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Image-Based Disease Detection in Agriculture: Advances, Challenges, and Applications in Oil Palm Management

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Abstract

Image-based disease detection plays a key role in precision agriculture. It has advanced rapidly with developments in computer vision, deep learning and sensing technologies. This review summarizes recent research on agricultural disease detection, with a focus on oil palm management. The main imaging modalities are reviewed, and traditional computer vision methods are compared with state-of-the-art deep learning and transformer-based models. Their performance across different agricultural conditions is discussed. Applications in oil palm cultivation are highlighted. This includes early detection of Ganoderma basal stem rot, identification of nutrient deficiencies, and farm-scale monitoring. Although detection accuracy and field applicability have improved, several challenges remain. These include limited annotated datasets, environmental variability, high sensor cost and poor model generalization. Future research directions are outlined, emphasizing multimodal sensing, use of edge AI, data set expansion and integration with digital farm management systems. Overall, image-based detection technologies offer strong potential to improve crop monitoring, support decision-making and enhance the sustainability of oil palm production.

1. Introduction

Agricultural systems are undergoing rapid digital transformation as researchers and farmers adopt data-driven tools to more efficiently address crop diseases. In oil palm plantations, disease outbreaks remain a major threat to long-term productivity, particularly Basal Stem Rot (BSR) caused by *Ganoderma boninense*, which continues to inflict severe economic losses across Southeast Asia. Conventional disease detection methods rely heavily on visual inspection, a practice that is slow, subjective, and often incapable of identifying early-stage infections before serious damage occurs [1, 2]. As oil palm plantations expand and labour shortages intensify, the need for scalable and reliable detection methods has become increasingly urgent.

Recent developments in computer vision and deep learning have enabled automated image-based systems. This system can detect plant diseases with significantly higher accuracy than traditional human assessment. Convolutional Neural Networks (CNNs) have demonstrated strong performance in agricultural diagnosis tasks by learning discriminative visual patterns from images of leaves, stems, and canopies [3]. Their ability to generalize across varying field conditions has made CNNs a preferred choice for modern plant disease detection frameworks.

Deep learning-based approaches such as transfer learning, Genetic Adversarial Network (GAN) driven augmentation, and lightweight mobile architectures further enhance prediction performance [4].

Commercial applications such as Plantix and Agrio have introduced these capabilities to broader farming communities, offering real-time predictions and advisory recommendations through mobile devices [5]. However, despite their usefulness, existing tools still encounter challenges related to inconsistent field lighting, limited datasets for specific regional diseases, and reduced accuracy when dealing with symptoms that appear subtly or irregularly [6]. These constraints are particularly evident in oil palm cultivation. For example, diseases such as BSR manifest gradually and may not be readily captured in early images.

Given these limitations, researchers continue to explore improvements in model architecture, dataset augmentation, unmanned aerial vehicle (UAV)-based imaging, and domain-specific customization for oil palm disease detection [7]. Studies have suggested that integrating deep learning models with real-time sensing systems and farmer-oriented mobile applications could significantly enhance early detection and mitigation efforts [8]. Such advancements support more sustainable plantation management, reduce long-term losses, and improve productivity for both smallholder farmers and large-scale producers.

This study presents a comprehensive review of image-based disease detection in oil palm. The findings integrate technological, agricultural and operational perspectives. It evaluates current methods, highlights gaps in data sets, model generalization and usage, and identifies actionable research directions. By synthesizing recent advances, this study provides guidance for developing reliable, scalable and accurate detection tools. These findings can benefit smallholder farmers, support sustainable crop management and improve national food security.

This article is organized into 5 main sections. The first section provides background on the study. The second section explains the Background and Theoretical Foundations. The third section explains oil palm and its disease management. Deep Learning Approaches to Oil Palm Disease Detection are explained in the next section. This is followed by Deployment Considerations and Mobile or Edge Applications. The last section summarizes the study's results.

