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Leveraging computer Vision and AI for real-time crop disease detection and prevention in smallholder farming systems

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Abstract

This research explores the potential of leveraging computer vision and artificial intelligence (AI) to revolutionise crop disease detection and prevention specifically within smallholder farming systems. Smallholder farmers, who are critical to global food security, face significant challenges due to crop diseases that can lead to substantial yield losses. Traditional disease management methods are often inadequate, highlighting the urgent need for scalable, accurate, and timely solutions. This paper presents a conceptual framework for integrating AI-driven image recognition and data analytics to enable real-time disease detection and facilitate proactive prevention strategies tailored to the constraints of resource-limited smallholder farms. By examining existing methodologies, the applications of computer vision in agriculture, and current research gaps, this work outlines a system design, compares suitable AI models, and discusses crucial implementation considerations such as scalability, accessibility, and ethical implications. Ultimately, this paper envisions the transformative impact of AI in bolstering resilience against disease outbreaks, promoting sustainable farming practices, and ensuring global food security by empowering smallholder farmers with advanced technological tools.

Keywords: Artificial Intelligence; Computer Vision; Crop Disease Detection; Precision Agriculture; Smallholder Farming; Real-Time Detection

1. Introduction

Smallholder farming plays a pivotal role in global agriculture, contributing significantly to food production, particularly in developing countries (Economics, 2018, Ouma et al., 2024). These farms, typically characterised by limited landholding, labour, and capital, are crucial for the livelihoods of millions of people and are integral to ensuring regional and global food security (Ouma et al., 2024). However, the productivity and sustainability of smallholder farming are consistently threatened by various factors, among which plant diseases stand out as a major impediment (Anjna et al., 2019).

Crop diseases, primarily caused by pathogens such as bacteria, fungi, and viruses, can lead to significant destruction and reduction in both the quality and quantity of plant and crop yields (Anjna et al., 2019; Brahimi et al., 2018). The impact of these diseases extends beyond mere economic losses for individual farmers; they can have far-reaching consequences on national economies and even contribute to food shortages and famine (Brahimi et al., 2018; Kasare, 2024.). The interconnectedness of global food systems further amplifies the threat, as disease outbreaks in one region can potentially affect others. Smallholder farmers often face unique challenges in managing crop diseases. Limited access to

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expert knowledge, diagnostic tools, and effective control measures makes them particularly vulnerable (Ouma et al., 2024). Traditional methods of disease identification rely heavily on manual observation, which is often time-consuming, labour-intensive, and less accurate. Farmers may struggle to accurately detect and identify various plant diseases without specific training and experience (Anjna et al., 2019). Consequently, they might resort to using familiar fertilisers or pesticides, sometimes based on advice from local shopkeepers, which can prove ineffective or even detrimental, leading to reduced overall plant production (Francis et al., 2018).

The increasing frequency and severity of pest and disease outbreaks, potentially exacerbated by climate change and evolving environmental conditions, further compound these challenges (Sharada et al., 2025) This necessitates a shift towards more proactive and precise disease management strategies that can empower smallholder farmers to protect their crops effectively.

1.1. Problem Statement

The traditional reliance on manual inspection and expert-based diagnosis for plant diseases presents several critical limitations, particularly within the context of smallholder farming:

- **Subjectivity and Inaccuracy:** Visual identification of plant diseases is inherently subjective and prone to errors, especially in the early stages when symptoms may be subtle or non-specific (Anjna et al., 2019; Ouma et al., 2024). This can lead to misdiagnosis and the application of inappropriate or ineffective treatments (Francis et al., 2018; Ouma et al., 2024).
- **Delayed Detection:** Disease symptoms often become visible only after the pathogen has significantly progressed, making timely intervention more challenging and reducing the effectiveness of control measures (Kasare, 2024.; Ouma et al., 2024). Early detection is crucial for preventing widespread crop damage (Kasare, 2024.; Nagaraju & Chawla, 2020). AI tools have shown the potential to detect diseases 20-30% earlier than traditional methods
- **Dependence on Expert Knowledge:** Access to agricultural experts and plant pathologists is often limited for smallholder farmers, particularly in remote areas . Relying on expert consultation can be slow and may not be feasible for timely decision-making (Anjna et al., 2019)
- **Time and Labour Intensive:** Manually monitoring large fields for disease symptoms is a time-consuming and laborious task. This can be particularly challenging for smallholder farmers with limited resources.
- **Scalability Issues:** Traditional methods are difficult to scale for large agricultural areas or to handle widespread disease outbreaks efficiently.

To overcome these limitations, there is a pressing need for scalable, cost-effective, and user-friendly solutions that can provide real-time and accurate crop disease detection and support proactive prevention strategies for smallholder farming systems (Francis et al., 2018; Ouma et al., 2024). Artificial intelligence (AI) and computer vision technologies offer promising avenues for addressing these challenges (Ghazal et al., 2024; Restrepo-Arias et al., 2024).

