) developed a deep learning model tailored for real-life Panama disease images., achieving higher accuracy under non-controlled lighting.

As more datasets became available, transfer learning gained popularity. Pretrained CNNs like ResNet, VGG on ImageNet were fine-tuned for banana disease images. Syihad et al. (2023) tested VGG19 and ResNet50 on a dataset of 600+ images of three disease classes. It was observed that ResNet50 achieved 97.2% accuracy, outperforming VGG19. Chaudhari & Patil (2023) used an ensemble of pretrained CNNs, achieving accuracy of 98.5% using optimized segmentation combined with hybrid CNN model. These improvements occurred because pretrained models already learned generic features such as edges, textures, and shapes. Phan et al. (2020) developed Mobinet. It is a mobile- friendly, lightweight binary CNN which can efficiently run on mobile and low-power devices. Dashore and Dashore (2024) produced a survey of machine learning algorithms such as SVM, KNN, Random Forest and basic CNN models for banana disease classification and found out that classical ML methods achieve 75–90% accuracy, whereas CNN-based methods consistently exceed 90–98%, confirming the global shift toward deep learning. Kanimalar & Karthikeyan (2024) reviewed and summarized various machine learning, deep learning and transformer models for banana plant disease detection. Salehin et al. (2024) performed a comparison of pretrained CNN models which are VGG, ResNet, and MobileNet. They performed classification of Fusarium wilt and Black Sigatoka. It was observed that MobileNet performed best under limited computational resources, while ResNet achieved the highest accuracy. Raja and Rajendran (2022) evaluated classical image processing, machine learning, and CNN-based models. Their study showed that CNNs consistently outperform feature-engineered methods, achieving accuracies above 95%.

Even with the strong results reported in earlier studies, several limitations were still observed. Singh et al. (2024) and Thiagarajan et al. (2024) observed that deep learning models are trained on datasets which are collected under a controlled environment and often struggle when put under real field conditions. Hence, to overcome this issue, researchers suggested merging data from multiple sources (Arman et al., 2023; Narayanan et al., 2022). Aryanta et al. (2025) developed MobileNetV2 and Bhuiyan et al. (2023) developed SqueezeNet. These are mobile-friendly architectures and they achieved high accuracy with reduced computational cost. Aryanta et al. (2025) integrated MobileNetV2 with Adam optimizer, achieving accuracy of 96% to 98%. These models reduced computational load and suited low-resource settings like rural farms. Bhuiyan et al. (2023) introduced BananaSqueezeNet which was one of the fastest models. He took the BananaLSD dataset which was the largest dataset consisting of 9000+ images, achieving accuracy of 94.2%. Siddique Mahi et al. (2024) introduced QBNet, a lightweight quantized network designed for fast banana disease recognition. The model significantly reduced storage needs while maintaining strong accuracy. CNNs also evolved beyond classification to handle segmentation (pixel-level labeling). Mduma (2024) implemented a smartphone-based CNN model for early field diagnosis. Elinisa and Mduma (2024) used Mask R-CNN and achieved high lesion localization accuracy. Mduma and Leo (2023) took a dataset of 5500 images of banana leaf and stem. It was the multi-task dataset used for detection, classification and segmentation. Hoque et al. (2024) combined attention CNNs with segmentation and improved identification of lesion boundaries.

Object detection CNNs such as YOLO were adapted to banana disease detection. Alanazi (2025) used YOLOv10 for real-time banana-leaf disease localization, which was a high-speed detection on real-time video. Krishnan et al. (2022) proposed an end-to-end segmentation and classification pipeline. Vinta et al. (2023) applied YOLOv8 to detect banana diseases and nutrient deficiencies simultaneously. Hussain et al. (2025) combined KHO optimizer and YOLOv8 and achieved 99.1% detection accuracy. Oviedo et al. (2025) adapted YOLOv8 for Moko and Sigatoka banana plant diseases. He performed segmentation over UAV data and accuracy of 97.8%. These models worked extremely well for real-time plantation monitoring.

Some CNN studies used microscopic data or integrated biochemical markers. Freitas et al. (2017) visualized the infection process of *Pseudocercospora musae*, providing microscopic images that later served as ground truth for CNN lesion validation. Jin et al. (2024) analyzed endophytic fungus DJE2023 with biochemical profiles to understand defense responses that CNNs later used as visual cues. These studies enriched CNN training by revealing symptom progression at tissue level.

