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DAHONRX: Plant Leaf Disease Identification And Detection Using Efficientnetb4 Architecture

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Abstract

Background: Plant diseases significantly threaten global crop productivity, yet traditional manual inspections remain time-consuming and frequently inaccessible to remote farmers. Objectives: To address this challenge, this study introduces DahonRx, an AI-powered mobile application engineered for the precise, early identification of plant leaf diseases in corn and peanut crops. Method: The system is built on the EfficientNetB4 architecture, specifically selected for its optimal balance of high diagnostic accuracy and the computational efficiency required for mobile deployment. Developed using the TensorFlow and Keras frameworks, the model processes 160 × 160 input images and is optimized into a TensorFlow Lite format for on-device inference. The user-facing mobile interface, developed with Flutter, allows farmers to capture or upload leaf images to receive instant disease predictions, confidence scores, and historical scan logs. Results: Following rigorous training and strategic fine-tuning, the model achieved a final test accuracy of 98.96%. Conclusion: By integrating sophisticated deep learning into an accessible interface, DahonRx demonstrates a scalable solution for modern agriculture. Contribution: This provides farmers with a reliable tool to significantly enhance crop management and productivity in real-world environments.

Keyword: Convolutional Neural Networks, EfficientNetB4 Architecture, Plant Disease Detection, Mobile Application, TensorFlow.

1. Introduction

Agriculture serves as the backbone of the Philippine economy, ensuring food security and employment for a significant portion of the workforce (Dacul and Macabasco, 2025; Manila Observatory, 2025). In the province of Antique, small and medium-scale farmers are the lifeblood of local communities, yet they face persistent threats from plant diseases that can decimate harvests if not promptly identified. Traditional disease identification relies heavily on manual visual inspection by farmers or agricultural extension workers. This method is highly subjective, time-consuming, and frequently inaccessible to those in remote barangays. Consequently, the lack of immediate diagnostic tools leads to significant crop yield losses and improper management decisions, most notably the pre-emptive overuse of chemical pesticides.

Recent advancements in artificial intelligence (AI) and computer vision offer transformative solutions to these critical agricultural challenges. Convolutional Neural Networks (CNNs), a class of deep learning models specialized for image analysis, have demonstrated remarkable capabilities in recognizing patterns in leaf images with accuracy levels rivaling human experts (Krishna et al., 2025; Anthony and Abamo, 2024). By leveraging mobile applications and smartphone cameras, these technologies can democratize expert-level diagnostic knowledge (Reddy et al., 2025). This shift allows farmers to receive instant, accurate diagnoses without needing immediate physical access to specialists, while simultaneously augmenting the capacity of extension workers to serve larger rural areas more effectively.

To address the specific agricultural needs of Antique, this study introduces DahonRx, an AI-powered mobile application designed for the precise and early identification of plant leaf diseases. Built upon the EfficientNetB4 architecture, the system delivers high diagnostic accuracy while maintaining the computational efficiency required for seamless mobile deployment (Saddami et al., 2024). Developed using the Flutter framework, DahonRx enables users to capture leaf images via their device's camera or gallery to receive instant predictions and confidence scores. The application specifically focuses on detecting health issues in corn and peanut crops across ten distinct categories, including bacterial leaf streak, common rust, and peanut rosette.

The implementation of DahonRx holds profound significance for promoting sustainable farming practices and protecting farmer livelihoods in the region. By providing accessible, data-driven solutions, the application helps reduce crop losses and minimizes the environmental impact associated with traditional disease management, specifically by curbing the reliance on synthetic pesticides (Amalan and Aram, 2025). Furthermore, this study directly contributes to several United Nations Sustainable Development Goals (SDGs), specifically supporting No Poverty (SDG 1), Zero Hunger (SDG 2), Industry, Innovation, and Infrastructure (SDG 9), and Responsible Consumption and Production (SDG 12) (Balasooriya and Sedera, 2025). Ultimately, DahonRx demonstrates how integrating deep learning into mobile tools can enhance both agricultural productivity and digital literacy in rural environments.

