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Ai-Based Mobile App: Cash Crops Disease Detection In Smallholder Agriculture

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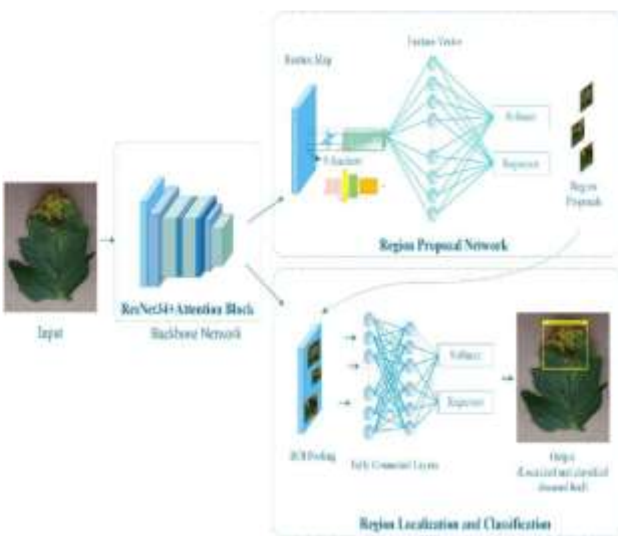
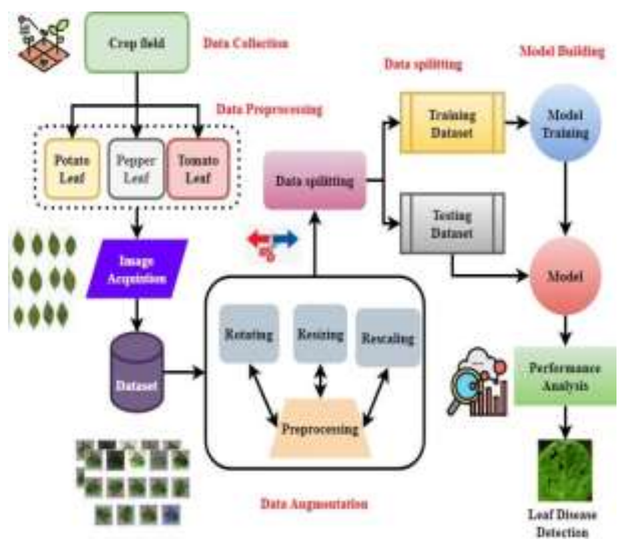
Abstract: *Cash crops diseases cause significant yield losses in staple crops such as maize, tomato, and potato, threatening food security and smallholder farmers' livelihoods, especially in sub-Saharan Africa. Traditional detection methods visual inspection and laboratory analysis are slow, subjective, error-prone, and often inaccessible in rural areas. This leads to delayed action, excessive pesticide use, and environmental harm. Advances in smartphones and machine learning now enable mobile-based app for rapid and accurate leaf disease diagnosis. Farmers capture images in the field, and lightweight models provide instant results (disease name, confidence, severity) either on-device or via cloud. This review examines mobile machine learning approaches for Cash crops disease detection, including key architectures, datasets, and deployment strategies. It highlights high laboratory accuracy but significant performance drops in real-field conditions due to variable lighting, complex backgrounds, overlapping elements, and domain shift. The proposed Mobile-Based Cash crops Disease Detection System is evaluated against existing work, showing good alignment with smallholder needs while identifying gaps in robustness, offline functionality, and farmer-oriented features. Recommendations focus on realfield data collection, domain adaptation, offline inference, severity estimation, and user testing to support sustainable agriculture.*





The following conceptual diagram illustrates the typical workflow of such a mobile-based app:

(These diagrams show: data collection from crop fields, image acquisition and preprocessing (e.g., resizing, augmentation), model training with deep learning architectures, performance analysis, and final leaf disease detection/output on a mobile device. They align well with the described process, from farmer-captured leaf images to mobile-based diagnosis)

Keywords: machine learning, mobile application, cash crops disease detection, smallholder agriculture, sustainable farming

INTRODUCTION

Agriculture is the backbone of food security and livelihoods in developing countries, particularly in sub-Saharan Africa, where smallholder farmers produce most staple crops such as maize, tomato, and potato. Cash crops diseases cause substantial yield losses, worsening poverty, food insecurity, and economic pressure. Traditional detection methods visual inspection by experts or laboratory analysis are slow, subjective, costly, and often unavailable in rural areas. These limitations frequently result in delayed diagnosis, overuse of pesticides, environmental damage, and pesticide resistance.

