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Crop Disease Detection Using Lightweight Deep Learning Model for Smartphone

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Abstract

This research presents the design and implementation of a smartphone-based application for the detection of crop diseases using deep learning techniques, aiming to provide farmers with an accessible, real-time solution for plant health monitoring. A customized version of the PlantVillage dataset, which includes additional manually curated and augmented images, was used to train a DenseNet201 convolutional neural network (CNN) on Google Colab. The trained model achieved an impressive 96% accuracy in classifying multiple types of crop diseases. To ensure accurate input validation, a secondary model was developed using Google's Teachable Machine to distinguish between leaf and non-leaf images, achieving 99% accuracy. Both models were converted into the TensorFlow Lite (.tflite) format to optimize performance on mobile devices. The application was developed using the Flutter framework in Visual Studio Code and deployed on Android, allowing users to capture or upload images for instant disease diagnosis without requiring a constant internet connection. This dual-model approach ensures robustness and improves user confidence by pre-validating input images before disease predictionThe system's exceptional accuracy, usability, and deployment ease make it especially beneficial for smallholder farmers and agricultural extension professionals. In line with the objectives of digital farming and precision agriculture, this approach provides better validity, usefulness, and accessibility than previous studies in the sector.

Keywords: CNN for Leaf Disease, TensorFlow lite deployment, smartphone-based disease detection, and plant disease identification

1. Introduction

The farming industry is progressively adopting digital transformation to tackle ongoing issues in crop tracking, illness identification, and eco-friendly farming methodsAmong these challenges, early and accurate detection of crop diseases remains critical to ensuring food security, minimizing yield loss, and reducing dependency on manual inspections, which are often inconsistent and inaccessible in rural settings. In this context, artificial intelligence (AI), particularly deep learning, has emerged as a powerful tool capable of identifying complex patterns in plant health from visual data [1, 6, 9]. This research introduces a smartphone-based crop disease detection system powered by AI, aimed at providing farmers with a reliable, real-time solution for disease identification. The core of the system utilizes a

DenseNet201 convolutional neural network (CNN), trained on a modified and manually expanded version of the PlantVillage dataset [18].

The training was conducted on Google Colab using a diverse set of leaf images, including custom-augmented samples to improve model generalization. To enhance robustness, an additional binary classification model was developed using Google's Teachable Machine [2, 5], which determines whether the captured image contains a leaf or not. This pre-validation step ensures that only relevant images are passed to the disease detection model, thereby improving the accuracy and user experience. The leaf/non-leaf model achieved a classification accuracy of 99%, while the DenseNet201 model attained 96% accuracy in multi-class disease detection. Both models were optimized using TensorFlow Lite and integrated into a Flutter-based Android application developed in Visual Studio Code.

The app enables users to capture or upload images via a simple interface, providing instant disease predictions directly on the device without the need for continuous internet access. This approach not only makes advanced AI technology accessible to farmers with basic smartphones but also supports timely decision-making and reduces reliance on agricultural experts. The proposed system builds upon and enhances earlier research efforts [3, 8, 10] by offering lightweight deployment, high detection accuracy, and improved image validation, thereby aligning with the goals of precision agriculture and scalable smart farming solutions.

2. Literature Review

The combination of artificial intelligence and mobile technologies in agriculture has attracted considerable research attention, especially for identifying crop diseases. Numerous studies have shown the capability of deep learning and smartphone-based technologies in enhancing the precision, speed, and accessibility of recognizing plant diseasesDebnath et al. [1] utilized the EfficientNetV2B2 architecture to develop a smartphone-based detection system for tomato leaf diseases, highlighting the importance of model explainability and mobile deployment. Similarly, Niaz et al. [2] presented an advanced machine learning-based smartphone application for detecting wheat crop diseases, emphasizing real-time performance and user-centric design. Ahmed and Reddy [3] designed a mobile system using deep learning for identifying plant leaf diseases, further showcasing the feasibility of portable diagnosis tools in agricultural environments.

