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Examining the Use of Machine Learning Approaches in Classifying Banana Crops Diseases: A Systematic Literature Review

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Abstract:

Banana diseases can have significant and wide-ranging impacts on agriculture, affecting both small-scale farmers and larger commercial plantations.Banana crops face significant challenges due to various diseases that can impact their yield and quality. This review delves into the current state of research, emphasizing the emerging role of machine learning in identifying and managing banana diseases. The literature surveyed highlights diverse approaches and methodologies employed to diagnose and mitigate these diseases. Furthermore, the abstract underscores the transformative potential of machine learning algorithms, demonstrating their efficacy in enhancing accuracy and speed in disease detection. The synthesis of existing knowledge in this area not only provides a comprehensive overview of the advancements made but also sets the stage for future research endeavors. Ultimately, this abstract serves as a valuable resource for researchers and practitionersinvolved in addressing the complexities of banana diseases to ensure sustainable banana cultivation and global food security.

Keywords **—Machine Learning, Algorithm, Efficacy, Accuracy and Speed.**

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I. INTRODUCTION

Bananas are the third most widely sold crop in the Philippines. The Philippines is Asia's largest banana exporter, accounting for more than 80% of Asian countries' total banana exports. It is essential as a source of local and international cash for farmers, as well as a staple in all Filipinos' daily diets. However, for as long as the banana exportation industry has been, banana plantations have been under constant threat from various illnesses that have emerged over time. But the affliction that has greatly harmed the Philippines' export sector is Fusarium oxysporum, Panama Tropical Race 4, and Panama Wilt, also known as Panama Disease [1].

Banana leaf diseases have a significant impact on agricultural productivity, leading to a decrease in quantity and quality of agricultural produce. Visual observation, the traditional method of disease identification, is no longer sufficient as it requires expertise that many farmers lack. Therefore, ICT-based approaches, such as autoML, deep learning, and natural language processing are utilized to improve the efficiency and accuracy of disease identification. These technologies can help in early detection and classification of banana leaf diseases, enabling timely intervention[2].

Traditional pest and disease identification approaches rely on agricultural extension specialists, but these approaches are limited in developing countries with low human infrastructure capacity. Many smallholder farmers rely on empirical knowledge, which is less effective in overcoming farming challenges [3]. The early identification of a crop disease or pest can lead to faster interventions with resulting reduced impacts on food supply chains.Artificial intelligence (AI) with deep learning models which help to identify plant diseases by the plant’s appearance and visual symptoms that mimic human behaviour should be considered [4]. Smartphone-based AI apps could alert farmers and expedite disease diagnosis, thus preventing the possible outbreak of pests and diseases [5].

A. *Aims*

This systematic review aims to comprehensively synthesize the latest research gathered from reputable databases regarding the use of machine learning approaches in classifying banana diseases. The primary goal is to provideacomprehensiveanalysisofthe current state of machine learning approaches in classifying banana diseases, including its benefits and limitations. The reviewwillassesstheeffectivenessofmachine learningtechnology in early detection and classification of banana leaf diseases, enabling timely intervention. Moreover, it will compare the traditional methods of classifying specific banana diseases to its existing modern counterparts in terms of resource utilization, environmental impact, and economic feasibility. Lastly, it will identify and prioritize key areas for future research and development in banana disease detection, with a particular focus on optimizing disease detection and mitigation.

II. METHODOLOGY

A. *SystematicLiteratureReview*

The next section clarifies the mechanism for controlling theconsistent review was included in the investigation. asseen in Figure. 1. The review strategy obtained in the examination is divided into three phases:the plan ofaction, management, and description [6].

