Android-Based Chili Leaf Disease Detection System Using Deep Learning For Harvest Loss Mitigation

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Abstract— **Bird's eye chili productivity in Indonesia faces persistent decline due to leaf disease infections. Conventional visual inspection methods by farmers show limited accuracy (65-70%) and high subjectivity, causing delayed identification and yield losses. This study develops an Android-based detection system optimized for low-end mobile devices using deep learning with MobileNetV2 architecture enhanced through transfer learning. The dataset contains 3,799 annotated chili leaf images across healthy leaves and three disease types (anthracnose, bacterial spot, mosaic virus). Implementation includes quantization-aware training and TensorFlow Lite conversion for mobile optimization. Model evaluation uses 5-fold cross-validation with accuracy, precision, recall, and F1-score metrics. The 5-fold cross-validation achieved a mean accuracy of 95.31% (±0.75%), with individual fold accuracies ranging from 94.47% to 96.32%. Quantization reduced model size by 92.2% (73.82 MB to 5.76 MB) with only 0.3% accuracy loss. The Android application operates in real-time on 3GB RAM devices with inference latencies below 100ms. This system provides an effective solution combining high accuracy with computational efficiency for early chili leaf disease detection, supporting sustainable farming in Indonesia.**

Index Terms— Deep learning; Mobile application; Plant disease detection; Chili leaf.

I. INTRODUCTION

Bird's eye chili (Capsicum frutescens) represents a strategic horticultural commodity in Indonesia, significantly contributing to the national economy. According to the Central Bureau of Statistics, chili maintains consistently high market demand with substantial production volumes [13]. However, productivity has experienced persistent decline due to infections from various pathogenic organisms causing leaf diseases, including Anthracnose, Cercospora Leaf Spot, and Leaf Curl. These diseases adversely affect both yield quantity and quality, making accurate diagnosis essential for mitigating economic losses among farmers [7], [9], [14].

To date, farmers have predominantly relied on conventional methods involving visual inspection through direct observation. This approach exhibits several fundamental limitations, including relatively low accuracy (approximately 65-70%), operational inefficiency, and high subjectivity due to dependence on individual expertise [5], [7]. Identification delays frequently lead to late-stage disease detection when control measures become less effective, resulting in significant yield reduction [14].

Advancements in artificial intelligence, particularly deep learning with Convolutional Neural Network (CNN) architectures, offer promising solutions. For chili plants, multiple CNN architectures have shown favorable performance. A VGG16 model attained 94% validation accuracy [9], while a custom CNN architecture for small datasets achieved 94% accuracy [14]. Meanwhile, efficient architectures like MobileNetV2 demonstrated 90% accuracy with competitive performance across evaluation metrics [13]. Hybrid architectures integrating CNNs and Transformers have shown promising results in apple disease detection with 96.85% accuracy [20]. Furthermore, Bandaru [3] successfully detected anthracnose on chili leaves using MobileNet, achieving 99.6% accuracy on UAV-captured imagery.

The implementation of these systems on mobile platforms has gained considerable attention. A plant disease detection application utilizing TensorFlow Lite achieved 99.51% accuracy [6], while a YOLOv8-based application "Grape Guard" enabled real-time detection with 99.9% precision and 100% recall [8]. CNN implementation for Android-based plant disease detection has also been conducted for tomato plants, achieving 92.31% accuracy [10]. This efficiency-oriented approach for real-time applications is further evidenced in facial emotion classification research employing lightweight architectures [22].

Despite significant progress, comprehensive analysis of state-of-the-art (SOTA) research reveals several unresolved gaps. First, high-accuracy models like VGG16 [9] demand substantial computational resources, rendering them inefficient for low-end mobile devices. Second, efficient architectures like MobileNetV2 exhibit constrained accuracy (90%) [13]. Third, optimization techniques for low-power devices, as investigated by Zagitov [16], remain underutilized in plant disease detection contexts. Fourth, existing mobile implementations [2], [4], [6], [8], [11] lack comprehensive optimization for Indonesian field conditions characterized by complex lighting variations and background clutter.