Objectives

This research aims to explore the potential of leveraging computer vision and AI to develop conceptual frameworks for real-time crop disease detection and prevention in smallholder farming systems. The specific objectives of this paper include

- To review existing traditional and AI-driven methods for plant disease detection, highlighting their strengths and limitations.
- To examine the applications of computer vision techniques in agriculture, particularly in the context of disease identification and monitoring.
- To identify the research gaps and challenges related to the accessibility and scalability of AI-based solutions for smallholder farmers.
- To propose a conceptual framework for a real-time crop disease detection and prevention system tailored to the needs and constraints of smallholder farming.
- To compare suitable AI models for accuracy and usability in resource-limited settings.
- To discuss key implementation considerations, including scalability, accessibility, and ethical implications.
- To outline the potential benefits, challenges, and future directions for advancing research in this critical area.

By addressing these objectives, this paper seeks to contribute to the development of innovative and practical solutions that can empower smallholder farmers to effectively manage crop diseases, enhance their productivity, and contribute to sustainable agricultural practices and global food security.

2. Literature review

2.1. Existing Methods

2.1.1. Conventional Approaches

As previously mentioned, conventional plant disease detection primarily relies on visual inspection by farmers or agricultural experts (Anjna et al., 2019; Francis et al., 2018; Vijai & Goel, 2019., 2019; Ouma et al., 2024). This process involves observing the leaves, stems, or fruits of plants for characteristic symptoms such as spots, discolouration, wilting, or lesions. Accurate identification requires significant experience and knowledge of various plant species, their common diseases, and the subtle visual cues associated with each.

Beyond visual inspection, other conventional methods may involve laboratory analysis of plant samples to identify the specific pathogen causing the disease. However, these methods are often **time-consuming**, **expensive**, and not readily accessible to many smallholder farmers (Ouma et al., 2024) Farmers may also consult local agricultural extension officers or rely on information from local input suppliers, but the accuracy and timeliness of this advice can vary (Francis et al., 2018; Vijai & Goel, 2019, 2019; Ouma et al., 2024)

2.1.2. Advancements in AI-Driven Solutions

In recent years, there has been a surge of interest in leveraging artificial intelligence (AI) and related technologies to automate and improve plant disease detection (Restrepo-Arias et al., 2024; Ghazal et al., 2024). These AI-driven solutions aim to overcome the limitations of traditional methods by offering faster, more accurate, and more scalable approaches (Kasare, 2024.). The key AI techniques being explored in this domain include:

2.1.3. Machine Learning (ML)

ML algorithms can be trained on datasets of plant images and associated disease labels to learn patterns and build predictive models for disease classification (Kasare, 2024.; Ouhami et al., 2021). Various ML algorithms have been employed, including Support Vector Machines (SVM) (Vijai & Goel, 2019; Sharada et al., 2025), decision trees, and neural networks (Francis et al., 2018).

2.1.4. Deep Learning (DL)

DL, a subfield of ML, has shown remarkable success in image recognition tasks (Brahimi et al., 2018; Fuentes et al., 2020). Convolutional Neural Networks (CNNs) are particularly well-suited for analysing image data and have achieved high accuracy in plant disease detection and classification (Brahimi et al., 2018; Fuentes et al., 2020; Joshi, 2024; Roy et al., 2023; Ma et al., 2017; Islam et al., 2024). Pre-trained models like ResNet (Sharada et al., 2025; Joshi, 2024; Roy et al., 2023), InceptionV3 (Ghazal et al., 2024; Joshi, 2024; Ashraf et al., 2024, and YOLO (Joshi, 2024; Li et al., 2022)are often fine-tuned for specific crop and disease detection tasks.

2.1.5. Computer Vision

Computer vision techniques encompass the methods used to acquire, process, analyse, and understand digital images (Ghazal et al., 2024). In plant disease detection, these techniques involve image acquisition (using cameras on smartphones, drones, or dedicated sensors), image preprocessing (e.g., noise reduction, colour correction, image enhancement) (Sharada et al., 2025; Ashraf et al., 2024), feature extraction (identifying relevant visual characteristics), image segmentation (isolating the diseased areas) (Ma et al., 2017; Ashraf et al., 2024), and image classification (assigning a disease label to the image) (Fuentes et al., 2020; Ghazal et al., 2024; Restrepo-Arias et al., 2024).

2.1.6. Edge Computing

Deploying AI models on edge devices (e.g., smartphones, low-power microcontrollers) located within the agricultural fields allows for real-time data processing and disease classification without relying on constant internet connectivity (Joshi, 2024; Restrepo-Arias et al., 2024). This is particularly relevant for smallholder farmers in areas with limited network infrastructure.

