Harnessing artificial intelligence for early detection of oil palm diseases in Benin

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Abstract
Oil palm (Elaeis guineensis) cultivation is vital to Benin's agricultural sector, significantly contributing to the livelihoods of rural farmers. However, the industry faces considerable challenges, particularly from diseases such as Fusarium wilt, leading to substantial crop losses. Traditional disease detection methods are often slow and unreliable. This study examines the potential of Artificial Intelligence (AI), particularly machine learning (ML) techniques, to improve early disease detection in oil palm cultivation. Using a Convolutional Neural Network (CNN) model trained on a dataset of healthy and diseased oil palm images, the study demonstrates that AI outperforms traditional methods in speed and accuracy. The results show that the DenseNet architecture achieved the highest performance in early disease detection, proving a promising tool for enhancing disease management in Benin's oil palm sector. The study also identifies key barriers, including limited access to technology, poor digital infrastructure, and a lack of quality datasets in rural areas. Recommendations for policymakers include investing in technology infrastructure, enhancing digital literacy among farmers, and creating comprehensive datasets to support AI-driven agricultural solutions.

Keywords
Artificial Intelligence, Oil Palm, Disease Detection, Convolutional Neural Networks, Machine Learning, Agriculture, Benin

1. Introduction

Oil palm (*Elaeis guineensis*) is a crucial crop for Benin, particularly in its southern regions. Historically, it expanded during King Ghézo's reign (1818–1858) to meet the rising demand for palm oil from Western countries, primarily for soap production. Today, oil palm is a key economic driver, contributing significantly to Benin's agricultural GDP and providing livelihoods for rural communities [1, 2]. However, despite its economic importance, the oil palm industry faces considerable challenges, most notably diseases such as Fusarium wilt.

Fusarium wilt is caused by the Fusarium fungus and leads to wilting, yellowing, and eventual death of palm trees, often spreading rapidly. Early symptoms are difficult to recognize using traditional methods, which rely on visual inspections. This results in delayed detection, contributing to significant crop losses [3]. Traditional disease detection methods are time-consuming and prone to error, particularly in large plantations where disease symptoms overlap with environmental stress factors.

AI presents a promising solution to this challenge. By using machine learning models, particularly Convolutional Neural Networks (CNNs), AI can analyze images of oil palm leaves and detect early signs of diseases with high accuracy, offering a faster, more reliable alternative to traditional methods [4]. AI-powered tools can provide farmers with real-time, automated diagnostics, which can be integrated

CITA 2025 — Emerging Technologies and Sustainable Agriculture, 26–28 June 2025, Cotonou, Benin
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into mobile applications, making them accessible even in areas with limited technological infrastructure [5].

This study aims to explore how AI, specifically CNNs, can improve early disease detection in oil palms and enhance overall disease management in Benin's oil palm industry.

2. Literature review

In Benin, oil palm (*Elaeis guineensis*) cultivation is significantly threatened by diseases such as Fusarium wilt and leaf spot, which adversely affect productivity and farmer livelihoods (Asyari and Mutawally, 2019). Fusarium wilt, caused by the soil-borne fungus Fusarium oxysporum f. sp. elaeidis, is one of the most destructive diseases impacting oil palms in Africa (Adusei-Fosu et al., n.d.). The pathogen invades the plant's vascular system, leading to wilting, yellowing of fronds, and eventual death of the palm, as shown in Figure 1. Early detection is challenging due to the pathogen's subterranean activity, often resulting in significant disease progression before visible symptoms emerge. A 2018 survey across 16 plantations in Benin's major oil palm-producing regions revealed varying disease incidences, with some areas reporting rates as high as 30 %, underscoring the widespread nature of Fusarium wilt in the country [3].

Leaf spot diseases, primarily caused by fungal pathogens such as Cercospora elaeidis, present another significant challenge to oil palm health in Benin. These diseases manifest as small, yellowish spots on the leaves, which can coalesce into larger necrotic areas, leading to reduced photosynthetic capacity and overall vigor of the palms (Figure 2). Seedlings and young palms are particularly susceptible, with severe infections potentially leading to defoliation and stunted growth [6].

Figure 1: Fusarium wilt symptoms in oil palm

Currently, the detection of these diseases in Benin largely depends on the expertise of agricultural extension officers, who visit farms to conduct inspections. However, these officers are limited in number and coverage, often unable to reach all farms in a timely manner. Furthermore, their inspections can be subjective and may miss early, subtler signs of disease. As such, there is a pressing need for more efficient, accessible, and accurate methods of disease detection to protect the oil palm industry in Benin.