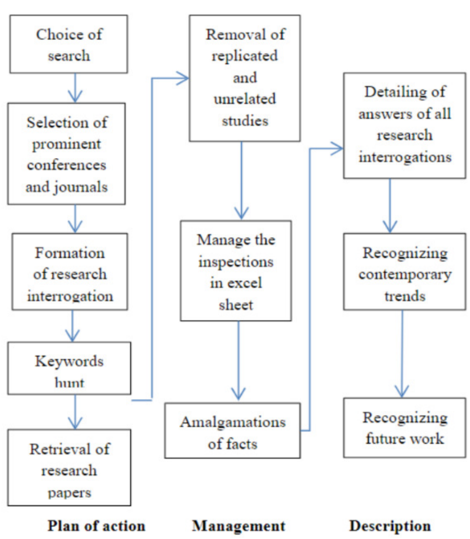

Fig.1 Review Methodology

B. *Data Collection*

Five unique keywords strings namely: crop disease detection, banana disease classifier, banana cultivation, crop disease management, and crop disease mitigation were used to conduct a comprehensive search across various databases, including IEEE Explore, Google Scholar, ScienceDirect, and PubMed, focusing on records related to the study [7].A comprehensive organization was made to improve the dataset prior to the screening stage. First records were obtained from different sources, therefore there was a complete count. In preparation for further analysis, the dataset was refined by removing duplicate items and omitting records that were not in English. This made sure that the dataset for the systematic review was more pertinent and focused [8].

C. *Screening Evaluation*

The screening process entailed evaluating allpapers based on their titles and abstract. Each identified record was rigorously evaluated to establish eligibility for inclusion in the systematic review [9]. This included applying predetermined criteria, which resulted in the exclusion of certain records to make a more specific selection. Simultaneously, efforts were made to retrieve reports linked with these records, but not all were successful. Following this, the retrieved reports were subjected to a rigorous eligibility assessment, which resulted in the exclusion of the specified reports for the reasons stated in the study protocol. The rigorous screening procedure ensures that relevant research is selected for a complete assessment of the use of machine learning approaches in banana disease classification.

D. *Selection of Studies*

Following the screening process, the systematic review included studies that satisfied the established criteria. These findings constitute the foundation of our inquiry into the use of machine learning methodologies in banana disease categorization. The reports linked with this included research were thoroughly evaluated and incorporated into our study to provide a detailed understanding of the subject. This final set of included studies serves as the foundation for assessing and synthesizing the current literature, providing useful insights into banana agriculture [10]. After applying the methodologies, 20 studies were selected as satisfying the criteria for inclusion in this systematic review, as shown in Figure 1. The inclusion criteria ensured that the selected studies aligned with the objectives of our review, enhancing the accuracy and relevance of our findings.

III. FUNDAMENTALS OF CLASSIFYING BANANA CROPS DISEASES

A. *Traditional Methods*

1. Visual inspection

Visual inspection is a crucial method for classifying banana diseases based on observable symptoms [11]. Plant pathologists and farmers rely on the distinctive visual features exhibited by banana plants to identify and categorize diseases. The process involves careful examination of both leaves and fruits for abnormal patterns, discoloration, lesions, and other indicators of pathogenic infections. Examining the leaves for any abnormal discoloration, spots, streaks, or wilting may help in visual inspections for identifying banana diseases. Additionally, taking in consideration the fruit symptoms like abnormalities on the banana fruit, such as discoloration, lesions, or deformities may lead to a conclusion if the banana is infected with a disease thru visual inspection. Visual inspection, while a conventional method, remains a fundamental and cost-effective approach for early disease detection in banana farming. It serves as the foundation for further, more complex analysis, such as laboratory testing and pathogen detection [11].

2. Laboratory Testing

Laboratory testing plays a crucial role in accurately classifying banana diseases by identifying the specific pathogens responsible. This involves a combination of techniques to isolate, culture, and analyse pathogens present in infected plant material [12]. Procedures like pathogen isolation and microscopic examination may also lead to a conclusion if the banana is infected with a disease thru laboratory testing.Laboratory testing allows for a precise identification of banana diseases at the pathogen level, facilitating targeted disease management strategies [12].

B. *Introduction to Machine Learning*

Machine learning (ML) approaches have transformed the classification of banana diseases, providing a more efficient and accurate approach to diagnosis [13]. ML algorithms, particularly those based on image recognition and pattern analysis, have shown great promise in detecting and categorizing banana diseases based on visual indications. These algorithms can learn to discover tiny patterns that humans may find difficult to detect by training models on vast datasets of photos exhibiting various medical signs. Furthermore, ML allows for real-time monitoring of plant health, permitting early identification and proactive management measures [14]. Researchers have investigated the use of convolutional neural networks (CNNs) and other advanced machine learning models for automated disease detection in several crops, including bananas.This integration of technology holds promise for enhancing precision in disease identification, ultimately contributing to more effective strategies for disease management in banana cultivation [15].