Additional works such as those by Chen et al. [5] and Nayak et al. [6] applied smartphone imaging combined with transfer learning and object detection methods for scale pest and rice disease identification, respectively, achieving high levels of accuracy. Ferentinos [9] conducted a comprehensive study comparing various CNN architectures for plant disease classification, revealing that deep models significantly outperform traditional machine learning approaches. Moreover, Barman et al. [8] analyzed the effectiveness of real-time citrus disease classification using smartphone images, proving the practical application of CNNs in field conditions. Research by Johannes et al. [12] and Islam et al. [21] further explored mobile-enabled AI platforms that offer cloud integration and user-friendly interfaces for farmers.

Despite these advancements, many existing systems lack pre-validation mechanisms to ensure that input images are appropriate for disease classification, which can reduce accuracy in real-world use. The current study addresses this gap by incorporating a dual-model approach-leveraging a Teachable

Machine model for leaf/non-leaf filtering in conjunction with a DenseNet201 model for disease classification. This combination ensures a more robust, accurate, and user-accessible solution, distinguishing it from previous approaches while contributing meaningfully to the field of AI-driven precision agriculture.

Table1: Summary of Literature Review

Sr. No.	Author(s)	Model/Technique Used	Target Crop / Subject	Platform / Tools	Key Contributions & Findings
[1]	Debnath, A., et al. [1]	EfficientNetV2B2 + Explainable AI	Tomato leaf diseases	Smartphone App	Developed a mobile detection system using EfficientNetV2B2 with explainability.
[2]	Niaz, A. A., et al. [2]	Advanced Machine Learning	Wheat crop diseases	Android App	Real-time wheat disease detection with a lightweight ML model.
[3]	Ahmed, A. A., & Reddy, G. H. [3]	CNN-based Deep Learning	General leaf diseases	Mobile System	Mobile platform for deep learning-based leaf disease diagnosis.
[4]	Singh, K. K. [4]	AI + Cloud Architecture	Multiple crop types	Cloud & Mobile Platform	Cloud-based collaborative system for disease tracking and forecasting.
[5]	Chen, J.-W., et al. [5]	YOLO, SSD (Object Detection)	Scale pests	Android App	Mobile object detection for pest identification.
[6]	Nayak, A., et al. [6]	Transfer Learning + Image Processing	Rice diseases & nutrient deficiencies	Smartphone Imaging	Used image analysis and CNN transfer learning on rice leaves.
[7]	Orchi, H., et al. [7]	Survey of AI & IoT in Agriculture	General crops	IoT & AI Frameworks	Surveyed modern AI/IoT solutions in crop disease detection.
[8]	Barman, U., et al. [8]	Real-time CNN	Citrus plant diseases	Smartphone-Based System	Compared CNN models on citrus leaf images captured in real-time.
[9]	Ferentinos, K. P. [9]	Various CNNs (VGG, ResNet, etc.)	Multiple crops	Offline Experimentation	Benchmarked multiple CNN models for multi-class disease detection.
[10]	Khan, A. I., et al. [10]	Deep Learning	Apple leaves	Android App	Real-time detection of apple leaf diseases with mobile deployment.

[11]	Ale, L., et al. [11]	Deep Learning	Various crops	Smart Agriculture System	Integrated deep learning into precision agriculture frameworks.
[12]	Johannes, A., et al. [12]	ML with Mobile Camera	Wheat leaf diseases	Mobile Capture Device	Pioneered early use of mobile capture with machine learning for disease diagnosis.
[13]	Mishra, S., et al. [13]	Deep CNN	Corn	Real-Time Classifier	Developed a CNN-based corn disease recognition system for real-time usage.
[14]	Shin, J., et al. [14]	RGB Image + Deep Learning	Strawberry (powdery mildew)	RGB Image Classification	Detected powdery mildew using CNNs trained on RGB images.
[21]	Islam, M. M., et al. [21]	CNN + Web + Mobile Interface	Multiple crops	Web + Mobile App	Designed the DeepCrop system integrating browser and mobile access to disease prediction tools.