2.1.7. Remote Sensing

The integration of AI with remote sensing technologies, such as satellite and drone imagery, enables the monitoring of large agricultural areas for signs of disease stress (Sharada et al., 2025) AI models can analyse multi-spectral and hyper-spectral data to detect subtle changes in crop health that may not be visible to the naked eye .

2.1.8. Internet of Things (IoT)

IoT devices, including sensors deployed in fields, can collect various environmental data (e.g., temperature, humidity, soil moisture) that can be integrated with image data and AI models to provide a more holistic understanding of plant health and disease risk (Restrepo-Arias et al., 2024; Elbasi & Mostafa, 2023).

These AI-driven solutions offer the potential for early detection of diseases, even before visible symptoms manifest (Kasare, 2024.), enabling prompt mitigation measures such as targeted application of pesticides or biocontrol agents. Furthermore, AI systems can continuously learn and improve their diagnostic accuracy through iterative training on diverse datasets (Kasare, 2024).

2.2. Applications of Computer Vision

Computer vision plays a fundamental role in enabling AI-driven plant disease detection. Several key techniques are employed in this context:

- **Image Acquisition**: Images of plant leaves, stems, or fruits are captured using various devices, ranging from low-cost smartphone cameras (Ouma et al., 2024) to high-resolution cameras mounted on drones (Sharada et al., 2025) or integrated into ground-based robots (Ghazal et al., 2024). The quality of the acquired images is crucial for the performance of subsequent analysis steps.
- **Image Preprocessing:** Raw images often require preprocessing to enhance their quality and prepare them for analysis (Ashraf et al., 2024; Sharada et al., 2025). Common preprocessing steps include:
- **Noise Reduction:** Filtering techniques are used to remove unwanted noise from the images.
- **Image Enhancement:** Techniques such as contrast stretching and histogram equalisation can improve the visibility of relevant features.
- **Colour Correction:** Adjusting the colour balance can compensate for variations in lighting conditions.
- **Image Resizing and Normalisation:** Standardising the size and pixel values of images ensures consistency for AI model training and inference (Ashraf et al., 2024).
- **Feature Extraction:** This step involves identifying and extracting relevant visual features from the preprocessed images that can help distinguish between healthy and diseased plants, as well as differentiate between various diseases (Francis et al., 2018; Vijai & Goel, 2019). Traditional methods relied on **hand-crafted features** based on colour, texture, and shape. However, deep learning models like CNNs can **automatically learn hierarchical features** directly from the image data, eliminating the need for manual feature engineering (Brahimi et al., 2018).
- **Image Segmentation:** Segmentation aims to partition the image into meaningful regions, such as isolating the diseased area on a leaf from the background (Ma et al., 2017; Lei et al., 2024; Ashraf et al., 2024). This allows for focused analysis of the affected regions and can provide valuable information about the severity and extent of the disease (Ashraf et al., 2024). Techniques like thresholding-based segmentation (Francis et al., 2018; Vijai & Goel, 2019) and more advanced deep learning-based segmentation models (Ashraf et al., 2024) are employed.
- **Image Classification:** The final step involves classifying the segmented diseased regions or the entire image into predefined categories, such as "healthy," "disease A," "disease B," etc. (Fuentes et al., 2020; Restrepo-Arias et al., 2024). Machine learning and deep learning classifiers are trained on labeled datasets to perform this task (Francis et al., 2018; Vijai & Goel, 2019; Brahimi et al., 2018; Joshi, 2024).
- These computer vision techniques have been applied to detect a wide range of plant diseases across various crops, including:
- **Capsicum (Pepper):** Anthracnose, bacterial spot, powdery mildew, cercospora leaf-spot, and gray leaf-spot (Anjna et al., 2019).
- **Pepper Plants:** Berry spot and quick wilt (Francis et al., 2018).
- **Banana, beans, jackfruit, lemon, mango, potato, tomato, and sapota:** Bacterial/fungal disease in beans, lemon sunburn disease, banana leaf with early scorch (Vijai & Goel, 2019;)
- **Rice:** Various diseases and pests
- **Tomato:** Early blight, late blight, and other diseases and pests (Fuentes et al., 2020; Roy et al., 2023).
- **Orange:** Various diseases (Joshi, 2024).

- **Wheat, coffee, citrus, grape, and cassava:** While studies involving IoT platforms with image classification in these crops are scarcer, research is emerging (Restrepo-Arias et al., 2024).
- **Vegetables (general):** Deep learning techniques are increasingly being applied to detect diseases in various vegetables

The PlantVillage dataset (Mohanty et al., 2016) has been a widely used benchmark dataset for training and evaluating plant disease detection models (Restrepo-Arias et al., 2024; Joshi, 2024; Ashraf et al., 2024).