2. Materials and Methods

2.1 Dataset Collection and Preprocessing

The study utilized a comprehensive dataset of plant leaf images focused specifically on corn and peanut crops. The dataset encompassed 10 distinct classes, representing both healthy plant leaves and various disease categories, including Corn Bacterial Leaf Streak, Corn Common Rust, Peanut Alternaria Leaf Spot, and Peanut Rosette. To ensure robust model evaluation and prevent overfitting, the dataset was partitioned into an 80:10:10 split for training, validation, and testing, aligning with established best practices in CNN-based agricultural diagnostics (Rahman et al., 2025).

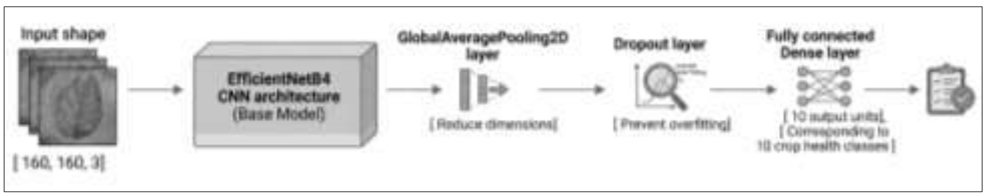


FIGURE 1: Workflow of Dataset Collection, Partitioning, and Preprocessing

Using a fixed random seed (1337) to guarantee reproducibility, this allocation yielded 2,279 images for training, 282 for validation, and 289 for testing. During preprocessing, all images were resized to standardized input dimensions of 160 x 160 pixels and batched into sets of 32 to ensure efficient memory utilization and optimal convergence during model training.

2.2 Model Architecture

The disease detection model utilizes the EfficientNetB4 Convolutional Neural Network (CNN) architecture. This base model was selected for its optimal balance between high diagnostic accuracy and the computational efficiency necessary for mobile deployment, a standard supported by recent advancements in resource-constrained plant disease detection (Ranga, 2025). The architecture was instantiated to accept input tensors of 160 x 160 x 3 (RGB channels). To adapt the base model for this classification task, custom top layers were appended. Following established transfer learning protocols for agricultural image classification (Ranga, 2025), these adaptations included a GlobalAveragePooling2D layer for spatial dimension reduction, a Dropout layer to mitigate overfitting, and a fully connected Dense layer with 10 output units corresponding to the crop health classes. The complete network architecture comprised 17,691,753 total parameters.

FIGURE 2: EfficientNetB4 Model Architecture and Diagnosis Workflow

2.3 Model Training and Fine-Tuning

The neural network was developed using the TensorFlow and Keras frameworks within a GPU-accelerated Google Colab environment. Training was executed in two phases: an initial training phase followed by fine-tuning. During fine-tuning, the top layers of the EfficientNetB4 model were unfrozen, resulting in 17,479,786 trainable parameters. This allowed the network to adapt its pre-trained weights to the granular features of the dataset. The model was trained for a total of 16 epochs. Performance was tracked using categorical accuracy and loss metrics across both the training and validation sets. The complete workflow for model training and fine-tuning using these frameworks is illustrated in Figure 3.