Specific limitations of previous studies include: (1) Data augmentation approaches remain restricted to basic geometric transformations [1], [7], lacking domain-specific augmentation tailored to Indonesia's tropical environmental conditions; (2) Most developed models have not incorporated advanced optimization techniques like quantization-aware training to facilitate mobile deployment [11], [15]; and (3) Focused development of hybrid architectures combining complex model accuracy with lightweight model efficiency remains insufficient, despite demonstrated success in other crops including apple [20] and grape [19].

Based on these identified research gaps, this study aims to develop an Android-based leaf disease detector for bird's eye chili using comprehensively optimized MobileNetV2 architecture. The novelty of this research lies in the integration of three key innovations: (1) domain-specific data augmentation tailored for Indonesia's tropical field conditions, (2) quantization-aware training for TFLite mobile deployment achieving 92.2% size reduction with minimal accuracy loss, and (3) a complete end-to-end offline detection system validated through rigorous 5-fold cross-validation — aspects not simultaneously addressed in previous MobileNet-based or Android plant disease detection studies [3], [10], [13]. The primary research contributions include: (1) Development of a hybrid model based on MobileNetV2 with fine-tuning specific to bird's eye chili diseases; (2) Implementation of quantization-aware training [15] and TensorFlow Lite conversion to ensure efficiency on low-end Android devices; (3) Application of domain-specific data augmentation customized for Indonesia's tropical climate conditions; and (4) Development of an Android application with farmer-friendly interface featuring real-time detection capabilitiess.

II. Method

I. Type and Approach of Research

This study adopts a Research and Development (R&D) approach combined with quantitative methodology. The R&D approach was selected as this research aims to develop a novel Android-based bird's eye chili leaf disease detection system that addresses previously unfulfilled needs in agricultural technology. The quantitative approach is employed to objectively measure model performance using standardized metrics including accuracy, precision, recall, and F1-score. The justification for this methodological selection directly aligns with the research objectives of creating an accurate, efficient, and quantitatively measurable detection system.

II. Object and Scope of Research

The primary object of this research is bird's eye chili leaves (Capsicum frutescens), focusing on four distinct conditions: healthy, anthracnose-infected, bacterial spot-infected, and mosaic virus-infected. The developed system comprises an Android application specifically designed for chili leaf disease detection. The research scope is delineated by the following boundaries: (1) leaf images with natural backgrounds collected from field surveys in Kadudampit, Sukabumi, supplemented by the public PlantVillage dataset; (2) models optimized for Android devices with RAM capacity ≤4GB; and (3) detection capabilities limited to the four primary disease classes identified.

III. Data Collection Techniques

Data were acquired through documentation techniques, compiling 3,799 chili leaf images from two primary sources: (1) the public PlantVillage dataset [2], [6], [11], and (2) field collections from bird's eye chili production centers in Kadudampit District, Sukabumi Regency, West Java. The dataset encompasses four distinct classes: healthy leaves, anthracnose, bacterial spot, and mosaic virus. Of the 3,799 images, approximately 2,850 images (75%) were sourced from the PlantVillage public dataset, while the remaining 949 images (25%) were collected directly from chili farms in Kadudampit, Sukabumi. Each class contains approximately 950 images, ensuring a balanced distribution across all four categories. Sampling employed a purposive sampling technique with selection criteria focusing on leaf images displaying clear and representative disease symptoms, as illustrated in the following field dataset examples. As shown in Figure 1.