2.3. Accessibility and Scalability Challenges for Small-Scale Farming Systems

Despite the significant advancements in AI and computer vision for plant disease detection, several critical research gaps and challenges hinder their widespread adoption, particularly within small-scale farming systems:

2.3.1. Data Scarcity and Quality

The performance of AI models heavily relies on the availability of large, diverse, and high-quality labeled datasets (Brahimi et al., 2018; Kasare, 2024; Joshi, 2024). Obtaining such datasets, especially for the wide variety of crops and diseases prevalent in different geographical regions and smallholder farming environments, can be challenging and expensive (Brahimi et al., 2018). Datasets collected in controlled laboratory settings may not accurately reflect the complexities of real-field scenarios, including variations in lighting, background, and plant growth stages (Fuentes et al., 2020; Joshi, 2024)

2.3.2. Model Robustness and Generalisation

AI models trained on specific datasets or under particular environmental conditions may not generalise well to new, unseen data or different field conditions (Kasare, 2024.; Joshi, 2024). Ensuring the robustness of models across diverse crop varieties, disease symptoms at different stages, and varying environmental factors remains a significant challenge (Kasare, 2024). Data from one part of the world may not be directly useful for another due to variations in weather and geological locations

2.3.3. Computational Constraints and Deployment

Many state-of-the-art deep learning models are computationally intensive, requiring significant processing power and memory (Joshi, 2024; Li et al., 2022; Brahimi et al., 2018). Deploying these models on resource-limited edge devices, which are often the most accessible option for smallholder farmers, poses a considerable challenge (Joshi, 2024; Li et al., 2022_. There is a need for lightweight and efficient models that can achieve high accuracy with minimal computational overhead (Joshi, 2024; Li et al., 2022).

2.3.4. Accessibility and Affordability

The cost of implementing and maintaining AI-based disease detection systems, including hardware (e.g., smartphones, cameras, sensors) and software, can be a significant barrier for smallholder farmers with limited financial resources (Ouma et al., 2024;). Solutions need to be affordable and accessible to a wide range of users, regardless of their economic status or technical expertise (Ouma et al., 2024).

2.3.5. Infrastructure Limitations

The lack of reliable internet connectivity and access to electricity in many rural agricultural areas can hinder the deployment and functioning of cloud-based AI solutions (Ouma et al., 2024; Elbasi & Mostafa, 2023). Edge computing solutions can mitigate the connectivity issue but still require access to power.

2.3.6. Digital Literacy and Farmer Adoption

The successful adoption of AI-based technologies requires a certain level of digital literacy among farmers ([Ouma et al., 2024; Elbasi & Mostafa, 2023). Many smallholder farmers may lack the necessary skills and training to effectively use these tools (Ouma et al., 2024; Elbasi & Mostafa, 2023). User interfaces need to be intuitive and farmer-friendly, and adequate training and support mechanisms need to be in place.

2.3.7. Integration with Existing Farm Management Practices

Integrating new AI-based disease detection systems seamlessly into existing farm management practices and workflows is crucial for their effective adoption (Kasare, 2024.). Solutions should be designed to complement, rather than complicate, farmers' current activities.

2.3.8. Ethical Considerations and Data Privacy

Issues related to data ownership, privacy, and security need to be addressed when collecting and using agricultural data for AI model training and deployment (Elbasi & Mostafa, 2023). Farmers need to trust that their data will be handled responsibly and ethically.

Addressing these research gaps and challenges is essential to ensure that the benefits of AI and computer vision for plant disease detection can be realised by smallholder farmers, contributing to more sustainable and resilient agricultural systems.

3. Conceptual framework

To address the challenges faced by smallholder farmers in crop disease detection and prevention, a conceptual framework leveraging computer vision and AI is proposed. This framework aims to be **s**calable, accessible, and suitable for real-time application in resource-limited settings.