IV. MACHINE LEARNING TEHNIQUES FOR BANANA DISEASE DETECTION AND CLASSIFICATION

A. *Image Processing and Computer Vision*

Image processing and computer vision algorithms have been utilized in several studies to analyze the visual characteristics of bananas for disease detection. These studies aim to provide accurate, precise, and fast methods for determining banana diseases.

Table 1 - Related studies for image processing and computer vision

Lead Author and Year	Title	Databases searched	Total studies included	Image processing and computer vision algorithm	Findings
Narayanan, K. (2022)	Banana Plant Disease Classification Using Hybrid Convolutional Neural	hindawi	25	Artificial neural network, Principal component analysis	In the classification of diseases, ANN, KNN, PCA, and other image processing techniques frequently

	Network.				show reduced accuracy and longer processing times [16].
Baki, A. (2023)	BananaSqueezeNet: A very fast, lightweight convolutional neural network for the diagnosis of three prominent banana leaf diseases.	sciencedirect Elsivier BV	49	DL Convolutional neural network	presented BananaSqueezeNet, a low-power CNN architecture that guarantees quick and precise diagnosis of diseases affecting banana leaves from pictures [17].
Tugrul, B. (2022)	Convolutional Neural Networks in Detection of Plant Leaf Diseases: A Review. Agriculture	mdpi	142	DL Convolutional Neural Networks	It presents a brief comparison of different CNN models and provides insights into dataset preparation, problems, and solutions in plant leaf disease detection [18].
Patel, H. (2022)	Automated Identification and Classification of Banana Fruit Diseases: An Intelligent Grading System	IJFANS international journal of food and nutritional sciences	30	Deep Neural network, Gaussian and median filters	By precisely identifying and categorising a range of banana plant diseases and symptoms, the suggested system helps farmers. Its high accuracy rate allows for efficient disease control, stopping the spread of the disease to neighbouring plants and enabling timely management responses [19].
					Modern convolutional neural

Andrew, J. (2022)	Deep Learning-Based Leaf Disease Detection in Crops Using Images for Agricultural Applications.	Mdpi, Agronomy	55	Multi-class support vector machine (SVM)	networks were standardised and assessed. The results showed that DenseNet-121 performed better than ResNet-50, VGG-16, and Inception V4 in terms of F1 score, sensitivity, specificity, and classification accuracy [20].
Barman, U. (2020).	Comparison of convolution neural networks for smartphone image based real time classification of citrus leaf disease.	Sciencedirect Elsivier BV	27	Convolutional Neural Network (CNN), MobileNet and Self-Structured (SSCNN), support vector machine (SVM)	The SSCNN model was judged to be more acceptable than MobileNet CNN, even though both models produced accurate results. In general, the SSCNN architecture outperformed MobileNet CNN [21].
KIZILOLUK, S. (2021)	Comparison of Standard and Pretrained CNN Models for Potato, Cotton, Bean and Banana Disease Detection.	NATURENGS MTU Journal of Engineering and Natural Sciences Malatya Turgut Ozal University	23	Convolutional Neural Network (CNN), ImageNet	Using image processing technology, this study uses popular CNN models—DarkNet-19, GoogleNet, Inception-v3, Resnet18, and ShuffleNet—for automatic disease classification in potato, banana, cotton, and bean leaf images [22].
					Accuracy is improved by expanding the dataset size through rigorous

Wubetu Barud Demilie. (2024)	Plant disease detection and classification techniques: a comparative study of the performances.	Journal of Big Data	168	Convolutional neural network (CNN)	testing and training. The effective management of crop or plant diseases depends on the ongoing development and use of new and improved deep learning algorithms for increased accuracy [23].
Sanga, S. (2020)	Mobile-based Deep Learning Models for Banana Disease Detection.	Engineering, Technology & Applied Science Research	21	Deep Convolutional Neural Network Models	Assessed transfer learning and deep learning models for an offline mobile app that diagnoses banana diseases. The software evaluates performance using three target datasets and requires a detection confidence of at least 70%; if not, it recommends taking a clearer picture of a leaf [24].
Dhaka, V. S.	A Survey of Deep Convolutional Neural Networks Applied for Prediction of Plant Leaf Diseases	Sensors	124	Deep Convolutional Neural Networks (DCNN), CNN architectures, CNN frameworks	With a focus on plant diseases, dataset features, image pre-processing, CNN architectures, frameworks, performance metrics, and experimental outcomes, they compare different DCNN architectures [25].
S.	Deep Learning Based Dual Channel	Journal of Food	39	convolutional neural network (CNN), The	The framework creates a multi-input model by combining DL with RGB and hyperspectral imaging. In

