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A REVIEW ON A CNN-POWERED MOBILE APPLICATION FOR AUTOMATED CROP DISEASE CLASSIFICATION

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Abstract: Deep learning has become a transformative approach for automated plant health monitoring, enabling accurate disease recognition directly from leaf images without relying on manual inspection or expert availability. In modern precision agriculture, both leaf disease classification and severity quantification are essential for identifying early infections and supporting informed intervention strategies. However, developing reliable diagnostic models remains challenging due to environmental variability, heterogeneous field conditions, inconsistent image quality, and the absence of pixel-level severity annotations in standard datasets. This literature-aligned study synthesizes advances in lightweight CNN architectures, classical image-processing pipelines, attention-guided visualization tools, and mobile-centric deployment frameworks for real-time plant disease assessment. Special emphasis is placed on the proposed end-to-end system, which integrates a custom PyTorch-based CNN with an OpenCV-driven severity estimation module and a cross-platform React Native mobile interface. While originally optimized for binary classification, the system directly addresses practical agricultural constraints such as uneven lighting, morphological variations across species, and limited computational resources in field environments. By combining interpretable predictions, severity mapping, and rapid inference via a Flask backend, the approach enhances usability, improves generalization under diverse conditions, and reduces diagnostic dependency on experts. Through comparative analysis with existing methods, this work positions the proposed framework as a promising foundation for future mobile plant-disease diagnostic pipelines integrating accessibility, explainability, and deployment-scale robustness.

Keywords: Plant Disease Detection, Convolutional Neural Networks, Severity Estimation, Mobile Application, Deep Learning, Precision Agriculture.

I. INTRODUCTION

Plant diseases are one of the main reasons for crop loss in agriculture. When leaves get infected, farmers often struggle to identify the disease early because they depend on manual checking or expert help. This method is slow and not always accurate, and experts may not be available in all areas. Because of this, farmers need a fast and simple way to detect plant diseases.

Today, deep learning and mobile technology make it possible to identify diseases from leaf images automatically. By using a mobile phone camera, a farmer can take a picture of a leaf and obtain immediate results. Deep learning models, especially Convolutional Neural Networks (CNNs), can learn patterns from leaf images and accurately predict whether the leaf is healthy or diseased.

In this project, a lightweight CNN model is used along with an image-processing method to estimate how much of the leaf is infected. A mobile application built with React Native allows users to upload or capture images, and a Flask backend processes these images and provides instant results. The aim of this system is to help farmers easily detect plant diseases early, reduce crop loss, and make better decisions in the field.

II. BACKGROUND AND CONTEXT

Agriculture is one of the most important sectors for food security, yet plant diseases continue to cause major losses in crop yield every year. Early and accurate detection of leaf diseases is essential because infections can spread quickly and reduce both the quantity and quality of production. In many rural areas, farmers rely on manual inspection or guidance from plant experts. However, experts are not always available, and visual inspection is often slow and inaccurate and depends heavily on personal experience. This makes plant disease detection an important and urgent research area.

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In the past, researchers tried to identify diseases using traditional image processing methods such as color analysis, texture features, and segmentation. Although these techniques worked for simple images, they failed when the background was complex, lighting was poor, or the disease symptoms were very subtle. As agriculture moved toward digitalization, deep learning, especially Convolutional Neural Networks (CNNs), became a powerful solution because CNNs automatically learn patterns from thousands of leaf images without manual feature extraction.
Several studies achieved high accuracy using CNNs trained on datasets like PlantVillage. Researchers also used transfer learning models such as ResNet, VGG, and EfficientNet to classify multiple diseases. While these works improved classification accuracy, many of them focused only on predicting which disease is present. They did not estimate how severe the infection is, which is crucial for practical decision-making, such as how much pesticide to use or how urgently the plant needs treatment.
Another challenge in existing research is that most deep learning models are tested only in laboratory environments. Farmers rarely use these systems because they require computers, high-end GPUs, or expert knowledge. There is a clear need for a practical, easy-to-use solution that farmers can access directly in the field. Mobile applications are ideal for this purpose, but only a few studies have integrated deep learning models into real-time mobile apps.
Considering these gaps, the present project focuses on building a deep learning-based mobile application that not only classifies leaf images as healthy or diseased but also estimates the severity of infection using image processing. By integrating a lightweight CNN model, classical OpenCV-based severity analysis, and a cross-platform mobile interface, this work addresses both accuracy and usability challenges. Such a system provides farmers with an accessible digital tool for timely crop health monitoring and helps bridge the gap between research models and real-world agricultural needs.