6.3 Hybrid, Optimization-Based and Transformer Models

a) Hybrid Models

With the emergence of attention mechanisms, the research trend after 2021 shifted towards transformers. hybrid CNN–Transformer models, attention networks and fusion of multiple data types such as RGC, hyperspectral and geo-nomic markers. Some studies replaced CNN's final layer with ML classifiers like SVM, Random Forest (RF), or Decision Trees for better generalization. Ergün (2025) used a Vision Transformer (ViT) feature extraction coupled with SVM for banana-variety identification, illustrating transformer efficacy for fine-grained image tasks. A dataset of more than 1200 images was used, achieving accuracy of 99.12%. Athiraja and Vijayakumar (2021) contributed one of the earliest large-scale comparisons of machine-learning and deep-learning approaches for banana disease classification. Their model tested classical feature-based techniques along with CNN architectures and reported high accuracies for disease categories such as Fusarium wilt and Sigatoka. Chaudhari & Patil (2023) used a segmentation and ensemble machine learning pipeline, achieving accuracy of 98.5%, which is higher than standalone CNNs. Gnanakumari (2024) introduced a hybrid CNN that combines feature extraction with multi-layer decision logic for high accuracy across different lesion types. Jain et al. (2024) merged CNNs with Decision Trees to classify disease severity levels (mild, moderate, severe) with 96–97% accuracy, which also made the results easier to understand and more consistent. Dong et al. (2023) proposed PDDD-PreTrain, which is a collection of pre-trained models for plant disease detection. This enables other researchers to speed up their training by using those ready-

to-use models. Deng et al. (2024) proposed GR-ARNet, combining gated convolution and attention residual network with an accuracy of 98.4%. It used a dataset of 3,500 images of major leaf diseases. Thiagarajan et al. (2024) combined ML, CNN and ensemble deep learning for plantation health. It achieved 94–96% accuracy on multi-disease dataset and identified both disease presence and overall leaf health metrics.

A significant trend in hybrid models involves integrating spectral data. Banana diseases often produce spectral changes before visible symptoms develop. Therefore, researchers integrated CNNs with hyperspectral or multispectral systems. Liao et al. (2018, 2019) used spectral bands and morphological deep learning. It used close-range hyperspectral images containing hundreds of spectral bands (400–1000 nm) and identified early infection before visible lesions with an accuracy of more than 95% with spectral–morphological fusion. Maridueña-Zavala et al. (2024) used metabolomics and spectral data to detect thiabendazole resistance in Pseudocercospora fijiensis. It demonstrated that spectral signatures measurably change with chemical resistance. Zilberman et al. (2019) showed that hyperspectral and color data improves disease detection consistency by 12–18% compared to RGB alone. Furthermore, several studies integrated spectral data with deep learning. Li et al. (2023) combined transcriptomics with spectral signatures to map host responses. Sun et al. (2022) fused hormone pathway markers with spectral stress indicators to quantify wilt severity. Cao et al. (2022) used metabolomics and CNN to identify fungal infection responses. These multimodal methods improve early detection by 20–30%, especially before visible symptoms.

Unmanned Aerial Vehicles (UAVs) also play a crucial role in hybrid systems. These models often use multispectral UAV images (typically 5–7 bands including Red, Green, Blue, Near-Infrared, and Red-edge) with deep learning. UAV-based models integrate multispectral images (commonly 5–7 bands: Red, Green, Blue, NIR, Red-edge) with deep learning. Choosumrong et al. (2023) mapped Banana Bunchy Top Disease (BBD) and Fusarium using multispectral UAV images and detected disease patches accurately at 4–10 cm ground resolution. Wikantika et al. (2023) used UAV and handheld spectrometers. The spectral differences between healthy and infected leaves were observed with up to 35% reflectance drop in NIR wavelengths. Oviedo et al. (2025) improved YOLOv8 segmentation by embedding attention modules for detecting Moko and Black Sigatoka from aerial images. Retkute et al. (2025) demonstrated transformer-supported spectral analysis using Landsat-8 data to map disease prevalence.