3.1. System Design: Overview of Proposed Architecture

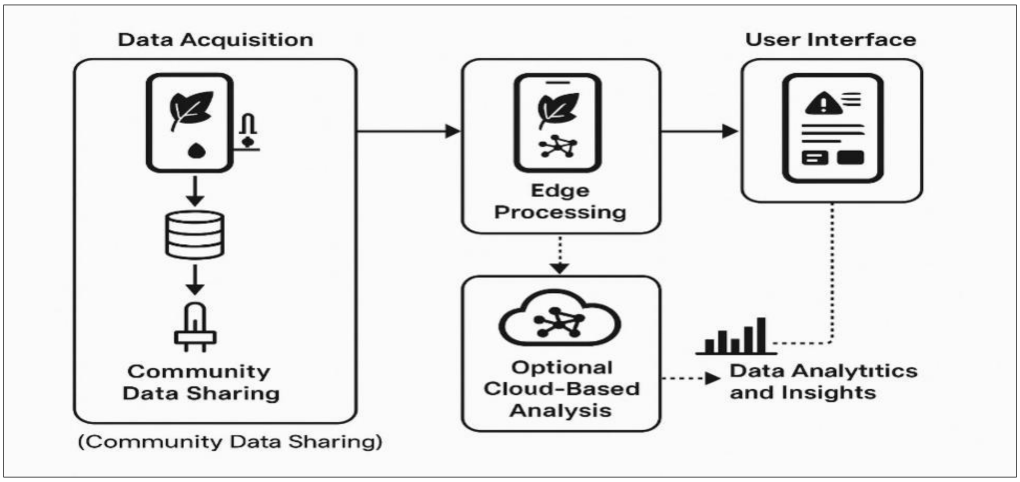

Figure 1 Proposed System Architeture

The proposed system architecture as depicted in Figure 1 above comprises the following key components:

3.2. Data Acquisition

- On-site Image Capture: The primary method of data acquisition involves farmers using smartphone cameras to capture images of potentially diseased plant parts (leaves, stems, fruits) (Ouma et al., 2024). Smartphones are increasingly accessible and offer a cost-effective means of image
- Optional Sensor Integration: For more advanced monitoring and data fusion, the system can optionally integrate data from low-cost environmental sensors (e.g., temperature, humidity) that can provide contextual information relevant to disease development (Restrepo-Arias et al., 2024; Elbasi & Mostafa, 2023).
- Community Data Sharing (Aggregated and Anonymised): Farmers can optionally contribute their anonymised and aggregated image and sensor data to a central platform to enhance the system's overall performance and generalisation capabilities. This can help address the data scarcity issue in diverse local contexts.

3.2.1. Edge Processing (on Smartphone):

- Image Preprocessing: Basic image preprocessing steps, such as resizing and noise reduction, can be performed directly on the farmer's smartphone to optimise the image for analysis and reduce the amount of data to be transmitted (if cloud analysis is used).
- Lightweight AI Model for Real-Time Inference: A lightweight and efficient AI model (e.g., a compressed CNN or a mobile-friendly architecture) is deployed directly on the smartphone (Joshi, 2024; Li et al., 2022). This enables real-time disease detection and provides immediate feedback to the farmer without requiring internet connectivity for the primary analysis. The model would be trained to identify the most common diseases prevalent in the local area.

3.2.2. Cloud-Based Analysis

- Data Transmission (when connectivity is available): If internet connectivity is available, farmers can optionally upload images and sensor data to a secure cloud platform for more comprehensive analysis using more complex and potentially more accurate AI models (Restrepo-Arias et al., 2024).
- Advanced AI Model Inference: Cloud servers can host more computationally intensive AI models capable of identifying a wider range of diseases and providing more detailed information about disease severity and potential spread (Restrepo-Arias et al., 2024).
- Data Analytics and Insights: The cloud platform can aggregate data from multiple farms (while ensuring anonymity) to generate valuable insights into disease outbreaks, regional trends, and the effectiveness of different management practices (Ouma et al., 2024). This information can be used to provide farmers with predictive alerts and tailored advice (Ouma et al., 2024).

3.2.3. User Interface (Mobile Application)

Intuitive Interface for Image Capture and Submission: A user-friendly mobile application guides farmers through the process of capturing clear images of affected plants and optionally submitting them for analysis.

- Real-Time Disease Diagnosis Feedback: The app displays the results of the on-device AI analysis immediately to the farmer.
- Detailed Information on Identified Diseases: For each identified disease, the app provides relevant information, including symptoms, causes, and recommended management practices (potentially drawing from local agricultural knowledge bases).
- Optional Cloud Analysis Request and Feedback: Farmers can easily request more detailed cloud-based analysis through the app and receive the results once available.
- Offline Access to Information: Key information about common diseases and basic troubleshooting tips can be stored offline within the app for use in areas with limited connectivity.
- Integration with Local Agricultural Resources: The app can provide links to local agricultural extension services, input suppliers, and other relevant resources.

3.3. AI Models: Comparison of Suitable Techniques for Accuracy and Usability

Selecting the appropriate AI models is crucial for the success of the proposed framework, particularly considering the resource constraints of smallholder farmers.