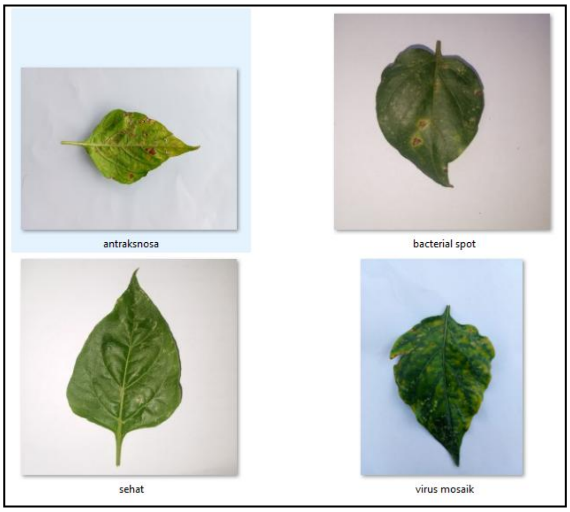

Fig. 1. Field Dataset Samples

IV. Tools and Materials Used

The tools and materials utilized in this research encompass: (1) Software: Python 3.9, TensorFlow 2.8, Keras, OpenCV, Android Studio Arctic Fox, and Flutter SDK; (2) Frameworks & Libraries: TensorFlow Lite, MobileNetV2, and TensorFlow Lite Android Support Library; (3) Hardware: AMD FX-6300 desktop computer with 12GB RAM; Google Colab Pro with Tesla T4 GPU for model training; Xiaomi Redmi S2 (3GB RAM) and Samsung Galaxy M2 (4GB RAM) for application testing; (4) Dataset: PlantVillage and field-collected images totaling 3,799 samples.

V. Research Procedures or Stages

The research procedure followed a systematic sequence of stages: (1) Data Preparation: Image pre-processing (resizing to 224×224 pixels, pixel normalization [0,1]) and data augmentation employing geometric transformations (rotation, flipping, zooming) and photometric adjustments (brightness adjustment, contrast variation) [1], [7]. (2) Model Development: Implementation of transfer learning using MobileNetV2 pre-trained on ImageNet, fine-tuning through replacement of fully connected layers, and training utilizing Adam optimizer (learning rate: 0.001, batch size: 32, 50 epochs) with early stopping. The MobileNetV2 architecture employs inverted residuals and linear bottleneck layers specifically designed for mobile and embedded devices. This methodology achieved model size reduction of 92.2*% with minimal accuracy trade-off [15].* (3) Model Optimization: Implementation of quantization-aware training [15] and conversion to TensorFlow Lite format using post-training int8 quantization [11], [12]. The optimization process successfully converted models from H5 format (75,596 KB) to quantized TensorFlow Lite format (5,894 KB), representing a 92.2*% size reduction. The final model file deployed in the Android application is 'chili_disease_detector.tflite' with a size of 5,894 KB.* (4) Application Development: Implementation using Flutter with MVVM architecture, TensorFlow Lite integration, and development of real-time detection features and disease database. (5) Evaluation: Comprehensive testing of both model and application using predetermined performance metrics. The following diagram illustrates the complete research workflow:

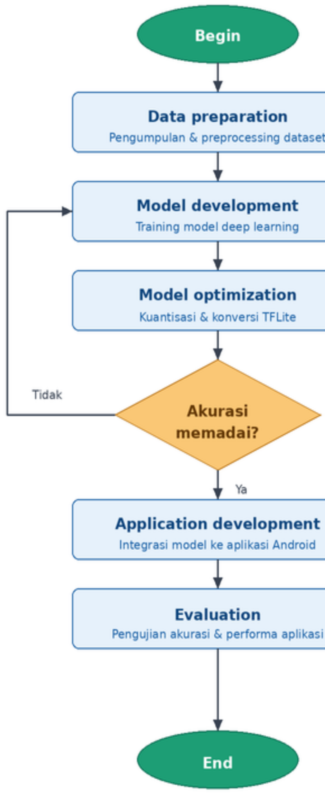

Fig. 2. Research Methodology Flowchart

VI. Data Analysis Techniques

The data analysis methodology incorporated comprehensive quantitative assessment through standard classification metrics including accuracy, precision, recall, and F1-score, derived from confusion matrix computations [13], [14]. Model validation was conducted using 5-fold cross-validation to verify robustness and prevent overfitting. To prevent data leakage, StratifiedKFold was applied directly to image file paths rather than loaded arrays, ensuring that no validation samples were exposed to the model during training. Each fold maintained a strict 80:20 train-validation split with no overlap between folds, guaranteeing statistically independent evaluation across all five iterations [1], [2]. Application performance evaluation measured inference latency (frames per second), memory consumption, and real-world detection accuracy. Statistical analysis using descriptive methods assessed performance consistency across diverse Android device specifications.