AI in agriculture has gained traction over the past decade, particularly for plant disease detection. Traditional methods often rely on manual inspections, which are both slow and prone to errors. AI systems, especially those using machine learning and deep learning algorithms like CNNs, have demonstrated significant improvements in early disease identification [7, 8].

Machine learning techniques, especially CNNs, have been widely adopted for disease detection in crops due to their ability to analyze large image datasets and identify patterns that may not be visible

Figure 2: Leaf spot disease on oil palm leaves

to the human eye. For instance, CNN-based systems have achieved over 90 % acuracy in detecting palm diseases including Ganoderma rot, using smartphone or drone imagery for early diagnosis [9]. More sophisticated ensemble CNN models applied on UAV data have also enabled effective identification of basal stem rot (Ganoderma), reaching up to 91.8 % accuracy [10]. However, AI adoption in Sub-Saharan Africa faces several substantial barriers, including limited digital infrastructure, high data costs, poor connectivity, inadequate data management protocols, and low digital literacy among farmers [11, 12].

3. AI Applications in Agriculture

AI's application in agriculture has proven particularly useful in disease detection. Traditional methods typically rely on expert knowledge and visual inspections, which are time-consuming and often inaccurate. AI-based systems, particularly those utilizing machine learning algorithms, offer a more efficient and accurate approach. For example, CNNs have been used to detect various crop diseases, including cassava brown streak disease and cassava mosaic disease, with high accuracy [13].

AI systems, in combination with remote sensing technologies such as drones and satellites, can monitor large agricultural areas by capturing high-resolution images and analyzing them for signs of disease or environmental stress. These technologies enable real-time monitoring, which is critical for preventing disease outbreaks in large plantations [14].

While the potential of AI in agriculture is significant, its adoption in Sub-Saharan Africa, including Benin, faces challenges such as technological infrastructure deficits and the need for more accessible data and tools for farmers [15].

4. Research methodology

This study adopts a mixed-methods approach, combining the development of an AI model for early disease detection with a survey of local farmers. The goal is to integrate both technological innovation and community insights, ensuring the solution is scientifically valid and practical for the local context.

4.1. AI Model Development

We compiled a dataset of 3,200 high-resolution images sourced from field surveys, agricultural extension agents, and local research institutions. The dataset includes four classes: healthy, Fusarium wilt (1,100 images), leaf spot (850), black rot (650), and healthy leaves (600). Images were annotated with expert validation. Augmentation techniques included random rotations, flips, brightness adjustments, and noise injection to simulate variable field conditions. The data was split 80-10-10 for training, validation, and testing, ensuring class and regional diversity).

4.2. Farmer surveys

A structured survey was conducted with 123 farmers across three regions (Mono, Plateau, and Ouémé). Participants were selected using stratified random sampling. The survey explored AI awareness, digital access, disease management practices, and openness to innovation. The average age was 46 years, with 63 % of respondents owning less than 2 hectares.

4.3. AI model selection and performance evaluation

To identify the optimal AI model, we evaluated three CNN architectures: ResNet, DenseNet, and VGG16. ResNet was selected for its ability to train deep networks while avoiding vanishing gradient issues through residual blocks, facilitating the learning of complex features [16]. DenseNet was chosen for its efficient learning from fewer parameters, thanks to dense connections between layers that enhance the model's capacity [17]. VGG16, a simpler model, served as the baseline for comparison due to its established performance in image classification tasks [18].

Each model was trained on the prepared dataset and evaluated using key performance metrics: accuracy, precision, recall, and the F1 score. Accuracy measures the proportion of correctly classified images, while precision and recall evaluate the model's ability to predict positive cases and correctly identify actual positives, respectively. The F1 score balances precision and recall, particularly useful for imbalanced datasets.

Performance was assessed on the test set, and confusion matrices were used to identify areas of misclassification. This evaluation approach combines AI model development with insights from local farmers, ensuring the disease detection tool is not only accurate but also practical and accessible for implementation in Benin's oil palm sector.

5. Results

This section presents the findings from both the development of the AI model for disease detection in oil palms and the survey conducted with local farmers in Benin. The results are discussed in two main areas: the performance of the AI model compared to traditional disease detection methods, and the insights gained from the farmer survey, including their readiness for AI adoption and the barriers they face in implementing such technologies.