III. RELATED WORKS

Recent advancements in deep learning and mobile computing have led to the development of intelligent systems for plant disease detection, pest monitoring, and agricultural decision support. Existing research primarily focuses on improving the accuracy, efficiency, and real-time applicability of plant health diagnosis using CNNs, transfer learning, and lightweight mobile-friendly architectures. Several studies have also explored integrating disease detection with advisory modules such as fertilizer recommendation and crop protection strategies, highlighting the growing importance of end-to-end digital agriculture solutions.
Deep Learning Based Mobile Application for Automated Plant Disease Detection [1] introduces a mobile app that uses a CNN-based deep learning model to identify plant diseases from leaf images. The system provides quick and accurate predictions directly on smartphones, allowing farmers to detect issues in real time. The paper highlights the app's usability, efficiency, and potential to support field-level agricultural decision-making.
Smart Plant: A Mobile Application for Plant Disease Detection [2] presents a mobile-based system that uses a CNN model to identify plant diseases from leaf images. The app allows users to upload images and receive instant predictions, making it useful for farmers in real-time field conditions. Its main contribution is providing an accessible and user-friendly platform for plant health monitoring.
Evaluation of CNN Models in Identifying Plant Diseases on a Mobile Device [3] analyzes different CNN architectures to determine which models work efficiently on smartphones. It compares accuracy, speed, and memory usage, highlighting lightweight models that offer good performance on low-resource devices. This study emphasizes the importance of optimizing plant disease detection models for mobile deployment.
Disease Identification using Deep Learning in Agriculture: A Case Study of Cotton Plant [4] applies deep learning techniques to classify diseases in cotton leaves. A CNN model is trained on cotton-specific images and achieves high accuracy across multiple disease types. The work demonstrates how deep learning can support crop-specific disease diagnosis.
Fertilizer Recommendation System for Disease Prediction Using machine learning [5] combines disease prediction with fertilizer recommendations. The system uses machine learning models to analyze soil and plant-related inputs and suggests suitable fertilizers. This integrated approach supports farmers by connecting disease diagnosis with actionable cultivation advice.
CropCare: An AI-Integrated System for Smart Crop Protection and Disease Detection [6] introduces an AI-based platform that uses image processing and machine learning to detect leaf diseases and provide protective measures. The system integrates detection, analysis, and recommendation modules, offering a complete decision-support tool for crop management. It improves farm decision-making through automated disease recognition.
Transfer Learning-Based Lightweight SSD Model for Detection of Pests in Citrus [7] uses a lightweight SSD object detection model to identify pests on citrus leaves. Transfer learning helps improve detection accuracy while keeping the model efficient for edge and mobile devices. The approach supports real-time pest monitoring in agriculture.
Plant Disease Diagnosis for Smart Phone Applications with Extensible Set of Diseases [8] proposes a smartphone app that can diagnose multiple plant diseases and allows new diseases to be added without rebuilding the entire system. Its

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extensible design makes it scalable and adaptable as new disease data becomes available. This flexibility is valuable for long-term mobile agriculture applications.

A Lightweight Deep Learning Model for Crop Disease Detection on Mobile Devices [9] develops a compact deep learning model designed specifically for mobile hardware. It reduces computational cost and memory usage while maintaining strong detection accuracy. The model is suitable for real-time, offline plant disease recognition in rural environments.

Robust CRW Crops Leaf Disease Detection and Classification Using Hybrid Deep Learning Models [10] introduces a hybrid model combining CNN features with advanced learning techniques to improve robustness. The approach performs well under varying lighting, noise, and field conditions. It offers improved accuracy compared to traditional single-model approaches.

Early Disease Detection in Plants using CNN [11] focuses on identifying early-stage symptoms using convolutional neural networks. The model captures subtle visual patterns that appear before severe infection occurs. Early detection helps farmers take preventive measures and reduce overall crop damage.

Plant Disease Detection Using Convolution Neural Network [12] uses a basic CNN architecture to classify different plant diseases from leaf images. It demonstrates that CNN-based feature extraction outperforms traditional machine learning approaches. This work serves as a strong foundation for CNN-based agricultural image analysis.

The ANFIS Fuzzy Convolutional Neural Network Model for Leaf Disease Detection [13] combines CNNs with an Adaptive Neuro-Fuzzy Inference System. The hybrid model improves classification accuracy and handles uncertainty in leaf images more effectively. It provides both robustness and better interpretability in disease detection tasks.

IV. SYSTEMATIC ANALYSIS

A systematic analysis of existing work on plant disease detection and smart agriculture systems shows that while a wide range of CNN, lightweight deep learning, hybrid models, and mobile-based frameworks have been proposed, each study presents specific trade-offs in accuracy, model complexity, deployment feasibility, and real-world generalization. In this section, we critically evaluate the performance, strengths, and limitations reported in the related works to identify existing gaps and motivate the need for an improved, more robust plant-disease detection approach.

Reference no.	Methodology	Dataset(s)	Accuracy	Merits	Demerits
B. Ramana Reddy [1]	Uses a CNN-based deep learning model in a mobile app to classify plant diseases from captured or uploaded leaf images in real time.	PlantVillage	92.06%	Real-time disease detection on a mobile device, automated and quick diagnosis	Performance reduces under poor lighting or complex backgrounds.
Jali Suhaman [2]	Lightweight CNN for mobile; simple architecture for elderly farmers	Tomato leaf images	89%	Simple model suitable for older farmers; low-resource; app connects farmers with scientists; field-ready	Accuracy is lower than deeper CNNs;it is limited to tomatoes and may not generalize to multi-crop settings.
Teddy Aristan [3]	MobileNetV3, EfficientNetB0, Mason Model and ShuffleNetV2 evaluated on mobile	Merged dataset of 79 disease classes from multiple public repositories	90.54%	The Mason model achieves the best accuracy & smallest size (0.85 MB); fits offline mobile deployment; low resource usage	Accuracy drops on mobile deployment; requires a multi-class balanced dataset.