- Lightweight Convolutional Neural Networks (CNNs): CNNs have demonstrated high accuracy in image classification tasks, including plant disease detection (Brahimi et al., 2018; Joshi, 2024). For edge deployment on smartphones, lightweight CNN architectures such as MobileNet, ShuffleNet, and SqueezeNet are suitable due to their reduced computational complexity and memory footprint while still maintaining reasonable accuracy [Joshi, 2024]. Techniques like model compression (e.g., pruning, quantisation) can further reduce the size and computational demands of larger CNN models like ResNet for edge deployment (Joshi, 2024).
- Transfer Learning: Leveraging pre-trained deep learning models (trained on large image datasets like ImageNet) through transfer learning can significantly reduce the amount of data and training time required to develop accurate disease detection models for specific crops and regions (Brahimi et al., 2018; Kasare, 2024.; Joshi, 2024; Ashraf et al., 2024). This is particularly beneficial when labeled data for local diseases is limited. Fine-tuning pre-trained lightweight models on smaller, locally relevant datasets can yield good performance on edge devices (Joshi, 2024)
- Vision Transformers (ViTs): While relatively newer than CNNs in the agricultural domain, Vision Transformers have shown promising results in image classification (Joshi, 2024; Anam et al., 2024). Some research indicates they can achieve high accuracy in tasks like orange species classification (Joshi, 2024). However, their computational demands might currently limit their direct deployment on low-end edge devices, making them potentially more suitable for cloud-based analysis or future, more powerful edge devices.

3.3.1. Traditional Machine Learning Algorithms

While deep learning models often offer superior accuracy, traditional ML algorithms like Support Vector Machines (SVMs) and K-Nearest Neighbors (KNN) can be less computationally intensive and may be suitable for simpler disease detection tasks or as baseline models for comparison (Francis et al., 2018; , 2019; Sharada et al., 2025; Sasirekha & Suganthy, 2019). They can also offer better interpretability, which can be valuable for understanding the features driving the classification.

The choice of AI model will depend on a trade-off between accuracy, computational efficiency (for edge deployment), data requirements, and ease of implementation and maintenance. For the initial on-device real-time detection, lightweight CNNs fine-tuned using transfer learning on locally relevant datasets appear to be a promising approach. More complex models, including ViTs and larger CNNs, can be reserved for optional cloud-based analysis when higher accuracy or the identification of less common diseases is required.

3.4. Implementation Considerations

Successful implementation of the proposed framework for smallholder farmers requires careful consideration of scalability, accessibility, and ethical implications:

3.4.1. Scalability:

- Mobile-First Design: Leveraging the widespread adoption of mobile phones is key to scalability (Ouma et al., 2024; Elbasi & Mostafa, 2023). Developing a user-friendly mobile application that can be easily downloaded and used on a variety of smartphones is essential
- Cloud Infrastructure: Utilizing a robust and scalable cloud infrastructure (for optional advanced analysis and data management) can accommodate a growing number of users and increasing data volumes (Restrepo-Arias et al., 2024).
- Community-Driven Data Contribution: Encouraging farmers to contribute their data (in an anonymised and aggregated manner) can help build larger and more diverse datasets, improving the generalisability and scalability of the AI models across different regions and farming systems
- Open-Source Development: Considering an open-source approach for parts of the software and model development can foster wider adoption and allow for community-driven improvements and customisations for specific local needs [IET Image Processing].

3.4.2. Accessibility:

- Affordability: The cost of the mobile application should be minimal or free. The system should primarily rely on readily available smartphone technology to avoid the need for expensive dedicated hardware (Ouma et al., 2024). Exploring partnerships with mobile network operators or agricultural organisations could help subsidise data costs associated with optional cloud analysis.
- Language and Literacy: The mobile application should support multiple local languages and utilise intuitive visual elements to cater to farmers with varying levels of literacy (Ouma et al., 2024). Voice-based interfaces could be explored for further accessibility.
- Offline Functionality: The core real-time disease detection functionality should work offline to address connectivity limitations in rural areas (Joshi, 2024). Key disease information and troubleshooting tips should also be accessible offline.
- Training and Support: Providing accessible training and support to farmers on how to use the mobile application and interpret the results is crucial for adoption (Ouma et al., 2024). This can be done through workshops, video tutorials, and collaborations with local agricultural extension officers.

Integration with Existing Practices: The system should be designed to complement existing farming practices and provide actionable insights that farmers can easily incorporate into their routines (Kasare, 2024).

3.4.3. Ethical Implications

- Data Privacy and Security: Robust measures must be implemented to ensure the privacy and security of any data collected from farmers (Elbasi & Mostafa, 2023). Clear guidelines on data usage and ownership should be established.
- Bias in AI Models: Efforts should be made to ensure that the AI models are trained on diverse and representative datasets to avoid biases that could lead to inaccurate diagnoses for certain crop varieties or disease manifestations prevalent in specific smallholder farming systems (Kasare, 2024.; Joshi, 2024).
- Impact on Labour: While the aim is to empower farmers and improve efficiency, the potential impact of automated disease detection on agricultural labour should be considered and addressed proactively through training and upskilling initiatives.
- Transparency and Trust: The system should strive for transparency in how the AI models work and how diagnoses are made to build trust among farmers (Kasare, 2024). Providing explanations or visual cues related to the model's decision-making process could be beneficial (though challenging for complex deep learning models).