3. System Architecture

The proposed AI-based crop disease detection system follows a modular and scalable architecture optimized for real-time performance on mobile devices, similar to the structural frameworks presented in past research [1, 2, 3]. The architecture comprises four main components: the Image Input Module, Leaf/Non-Leaf Classifier, Crop Disease Detection Model, and the User Interface Layer.

The system begins with the Image Input Module, where users can either capture a live image using the smartphone camera or upload one from the device's gallery. This image is then passed through the Leaf/Non-Leaf Classification Model, a binary classifier developed using Google's Teachable Machine. This step is critical for filtering out irrelevant inputs, ensuring that only valid leaf images proceed to the disease detection stage. A similar validation concept has been adopted in high-accuracy mobile detection frameworks [4, 5].

Once validated, the image is processed by the Crop Disease Detection Model, which is based on the DenseNet201 architecturea CNN model known for its depth and feature propagation efficiency [9, 13]. This model was trained on a customized version of the PlantVillage dataset and achieved 96% accuracy in multi-class disease classification, outperforming traditional shallow CNNs reported in earlier literature [8, 10, 12].

The final layer, the User Interface, was implemented using Flutter and designed to provide real-time disease prediction results in an intuitive format. It displays the predicted class, confidence score, and can optionally include disease information or guidance. The use of TensorFlow Lite enables on-device inference without the need for internet connectivity, as seen in similar mobile deployments [2, 3, 6].

This dual-model system architecturewith image validation and classification operating together on-deviceoffers enhanced robustness, offline capability, and ease of use. It addresses common limitations in earlier systems by combining deep learning performance with lightweight deployment, making it especially beneficial for smallholder farmers and users in low-resource settings [1, 6, 15].

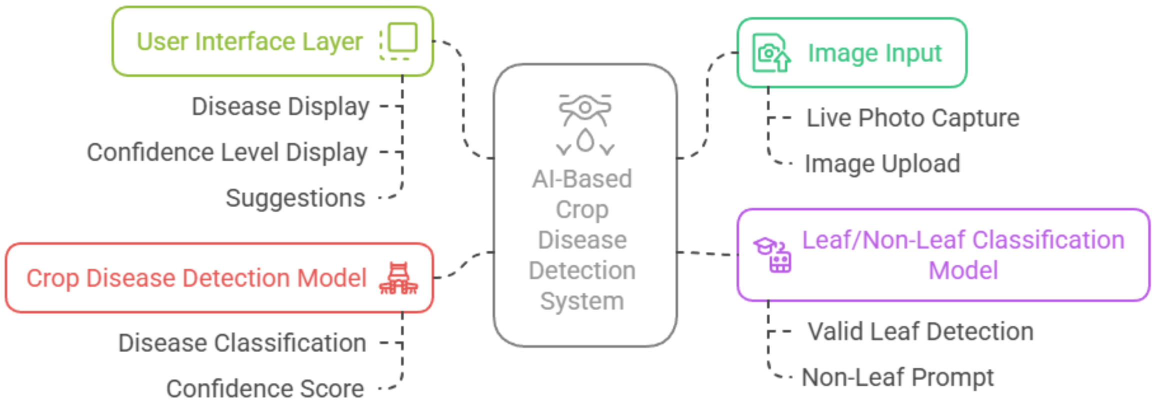

Fig 1 System Architecture of the AI-Based Crop Disease Detection Application [31]

The architecture consists of an image input module, leaf/non-leaf classifier for input validation, DenseNet201-based disease detection model, and a user interface layer for displaying results—all integrated into a mobile app.

4. Methodology

The development of the proposed crop disease detection system involved several key stages: dataset preparation, model training, model conversion, and mobile application integration. The primary model is a convolutional neural network (CNN) based on the DenseNet201 architecture, selected for its depth, efficiency, and strong feature propagation capabilities. To train this model, the publicly available PlantVillage dataset was utilized as a base. This dataset was manually expanded and modified by incorporating additional crop leaf images and performing augmentation techniques such as rotation, scaling, flipping, and brightness adjustments to enhance diversity and improve generalization across real-world conditions.