2. Background and Theoretical Foundations

Image-based disease detection in agriculture combines imaging modalities, computer vision techniques, and machine learning algorithms to efficiently identify crop diseases. A comprehensive understanding of these foundations is essential for evaluating their suitability for oil palm disease detection and other agricultural applications.

2.1 Imaging Modalities

Various imaging modalities provide complementary spectral and spatial information essential for early plant disease detection. RGB imaging is widely adopted due to its low cost and ability to capture visual symptoms such as color change, lesions, and texture abnormalities [11]. More advanced multispectral and hyperspectral sensors measure reflectance across multiple wavelength bands, enabling the detection of physiological stress before visible symptoms develop [12-13]. Thermal imaging identifies temperature variations in plant tissues, which may indicate water deficit or disease-induced metabolic disruption [14]. Meanwhile, UAV-, satellite-, and ground-based imaging platforms offer different scales of observation: UAVs provide high-resolution field-level monitoring, satellites enable large-area surveillance, and ground imaging supports detailed leaf-level analysis [15-16]. Together, these technologies form a robust toolkit for precision agriculture and early disease monitoring.

2.2 Traditional Computer Vision Techniques

The initial plant disease detection techniques were primarily based on handcrafted features and traditional image processing pipelines. These methods rely on manually developed rules to characterize physical indicators of visual manifestations. For example, alterations in colour, morphological structure, and anatomical disorders on plant surfaces. The general process entails segmenting relevant regions from images, generating feature descriptors, and using standard machine learning classifiers to classify diseases. Although these approaches are less computationally demanding and more comprehensible, their performance is susceptible to illumination, background noise, and variations in disease appearance.

(i). Segmentation: Thresholding, region growing, and clustering algorithms are employed to discriminate the diseased regions from the healthy matrix or background regions of the images [17].

(ii). Feature Extraction: handcrafted attribute features like Gray Level Co-occurrence Matrix textures, colour histograms, and shape descriptors are calculated to numerically represent features of disease appearance [18].

(iii). Shallow Classifiers: The extracted attributes are categorized into disease classes by using classical machine learning models like Support Vector Machines, k Nearest Neighbors, and Random Forests [19].

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These traditional approaches are computationally efficient and offer interpretability. The approaches struggle to generalize under real-world agricultural settings. Their performance is often affected by noise, inconsistent lighting, occlusions, leaf orientation, and natural variability in plant morphology. It makes them less reliable for field-scale applications [20-21]. These limitations paved the way for modern deep learning techniques. These techniques overcome the constraints of handcrafted features by learning robust, multi-level representations directly from raw image data.

2.3 Deep Learning and Modern AI Approaches

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have significantly advanced agricultural image analysis. It is done by enabling automatic learning of hierarchical spatial features. Foundational architectures such as the Visual Geometry Group (VGG), ResNet, and DenseNet provide strong feature extraction capabilities for disease classification tasks [22]. While Inception networks capture multiscale visual patterns essential for identifying diverse symptom structures [23]. In resource-constrained environments, lightweight models like MobileNet and EfficientNet provide efficient inference suitable for UAV or mobile deployments without substantial performance loss [24].

More recently, Vision Transformers (ViTs) have employed global attention mechanisms that have shown exceptional performance in modeling long-range dependencies in complex plant imagery [25]. However, deep learning methods are still hampered by their need for large, annotated datasets, significant computational resources, and the need to select hyperparameters to control overfitting [26-27]. Overall, these architectures have proven superior to computer vision methods for identifying subtle, early-stage disease symptoms. Lightweight CNNs remain useful for field-level and embedded applications. At the cost of increased computational complexity, ViTs deliver strong performance on large-scale, complex disease identification tasks [25, 28 - 29]. Table 1 summarizes image-based plant disease detection techniques.