5.1. Model Performance

The AI model developed for this study utilizes CNNs to detect diseases in oil palms. Three different CNN architectures were evaluated: ResNet, DenseNet, and VGG16. Each model was trained using a dataset of images depicting both healthy and diseased oil palms, and their performance was assessed with a test set. The key evaluation metrics include accuracy, precision, recall, and the F1 score, which provide a comprehensive view of the model's effectiveness in identifying oil palm diseases.

5.1.1. ResNet model

The ResNet model, which employs residual connections to facilitate the training of deep networks, achieved an accuracy of 86% in identifying diseases in oil palms. This model outperformed VGG16, especially in detecting more complex diseases like Fusarium wilt. However, it struggled with identifying early-stage symptoms of disease, where subtle signs were often missed. The precision for Fusarium wilt detection was 84%, but the recall was slightly lower at 80%, indicating that the model was more effective at predicting diseased palms when the symptoms were more apparent but missed some of the earlier-stage cases.

5.1.2. DenseNet model

The DenseNet model, known for its efficiency in learning from fewer parameters through dense layer connections, demonstrated the highest accuracy among the three models, achieving 89.7%. DenseNet performed strongly both in precision (87%) and recall (91%), suggesting it was better at detecting diseases in their early stages. The high recall rate indicates that DenseNet successfully identified a larger proportion of diseased oil palms, even when the symptoms were not as visible. The confusion matrix for DenseNet revealed fewer misclassifications compared to ResNet and VGG16, particularly for diseases like leaf spot and black rot. These findings align with previous studies that have shown DenseNet's effectiveness in plant disease detection [19].

5.1.3. VGG16 model

The VGG16 model, being simpler and using fewer parameters, performed reasonably well but lagged behind the other two models. It achieved an accuracy of 79%, with precision and recall rates of 75% and 72%, respectively. While the model performed adequately, it struggled to distinguish between diseases with similar visual characteristics, especially in the early stages of Fusarium wilt. This highlights the trade-off between simplicity and performance in AI models for agricultural applications.

5.1.4. Comparison to traditional methods

When compared to traditional disease detection methods, the AI models significantly outperformed manual visual inspections by farmers and agricultural experts. Traditional methods heavily rely on manual inspection, which is time-consuming and prone to errors, particularly when diseases show subtle or overlapping symptoms. In contrast, the AI models could process thousands of images quickly and identify patterns that might not be immediately obvious to the human eye. This efficiency, combined with the high accuracy of the DenseNet model, suggests that AI could revolutionize disease detection in oil palm cultivation, enabling farmers to act proactively and reduce crop losses before the disease spreads. Figure 3 illustrates the performance metrics of the AI models in detecting oil palm diseases.

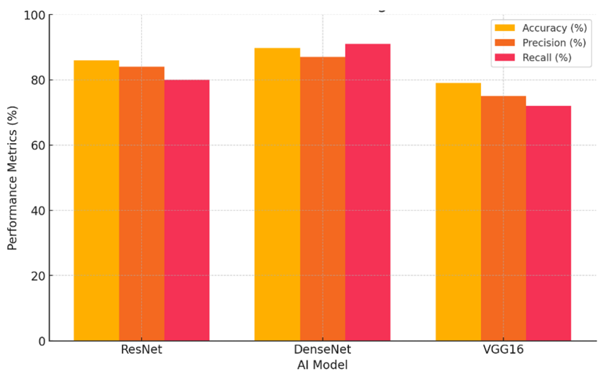

Figure 3: AI model performance in detecting oil palm diseases

5.2. Field survey results

The field survey was designed to assess the potential for AI adoption in the oil palm sector of Benin, focusing on farmers' readiness to use such technology and the challenges they face in managing oil palm diseases.

5.2.1. Farmer readiness

The survey results showed that a significant portion of farmers (63%) were open to adopting AI for disease detection, provided they received the necessary support. Approximately 75% of farmers who already owned smartphones expressed particular interest in using an AI tool if it were available on their devices. Figure 4 illustrates the level of farmer readiness for AI adoption..