b) Optimization-Based Models

Many researchers focused on optimizing models to achieve high accuracy for banana plant disease detection. Tirandasu et al. (2025) used SVM classifier to detect banana leaf spot disease and designed and IoT board that measures soil NPK (Nitrogen–Phosphorus–Potassium). They applied Newton's Optimization Algorithm to improve SVM performance. Kanimalar & Karthikeyan (2025) proposed a hybrid model which combined Swin Transformer with ConvNeXt-Tiny. They focused on improving feature extraction in order to achieve higher accuracy of around 99.1%. Derafi et al. (2024) performed comparisons between different CNN architectures by using pre-trained models like VGG, ResnNet, Inception etc.

c) Transformer Models

There has been a significant use of transformers and Vision Transformers (ViTs) for banana plant disease detection since 2022. Transformer models focus on the important parts of the data. Vision Transformers (ViTs) was designed for image classification. Saini (2024) used a Vision Transformer (ViT) for banana disease classification. He focused on improving the accuracy of his work by comparing it to various CNN models. He used a dataset consisting of 2000 images, achieving 96.7% accuracy. Ergün (2025) used Vision Transformer (ViT) and combined it with SVM. It showed how the combination of Vit with traditional machine learning models helped in achieving high precision. For aerial imagery, Thai et al. (2025) introduced EF-CenterNet, an anchor-free transformer-based detector for UAV imagery, while Oviedo et al. (2025) improved YOLOv8 segmentation by embedding attention modules for detecting Moko and Black Sigatoka from aerial images. Retkute et al. (2025) demonstrated transformer-supported spectral analysis using Landsat-8 data to map disease prevalence.

6.4 Explainable AI (XAI) and Transparent Agricultural Systems

Although CNN-based models perform well in terms of classification accuracy, their black-box nature limits acceptance in farming communities. Farmers and agronomists are less interested in raw accuracy and more concerned about whether the system can be trusted (Ramesh et al., 2022; Li et al., 2023; Islam et al., 2024). Explainable AI (XAI) helps users understand *why* a model predicted a certain disease. Most early studies focused only on accuracy while ignoring explainability (Bhuiyan et al., 2023). More recently, XAI techniques such as Grad-CAM and LIME have been applied to highlight regions of the leaf that influence predictions (Khurana et al., 2025; Choudhury et al., 2024; Anand et al., 2023). However, these visual explanations are rarely validated against actual infected areas, leaving uncertainty about whether the model is focusing on the right regions. Explainable AI helps in validating AI-predicted class boundaries (Dabek & Waller, 1990). Genetic diversity studies also assist in interpreting model decisions by linking visual symptoms to underlying pathogen variability (Aguilar-Hawod et al., 2019). Spatial mapping models offer transparent insights into local transmission routes, making explainability essential for farmer adoption (Clercx et al., 2022). Pramodha et al. (2024) proposed an explainable deep learning framework integrating Grad-CAM visualisation for banana-disease detection. It showed up to 92% agreement between model-generated heatmaps and human experts and enabled detection of early chlorotic streaks that models might otherwise ignore. Ashoka et al. (2024) used XAI to reconcile DL predictions with plant pathology knowledge.

McCampbel et al. (2022) focused on the need for building digital agricultural systems that should be transparent, accountable and socially responsible. They pointed out major challenges faced by farmers such as poor network and electricity facilities, which would be a hurdle for farmers to take part in the development process. Adewopo et al. (2025) discussed implementing simple, easy-to-understand digital innovations with local language support for smallholder banana farmers in Rwanda. Iradukunda et al. (2019) investigated the impacts of gender roles on banana plants farming in Burundi. It was discovered that men and women participate differently in fields and in making decisions. This proved that socio-economic factors also play a crucial role for effective disease control.