Careful consideration of these implementation aspects is crucial to ensure that the proposed AI-driven disease detection and prevention framework is truly beneficial and sustainable for smallholder farming communities.

4. Discussion

4.1. Benefits

The proposed framework offers several potential benefits for smallholder farmers:

4.1.1. Enhanced Detection Speed

Real-time on-device analysis provides immediate feedback to farmers, enabling them to identify potential disease outbreaks much faster than traditional manual inspection. Optional cloud analysis can provide more detailed results relatively quickly compared to sending samples for laboratory testing.

- Improved Accuracy: AI models, particularly deep learning-based approaches, have the potential to achieve higher accuracy in disease detection compared to subjective visual inspection, especially in the early stages of infection when symptoms are subtle (Kasare,2024.; Sharada et al., 2025). Continuous learning and refinement of the models through community data sharing can further enhance accuracy over time.
- Early Intervention and Reduced Crop Losses: Faster and more accurate detection allows for timely intervention with appropriate management practices, such as targeted application of treatments or isolation of affected plants This can significantly reduce crop losses and improve overall yields
- Optimised Resource Use: Accurate disease identification can help farmers make more informed decisions about the use of pesticides and other treatments, leading to more targeted applications and reducing the overall reliance on chemical inputs. This not only lowers costs for farmers but also promotes more sustainable agricultural practices and minimises environmental impact (Kasare, 2024.; Brahimi et al., 2018).
- Empowerment and Knowledge Building: Providing farmers with real-time diagnostic tools and information about plant diseases can empower them to become more knowledgeable and proactive in managing their crops (Ouma et al., 2024). Access to curated information and best practices through the mobile application can enhance their decision-making capabilities.
- Socio-Economic Impact: By reducing crop losses, optimising resource use, and improving yields, the proposed framework can contribute to increased income and improved livelihoods for smallholder farmers (Ouma et al., 2024; Brahimi et al., 2018). This can have positive ripple effects on local economies and contribute to greater food security at regional and national levels
- Community Learning and Resilience: Aggregated and anonymised data analysis on the cloud platform can provide valuable insights into disease patterns and effective management strategies at a community level, fostering collective learning and enhancing the resilience of farming systems to disease outbreaks

4.2. Challenges: Barriers to Adoption in Resource-Limited Settings

Despite the potential benefits, several challenges could hinder the adoption of this framework in resource-limited smallholder farming settings:

- Smartphone Penetration and Capabilities: While smartphone ownership is increasing, not all smallholder farmers may have access to smartphones with adequate camera quality and processing power required for effective image capture and on-device AI analysis (Ouma et al., 2024; Elbasi & Mostafa, 2023).
- Digital Literacy and Technical Skills: As mentioned earlier, a lack of digital literacy and technical skills among some farmers could make it challenging for them to use the mobile application effectively (Ouma et al., 2024; Elbasi & Mostafa, 2023).
- Data Connectivity and Costs: Reliable and affordable internet connectivity remains a significant challenge in many rural agricultural areas, limiting the use of optional cloud-based analysis and data sharing features. Data costs can also be a barrier for farmers with limited financial resources.
- Power Availability: Access to reliable electricity is crucial for charging smartphones and potentially powering sensor devices (Elbasi & Mostafa, 2023).
- Initial Investment and Maintenance: Even if the mobile application is free, farmers may incur costs related to purchasing smartphones (if they don't already own one) and potentially for data usage or future updates and support

- Trust and Acceptance: Farmers may be hesitant to adopt new technologies if they do not fully understand their benefits or if they have concerns about their accuracy, reliability, or ease of use (Ouma et al., 2024). Building trust through effective communication, training, and demonstrable success stories is crucial.
- Model Accuracy and Generalisation in Local Contexts: AI models trained on global datasets may not always perform optimally for the specific crop varieties and disease strains prevalent in particular local environments (Kasare, 2024.; Joshi, 2024). Ensuring the accuracy and generalisation of models in diverse smallholder farming systems requires access to locally relevant data and potentially localised model training.
- Integration with Existing Knowledge and Practices: The framework needs to be sensitive to and integrate with farmers' existing traditional knowledge and farming practices to ensure its relevance and facilitate adoption (Kasare, 2024.).

Addressing these challenges through targeted research, development, and implementation strategies is essential for the successful adoption of AI-driven disease detection and prevention in smallholder farming systems.