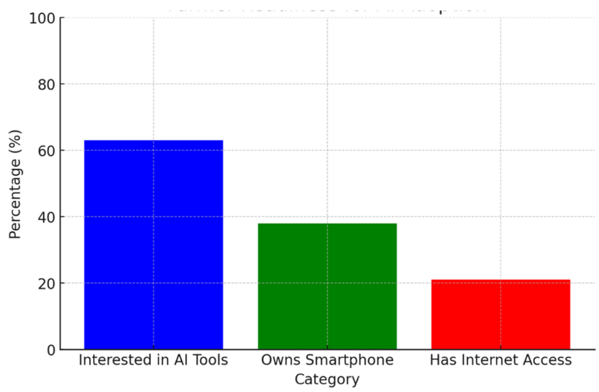

Figure 4: Farmer readiness for AI adoption

5.2.2. Technological access

Despite the interest in AI, access to technology remains a major barrier. Only 38% of farmers in the survey owned smartphones, and only 21% had access to reliable internet. In rural areas, where most oil palm cultivation is concentrated, internet connectivity is often unstable or nonexistent, preventing farmers from utilizing AI tools that require real-time data processing. Lack of infrastructure was the most cited barrier to AI adoption, with 82% of farmers acknowledging that they would need support to access smartphones or improve their internet connection to benefit from AI technology. This aligns with broader studies on digital adoption in West African agriculture, which highlight infrastructure and cost as significant barriers to technology adoption [20].

5.2.3. Barriers to AI Adoption

The survey identified several barriers to AI adoption in the oil palm sector:

The high cost of smartphones and data plans is a primary concern, as many farmers cannot afford these technologies. Even with the potential for improved disease management, many farmers are concerned about the initial investment required to access AI-based tools.

While some farmers expressed willingness to use AI, many lacked the technical skills necessary to operate these tools. Around 55% of respondents indicated they would need training to effectively use smartphones for crop management. This suggests that significant efforts are needed to build digital literacy and ensure that farmers can fully utilize AI for disease detection.

Some farmers expressed skepticism about relying on technology for disease detection, preferring traditional methods they perceive as more reliable. These concerns were particularly prevalent among older farmers who were less familiar with digital technologies.

Figure 5 illustrates the main barriers to AI adoption identified in the survey.

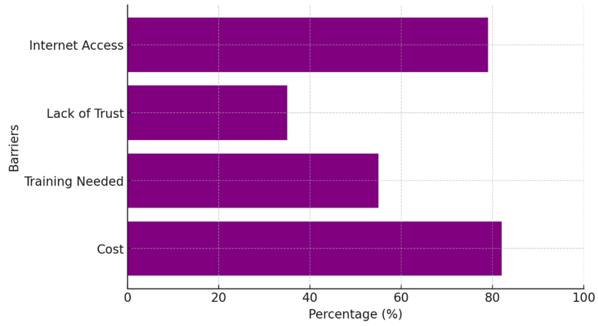

Figure 5: Barriers to AI adoption among farmers

5.2.4. Potential for Community-Based Solutions

Despite these barriers, the survey also revealed strong support for community-based solutions. Farmers indicated they would be more likely to adopt AI if they received guidance from local agricultural extension workers or through farmer groups. Collaborative efforts such as training programs or the creation of farmer cooperatives offering shared access to technology were viewed as viable solutions to overcome the challenges of cost and access. Figure 6 compares AI-based disease detection with traditional methods, highlighting the advantages of AI in terms of accuracy and efficiency.

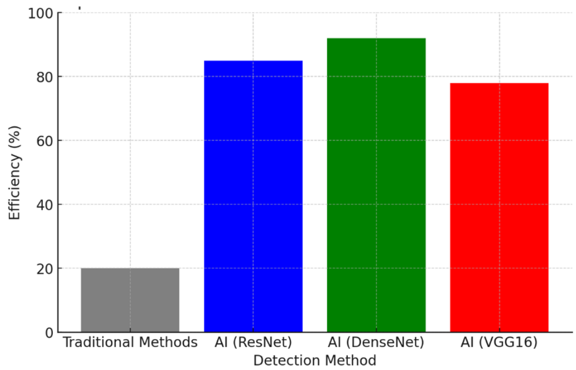

Figure 6: Comparison of AI and traditional disease detection

6. Discussion

This section discusses the implications of the findings from both the AI model development and the farmer survey, particularly in terms of disease management and economic resilience in Benin's oil palm sector. It also addresses the challenges of limited technology access and the need for robust digital infrastructure, which are crucial for successfully implementing AI in agricultural practices. The results demonstrate that while AI offers substantial potential for improving disease detection, its widespread adoption hinges on overcoming these infrastructure and socio-economic barriers.

