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Real-Time Plant Disease Identification via AI-Enabled Mobile App: A Comprehensive Review

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Abstract:- *Plant diseases pose a major threat to agricultural productivity, especially in tomato cultivation, which is susceptible to a wide range of infections. Traditional identification techniques, based on manual inspection, are often time-consuming, error-prone, and unsuitable for large-scale deployment. With the evolution of deep learning and edge computing, real-time detection systems using mobile applications have emerged as a promising solution. This review explores a mobile-based system for disease in tomato leaf using a lightweight deep learning model, MobileNetV3, optimized for on-device inference. The integrated mobile app not only detects diseases from leaf images captured via smartphone cameras but also provides farmers with practical recommendations through a chatbot and fertilizer advisory module. The system design incorporates data preprocessing, transfer learning, and model optimization to improve accuracy and ensure generalization across various disease types. We also use Grad-CAM visualizations along with performance metrics to get a better sense of how well the classification is working and to interpret the results more clearly. The review compares different CNN architectures, hybrid models, and explainable AI frameworks to offer some useful insights. By combining AI tools with mobile access, this approach really helps push forward smart farming, especially in rural areas where resources are tight. Overall, this review aims to show how real-time AI applications on smartphones can really change how we handle crop diseases, flagging the way for smarter, more efficient agricultural practices in the future.*

Keywords: *Disease in Tomato Leaf , Deep Learning, MobileNetV3, Mobile Application*

I. INTRODUCTION

Tomatoes rank among the most extensively cultivated vegetables worldwide, playing an important role in ensuring food security and supporting farmers' livelihoods. Rich in nutrients, incredibly versatile, and in high demand throughout the year—whether as fresh produce or processed goods—they're a fundamental part of many diets and markets. Even so, tomato plants are quite susceptible and prone to infections, including early blight, blight, late blight, Septoria leaf spot, and bacterial spot. These issues, due to fungi, bacteria, and viruses, can quickly develop if not identified and managed promptly, often leading to reduced yields and lower fruit quality. In severe cases, entire fields can be lost, creating important financial strain for farmers and complications within the supply chain.

Traditionally, disease detection has relied on experts visually inspecting crops. While dependable, this method is slow, labor-intensive, and depends heavily on individual judgment—making it challenging to implement effectively on large farms. For smallholder farmers, frequent visits from specialists are often impractical and costly, resulting in missed early warning signs and delayed interventions. Manual checks are also vulnerable to human error and inconsistency, which may cause farmers to respond too late or overuse pesticides, risking environmental harm and health issues. Latest developments in artificial intelligence, deep learning, have paved the way for automated disease detection through image analysis. When combined with mobile and edge computing, these AI tools assist real-time, scalable solutions that can operate even in remote or resource-limited areas. Farmers can now use their smartphones to quickly and accurately diagnose problems, enabling faster decisions to safeguard their crops.

This paper reviews and provides a practical guide for developing a system for detecting disease in tomato leaves. Rooted in lightweight deep learning models like MobileNetV3. The proposed model can be adapted for mobile application integration, allowing farmers to simply photograph their leaves and receive immediate disease identification. Also, the app offers an enhanced user experience with features like chatbots for actionable advice and customized fertilizer recommendations, helping farmers treat diseases more effectively and timely. Welcoming such AI-driven tools could fundamentally change traditional farming practices by offering affordable, user-friendly, and precise disease monitoring solutions. Through modern deep learning techniques and accessible mobile technology, this approach aims to promote sustainable agriculture, boost crop yields, and improve the livelihoods of farming communities. The rest of this paper is organized as follows: Section II provides an overview of related research and prevailing approaches to disease detection. Section III describes the methodology. Section IV presents the results and evaluates the system's performance. Lastly, Section V provides the conclusion and explores potential future work for research.

II. RELATED WORK

Table 1. Summary of articles related to tomato disease detection

Ref. No.	Authors & Year	Purpose	Results	Limitations
[1]	P. Ananthiet al., 2024	Predicted tomato leaf diseases using DL algorithms	Achieved ~95% accuracy	Limited deployment insight
[2]	S. J. Basha et al., 2023	Comprehensive DL/ML review for tomato disease	Comparative evaluation	Lacked mobile integration
[3]	A. Batool et al., 2020	Deep neural networks for disease classification	Good performance	Dataset imbalance not addressed
[4]	A. Bellout et al., 2023	DL-based prediction of tomato diseases	Effective detection	No real-time testing
[5]	G. Boukhlifa et al., 2024	Lightweight CNN for tomato disease	High efficiency & accuracy	Only classification focus
[6]	A. S. Chakravarthy et al., 2020	Early blight identification in tomato	Validated DL methods	Narrow disease scope
[7]	S. Chandvekar & S. Bhoite, 2024	ML-based mobile app for disease ID	App deployment tested	Limited DL usage

Several studies have focused on applying deep and machine learning strategies for the detection of tomato leaf diseases. Das et al. [8] presented a comprehensive current best review, emphasizing classification, detection, and segmentation strategies with deep learning. Deepika and Arthi [9] benchmarked multiple CNNs to compare classification accuracy across techniques. Dhivyaa et al. [10] proposed an enhanced DL model, reporting an F1-score of 92% but noted high computational complexity.