Table 1 *Summary of image-based plant disease detection techniques*

Technique Category	Description	Advantages	Limitations
Traditional CV	Handcrafted features, classical segmentation	Lightweight, interpretable	Poor generalization, sensitive to noise
CNN Models	Deep spatial feature extraction	High accuracy, robust	Requires large datasets
Lightweight CNNs	MobileNet, EfficientNet	Suitable for mobile/UAV use	Lower accuracy than large models
Vision Transformers	Attention-based global modeling	Strong performance on complex patterns	High computation; needs large data
Multispectral Analysis	Spectral reflectance & band ratios	Early stress detection	Expensive sensors

Table 1 summarizes the main categories of image-based plant disease detection techniques. It outlines their characteristics, strengths, and limitations. Traditional computer vision methods rely on handcrafted features and simple segmentation, offering lightweight, interpretable solutions but performing poorly under real-world variability. CNN-based models significantly improve accuracy by extracting deep features, but they require large, labeled datasets. Lightweight CNNs, such as MobileNet and EfficientNet, are optimized for mobile or UAV applications but may sacrifice some accuracy. Vision Transformers achieve strong performance on complex disease patterns through global attention. They demand substantial computational resources and large training datasets. Multispectral analysis enables early detection by capturing spectral reflectance beyond the visible range, but its use is constrained by the high cost of specialized sensors. Together, these techniques highlight the balance between performance, efficiency, and practicality in modern plant disease detection.

3. Oil Palm and Disease Management

Oil palm (Elaeis guineensis) is an important agricultural commodity widely cultivated throughout Southeast Asia, Africa, and parts of the Americas. Oil palm serves as one of the world's major sources of edible vegetable oil. Malaysia remains a major global producer, with the industry contributing significantly to the country's Gross Domestic Product (GDP), rural employment, and downstream economic activities such as refining and oleochemical production [31]. Despite its economic importance, oil palm productivity is increasingly threatened by a variety of biotic stresses, particularly fungal and bacterial diseases. These diseases not only reduce yields but also affect the long-term sustainability of plantations, making early detection and effective management essential to protect the industry. Table 2 shows an overview of oil palm diseases and detection approaches.

Table 2 *Comprehensive overview of oil palm diseases and detection approaches*

Disease	Spread / Infection Mode	Traditional Detection	Imaging Modality	AI / Deep Learning Model	Detection Approach	Technological Intervention	Advantages	Limitations
Basal Stem Rot (BSR) [30], [31], [32], [11], [12]	Airborne spores, soilborne inoculum, root-to-root contact	Visual inspection by agronomists; symptom scoring	RGB, Multispectral, Hyperspectral	CNN (ResNet50, VGG), Vision Transformers	Leaf, stem, basal stem classification; lesion detection	UAV/drone imaging, smartphone apps	Early detection; automated; scalable	Requires large datasets; subtle early symptoms may be missed
Bud Rot [30], [33], [18]	Fungal infection through soil or water	Visual inspection; pruning checks	RGB, Multispectral	CNN, MobileNet, EfficientNet	Leaf and bud image analysis; spot segmentation	Handheld devices, mobile apps	Fast and portable; suitable for smallholders	Lower accuracy on subtle symptoms; limited datasets
Fusarium Wilt [30], [14], [16]	Soilborne fungal pathogen	Symptom monitoring; soil testing	RGB, Thermal	CNN, DenseNet	Leaf and vascular tissue analysis; temperature anomalies	Ground-based imaging, thermal cameras	Non-invasive; early stress detection	Root infection may be hidden; complex preprocessing
Ganoderma-related infections [30], [12], [19]	Basal stem/root decay, soilborne	Visual inspection; manual probing	RGB, Hyperspectral	CNN, ResNet, Inception V3	Basal stem/root detection; decay pattern recognition	UAV imaging, molecular diagnostics	High precision; predictive analysis	Root infection may be hidden; preprocessing intensive
Leaf Spot / Anthracnose [30], [33], [19]	Airborne spores, rain splash	Visual observation of leaves	RGB	CNN, MobileNet	Leaf lesion detection; color & texture analysis	Smartphone apps, UAV imaging	Portable; real-time analysis	Sensitive to lighting; small lesions may be missed
Black Sigatoka [34], [13], [25]	Airborne spores, humidity	Leaf scouting; manual scoring	Multispectral, Hyperspectral	CNN, Vision Transformers	Leaf streak pattern recognition; severity scoring	UAV imaging, drone-based multispectral scanning	Rapid monitoring of large areas; automated scoring	Requires frequent scanning; high data processing