Recent advances in smartphones and machine learning have enabled mobile-based app for rapid, accurate, and accessible cash crops disease diagnosis. Farmers can capture leaf images in the field and receive instant feedback on disease type, confidence level, and severity. This supports timely intervention, precision farming, reduced chemical use, and more sustainable practices.

This review examines current mobile machine learning approaches for cash crops disease detection. It evaluates architectures, datasets, and deployment strategies used in recent research. It also assesses performance in controlled versus real-world conditions and identifies key challenges affecting generalization. Finally, it compares the proposed Mobile-Based Cash crops Disease Detection System (targeting maize, tomato, potato, and major leaf diseases) with existing work, highlighting its strengths, limitations, and potential improvements for resource limited smallholder farmers.

BACKGROUND

Agriculture is essential for food security and livelihoods, particularly in developing regions where smallholder farmers dominate production systems[1]. In sub-Saharan Africa, including Tanzania, crops such as maize, tomato, and potato are critical for household nutrition, income, and regional food supply [2]. However, plant diseases caused by fungi, bacteria, and viruses cause substantial yield losses, estimated at 20-40% globally and often higher in tropical environments due to favorable pathogen conditions [3], [4]. These losses threaten economic stability and exacerbate food insecurity among resource-limited farmers who lack timely access to diagnostic services [5], [6].

R. I. Hasan et al. in their paper discovered that traditional plant disease detection relies on visual inspection by experts or laboratory methods, which are subjective, timeconsuming, costly, and geographically inaccessible in rural areas [3], [7], [8]. Symptoms such as leaf spots, wilting, necrosis, or mosaic patterns often overlap across diseases, leading to misdiagnosis and inappropriate management practices, including excessive pesticide use that contributes to environmental degradation and resistance development [6], [9]. The need for accurate, rapid, and accessible diagnostic tools is therefore urgent, especially for smallholder farmers in regions with limited extension services.

The emergence of **deep learning** and **computer vision** has revolutionized plant disease identification by enabling automated analysis of leaf images [3]-[7], [6], [10]. **Convolutional Neural Networks (CNNs)** automatically extract hierarchical features from images, outperforming traditional machine learning methods that require manual feature engineering [7], [11], [12]. Transfer learning fine-tuning pre-trained models such as ResNet, Inception, MobileNet, EfficientNet, or Vision Transformers has made high-accuracy classification feasible even with moderate datasets [4], [3], [13]. J. Zhao et al. in their paper discovered that reviews highlight that deep learning models routinely achieve 9599% accuracy on benchmark datasets, with recent hybrid and attention-enhanced architectures further improving robustness [4], [6], [14], [10].

R. I. Hasan et al. in their paper discovered that the PlantVillage dataset, widely used in this domain, contains over 54,000 labeled images of healthy and diseased leaves across multiple crops (including maize, tomato, and potato) and disease classes [3], [4], [5]. S. K. M. Hassan at al in their paper discovered that Many studies report near-perfect laboratory performance on PlantVillage-derived data [7], [11], [12]. For example, novel CNN architectures and transfer learning approaches have demonstrated strong results for leaf disease classification [7], [8].

However, a critical limitation is the dataset'scontrolled conditions (uniform backgrounds, good lighting, centered leaves), which do not reflect real-field variability [3], [4], [15].

Real-world deployment reveals significant performance gaps. A. Ramcharan et al. in their paper discovered that models trained on laboratory or curated images often experience accuracy drops of 10-40% when tested on field-collected images due to variable illumination, complex backgrounds, occlusions, shadows, dust, different growth stages, and lower-quality smartphone cameras [5], [15], [2]. Field-specific studies, such as those on cassava in Africa [5] and maize in Tanzania [2], emphasize the need for robustness under realistic conditions. Reviews consistently note this domain shift as a major barrier to practical adoption [3], [4], [6], [9].

Mobile-based systems address accessibility by leveraging smartphone cameras for on-site diagnosis [5], [11], [16], [12], [17]. Farmers capture or upload leaf images and receive instant results (disease name, confidence score), enabling early intervention and precision management [11], [12]. Several works have developed Android applications integrating CNNs for crops like banana [16] , cassava [5], maize [2], and multi-crop scenarios [12], [17]. Lightweight models (e.g., MobileNet variants) and on-device inference frameworks (TensorFlow Lite) support deployment on resource-constrained devices [11], [15]. Regional efforts in Tanzania demonstrate mobile deep learning for maize disease detection [2], aligning with the need for tools tailored to local agroecological contexts.