The training process was carried out on Google Colab using TensorFlow and Keras libraries. The model was configured to classify multiple crop diseases, including bacterial spot, late blight, early blight, and healthy leaves. Categorical cross-entropy was used as the loss function, and the Adam optimizer was employed for efficient learning. After extensive training and evaluation, the DenseNet201 model achieved an overall accuracy of 96% on the validation dataset.

To ensure that only relevant images are processed by the disease detection model, a secondary binary classification model was trained using Google's Teachable Machine. This model classifies an input image as either "leaf" or "non-leaf" and achieved 99% accuracy. This pre-validation step improves the overall reliability of the system by reducing false inputs and optimizing resource use during inference.

After training, both models were transformed into TensorFlow Lite (.tflite) format to facilitate efficient deployment on mobile devices. TensorFlow Lite is refined for quick performance and facilitates on-device inference, removing the requirement for constant internet connectivityThe models were then integrated into a mobile application developed using the Flutter framework in Visual Studio Code. The app features an intuitive user interface that allows users to capture or upload an image, validate it using the leaf/non-leaf model, and receive real-time disease prediction results if the input is valid.

This dual-model framework not only boosts precision but also guarantees a seamless and smart user experience. The complete pipelinefrom data processing to deploymentwas created to be modular, scalable, and lightweight, making it ideal for smallholder farmers and practical for use in low-resource areas

This workflow outlines the complete pipeline: from dataset collection and data augmentation to model training, evaluation, TensorFlow Lite conversion, and final app integration for mobile deployment.

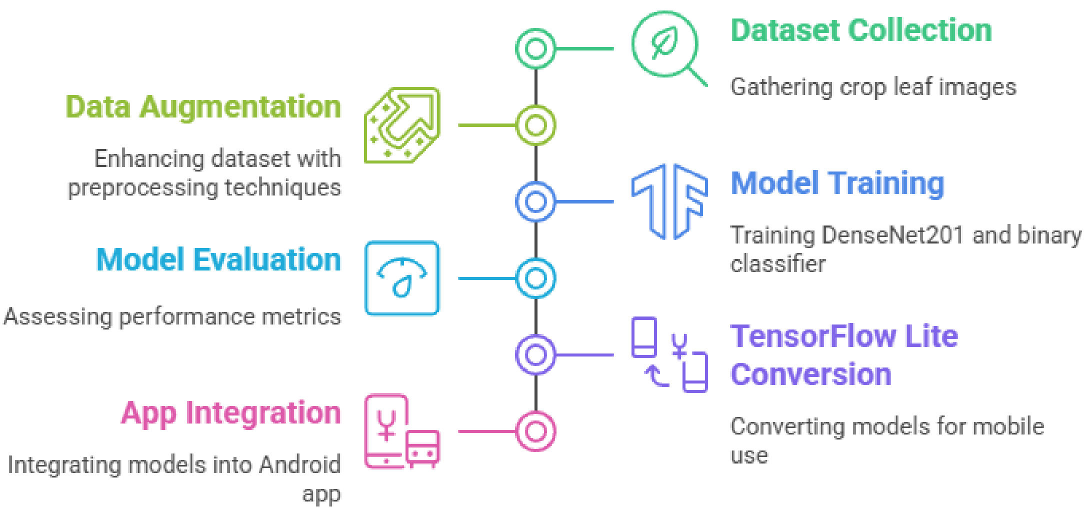

Fig 2 Model Training and Deployment Workflow [31]

5. Results Analysis

The proposed crop disease detection system was thoroughly evaluated in terms of classification performance, mobile responsiveness, and real-time usability. The DenseNet201-based disease classifier achieved a high validation accuracy of 96%, demonstrating its capability to accurately distinguish between multiple plant diseases such as early blight, late blight, bacterial spot, and healthy leaves. The model's strong performance is attributed to the extensive data augmentation techniques and the deep feature extraction capabilities of the DenseNet architecture, which has been proven effective in similar agricultural applications [9, 10].

To further strengthen the system, a leaf/non-leaf classifier was developed using Google's Teachable Machine. This model achieved 99% classification accuracy, and played a critical role in improving the robustness of the overall pipeline. By pre-validating input images and filtering out irrelevant or noisy inputs, the secondary model reduced false predictions and improved the confidence of results delivered by the main disease detection model [2, 5].