6.1. Implications for disease management

The integration of AI-driven image analysis into oil palm disease management holds significant promise for early detection and control of devastating pathogens. In particular, diseases like Fusarium wilt – caused by *Fusarium oxysporum* f. sp. *elaeidis* – are the most destructive in African oil palm cultivation and notoriously difficult to manage with conventional methods [21, 22]. Outbreaks of Fusarium wilt can cause severe yield losses (up to $\sim$50% mortality of young palms in affected plantations) [21], underscoring the need for timely intervention. By leveraging convolutional neural networks (CNNs) such as DenseNet, farmers and agronomists can identify early visual symptoms that might otherwise be missed until an epidemic is well underway. For example, deep learning models have achieved high accuracy in classifying plant leaf diseases; a DenseNet201-based classifier attained over 98% validation accuracy on a diverse crop disease dataset [23]. In oil palm, [24] demonstrated that a CNN (GoogLeNet) could detect leaf pests and diseases with over 93% precision and recall, which was deemed "highly satisfactory, warranting [its] application in oil palm companies to enhance pest and disease management". These results suggest that similar models – including modern architectures like DenseNet – can be trained to recognize early symptoms of oil palm diseases from leaf or canopy images, enabling earlier and more accurate diagnosis than traditional field scouting.

Early detection through AI has direct implications for disease management strategies. Proactive surveillance powered by smartphone cameras or drones could allow plantation managers to isolate or treat infected palms before a disease spreads widely. For instance, a recent study integrated a CNN model into a smartphone app for *Ganoderma* basal stem rot detection, facilitating real-time monitoring of infection stages in oil palm plantations [25]. By catching infections in their initial phases, growers can perform targeted sanitation (e.g. rouging of Fusarium-infected palms or localized fungicide application for other diseases) and thereby prevent epidemic outbreaks. AI-based tools also contribute to improved precision in interventions. Farmers can distinguish among different diseases or nutrient issues, avoiding misdiagnosis and the unnecessary use of chemicals. This aligns with findings in other crops: digital disease surveillance platforms, such as IITA's cassava disease detector in Nigeria, have enabled farmers to identify and treat crop diseases early, resulting in higher yields and reduced losses [26]. In oil palm, timely action is critical because perennial crops do not allow for easy crop rotation; AI monitoring can therefore be a key component of an integrated disease management program.

It should be noted that AI-driven detection for certain oil palm diseases is still in nascent stages. In the case of Fusarium wilt of oil palm, there have been virtually no reported implementations of AI detection to date [22], likely due to the subtle and mostly internal symptoms of this vascular wilt. Our study serves as a novel proof-of-concept that CNN models can pick up early visual cues (such as foliar discoloration or wilting patterns) associated with Fusarium infection. While further work is needed to validate such models in field conditions, the successful application of AI here could fill a crucial gap in the plant health toolkit.

6.2. Economic Resilience and the role of AI

Beyond crop health, the use of AI in disease detection carries important implications for the economic resilience of oil palm farmers in Benin and similar contexts. Oil palm is a critical cash crop, and losses due to diseases like Fusarium wilt directly translate into lost income for rural communities. By minimizing disease-related damage, AI-based early warning systems can help stabilize yields and safeguard farmers' livelihoods. According to a United Nations report [27], deploying a DenseNet model for early oil palm disease detection enables "timely interventions and reduces crop losses," which in turn improves yields and income for farmers. Studies in African agriculture show that digital tools can significantly bolster productivity and profitability for smallholders. [27] notes that AI-powered crop disease detection systems have already "enabled farmers to identify and treat diseases early, resulting in higher yields and reduced crop loss".

Moreover, AI tools can promote cost savings and efficiency that enhance economic resilience. Traditional disease surveillance often requires labor-intensive field inspections or laboratory tests, which can be costly and slow. In contrast, an AI disease-detection model can analyze leaf images in seconds at virtually no marginal cost, allowing even resource-constrained farmers to monitor crop health more frequently. Over time, early detection also helps avoid the expenses associated with severe outbreaks. These avoided costs act like a form of insurance, preserving farmers' capital. Scaling up AI in agriculture could contribute to rural development by boosting overall productivity and ensuring food security [26].

6.3. Barriers to adoption: technology access and digital infrastructure

Notwithstanding the clear benefits, there are substantial barriers to the adoption of AI technologies in rural oil palm farming. A foremost challenge is the limited digital infrastructure in many farming communities of Benin and across sub-Saharan Africa. Internet connectivity is often poor or non-existent on smallholder farms; in rural Africa, less than 30% of adults have any access to the internet, and those who do are usually limited to narrow-band 2G/3G networks [26]. Power supply is another infrastructure issue. Some remote villages lack electricity to consistently charge smartphones or run computers [28]. Without reliable power and internet, the effectiveness of an AI disease detection system is greatly diminished. Another barrier lies in technology access and usability for farmers. The majority of smallholder farmers do not own high-end smartphones or devices capable of running advanced apps. Many digital agriculture solutions today rely on smartphone apps or web interfaces [29], yet a typical farmer in a rural Beninese community may only have a basic mobile phone. Additionally, farmers may face challenges in using such tools due to low digital literacy [28].