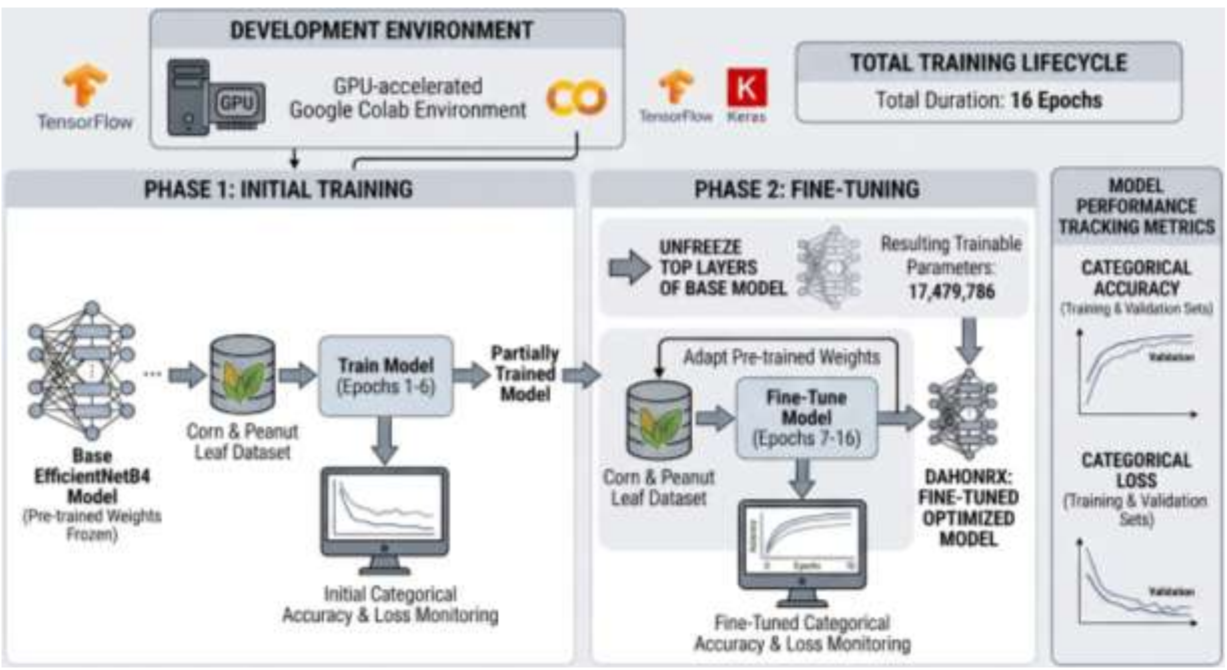


FIGURE 3: Model Training and Fine-Tuning TensorFlow and Keras

2.4 System Integration and Mobile Deployment

Upon completing the training phase, the model achieved a validation accuracy of 99.65%. To deploy the system, the fully trained Keras model was optimized and converted into a lightweight TensorFlow Lite format (.tflite) using the TFLiteConverter utility. This model was subsequently embedded into the DahonRx mobile application. The application interface allows users to utilize their smartphone camera or image gallery to analyze plant leaves. The embedded AI analyzes the image entirely on-device, yielding real-time disease identification without relying on cloud computing. Figure 4 provides a schematic representation of this end-to-end system integration and diagnostic workflow.

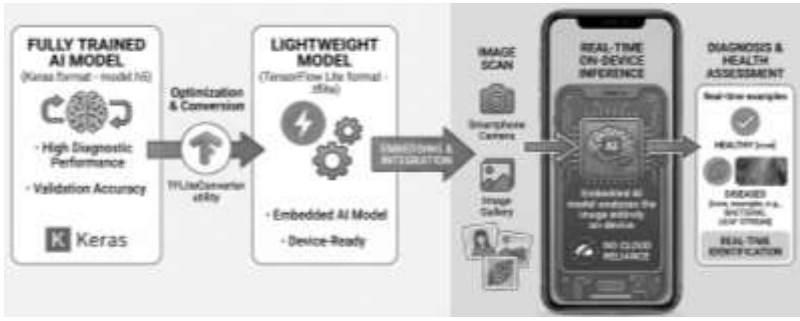


FIGURE 4: Schematic Representation of the System for Plant Leaf Disease Identification and EfficientNetB4-based Model Architecture for Diagnosis

3. Results and Discussion

3.1 Model Performance and Training Dynamics

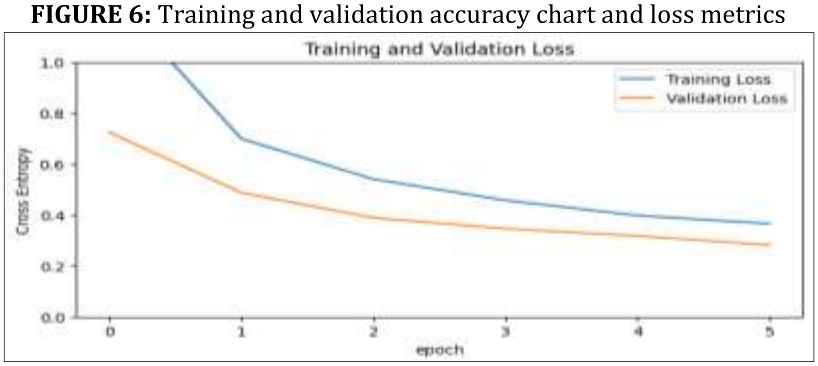
The EfficientNetB4 model demonstrated exceptional learning capabilities, exhibiting rapid and stable convergence over the 16-epoch training process. The initial training phase established a strong baseline, while the subsequent fine-tuning phase further optimized parameter weights. By the final epoch, the model achieved a validation accuracy of 99.65% and a validation loss of 0.0385. The training and validation accuracy curves closely mirrored each other, indicating successful generalization to unseen data without significant overfitting. Examples of the diverse leaf classes used to train the network can be seen in Figure 5.