Raghavendra (2022)	Banana Grading System Using Convolution Neural Network	Quality		combined merits of RGB and HSI (hyperspectral imaging)	classifying bananas, it obtains 98.4% accuracy and 0.97 F1-score by applying CNN and MLP to extracted features. With a 99% accuracy rate, it also predicts size and view with accuracy [26].
Cristian A. Escudero (2022)	Black Sigatoka Classification Using Convolutional Neural Networks.	International Journal of Machine Learning and Computing	21	LeNet convolutional neural network	Developed an automated technique for detecting Black Sigatoka in banana leaves at an early stage using CNN LENET. The method allows for the timely correction of disease stages in leaf segments, thereby averting economic losses [27].
Selvaraj, M. G. (2019)	AI-powered banana diseases and pest detection.	Plant Methods	37	Deep convolutional neural networks (DCNN), Deep transfer learning (DTL)	To identify banana pest and disease symptoms in real-time from field photos, this paper introduces a novel deep transfer learning technique. Unlike other approaches, the system finds and classifies banana plant diseases, providing a workable solution [28].
Sanga, S. (2020)	Mobile-based Deep Learning Models for Banana Disease Detection	Engineering, Technology & Applied Science Research	16	Vgg16, Resnet18, Resnet50, Resnet152 and InceptionV3	This study suggests a deep learning method for banana disease detection by using five architectures (Vgg16, Resnet18, Resnet50, Resnet152, and InceptionV3). The models' high

					accuracy ranges from 99.2% (Resnet152) to 95.41% (InceptionV3). Because InceptionV3 requires less memory, it is selected for mobile deployment [29].
Sapkal, A. (2018)	Comparative study of Leaf Disease Diagnosis system using Texture features and Deep Learning Features	International Journal of Applied Engineering Research	26	Gray Level Covariance Matrix (GLCM), Backpropagation neural network (BPNN)	Achieving an average 10-fold validation accuracy of 93.85%, they extract texture and deep learning features from leaf images and apply them to the Backpropagation neural network for disease detection [30].
Garg, D. (2022)	Integration of Convolutional Neural Networks and Recurrent Neural Networks for Foliar Disease Classification in Apple Trees	International Journal of Advanced Computer Science and Applications	34	LSTM (Long Short-Term Memory networks), CVPR (Computer - Vision and Pattern-Recognition)	Comparative analyses show that integrated models perform better than individual ones. Notably, the accuracy of InceptionV3-LSTM is the highest at 99.8%, followed by that of Xception-LSTM at 99.5%, and the lowest at 99% for VGG16-LSTM [31].
					Our project suggests a deep learning method for identifying and

Pukale, D. D. (2018)	A Deep Learning Based Approach for Banana Plant Leaf Diseases Classification and Analysis	BTW 2017	17	LeNet architecture, convolutional neural network	categorising diseases of banana leaves using the LeNet architecture. This system effectively forecasts illnesses and provides appropriate treatments [32].
Araya, R. J. (2019)	Review of the publication: A Deep Learning-based Approach for Banana Leaf Diseases Classification	medium.com	1	LeNet architecture as a convolutional neural network (CNN)	The suggested model functions well in real-world situations, adjusting to shifting parameters like lighting, intricate backgrounds, different resolutions, size, position, and orientation [33].
Kumar, Y. (2022)	Convolutional neural network architecture for detection and classification of diseases in fruits	Current Science	24	MobileNet, DenseNet121 and InceptionV3	To classify five fruits into categories of disease or health, this study presents a combination of CNN models, with an accuracy of more than 90% for both the fruit and its leaves [34].

V. RESULTS

The review carefully examined 20 research studies to compare the various machine learning techniques employed classifying banana crops diseases. Within those examined research studies, several image processing and computer vision algorithms were used in various studies for the specific goal of classifying banana crops diseases.

A. *Artificial Neural Network*

An artificial intelligence-based banana disease and pest detection system was proposed in [35], where the algorithm used is a deep convolutional neural network for disease detection. The author collected data sets for about 8 different diseases in bananas, totalling 30,000 images, and the proposed system achieves 90% accuracy. Machine learning algorithms were developed for the detection and classification of plant diseases [36]. This paper reviews various machine learning and deep learning algorithms for the detection and classification of plant diseases, as well as identifies some research gaps for detecting disease in plants even before symptoms appear.