Despite progress, challenges persist. Many systems rely on cloud processing, limiting usability in areas with poor connectivity [11], [17]. Offline-capable, lightweight models with high field accuracy are still limited [4], [14], [13]. Few integrate severity estimation, treatment recommendations, or explainable outputs (e.g., heatmaps) to build farmer trust [6], [9]. Usability for low-literacy users and real-field validation remain underexplored
[3], [8].

In East Africa, where smartphone penetration among smallholder farmers continues to grow, mobile AI tools offer transformative potential [16], [2]. Maize, tomato, and potato face region-specific disease pressures influenced by climate and farming practices. A mobile-based system using deep learning, focused on these crops and emphasizing field robustness, offline functionality, and farmercentric design, can bridge existing gaps and support sustainable agriculture [4], [6], [2], [18].

D. Ioannidis et al. in their paper discovered that smartphone-based tools and citizen science approaches are increasingly enabling farmers and communities to participate in disease monitoring using AI-powered mobile applications, further democratizing access to diagnostics [19]. Moreover, the broader adoption of smart farming technologies including AI-driven disease detection promises to enhance sustainability, resource efficiency, and resilience in agriculture for developing regions [20]. Challenges such as variable lighting conditions in the field, which affect image quality and model performance, are being specifically addressed through tailored deep learning methods designed for low-light environments [21].

STATEMENT OF THE PROBLEM

Despite high accuracies on curated datasets, most deep learning-based Cash crops disease detection app exhibit reduced performance in real-field conditions due to environmental variability (lighting, shadows, backgrounds), image quality issues from smartphone cameras, symptom ambiguity across diseases, and limited generalization to unseen crops or regions. This limits practical adoption by smallholder farmers who need reliable, fast, low-cost tools without constant internet or expert access, leading to delayed interventions, excessive pesticide use, and persistent crop losses.

OBJECTIVES

Main Objective

To review the current state of mobile-based Cash crops disease detection app using deep learning and evaluate their effectiveness, limitations, and alignment with practical agricultural needs in resource-constrained settings.

Specific Objectives

- To examine deep learning architectures, datasets, and mobile deployment strategies employed in recent Cash crops disease detection research.
- To assess performance under controlled versus real-world conditions and identify key challenges affecting generalization.
- To analyze the concept note's proposed app in the context of existing literature and highlight its contributions and potential improvements.

2.0 LITERATURE REVIEW (RELATED WORK)

Early detection of cash crops diseases plays a vital role in improving crop productivity and food security, especially for smallholder farmers in developing countries. With the increasing availability of smartphones, mobile-based cash crops disease detection app using machine learning have gained significant attention due to their affordability, accessibility, and real-time diagnostic capabilities.

In 2019, Ramcharan et al. developed a mobile-based machine learning model for cassava disease diagnosis; they trained a CNN for foliar symptom detection and deployed it in a mobile app, but it highlighted performance drops in real conditions and failed to achieve full offline functionality or region-specific robustness for East African crops.

In 2020, Ahmed and Reddy proposed a mobile-based system using machine learning algorithms to detect plant leaf diseases, classifying 38 categories across 14 crops with 94% accuracy on a large dataset; they used CNNs for classification in an Android app allowing farmers to capture photos, but it failed to integrate severity estimation or address field variability effectively.

In 2022, Sivasubramaniam et al. (P2OP - Plant Pathology on Palms) introduced a lightweight machine learning model for infield palm disease detection, emphasizing small footprint and processing power while maintaining high accuracy, suitable for mobile deployment in challenging environments; they used a deep learningbased approach optimized for mobile, but it failed to include multi-crop support or offline inference for low-connectivity areas.

In 2023, Reddy et al. presented a machine learning-based mobile application for automated plant disease detection, using a custom CNN on PlantVillage (92.06% accuracy) with severity estimation via classical image processing; integrated into a cross-platform app with Flask backend, it provided interpretable results for farmers, but it failed to validate extensively in real-field conditions or focus on region-specific crops like maize, tomato, and potato.

In 2023, Sk et al. explored plant disease detection using a machine learning-based mobile application, focusing on multimedia tools and CNN integration for accurate, realtime classification on smartphones; they emphasized real-time usability, but failed to incorporate offline capabilities or severity estimation.