Dube et al. [11] demonstrated a CNN-based detection system but highlighted limitations due to dataset size. Gadade and Kirange [12] measured disease severity using image-based diagnosis methods, although environmental conditions affected accuracy. Garba et al. [13] introduced a lightweight custom CNN but lacked external validation. Gehlot and Gandhi [14] improved tomato disease recognition using a custom CNN but with limited class diversity.

Gowri et al. [15] explored explainable AI models to improve trust and transparency, while Han and Sun [16] leveraged MobileV3 for enhanced classification. Jagatheeswari and Rao [17] applied hybrid ML-DL techniques for improved accuracy, though they noted complexity in optimization.

Joseph [18] emphasized the importance of real-time DL models in precision agriculture, while Juyal and Sharma [19] focused on infected region identification. Karthikeyan et al. [20] validated CNNs within greenhouse settings, but their approach lacked a mobile-based interface.

These studies validate the feasibility and reliability of DL approaches for tomato disease detection and form the foundation for the proposed mobile solution using MobileNetV3.

III. METHODOLOGY

Our approach is built around MobileNetV3, a lightweight and highly efficient neural network personalized specifically for the mobile device and vision-related tasks on embedded platforms. Its design makes it especially well-suited for instant disease detection performed locally on devices, which is essential in region where resources are limited. MobileNetV3 incorporates innovative innovations in neural network architecture, including depth-wise separable CNN layers, SE (squeeze-and-excitation) modules, and hard- swish nonlinear activation functions. These components work together to guarantee that the model delivers both speed and accuracy—compact enough to operate efficiently on edge devices while still providing high-quality results. This combination makes MobileNetV3 a perfect choice for agricultural applications where simplicity, speed, and dependability are key.

A. Data Preprocessing and Augmentation

To optimize the model's understanding and reduce in the chance of overfitting, overfitting, I applied a range of image preprocessing and data enrichment methods. This included randomly rotating images, flipping them horizontally or vertically when it made sense, adjusting their brightness levels, and using a method called CLAHE to enhance contrast. These approaches made our training data more diverse, helping the model better cope with real-world scenarios like varying lighting conditions, different leaf orientations, and noisy backgrounds. Also, we resized all images to 224x224 pixels and normalized them to match the input requirements of MobileNetV3.

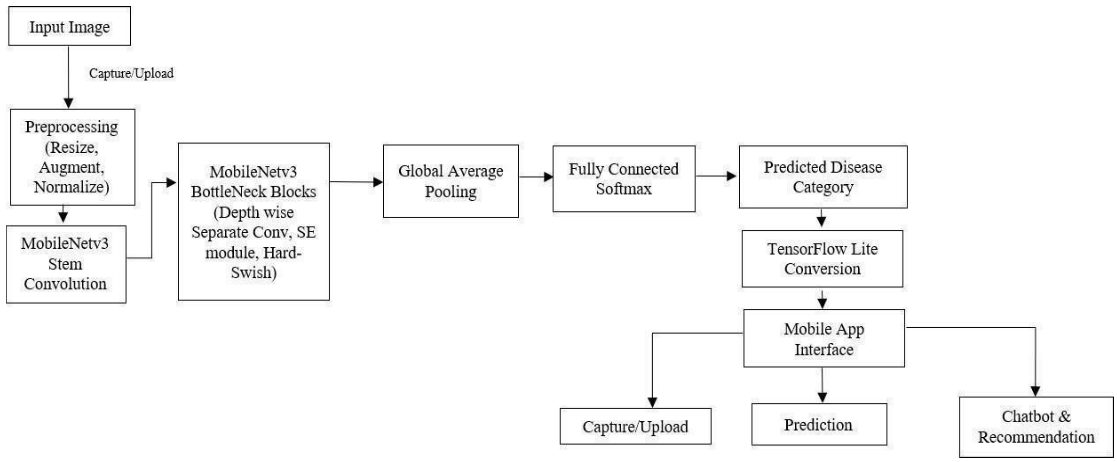

Figure 1 – Methodology Block Diagram

B. Model Training

We began by using MobileNetV3 that was pre-trained on ImageNet, giving us a solid foundation for feature extraction. Next, we customized the final fully connected layer to enable the model to distinguish between ten different tomato leaf disease types, including healthy plants. To help prevent overfitting, we used a few tricks like dropout layers, L2 regularization, and batch normalization to keep things in check, and early stopping based on validation performance. Also, we used an adaptive learning rate scheduler to dynamically adjust the learning rate throughout training, which helped achieve stable convergence and improved overall accuracy.