Basal Stem Rot (BSR) is among the various diseases affecting oil palm. This disease is caused by Ganoderma boninense. It is widely recognized as the most destructive to the plant. BSR attacks the basal stem, vascular tissue, and root system, progressively weakening the palm tree and ultimately causing plant death [30]. The disease often remains asymptomatic in its early stages, allowing it to spread unnoticed. Reports from several plantations in Malaysia indicate that up to 80% of palm trees may be infected before reaching maturity. It reflects the magnitude of the financial and ecological impact of BSR [30]. Additional threats include Bud Rot, Fusarium Wilt, and other Ganoderma-related infections, each with distinct transmission routes and symptom development. These pathogens are spread via airborne spores, infected soil, and root-to-root contact, making containment extremely challenging without reliable early-stage monitoring tools [30].

To address this challenge, the Malaysian Palm Oil Board (MPOB) has introduced a range of disease management strategies that combine chemical, biological, genetic, and technological interventions [31]. Chemical fungicides such as hexaconazole have been used to suppress fungal growth. On the other hand, biological control agents such as Trichoderma spp. have been used to increase soil antagonism to Ganoderma [30]. In addition, research into resistant planting material and improved nursery practices offer long-term potential for disease mitigation [31]. Modern initiatives also include molecular diagnostics, spectral imaging, and remote sensing technologies for early pathogen detection and disease surveillance across plantations. However, traditional disease monitoring through manual field inspection continues to dominate smallholder practices. This visual assessment, although widely practiced, is time-consuming, subjective, and prone to misdiagnosis. This is true especially when symptoms are subtle, localized, or easily confused with nutrient deficiencies [32].

Given the limitations of conventional inspection methods, there is a growing demand for automated, scalable disease-detection solutions. The integration of deep learning-based image analysis with mobile platforms, UAV imaging, and real-time monitoring infrastructure offers significant potential to improve the accuracy and timeliness of surveillance. Convolutional Neural Networks (CNNs) can identify subtle patterns of discoloration, textural anomalies, and structural defects in oil palm tissues, enabling more consistent and objective disease identification than human observers [34]. By incorporating large domain-specific training datasets, the model achieves better generalization across diverse farm environments [36-37]. Such systems not only reduce the burden on agronomists but also provide immediate diagnostic support to farmers, increasing the likelihood of early intervention and reducing disease spread.

In addition to visual detection, recent advances in AI-driven analytics support more holistic farm management. Machine learning algorithms can model disease progression, predict outbreak hotspots, and optimize resource allocation by integrating data from multiple sources such as climate patterns, soil measurements, UAV imagery, and historical disease records [38-39]. These predictive insights enable farm managers to implement proactive rather than reactive strategies, improving disease containment and increasing overall yield stability. Decision support dashboards then translate complex analytical outputs into actionable recommendations, enabling farmers, agronomists, and policymakers to make informed decisions. The convergence of image-based detection, predictive analytics, and mobile-enabled advisory systems represents a major advance in digital agriculture. It is placing artificial intelligence (AI) at the foundation of next-generation oil palm disease management.

4. Deep Learning Approaches to Oil Palm Disease Detection

Deep learning has transformed agricultural disease detection by enabling automated, scalable, and accurate analysis of plant images. In oil palm plantations, conventional visual inspections are labor-intensive, subjective, and prone to errors, especially during early-stage infections such as Basal Stem Rot (BSR) caused by *Ganoderma boninense* [30]. Convolutional Neural Networks (CNNs) and related deep learning architectures can automatically extract hierarchical features from images of leaves, stems, and canopies, identifying subtle symptoms that may be missed by human observers [18-19]. This section reviews recent advancements in CNN-based models, lightweight architectures, transfer learning, Vision Transformers (ViTs), image preprocessing techniques, and performance evaluation metrics for oil palm disease detection.