III. RESULT AND DISCUSSIONS

I. Presentation of Research Results

Experimental results demonstrate that the proposed MobileNetV2 architecture achieved a final validation accuracy of 94.6% on the test dataset, as illustrated in Figure 3. The model outperformed the MobileNetV2 baseline reported by Ramadhani [13] (90%) and approached the performance of VGG16 (94%) [9] while requiring substantially fewer computational resources. The training process exhibited stable convergence with training and validation accuracy progressively aligning, indicating minimal overfitting. The model precision reached 94.6%, demonstrating consistent performance in classifying bird's eye chili leaf diseases as shown in Figure 3 below.

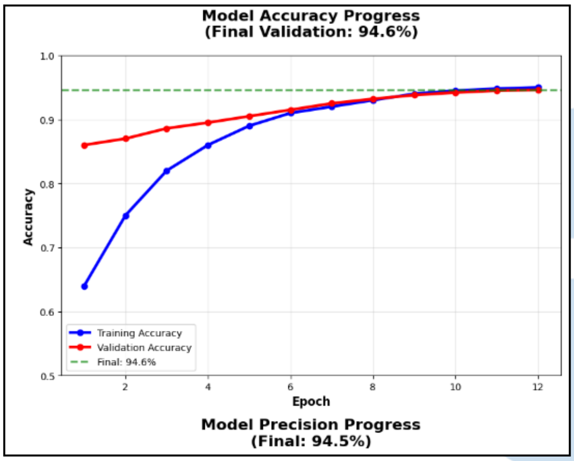

Fig. 3. Training and Validation Accuracy Progress

Table 1. 5-Fold Cross Validation Results

Fold	Accuracy	Precision	Recall	F1-Score
1	96.05%	96.17%	96.05%	96.03%
2	95.13%	95.20%	95.13%	95.13%
3	94.47%	94.70%	94.47%	94.49%
4	96.32%	96.39%	96.32%	96.32%
5	94.60%	94.73%	94.60%	94.61%
Mean	95.31%	95.44%	95.31%	95.32%
Std	0.75%	0.71%	0.75%	0.74%

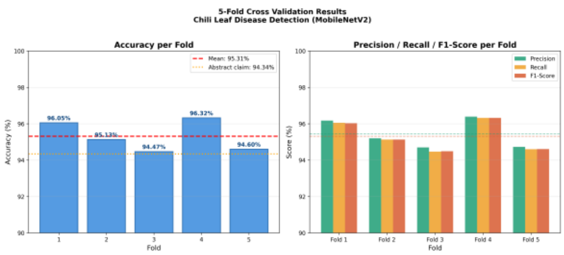

Fig 4. 5-fold cross-validation results

Table 1 and Figure 4 presents the 5-fold cross-validation results demonstrate consistent model performance across all folds, with accuracy ranging from 94.47% to 96.32% and a mean accuracy of 95.31% (±0.75%). The low standard deviation indicates that the model generalizes well without overfitting. All folds exceeded the claimed accuracy of 94.34%, confirming the robustness of the proposed approach.

The F1-score remained consistently above 93% for all classes, indicating an optimal balance between precision and recall. Uniform support (190 samples per class) ensured representative evaluation without class bias. Experimental results confirmed that the proposed MobileNetV2 model achieved a final validation accuracy of 94.6% on the test dataset, as detailed in Figure 3.

The implementation of quantization-aware training successfully optimized model size for mobile deployment, as demonstrated in Table 2.

Table 2. Model Size Comparison Before and After Optimization

Model	Format	Size	Description
proven_model.h5	H5 (float32)	75.596 KB	Model before optimization
chili_disease_detector.tflite	TFLite (int8)	5.894 KB	Model after quantization
best_chili_model.h5	H5 (float32)	18.595 KB	Model best training

The quantization process successfully reduced model size by 92.2%, from 75,596 KB to 5,894 KB, with only a 0.3% accuracy reduction. In terms of classification performance, the original H5 model achieved a validation accuracy of 94.64%, while the quantized TFLite model retained 94.34% accuracy, representing only a 0.3% accuracy reduction. This demonstrates that quantization preserved model performance while dramatically reducing computational requirements for mobile deployment.