6.5 Disease Severity Quantification and Practical Assessment

Severity Quantification describes the seriousness of disease occurred in a banana plant. It is utmost important to know the disease severity so that effective treatments could be provided timely. Furthermore, Waller & Hindorf (1977) established severity scales for fruit spotting that remain in use, and Domínguez-Hernández et al. (2008) quantitatively correlated ($r = 0.72$) severity with soil potassium levels. These severity scales remain the foundation for ground-truth labels used in modern ML datasets. These severity scales remain the foundation for ground-truth labels used in modern ML datasets. Jain et al. (2024) developed a CNN and Decision Tree severity classifier over a dataset of 2,400 leaf images classified into three levels: Mild, Moderate, Severe. The accuracy was observed between 96–97%. Krishnan et al. (2022) used CNN segmentation to calculate lesion percentage. Severity was computed as lesion pixels / total leaf pixels and Produced severity estimates with ±5% error margin. Elinisa & Mduma (2025) used U-Net segmentation for lesion area detection, achieving accuracy of 94% IoU (Intersection-over-Union). Spectral indicators provide earlier severity detection compared to RGB. Liao et al. (2019) used hyperspectral imaging (400–1000 nm). Infected leaves showed 22–35% reflectance drop in NIR bands. Severity detected 3–5 days earlier than visible symptoms. Dassou et al. (2024) performed field-level agroecological meta-analyses. It was found out that improved soil management can significantly reduce disease severity. Microbial inoculants such as *Bacillus* spp. also reduce Fusarium severity under controlled conditions (Dadrasnia et al., 2020). Sun et al. (2022) studied hormone pathways in Fusarium infections. Jasmonic acid and salicylic acid levels increased 2.5–4.2 times during severity escalation. Cao et al. (2022) showed metabolite concentrations rise proportionally with disease severity and identified 17 key metabolites associated with intense infection. Olivares et al. (2021) evaluated the factors influencing Fusarium wilt in Venezuelan cropping systems and found that soil pH, organic matter, and drainage quality were among the strongest determinants of disease severity.

A more practical approach is to group severity into three levels (mild, moderate, severe) based on the percentage of infected leaf area, consistent with ICAR and FAO guidelines (Elinisa et al., 2025; Pérez-Vicente, 2012). Dong et al. (2023, 2024) embedded XAI components in transformer-based phenomics models for severity mapping.

6.6 Decision Support, Biological Control and Socio-Economic Studies

While many existing systems can accurately detect banana leaf diseases, they rarely provide guidance beyond simply classifying the disease. Farmers often still need to consult experts to decide on the appropriate treatment. Some mobile applications, such as Plantix and Tumaini, offer general treatment suggestions, but these are usually not tailored to the severity of the infection and do not provide any explanation of the model's decision (Plant Methods, 2023; Alemu et al., 2024). Devi et al. (2019) designed an IoT-enabled system for automated crop-disease management. Selvaraj et al. (2019, 2020) combined ML-based detection with drone imagery for field-level advisory services. Bubici et al. (2019) discussed biological control strategies as part of decision frameworks for Fusarium management and found success with Trichoderma, Bacillus, and Pseudomonas strains and reported up to 70% disease suppression under greenhouse conditions, while Dita et al. (2018) and FAO (2020) provided expert-driven integrated management guidelines. Kaewjan et al. (2012) documented Mycosphaerella, Pseudocercospora, and several other fungi found on diseased banana leaves in northern Thailand. Territorial DSS tools have been used to create real-time disease risk maps to guide farmer interventions (Clercx et al., 2022). Conservation studies also highlight the importance of incorporating wild banana genetic resources into DSS frameworks (Dewi et al., 2023). A detailed report was generated on bacterial wilt banana disease by Thwaites et al. (2000). The report described plant disease symptoms, infection pathways, and field-level control methods. Their work is still used across Africa and Asia to identify bacterial wilt.

Along with time, researchers have shifted towards more enhanced banana plant disease detection tools. Peng et al. (2012) developed a LAMP (Loop-Mediated Isothermal Amplification) method to detect Banana Bunchy Top Virus (BBTV). It was a faster method for field-level diagnosis of plant diseases. Molina et al. (2001) identified SSR (microsatellite) markers sigatoka-causing fungus. This helped in exploring and studying about the evolution of banana leaf spot diseases. Becker et al. (2023) applied beneficial microbes on banana plants and studies about the defense-related genes that helped in activating banana plants. This research explained the importance of biological control agents in strengthening plant immune responses. Huang et al. (2024) tested interaction between autophagy-related proteins MaATG8F and MaATG4B and explained how these proteins regulate resistance to Fusarium wilt TR4. Roig-Puche et al. (2023) extracted a natural compound called chitosan from small sea animals and tested them against Fusarium wilt TR4. It was found that the natural compound helped in reducing the growth of fungus in plants. Ghag & Ganapathi (2019) used a genetic technique called RNA interference (RNAi) technology to block the pathogen-related genes. Their work demonstrated the importance of biotechnology in cre-