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Jawad Hassan [4]	CNN models for cotton disease classification	Cotton leaf images (healthy + diseased; custom dataset)	85.42%	Identifies major cotton diseases, improves diagnosis speed, optimizes CNN effectiveness, and is suitable for precision farming.	Accuracy moderate; dataset crop-specific; limited environmental variability
Sindu.P [5]	XGBoost for crop prediction, Random Forest for fertilizer recommendation, and MobileNet for disease detection	Structured soil data, rainfall data, leaf images	92%	Multi-function system; provides preventive tips; extremely high accuracy; supports sustainable farming	Multi-model ensemble increases complexity; mobile performance is not discussed.
Professor Dr. Sudha P [6]	CNN-based disease detection; Random Forest for fertilizer optimization; IoT real-time soil sensor integration	Real field images, IoT sensor data	92%	Real-field validated; 22% yield improvement; 15% fertilizer savings; integrates climate and soil sensors	Requires IoT hardware; performance depends on sensor quality; web-deployment dependency
Linhui Wang [7]	SSD with MobileNetV3, Residual Prediction Block (RPBM) using transfer learning	Citrus pest images	86.10%	Very low latency (185 ms); mobile-friendly; highly optimized	Dataset limited to two pests; may degrade in varied orchard lighting
Nikos Petrellis [8]	Lightweight feature extraction: color histograms, lesion area, fuzzy ranking; no server needed	Citrus leaf & fruit images	90%	Extensible by users; low computation; orientation-independent; works fully offline	Very small training samples; sensitive to segmentation thresholds; reduced robustness in uncontrolled environments
Qi Jing [9]	CNN, Random Forest, and SVM trained on simulation-based structured features	Synthetic dataset	87.5%	Mobile-ready; real-time inference; low computation	Dataset not real; poor generalization; CNN accuracy low; not image-based
Baiju B V [10]	Lightweight Slender-CNN with multi-scale convolution layers	Combined CRW dataset	88.54%	Excellent performance for corn/wheat; compact model;	Lower performance for rice; dependent on quality leaf images; may drop in field

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				outperforms VGG19, EfficientNet-B6, and YOLOv5.	conditions
Tejaswini [11]	Pretrained CNN models on tomato, potato, and bell pepper diseases	PlantVillage dataset	86.21%	Multi-crop detection; early-stage identification; pretrained CNN improves learning	PlantVillage: over-clean; lower real-farm generalization; moderate accuracy; computationally heavy
M. Shobana [12]	CNN with standard preprocessing	PlantVillage or a similar leaf-image dataset	86%	Simple pipeline, automatic feature extraction, real-time friendly	Dataset not specified; moderate accuracy; controlled environments only
Tae-hoon Kim [13]	Hybrid ANFIS-CNN with & without LBP descriptors	Pepper leaf disease dataset	84.78%	Enhanced fuzzy learning; LBP improves pattern extraction; strong cross-validation robustness	Higher computational complexity; focused on pepper only; needs high-quality images

V. CONCLUSION AND FUTURE WORK

This study presented a deep learning–based mobile application designed to support farmers with fast, accurate, and user-friendly plant disease detection. By integrating a lightweight CNN model for classification, an OpenCV-driven severity estimation module, and a React Native mobile interface, the system successfully bridges the gap between laboratory research and real-world field usage. The experimental results show that the model is capable of identifying leaf diseases effectively under varying environmental settings while maintaining low computational cost, making it suitable for mobile deployment. The use of a Flask backend further ensures rapid inference and seamless integration between model prediction and mobile user interaction.

Overall, the proposed system demonstrates that deep learning, when combined with mobile technologies, can offer farmers an accessible and efficient tool for early disease detection, supporting timely interventions, reducing crop losses, and contributing to smarter agricultural practices.

Although the system performs reliably for binary plant disease classification and severity estimation, several enhancements can extend its effectiveness and real-world applicability. Future work may focus on expanding the model to handle multi-class disease classification across diverse crop species using larger and more varied real-field datasets. Incorporating advanced architectures such as EfficientNet, MobileNetV3, or transformer-based models may further improve accuracy while maintaining mobile efficiency. Additionally, integrating explainable AI techniques like Grad-CAM heatmaps within the mobile interface can help users interpret predictions more clearly. On the deployment side, offline on-device inference using TensorFlow Lite or PyTorch Mobile can eliminate the need for constant server communication and make the system usable in low-connectivity rural regions. The severity estimation module may also be enhanced using segmentation models such as U-Net or DeepLabv3+ for more precise lesion mapping. Finally, incorporating IoT-based sensor data, weather inputs, or fertilizer recommendations could evolve this application into a comprehensive smart-agriculture decision support system.

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