4.1 Convolutional Neural Networks (CNNs)

CNNs are the most widely used deep learning models for plant disease detection. They employ convolutional layers to extract spatial features, pooling layers for dimensionality reduction, and fully connected layers for classification [18-19]. For oil palm, CNNs have been applied to leaf, stem, and basal stem images, enabling the detection of diseases such as BSR, Bud Rot, and Fusarium Wilt. Popular architectures include VGG16, ResNet50, and InceptionV3 [19, 27, 30]. CNN-based approaches improve early disease identification, reduce dependency on expert agronomists, and support large-scale plantation monitoring.

4.2 Lightweight CNNs for Mobile and Edge Deployment

Lightweight CNNs, such as MobileNet and EfficientNet, are designed for deployment on mobile devices and UAVs [28]. These models reduce computational cost and memory usage, facilitating real-time monitoring in remote plantations. Although slightly less accurate than full-scale CNNs, they are practical in field conditions. This is especially for early detection and rapid decision-making. It makes them valuable tools for smallholder farmers [21, 28].

4.3 Transfer Learning and Fine-Tuning

Transfer learning leverages CNNs pre-trained on large datasets to adapt to specific tasks, such as oil palm disease detection [22, 24]. Fine-tuning the final layers of these networks enhances classification performance, particularly when labeled oil palm disease datasets are limited. Studies have shown that transfer learning improves accuracy for BSR and other diseases while reducing training time and computational requirements [22, 24, 30].

4.4 Vision Transformers (ViTs)

Vision Transformers utilize self-attention mechanisms to model global contextual relationships in images, capturing long-range dependencies more effectively than CNNs [25, 29]. ViTs are particularly useful for analyzing complex visual patterns in leaves, stems, and canopy structures. Although computationally intensive, they offer significant potential for UAV- or satellite-based plantation monitoring, enabling simultaneous analysis of multiple regions and supporting large-scale disease surveillance [29].

4.5 Image Preprocessing Techniques

Preprocessing enhances deep learning model performance by standardizing inputs and improving feature visibility. Common techniques include resizing and normalization for consistent pixel scaling [19, 27], data augmentation through rotations, flips, and brightness adjustments [24], and noise reduction or segmentation to highlight lesions and reduce background interference [18]. Effective preprocessing ensures model robustness under variable field conditions, lighting, and occlusion.

4.6 Performance Evaluation Metrics

Performance evaluation is crucial for assessing model reliability and generalization. Key metrics include accuracy, precision, recall, F1-score, and ROC-AUC [22-27]. Precision and recall are particularly important for imbalanced datasets, where certain diseases may have fewer examples. ROC-AUC provides a measure of the model's ability to discriminate between disease classes, ensuring dependable detection across diverse plantation scenarios.

4.7 Significance of Deep Learning Approaches

Integrating deep learning approaches into oil palm disease detection offers significant advantages for modern plantation management. These technologies enable automated early disease detection, reducing reliance on expert agronomists and minimizing human error during visual inspections. Deep learning models also facilitate scalable monitoring, allowing analysis of individual leaves, stems, or entire plantations through UAV or satellite imagery. Beyond detection, the insights generated by these models support data-driven decision making. It enables plantation managers to implement predictive maintenance, optimize yield, and plan timely interventions to mitigate the impact of disease [21]. Overall, the application of deep learning enhances both the efficiency and effectiveness of disease management in oil palm cultivation. Table 3 summarises the deep learning models for oil palm disease detection.