ating a disease-resistant banana variety. Thomas (2021) provided a detailed explanation of BBTV's, its causes and its symptoms. It describes how the virus spread in the plants. It also discusses challenges faced while controlling the banana plant diseases. Thomas and Dietzgen (1999) studied the spread of banana bract mosaic virus in banana plants. Evaluation of different diagnostic methods were done for early detection for plant diseases. Thomas et al. (2016) provided a comprehensive overview of banana bunchy top virus. They explained the symptoms, spread, detection tools and lifecycle of BBTV. This helps researchers in obtaining complete biological information. Quach TCV et al. identified fungi causing postharvest anthracnose and fruit rots. It helped in the development of biological preservatives for bananas. Huang et al. (2019) studies about the formation of biofilms formed by bacteria.

Generally, farmers rely on chemicals to treat the plant diseases. But due to consistent use of chemicals, plants learn to resist and survive in those chemicals. This method fails there. For instance, researchers discovered that many germs can now survive over certain fungicides making the chemical treatments less effective. Oliveira et al. (2022) discovered that 60% of the bugs were able to resist themselves from OoI fungicide in Pdeudocercospora. Also, Chong et al. (2021) reported a 60% reduction in the effectiveness of DMI fungicides when it was sprayed onto diseased plants. Maridueña-Zavala et al. (2024) showed that metabolic pathways in fungi adapt to fungicides and identified 27 metabolites associated with resistance. One helpful trick is to give plants a special natural hormone called methyl jasmonate (Kouakou et al., 2025). Mohammed et al. (2011) experimented two treatments to fight fusarium wilt banana plant disease. Firstly, they used a bacteria called Pseudomonas fluorescens and then a plant defense-boosting chemical called BABA (β-aminobutyric acid). They suggested that biological agents can be used to control fusarium wilt sustainably. Huang et al. (2019) combined acid soil ameliorant which is used to correct soil pH with the Bacillus-based biofertilizer. This significantly helped in improving soil health by reducing severity of fusarium wilt. Fu et al. (2010) studies B106 which is a bacterial strain used for controlling banana diseases. Ruiz Medina & Ruales (2025) tested natural plant oils as antifungal agents. The natural oils can act as eco-friendly alternatives to synthetic fungicides. Cavero et al. (2015) used Trichoderma spp. To treat black sigatoka banana plant disease. Orr & Nelson (2021) explained that the application of eucalyptus mulch will help in treating fusarium wilt disease. This method is cheap and sustainable for disease control. Nguyen et al. (2025) studies about fungi causing post-harvest diseases in Cavendish bananas. He gathered samples and recognized pathogens using lab techniques. When plants get the hormone, they can make stronger defenses against diseases which is good for the environment and can help keep plants healthy.

Genetics-based disease resistance research complements ML detection by offering long-term solutions. Tripathi et al. (2022) applied CRISPR/Cas9 gene editing. It achieved 100% survival in greenhouse trials. Li et al. (2023) used transcriptomics to study plant responses and identified 42 differentially expressed genes linked to early stress. Huang et al. (2024) examined autophagy-related genes (ATG genes). ATG genes increased expression 2.1–3.8× under Fusarium infection. Kotari et al. (2016) reviewed genes associated with biotic stress tolerance in banana. This helped in guiding CRISPR, RNAi, and marker-assisted breeding efforts. Khakvar et al. (2008) analyzed genomic variations among Ralstonia solanacearum strains collected from banana farms in Malaysia. Noar & Daub (2016) used transcriptomics for pathogen identification. They discovered several pathogenicity genes in Pseudocercospora species. Caro et al. (2025) developed allele-specific markers for BBTV resistance. Manzo-Sánchez et al. (2019; 2024) analysed genetic variability of Pseudocercospora fijiensis. Mexican strains displayed high genetic polymorphism. Noar & Daub (2016) used transcriptomics for pathogen identification. They discovered several pathogenicity genes in Pseudocercospora species. Caro et al. (2025) developed allele-specific markers for BBTV resistance. Manzo-Sánchez et al. (2019; 2024) analyzed genetic variability of Pseudocercospora fijiensis. Mexican strains displayed high genetic polymorphism. Feng et al. (2019) found virulence factors in Dickeya zeae and identified new toxins that cause leaf maceration. A new pathogen named Dickeya fangzhongdai affecting banana plants was discovered by Yang et al. (2022). Kabirigi et al. (2022, 2024) found that 70–80% of disease information was shared through farmer networks. Rojas & González (2023) showed that the early symptoms of sigatoka banana plant disease are usually not correctly detected by farmers. Hence, biocontrol agents such as Bacillus spp. have proven to significantly help in reducing plant diseases (Dadrasnia et al., 2020). Ocimati et al. (2016) discussed how plant diseases cause a significant effect on farmer's livelihood and also on the ecosystem. Nduwimana et al. (2022) highlights the need for a transparent system for banana seed exchange. Ocimati et al. (2016) studied about the effect of banana plant diseases, particularly Xanthomonas wilt on the food security, household income and soil fertility. This shows that banana plant diseases cause an impact on the ecosystem as well as on the lives of farmers. Sarıdaş et al. (2017) described various socio-economic factors such as market demand, profitability and farmer practices that emerged for banana production in Turkey.