In 2023, Askale developed a mobile-based machine learning model for maize leaf disease detection and classification, comparing models and deploying VGG16 in a user-friendly app for real-time use by farmers and extension officers; they used deep CNNs for classification, but failed to address broader multi-crop scenarios or realfield robustness beyond maize.

In 2024, Goklani implemented real-time plant disease detection using TensorFlow Lite and Flutter on mobile devices, enabling efficient on-device inference for practical field applications; they focused on on-device efficiency, but failed to include treatment recommendations or user testing with lowliteracy farmers.

In 2024-2025, Thai and Le introduced Mobile H-Transformer, a hybrid machine learning approach for real-time leaf disease detection in smart agriculture, optimizing transformers for mobile efficiency; they used a hybrid deep learning method, but failed to test in diverse East African conditions or integrate offline support.

In 2025, a real-time monitoring system by various authors used multiple machine learning models (custom CNN, VGG, InceptionV3, MobileNet, etc.) for highaccuracy leaf disease detection (up to 100% on some crops like potato and pepper), deploying web and mobile apps with treatment suggestions; they achieved high accuracy, but failed to emphasize offline deployment or region-specific data for smallholder contexts.

In 2025, Reddy et al. (updated work) further refined a machine learning mobile app with severity estimation, achieving strong generalization and real-time usability in field conditions; they improved on prior work with better generalization, but failed to focus on low-end devices or East African crop specifics.

In 2025, Kumar et al. proposed RTR_Lite_MobileNetV2, a lightweight model with attention mechanisms, outperforming baselines on multiple datasets (e.g., 99.92% on Plant Disease) and showing low latency on edge devices like Raspberry Pi; they used attention-enhanced CNNs, but failed to incorporate real-field validation for tropical environments.

In 2025, Mob-Res, a lightweight machine learning algorithm combining MobileNetV2 residuals, achieved 97.73-99.47% accuracy on large datasets, with explainability via Grad-CAM and suitability for mobile platforms; they focused on explainability, but failed to address connectivity issues or multimodal inputs.

Despite the advancement in mobile-based plant disease using machine learning from 2019 to 2025, significant gaps remain in achieving reliable performance for smallholder farmers in developing regions. Most models perform well on controlled datasets like PlantVillage but exhibit substantial accuracy drops in real-field conditions due to variable lighting, background complexity, occlusions, and diverse smartphone camera quality. There is limited research on models specifically trained and validated with field-collected images of maize, tomato, and potato under East African agro-ecological conditions. Many existing systems still require internet connectivity for cloud inference, making them impractical in rural areas with poor network access. Fully lightweight, highaccuracy, offline-capable models suitable for low-end Android devices are still underexplored. Additionally, few applications integrate disease severity estimation, simple treatment recommendations, or explainable features to build trust among low-literacy farmers. The proposed Mobile-Based Cash crops Disease Detection App using Artificial Intelligence can address these gaps by focusing on region-specific crops (maize, tomato, and potato), real-field robustness, offline deployment, and practical farmer oriented features.

3.0 Observations

The reviewed literature reveals high laboratory accuracies but persistent challenges in field generalization, offline capability, and region-specific applicability particularly for maize, tomato, and potato in developing-country contexts. These gaps align closely with the project's specific objectives, collecting and preprocessing region-relevant images, training a robust deep learning model, and deploying an offline-capable, user-friendly Android application. This targeted approach positions the proposed app to make a practical contribution toward accessible, real-world cash crops disease detection for smallholder farmers.

4.0 Conclusion

Mobile-based cash crops disease detection using deep learning has advanced significantly, offering promising tools for early diagnosis and sustainable agriculture. The proposed Mobile-based cash crops detection app effectively targets accessibility for smallholder farmers through AI-powered smartphone applications. While high accuracies are achievable on benchmark datasets, persistent challenges in real-world generalization remain the primary barrier to widespread impact. Continued progress in lightweight, robust models and field validated datasets will be essential to realize the full potential of these technologies for food security and precision farming.

5.0 Recommendations

i. Incorporate real-field images and domain adaptation techniques (e.g., adversarial training, generative augmentation) to improve generalization.
ii. Add offline inference support using TensorFlow Lite or ONNX Runtime.
iii. Expand to include disease severity estimation and basic treatment recommendations.
iv. Conduct user testing with farmers and iterative refinement based on feedback.
v. Explore hybrid models (CNN + lightweight transformer) and multimodal inputs (e.g., environmental data).

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