A deep learning-based banana leaf disease classification is suggested [37], and they employ the LeNet architecture as a convolutional neural network to categorize the data. The findings of this study illustrate its usefulness in a variety of picture circumstances, including complicated backgrounds, varying sizes, and orientations. This approach is stabilized after 25 rounds and delivers high accuracy on the last iteration. A machine learning-based strategy to early diagnosis of banana disease using the SVM classifier is suggested [38]. The photos utilized are close-range hyperspectral remote sensing photographs. The classifiers' outcomes are assessed in terms of overall accuracy, which is the accuracy utilizing spectral and morphological information and is around 96% in early detection, 90% in mid detection, and 92% in late detection.

In [39], an image processing-based banana leaf disease detection method is proposed; the images are first acquired, and the RGB model is converted into an HSI colour model and then pre-processed, after which the image is segmented using the thresholding method, and histogram equalization is found for the HSI image. The categorization is then evaluated with three alternative classifiers: backpropagation neural networks, support vector machines (SVM), and principal component analysis (PCA). An artificial neural network-based banana leaf disease detection and classification is proposed in [40], in which the image is initially acquired and pre-processed, and then the colour and HOT (Histogram of Template) features are extracted, the data set is trained using the artificial neural network, and the query images are graded based on the total percentage of the affected area. Finally, the picture is categorized according to its illness kind.

Not only is more study being conducted on banana leaves, but also on identifying and categorizing diseases in most edible crops such as rice, maize, apple, cheerful, and other common plants. Some of these findings are presented below. [41] proposes better convolutional neural networks for classifying apple and cherry plant diseases. The enhancement in the CNN is based on combining a framework of inception functionality squeezing, excitation functionality, and a global pooling layer. This approach achieved an accuracy of around 91.7% on the test data set. A deep convolutional neural networks and object detection technique based on tomato disease identification have been implemented with two different techniques: Faster R-CNN, which is used for identifying the type of tomato disease, and Mask R-CNN, which is used to find and segment the location and shape of the infected areas. The results show that the proposed method gives an accuracy of 90% in detecting the disease and 99% in identifying the shape of the infection [42].

Automatic detection and classification of diseases in rice crops are proposed in [43], and here they use an artificial neural network-based technique to identify the disease. They have done research on many diseases that affect the rice crop and measured the accuracy of the classifier for each type of disease, and finally they have compared the ANN technique with other leading classifiers for detecting the same diseases and their accuracy were measured and concluded that ANN.A unique rice blast identification approach based on CNN is proposed in [44]. This approach was examined using several combinations, including CNN simply, CNN with SVM, LBPH with SVM, and Haar-WT with SVM, and their accuracy was compared, revealing that CNN with SVM provides an accelerating accuracy of around 96% with an AUC curve of 0.99. The present system's fundamental problem is that it relies on intricate picture segmentation algorithms, which may be time-consuming. Existing disease detection techniques, such as ANN, KNN, PCA, and other image processing methods, can be inaccurate and time-consuming for certain crops. Additionally, some diseases may blend with healthy parts of the leaf, making it difficult to detect [45].

B. Comparison with Traditional Methods

The classification of illnesses in banana crops has traditionally been based on visual inspection by agricultural professionals, which is subjective and possibly error-prone. Manual sampling and laboratory analysis have also been used, but these approaches are labor-intensive and time-consuming, and they may cause delays in prompt responses, increasing the risk of disease spread. Additionally, older systems frequently rely on the knowledge of human inspectors, restricting scalability and resulting in inconsistent diagnoses [46]. These techniques face a challenge in covering broad agricultural areas, which jeopardizes disease identification and could result in severe productivity losses.In contrast, machine learning (ML) technologies, notably artificial neural networks (ANNs), have emerged as effective tools for automated disease classification in banana crops. ANNs, particularly Convolutional Neural Networks (CNNs), achieve great accuracy by automatically learning complicated patterns from images [47]. This enables fast and timely illness identification, with real-time or near-real-time results and prompt measures to reduce disease spread. ML models may be trained on enormous datasets, allowing them to cover large agricultural areas. The data-driven aspect of machine learning improves illness classification by capturing complex patterns that the human eye may miss.However, there are several drawbacks to using machine learning approaches. Large labelled datasets are necessary for training, and any potential biases in the data must be addressed [48]. Regular updates and adjustments are required to account for changing disease strains and environmental variables. Despite these limitations, incorporating machine learning, particularly artificial neural networks, into banana crop disease categorization provides a considerable improvement over older methods. It improves precision, efficiency, and scalability, transforming disease management in agriculture. Continuous collaboration between agricultural professionals and data scientists is essential for building and maintaining robust and dependable models that contribute to sustainable and resilient banana growing.