FIGURE 5: Experiment Datasets

Cost Minimization and Classification Accuracy

Both training and validation loss metrics displayed a consistent downward trajectory as seen in Figure 6.

FIGURE 6: Training and validation accuracy chart and loss metrics



Training loss decreased substantially from 1.6399 at epoch 1 to 0.0164 at epoch 16 as seen in Table 1.

TABLE 1: Model Performance Metrics per Epoch

Epoch	Total Steps	Time Taken	Average Time per Step	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
1	72/72	173s	2s/step	0.4275	1.6399	0.7908	0.7236
2	72/72	98s	1s/step	0.7653	0.7537	0.8688	0.4866
3	72/72	108s	2s/step	0.8293	0.5631	0.9007	0.3881
4	72/72	142s	2s/step	0.8727	0.4506	0.9043	0.3459
5	72/72	98s	1s/step	0.8837	0.3922	0.8972	0.3172
6	72/72	108s	2s/step	0.8889	0.3674	0.9184	0.2814
7	72/72	304s	2s/step	0.8035	0.6251	0.9326	0.2065
8	72/72	101s	1s/step	0.9511	0.1645	0.9752	0.0573
9	72/72	101s	1s/step	0.9604	0.1557	0.9397	0.5028
10	72/72	152s	2s/step	0.9765	0.1052	0.9681	0.1141
11	72/72	141s	2s/step	0.9797	0.0926	0.9645	0.1525
12	72/72	142s	2s/step	0.9669	0.1547	0.9113	0.4194
13	72/72	110s	2s/step	0.9803	0.0663	0.8652	1.0341
14	72/72	101s	1s/step	0.9864	0.0478	0.9894	0.0451
15	72/72	110s	2s/step	0.9932	0.0199	0.9752	0.0396
16	72/72	132s	1s/step	0.9958	0.0164	0.9965	0.0385

This convergence confirms that the fine-tuning process progressively minimized generalized prediction errors. Corroborating the loss trends, a strong parallel upward trend was observed in accuracy scores (Figure 7). Training accuracy ascended from 42.75% to 99.58% by epoch 16, with validation accuracy peaking concurrently at 99.65%. The minimal gap between the training and validation curves strongly suggests the model successfully avoided overfitting, maintaining high accuracy on novel data. When evaluated against the entirely unseen test dataset, the model achieved a final test accuracy of 98.96%, confirming its robust diagnostic capability for real-world application.