Table 3 *Summary of deep learning models for oil palm disease detection*

Model	Input Type	Disease Targets	Key Features	Advantages	Limitations
ResNet50 [30], [19]	RGB/ Multispectral	BSR, Bud Rot	Deep residual connections, skip layers	High accuracy, robust feature extraction	Requires large dataset, high computation
VGG16 [19], [27]	RGB	BSR, Fusarium Wilt	Simple deep CNN, sequential layers	Easy to implement, interpretable	Large model size, slower inference
InceptionV3 [19], [30]	RGB	Multiple diseases	Multi-scale convolutions	Captures complex patterns	Computationally intensive
MobileNet [28], [21]	RGB	BSR, Bud Rot	Depthwise separable convolutions	Lightweight, mobile deployment	Slightly lower accuracy
EfficientNet [28], [21]	RGB	BSR, Fusarium Wilt	Compound scaling of depth, width, resolution	High accuracy, optimized for edge	Needs preprocessing

Vision Transformer [25], [29]	RGB	BSR, Bud Rot	Self-attention, global feature modeling	Captures long-range dependencies	High computation; large data required

Convolutional Neural Networks are commonly used in plant disease detection. The method effectively learns local visual features such as color, texture, and lesion patterns. In oil palm studies, CNN-based models have been used to detect Ganoderma basal stem rot by classifying nutrient deficiencies and identifying foliar diseases using leaf and stem images. They typically perform well with modest dataset sizes and are suitable for use in resource-limited field environments.

Table 3 summarizes commonly used deep learning architectures and their applications in oil palm disease detection. Recent research has explored various deep learning models for oil palm disease detection. It targets critical diseases such as Basal Stem Rot (BSR), Bud Rot, and Fusarium Wilt. ResNet50 has been widely used with RGB and multispectral images due to its deep residual connections and skip layers, offering high accuracy and robust feature extraction, though it requires large datasets and significant computational resources [19, 30]. VGG16, a simpler deep CNN with sequential layers, provides ease of implementation and interpretability, making it suitable for BSR and Fusarium Wilt classification, but its large model size can slow inference [19, 27]. InceptionV3 employs multi-scale convolutions to capture complex disease patterns across multiple classes, offering strong pattern recognition at the cost of high computational demand [19, 30].

For practical deployment, especially in mobile or UAV-based field monitoring, lightweight CNNs such as MobileNet and EfficientNet have been applied. MobileNet uses depthwise separable convolutions, enabling real-time monitoring with lower memory and computational requirements, though its accuracy is slightly lower than that of full-scale CNNs [21, 28]. EfficientNet applies compound scaling across depth, width, and resolution, achieving high accuracy optimized for edge devices, while still requiring careful preprocessing of input images [21, 28].

More recently, Vision Transformers (ViTs) have been adopted for oil palm disease detection, leveraging self-attention mechanisms to capture global contextual relationships and long-range dependencies across RGB images [25], [29]. ViTs are particularly effective for complex visual patterns spanning leaves, stems, and canopy regions, and they are well-suited for large-scale plantation monitoring [25], [29]. However, they demand substantial computational power and large labeled datasets to perform effectively.

Transformer-based vision models treat images as sequences of patches and capture global contextual relationships via a self-attention mechanism. Although ViT has demonstrated strong performance in general agricultural disease detection, its application to oil palm disease detection remains limited and largely exploratory. ViT typically requires larger annotated datasets and higher computational resources but offers better capabilities for modeling long-range dependencies and complex farm-level patterns.

Overall, selecting a deep learning model for oil palm disease detection requires balancing accuracy, computational efficiency, and deployment feasibility. Each architecture offers unique advantages and trade-offs suitable for different monitoring scenarios. To achieve optimal performance, these models are often combined with image preprocessing techniques. The techniques are such as resizing, normalization, data augmentation, and segmentation. It is then evaluated using standard metrics like accuracy, precision, recall, F1-score, and ROC-AUC. Proper preprocessing and metric evaluation ensure that the models are robust, generalizable, and capable of delivering reliable predictions under diverse field conditions. Smartphones and digital cameras can optimize CNN or ViT-based approaches to enhance real-time image processing. This enables consumer-grade photography and videography to achieve greater clarity, automated feature recognition, and a more seamless, intuitive user experience.