VI. DISCUSSION

Machine learning (ML), specifically artificial neural networks (ANNs), has emerged as a major and transformative tool in modern agriculture for disease classification of banana crops. ANNs, which are inspired by the structure and function of the human brain, excel at processing complicated data, making them ideal for image-based classification tasks like recognizing problems in banana crops. ANNs are used to train models using labelled datasets containing photos of healthy and diseased banana plants, allowing the network to understand detailed patterns and features associated with different diseases.Mohanty et al. (2016) [49] proved the efficacy of deep learning, including ANNs, in plant disease identification, laying the groundwork for its use in banana farming. The advantage of ANNs is their capacity to automatically extract essential information from photos, catching nuances that traditional approaches may struggle to detect. This automated feature extraction improves disease categorization accuracy, allowing for more precise and timely therapies.

In the field of banana crop disease classification, Convolutional Neural Networks (CNNs), a form of ANN specialized for image processing, have proven to be especially effective. CNNs can learn hierarchical representations of picture information, which enables them to detect complicated patterns and variations associated with various diseases. Kamilaris, Kartakoullis, and Prenafeta-Boldú's (2018) [50] study of deep learning in agriculture highlights the promise of CNNs for identifying agricultural diseases. Their capacity to adapt to various image scales and resolutions adds to the resilience of illness categorization models.

One major advantage of using ANNs in banana crop disease classification is the ability to do real-time or near-real-time analysis. This capability enables farmers and agricultural specialists to make quick decisions and perform early actions to avoid disease transmission. The effectiveness of ANNs in processing massive amounts of data is very useful in the setting of vast banana plantations. This scalability enables the use of ML models in a variety of agricultural environments, resulting in early disease identification and effective control.

Despite the gains, obstacles remain in deploying ANN-based models for banana crop disease categorization. Large and well-curated datasets are essential for accurate model training, as are initiatives to eliminate data biases. To account for changing disease strains and environmental variables, models must be updated on a regular basis. Collaboration among agronomists, plant pathologists, and data scientists is critical for successfully integrating ML into agriculture, ensuring that the models are not only accurate but also meet the practical demands of banana growers.

VII. CONCLUSION

In conclusion, the review of 20 research studies has provided a comprehensive overview of the current state of research in this critical domain of precision agriculture.The use of machine learning (ML) techniques, specifically artificial neural networks (ANNs), to classify banana illnesses represents a paradigm change toward more accurate, efficient, and scalable solutions. The findings of several research, such as those by Mohanty et al. (2016) [49] and Kamilaris et al. (2018) [50], highlight the effectiveness of deep learning, particularly ANNs, in image-based disease identification, opening a viable path for the agriculture sector.

The systematic research found that ANNs, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for automatically learning complicated patterns and traits linked with various banana illnesses. This automated feature extraction improves disease categorization accuracy, allowing for more prompt disease management measures. Because of their scalability, ANNs may be applied over huge agricultural landscapes, assisting in early disease diagnosis and successful control measures. The real-time or near-real-time analysis capabilities of ANNs highlight their potential for supporting rapid decision-making by farmers and agricultural specialists, thereby reducing the impact of illnesses on banana harvests.

Despite the successes, problems remain in the form of data requirements, potential biases, and the need for constant model upgrades. The systematic literature review underlined the relevance of big, well-curated datasets for training correct models, as well as the need for collaboration between domain experts and data scientists to effectively address these difficulties. According to the studied literature, incorporating machine learning into agriculture offers not just a technological achievement, but also a critical step toward sustainable and resilient banana farming practices.

Future research in this subject should focus on addressing the mentioned obstacles, improving model interpretability, and assuring the practical applicability of machine learning solutions for banana crop disease classification. The synthesis of findings from the studied literature paves the way for future advances in the interface of agriculture and machine learning, stimulating innovation and contributing to the worldwide effort to improve food security.

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