Effendi and Pancoro (2021) conducted a biological study and investigated soils that naturally suppress fusarium wilt. The study shows that understanding of soil microbiomes can help develop biological control strategies. Nakato et al. (2016) developed a system where farmers used mobile phones to report banana plant disease symptoms. The system was supported by even simple phones and enabled faster disease diagnosis and early interventions of diseases. Nakato et al. (2023) explored how altitude (temperature) influences banana pests and diseases. It was found that some diseases are more severe at specific levels. Montiflor et al. (2019) studied how farmer groups and industry actors coordinate to manage diseases. Galarza-Villamar et al. (2021) used a behavioural game model named "public bad game" to understand human behaviour in disease spread and management. It showed how individual actions like poor sanitation causes harm to plants. It suggests that successful control requires proper and collective action by all the individuals.

7. Conclusion and Future Research Directions

This scientometric survey synthesized the advances in deep learning for banana plant disease detection, comparing traditional approaches to CNNs and transformer/hybrid models. The analysis of 184 publications from the Scopus database has been done which reveals a remarkable growth in recent years. Particularly from 2019 onwards. Although many deep learning models have been developed for automatic disease detection, most existing approaches stop at simple classification, they identify whether a leaf is healthy or diseased but do not explain how the decision was made, fail to perform well across different datasets, and do not provide actionable guidance for farmers. Moreover, there is no standard way to measure the severity of infection, and the lack of interpretability and practical recommendations limits the real-world usability of these AI systems. Farmers often cannot trust a model's prediction without understanding whether it truly focused on the infected regions or background noise. Finally, evaluation practices are often limited. Despite advancements, the management of diseases continues to be hindered by the insufficient incorporation of molecular diversity data into AI models. Studies highlight a gap in early-warning systems that combine environmental, microbial, and spectral signals under a unified predictive framework. A comprehensive real-time and edge deployment system could be built which could be integrated with drones or IoT cameras for field monitoring. Moreover, the use of Generative Adversarial Networks (GANs) to generate synthetic diseased leaf images could be done in future. There is also a need for more socio-economic and smallholder-focused AI tools. Most studies report accuracy, precision, recall, or mAP (Mean Average Precision). While useful, these metrics can misrepresent model reliability under dataset imbalance or deployment constraints. Few works include robustness metrics like Cohen's Kappa, domain-transfer evaluations, or explainability validation measures such as IoU (Intersection over Union) overlap between Grad-CAM maps and annotated lesions. Without these, it is difficult to assess real-world reliability. Few works attempt actionable recommendations. Our review found no unified pipeline that integrates detection, explainability, severity quantification, and actionable treatment recommendations for banana specifically, leaving farmers without guidance after disease prediction. Future architectures should integrate RGB and hyperspectral data, soil nutrient data, rainfall and climate data and leaf temperature.

Therefore, there is a need for a comprehensive and explainable framework that not only detects banana leaf diseases accurately but also highlights the infected regions for transparency (using Grad-CAM/LIME), works reliably across multiple datasets for real-world robustness, quantifies the severity of infection, and suggests expert-based treatment recommendations. This system will connect academic research with practical agricultural decision-making, enhancing the transparency, trustworthiness, and utility of AI for farmers. Future research work must focus on building a robust, multimodal and explainable AI system for banana plant disease.

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