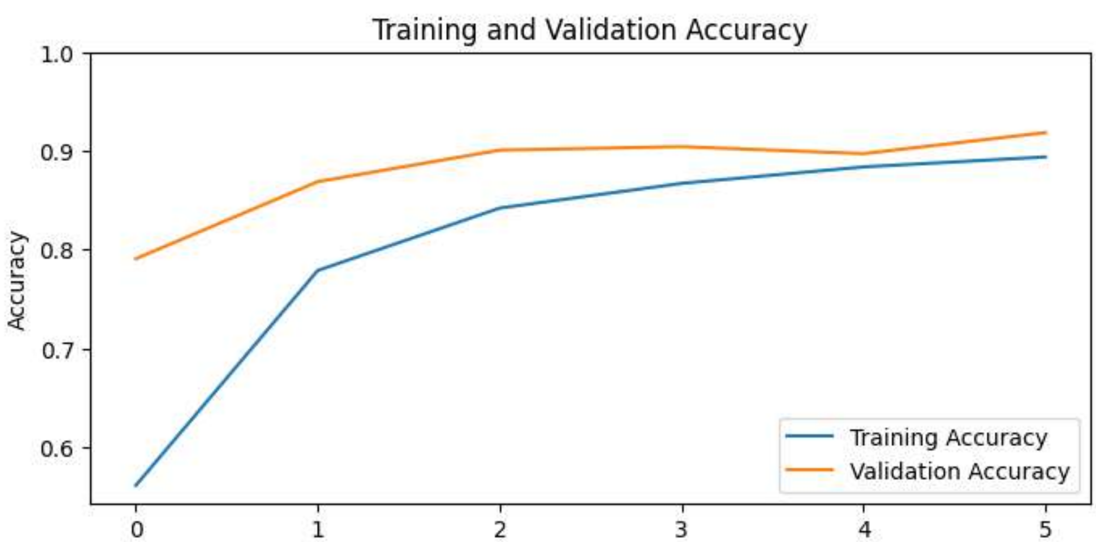


FIGURE 7: Training and validation accuracy chart

3.2 Mobile Application Integration and User Interface

The successful conversion of the trained Keras model into a lightweight TensorFlow Lite (.tflite) format proved highly effective for mobile deployment.

FIGURE 8: Mobile Application Interface

The resulting DahonRx application provides a seamless, intuitive user experience designed specifically for farmers and agricultural extension workers. A centralized dashboard features a prominent "Scan Leaf" function, granting users immediate access to real-time diagnostics via the device camera (Fig. 7a- 7b). The on-device inference engine rapidly processes captured images, providing instant feedback (Figure 7c). Additionally, the application maintains a "Recent History" log, capturing precise timestamps and quantitative confidence scores for temporal analysis of disease progression.

4. Discussion and Practical Implications

The results of this study clearly indicate that deep learning, specifically through optimized CNN architectures like EfficientNetB4, can bridge the gap between advanced agricultural science and practical, on-the-ground farming needs. Achieving over 99% accuracy in a mobile-deployable format is a significant milestone for agricultural technology in regions like Antique. The deployment of lightweight models directly to edge devices is increasingly recognized as the most effective method for overcoming the practical limitations of cloud-dependent agricultural tools, allowing for real-time automated disease control (Amanova et al., 2026). Traditional visual inspection is prone to human error and subjective interpretation, often leading to delayed interventions or improper chemical applications. DahonRx mitigates these issues by providing objective, expert-level diagnostics instantly. By accurately identifying specific conditions early in their progression, farmers can apply targeted treatments, thereby reducing chemical runoff, lowering operational costs, and preserving crop yields (Amalan and Aram, 2025).

5. Limitations and Future Work

While the model achieved near-perfect accuracy on the validation dataset, it is important to acknowledge that real-world field conditions such as variable lighting, shadows, camera quality, and leaf occlusion can introduce noise that may affect inference accuracy. This domain shift remains a persistent challenge when transitioning models from controlled laboratory datasets to open-field agricultural environments (Yang et al., 2025). Future iterations of DahonRx should focus on expanding the dataset to include images taken under diverse, uncontrolled environmental conditions to further enhance model robustness. Additionally, expanding the model's repertoire to include other high-value crops and integrating localized weather data could provide even more comprehensive disease forecasting and management recommendations, aligning with the emerging standard of multi-modal cyber-agricultural systems (Singh et al., 2025).

6. Conclusion

This study successfully developed and deployed DahonRx, an AI-powered mobile application designed to address the critical challenge of plant disease identification in corn and peanut crops. By leveraging the EfficientNetB4 convolutional neural network architecture, the system demonstrated exceptional diagnostic capabilities, achieving a validation accuracy of 99.65% across ten distinct plant health categories. The successful conversion of this robust deep learning model into a lightweight TensorFlow Lite format proved highly effective, enabling seamless, on-device image processing. This ensures that the application remains fully functional and accessible even in remote agricultural areas, where internet connectivity may be limited or entirely unavailable.

The implementation of DahonRx represents a significant technological leap in democratizing expert-level agricultural knowledge. By shifting away from traditional, subjective, and time-consuming manual visual inspections, the application empowers farmers and agricultural extension workers to obtain instant and precise diagnostic feedback. This timely access to actionable data is instrumental in preventing severe crop yield losses, optimizing disease management strategies, and reducing environmental degradation. Ultimately, DahonRx highlights the profound potential of integrating advanced computer vision technologies with accessible mobile platforms to foster sustainable agricultural practices. The project aligns with key United Nations Sustainable Development Goals, specifically targeting poverty reduction, zero hunger, innovation, and responsible production. Consequently, this contributes to both the immediate economic stability of local farming communities and the broader objective of long-term regional food security. Future iterations of the system will further solidify the role of artificial intelligence as an indispensable tool in the future of resilient agriculture.

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Declaration of competing interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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