4.3. Future Directions

Future research should focus on addressing the identified challenges and further advancing the practical application of AI and computer vision for smallholder farmers:

- Development of Highly Efficient and Lightweight AI Models: Continued research into developing more efficient deep learning architectures and model compression techniques is crucial for enabling accurate real-time disease detection on low-resource edge devices like smartphones (Joshi, 2024; Li et al., 2022).
- Leveraging Self-Supervised and Few-Shot Learning: Exploring self-supervised learning (SSL) and few-shot learning techniques can help reduce the reliance on large amounts of labeled data, which is often a bottleneck in agricultural applications, especially for less common diseases or in diverse local contexts (Mamun et al., 2024; Joshi, 2024).
- Improving Model Generalisation and Robustness: Research should focus on developing AI models that are more robust to variations in lighting, background, plant growth stages, and camera quality to ensure reliable performance in real-field conditions (Kasare, 2024.; Joshi, 2024). Techniques like domain adaptation and augmentation with synthetic data could be explored.
- Integration of Multi-Modal Data: Future systems should explore the integration of image data with other relevant data sources, such as environmental sensor data (temperature, humidity, soil moisture), weather forecasts, and historical disease outbreak data, to provide a more comprehensive understanding of disease risk and inform more effective prevention strategies (Restrepo-Arias et al., 2024; Elbasi & Mostafa, 2023).
- Development of User-Centric and Accessible Interfaces: Continued focus on developing intuitive and user-friendly mobile applications that support multiple languages and work effectively even with limited digital literacy is essential for widespread adoption (Ouma et al., 2024). Voice-based interfaces and augmented reality features could further enhance accessibility.
- Exploring Offline AI Capabilities: Further research into optimising AI models for offline operation, without any reliance on cloud connectivity, is crucial for reaching farmers in areas with poor network infrastructure (Joshi, 2024).
- Community-Driven Data Collection and Model Localisation: Developing mechanisms to facilitate community-driven data collection and enable the localisation and fine-tuning of AI models for specific regional contexts and prevalent diseases is crucial for improving accuracy and
- Investigating Cost-Effective Deployment and Sustainability Models: Research into sustainable and cost-effective deployment models, potentially involving partnerships with agricultural organisations, NGOs, and government agencies, is needed to ensure that these technologies are accessible to smallholder farmers with limited resources
- Addressing Ethical Considerations Proactively: Ongoing research and dialogue are needed to address the ethical implications of using AI in agriculture, including data privacy, algorithmic bias, and the potential impact on labour, ensuring that these technologies are deployed responsibly and equitably (Elbasi & Mostafa, 2023).

By focusing on these future directions, the research community can contribute to the development of practical and impactful AI-driven solutions that truly empower smallholder farmers in their efforts to manage crop diseases and achieve sustainable agricultural productivity.

5. Conclusion

This conceptual exploration has highlighted the significant challenges posed by crop diseases to smallholder farming systems and the limitations of traditional detection methods. It has underscored the transformative potential of leveraging computer vision and artificial intelligence (AI) to enable real-time and accurate disease detection and support proactive prevention strategies. The proposed framework, centred around a mobile-first approach with lightweight on-device AI analysis and optional cloud-based enhancement, aims to address the specific needs and constraints of resource-limited smallholder farmers. The review of existing literature and the comparison of suitable AI models suggest that fine-tuned lightweight CNNs are a promising approach for real-time edge deployment. However, successful implementation hinges on careful consideration of scalability, accessibility, and ethical implications, including data scarcity, computational constraints, digital literacy, and infrastructure limitations.

Recommendations

To translate the potential of AI for crop disease management in smallholder farming into tangible benefits, the following recommendations are proposed:

- Prioritise Research on Lightweight and Efficient AI Models: Increased investment in research focused on developing highly accurate yet computationally efficient AI models suitable for deployment on low-resource edge devices is crucial.
- Foster the Creation of Locally Relevant and High-Quality Datasets: Initiatives to support the collection, annotation, and sharing of high-quality image data of plant diseases prevalent in diverse smallholder farming systems are essential for training robust and generalisable AI models.
- Develop User-Centric and Multilingual Mobile Applications: Continued focus on user-centred design principles and the development of intuitive mobile applications that support multiple local languages and work effectively offline is critical for farmer adoption.
- Invest in Farmer Training and Extension Services: Comprehensive training programmes and strengthened agricultural extension services are needed to equip farmers with the necessary digital literacy and skills to effectively use AI-based disease detection tools.
- Promote Open-Source Collaboration and Knowledge Sharing: Encouraging open-source development and the sharing of data, models, and best practices within the agricultural AI community can accelerate innovation and facilitate the adaptation of solutions to local contexts.
- Explore Sustainable Business and Deployment Models: Innovative and sustainable business models that ensure the affordability and long-term maintenance of AI-based systems for smallholder farmers need to be explored, potentially involving public-private partnerships and community-based initiatives.
- Establish Supportive Policy Frameworks: Governments and policymakers should create supportive policy frameworks that promote the adoption of digital technologies in agriculture, including investments in rural infrastructure (connectivity, power), data privacy regulations, and incentives for technology adoption by smallholder farmers.

Compliance with ethical standards

Disclosure of conflict of interest

There is no conflict of interest.

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