Socio-economic factors also play a role in adoption barriers. Cost is a significant concern: while our AI model itself might be open-source, implementing it in the field could involve costs for devices, data connectivity, or training sessions. Many smallholders operate on thin profit margins, so without subsidies or financial support, they may be unwilling to invest. Furthermore, language barriers can impede adoption; if an app's interface or outputs are not available in local languages, farmers could struggle to interpret the recommendations. Finally, we must consider the availability of digital support services. When an AI system flags an infection, farmers need access to agronomic advice or inputs to act on that information. In many rural African contexts, the support infrastructure (such as extension services or input supply chains) is weak, which can negate the practical value of high-tech solutions.

6.4. Policy recommendations

To overcome the above barriers and realize the potential of AI for sustainable agriculture, a coordinated policy effort is required. Investing in rural digital infrastructure is a foundational step. Governments and development partners should prioritize extending broadband coverage to agricultural areas. In parallel, improving electrical infrastructure (such as rural electrification programs or solar charging stations) would support continuous use of digital tools in the field. These investments align with the African Union's Digital Transformation Strategy [29].

Another key recommendation is to strengthen capacity-building and extension services focused on digital agriculture. Farmers need training to effectively use AI-driven applications. Training content must be provided in local languages and culturally relevant formats, since literacy is a barrier [28]. Governments can support this by funding extension agent positions specializing in ICT for agriculture, and by collaborating with tech developers to simplify user interfaces for rural contexts. Bridging the human and technological gap in this way will help build trust in AI solutions.

Policymakers should additionally foster an innovation ecosystem around AI in agriculture. This involves supporting research, startups, and pilot projects that localize AI solutions for crops and diseases of regional importance. An example is the Okuafo AI initiative in Ghana, where a locally developed app uses AI to detect crop pests and recommends actions via an Android phone, including an option to notify agricultural officers [29].

Finally, we recommend establishing a supportive policy and regulatory framework that integrates AI tools into the agricultural advisory system. Ministries of Agriculture should officially recognize and promote validated digital tools as part of national plant protection strategies. Data governance is critical here: clear guidelines on data sharing and privacy will build confidence in digital services. Additionally, policies should encourage multi-channel approaches such as coupling AI diagnostics with SMS/USSD messaging or radio broadcasts to reach those on basic phones [29].

7. Conclusion

In conclusion, our study demonstrates the promising application of artificial intelligence for detecting diseases in oil palm farming in Benin. We showed that a deep learning model (specifically a DenseNet-based CNN) can accurately recognize early signs of oil palm diseases like Fusarium wilt from imagery, potentially well before traditional methods would notice widespread symptoms. These findings are significant for sustainable agriculture in sub-Saharan Africa: early disease detection enables timely, precise interventions that reduce crop loss and reliance on chemical controls, thereby supporting both environmental sustainability and farm productivity. By safeguarding yields, AI-driven disease management tools can improve the resilience of rural livelihoods.

However, realizing these benefits on the ground will require surmounting the practical barriers identified. The digital divide in rural areas – including patchy internet access, low-cost technology availability, and limited user training – must be addressed through targeted investments and inclusive policies. With enabling conditions in place, AI tools could become a transformative part of the agricultural extension toolkit in Benin. For example, an AI disease alert could prompt extension officers to visit a village for confirmation and assist in response, creating a hybrid approach that amplifies outreach efficiency [26, 27].

Looking ahead, future research should focus on field validation of AI-based tools, integration with remote sensing and mobile applications, and participatory approaches that involve farmers in co-designing technologies. Interdisciplinary research should also examine how AI-based disease detection can be integrated into broader climate-smart agriculture frameworks. In summary, the application of AI to oil palm disease detection is a promising frontier for enhancing sustainable agriculture in Benin and similar contexts.

Declaration on Generative AI

During the preparation of this work, the authors used X-GPT-4 for grammar and spelling check. After using these tools, the authors reviewed, edited, and corrected the content as needed and take full responsibility for the publication's content.

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