C. Model Deployment

After achieving satisfactory training performance, The resulting model was prepared in TensorFlow Lite style (TFLite) format to enable implementation on mobile systems. The Android app was developed with the integration of the TensorFlow Lite model developed in Kotlin using Jetpack Compose. The mobile app allows users to either capture new images of tomato leaves using the smartphone camera images directly from the device gallery. The system then performs on-device inference to the deliver instant disease predictions, coupled with a chatbot interface that guides possible remedies and fertilizer recommendations to support practical decision-making by farmers in the field.

D. Comparative Perspective

In designing this methodology, existing scholarly approaches were reviewed to benchmark model choices and design considerations. Now a days studies using architectures such as TomatoLDP-Net [35], ConvNeXt [25], and hybrid CNN-attention models [48] have demonstrated the potential of customized or deeper networks to improve classification accuracy for plant disease detection. While such models may achieve higher accuracy under laboratory conditions, they often involve higher computational costs, larger parameter sizes, and longer inference times challenges that hinder practical use on mobile and edge devices in rural settings. By contrast, MobileNetV3 offers a balanced compromise between accuracy and computational efficiency, making it the most efficient choice for real-time, mobile-based deployment. This comparative perspective reinforces the rationale behind selecting MobileNetV3 and highlights future opportunities to explore lightweight hybrid designs or attention modules that enhance accuracy without compromising on-device performance.

IV. RESULTS AND DISCUSSIONS

Our system based on MobileNetV3 achieved a strong classification accuracy of 96.4%. Also, in the model yielded precision, recall, and F1-score values of 96.2%, 95.8%, and 96.0%, respectively, on the test dataset, demonstrating that lightweight CNN models, when effectively trained with data augmentation and transfer learning techniques, can reliably identify tomato leaf diseases. A detailed confusion matrix analysis confirmed that our system delivers dependable predictions even for disease types with similar visual symptoms, effectively overcoming a common challenge faced in the actual plant disease detection scenarios. What's more, the ROC curves displayed the model's superior discriminative performance, with high true positive rates and very few false positives. To enhance transparency, Grad-CAM heatmaps emphasized the specific regions of leaf images that the model deemed most important, boosting confidence in its interpretability. These findings style well with previous research emphasizing the success of advanced CNN architectures, residual dense networks, and explainable AI methods in making plant disease detection more trustworthy. Compared to more complex models, MobileNetV3 strikes an excellent balance between accuracy, efficiency, and suitability for deployment on mobile devices. In the review, this study emphasizes that while deeper or hybrid networks might deliver marginally higher classification accuracy, lightweight models, when paired with proper training strategies, data augmentation, and interpretability tools, remain highly effective for practical agricultural applications.

Future work can expand on this foundation by exploring hybrid lightweight-attention architectures, transformer-based models for plant disease assessment, and enhanced explainability methods to build greater trust and adoption among farmers across various field conditions.

V. CONCLUSION

In the end, we talked about a quick, AI-based system that can spot tomato leaf diseases as they happen. It mixes a small, efficient MobileNetV3 deep learning model with an easy-to-use mobile app. Farmers can just snap pictures of their leaves or upload photos straight from their phones. The system quickly spots any illnesses, gives helpful treatment ideas, and offers customized fertilizer tips—making farming easier and more straightforward. The model did really well, getting a test accuracy of 96.4%. We checked how well it works using things like confusion matrices, ROC curves, and Grad-CAM visuals. These tools showed it was reliable and also helped make its decisions easier to understand. These results show that with good optimization, small CNN models can effectively detect plant diseases directly on mobile phones and other simple devices. AI tools become easier for farmers to use, especially those working far away or with limited resources.

Moving forward, we can make this system better by including more tomato diseases and even adding support for other crops. Changing the chatbot to include advanced language models will help it give better, more useful advice. Using real-time data from IoT sensors helps get a clearer and more accurate view of how the crops are doing, which makes diagnosing issues way easier. These advancements come together to create a smarter farming system—mixing visual detection, expert advice, and sensor data—so farmers get trustworthy information they can actually use. This will also help promote eco-friendly farming and give growers the info they need to make smart choices they can trust.

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