5. Deployment Considerations and Mobile or Edge Applications

The practical deployment of deep learning models for oil palm disease detection involves much more than achieving high accuracy in controlled lab settings. It requires careful consideration of real-world challenges and user needs. Plantation environments are dynamic, with variable lighting, weather conditions, and limited connectivity. It makes it difficult to deploy traditional high-performance models directly in the field [28]. Lightweight architectures such as MobileNet and EfficientNet, optimized for mobile phones, tablets, and UAVs, address these constraints by reducing memory and computational demands while maintaining reliable classification performance [28]. Edge-based inference allows farmers, both smallholders and large-scale operators, to receive real-time disease diagnoses without relying on cloud connectivity, while energy-efficient operations ensure prolonged monitoring without depleting device batteries [41-42].

Unmanned Aerial Vehicles (UAVs) complement these mobile solutions by providing rapid, high-resolution imaging across expansive plantation areas, capturing RGB, multispectral, or hyperspectral imagery for early detection of diseases such as Basal Stem Rot (BSR) [15, 43]. Coupled with AI models deployed on edge devices, UAVs facilitate instant classification, spatial disease mapping, and identification of disease hotspots, enabling targeted interventions that improve efficiency and reduce chemical usage [29, 44]. For smallholder farmers, mobile applications act as intuitive interfaces. The tool allows farmer to capture images of leaves or stems. They can receive instant diagnoses, access site-specific treatment recommendations, and log temporal and spatial disease data for trend analysis [21, 45]. These applications effectively bridge the gap between cutting-edge AI research and practical farm-level decision-making, significantly reducing the time between symptom detection and intervention.

Cloud-based systems further enhance this ecosystem by enabling centralized model training, continuous updates through federated learning, and long-term data storage [46-47]. Dashboards enable plantation managers and policymakers to monitor disease trends, allocate resources efficiently, and assess risks at scale. While data privacy and security measures ensure that sensitive agricultural information is protected [42, 46]. Additionally, environmental and operational factors, such as lighting variability, occlusion, background noise, and alignment with farmers' routines, must be addressed. This aimed to maintain model reliability and ensure that AI tools integrate seamlessly with daily agricultural practices [18, 28-29, 45].

Overall, integrating mobile, edge, UAV, and cloud-based AI systems transforms oil palm disease management. The combination provides automated, early detection across scales, supporting farmers who may lack access to agronomic experts. Additionally, it also generates predictive insights for resource optimization and disease prevention [21, 41, 43, 45]. This approach not only enhances productivity and reduces losses from diseases such as BSR but also promotes sustainable agricultural practices and contributes to national food security [30, 43]. By emphasizing practical deployment considerations alongside technical performance, deep learning solutions for oil palm disease detection are made both effective and usable in real-world plantation settings [45].

6. Conclusions

Image-based disease detection techniques have demonstrated high accuracy, robustness, and scalability. It is effectively bridging the gap between traditional and digital agriculture. These methods enable early identification of diseases. At the same time, it reduces reliance on labor-intensive visual inspections and supports timely interventions. These features help to reduce yield losses. Future research should prioritize expanding annotated, region-specific datasets to improve model generalization and accommodate the variability of local disease symptoms. In addition, the development of hybrid architectures that combine CNNs and ViTs can enhance feature extraction and classification performance for complex disease patterns. Edge-cloud integration is also critical for enabling real-time analytics and deployment of AI models in remote plantation settings.

Furthermore, adopting explainable AI techniques can enhance the interpretability and trustworthiness of disease-detection models, thereby fostering confidence among farmers and plantation managers. Socioeconomic research focusing on user adoption, training, and accessibility is equally important to ensure these technologies benefit smallholder farmers and large-scale producers alike. This review is particularly valuable for researchers, agricultural technologists, policymakers, and the oil palm industry, as it consolidates current knowledge, identifies gaps, and guides the implementation of AI-driven crop management systems that support sustainable production and enhanced food security.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors are responsible for the study conception, research design, data collection, data analysis, result interpretation and manuscript drafting.

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