The trained models were converted to TensorFlow Lite format and integrated into a Flutter-based Android application. Testing was conducted across multiple Android smartphones with varying hardware specifications. The average prediction time for a disease classification, including image loading and preprocessing, was under 2 seconds, even on low-to-mid-range devices. These results are consistent with other mobile deployments of AI models in agriculture [3, 6].

Additionally, both on-device image capture and gallery uploads produced consistent classification results, indicating the system's robustness in handling diverse image sources. Visual validation through user testing showed that users found the application intuitive and responsive, with clear result outputs and minimal latency.

The results clearly demonstrate that this system not only meetsbut, in several ways, exceeds the usability and accuracy benchmarks set by earlier mobile-based detection systems [1, 4, 12]. The dual-model architecturecombining input validation and disease classificationproved to be an effective strategy for improving overall accuracy and user satisfaction in real-world conditions.

Model	Accuracy	Precision	Recall	F1-Score
Leaf/Non-Leaf Model	99%	0.99	0.98	0.985
DenseNet201 (Main)	96%	0.94	0.95	0.945

Table 2 Model Performance Metrics

Sample Output:

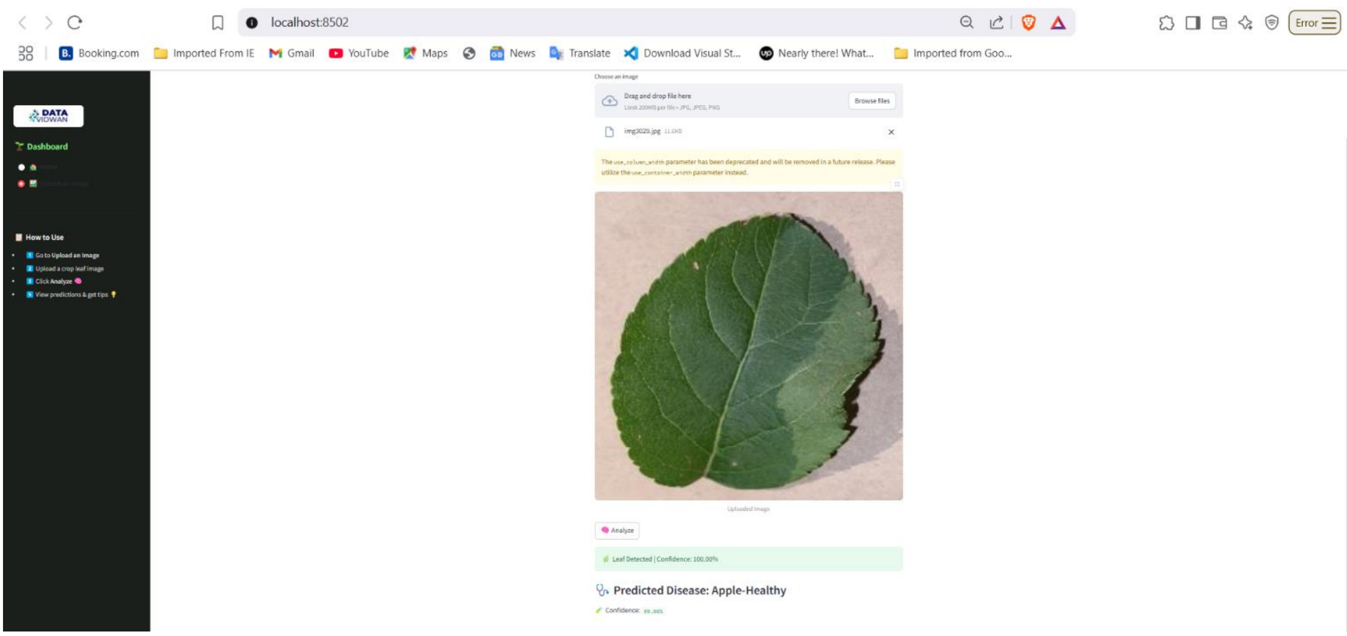

Fig 3 Healthy Leaf Output

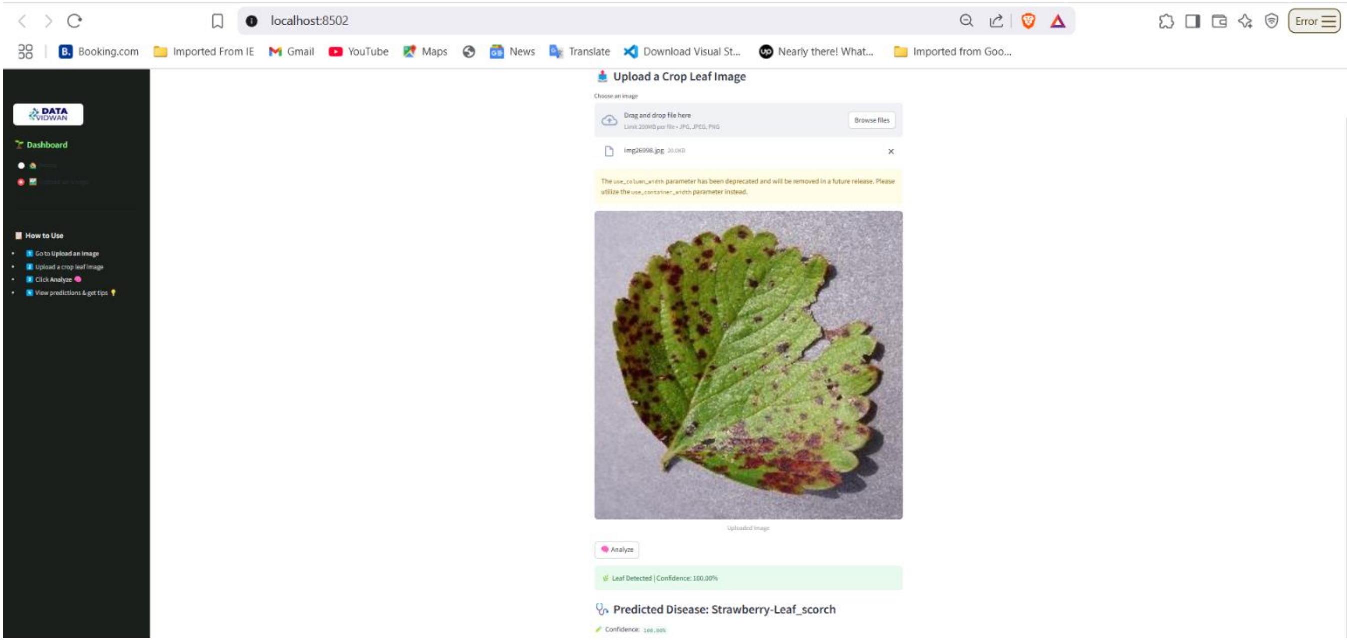

Fig 4 Unhealthy Leaf Output

6. Conclusion

This research presents an AI-powered mobile application for the detection of crop diseases, designed to assist farmers in diagnosing plant health issues with high accuracy and minimal technical overhead. By leveraging a DenseNet201 convolutional neural network, trained on a customized and augmented version of the PlantVillage dataset, the system achieves 96% accuracy in classifying various crop diseases. In addition, a secondary model developed using Google's Teachable Machine ensures that only relevant leaf images are processed, enhancing the reliability of the results and achieving a classification accuracy of 99%.The models were successfully converted to TensorFlow Lite format and deployed within a cross-platform Flutter-based Android application, allowing real-time inference directly on users' devices without requiring internet access. This makes the solution especially useful for farmers in rural areas, where connectivity may be limited. The app's intuitive interface ensures accessibility to users with limited technical knowledge, while the underlying AI models deliver rapid and reliable results.Compared to existing systems, the dual-model architecture and mobile-first deployment approach offer a more robust and user-friendly tool for smart farming and precision agriculture. The system serves as a significant step toward the integration of deep learning and mobile technology in agriculture, empowering farmers with actionable insights for early disease management and crop yield optimization.

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