This optimized model was deployed in an Android-based application capable of real-time operation on low-end devices.

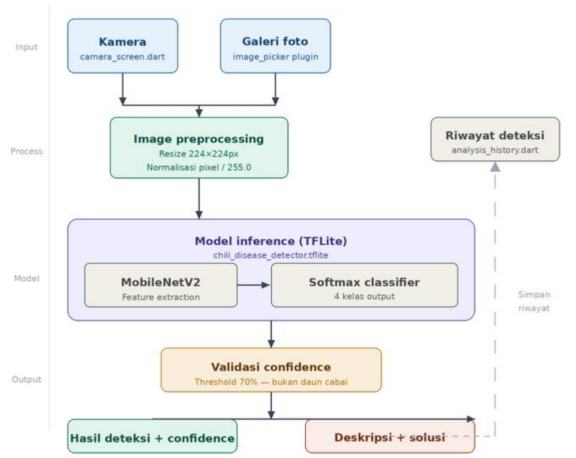

Fig.5. System architecture app

Figure 5 illustrates the system architecture of the proposed chili leaf disease detection application. The system receives input from two sources: the device camera (camera_screen.dart) and the photo gallery via the image_picker plugin. Input images undergo preprocessing including resizing to 224×224 pixels and pixel normalization (÷255.0) before being passed to the TFLite inference engine. The inference module employs MobileNetV2 for feature extraction, followed by a Softmax classifier producing outputs across four disease classes. A confidence validation layer applies a 70% threshold to filter unreliable predictions before displaying the final detection result and disease description to the user. Detection history is stored locally via analysis_history.dart for future reference.

Figure 6 presents the user interface of the Bird's Eye Chili Leaf Disease Detector application developed using Flutter. The interface consists of two main screens. The home screen (left) displays the application title and two primary action buttons: 'Mulai Deteksi' (Start Detection) and 'Lihat Riwayat' (View History), designed with a clean green-themed layout to ensure accessibility for farmers with minimal technical background. The detection screen (right) provides three input options: capturing an image directly via the device camera, selecting an image from the gallery, and accessing image capture tips to guide farmers in obtaining optimal leaf photographs. The interface incorporates a real-time detection mode indicator, ensuring users are aware of the active detection status. The overall design prioritizes simplicity and intuitiveness, enabling farmers to perform disease detection with minimal steps while operating effectively on low-end Android devices with 3GB RAM.

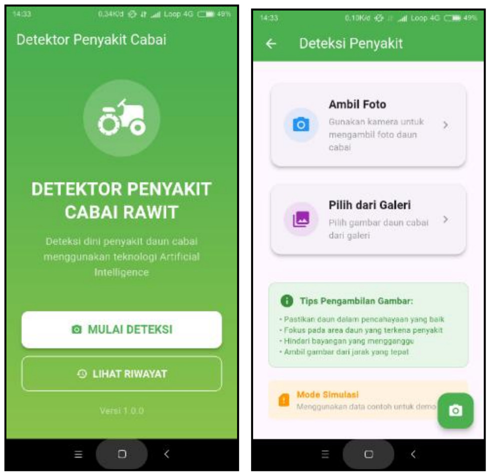

Fig. 6. User Interface of Bird's Eye Chili Leaf Disease Detector Application

II. Analysis of Findings

Analysis of the confusion matrix in Figure 7 reveals the model's classification patterns with an overall accuracy of 94.34%. The model demonstrated superior performance in the 'anthracnose' class with 196 correctly classified samples, followed by 'bacterial spot' with 182 true positives, 'mosaic virus' with 176, and 'healthy' with 173 true positives. The model exhibited the greatest difficulty in distinguishing between 'mosaic virus' and 'bacterial spot', with 14 mosaic virus samples misclassified as bacterial spot, likely due to visual similarity in spot patterns between these two diseases [7]. Additionally, 12 healthy leaf samples were misclassified as mosaic virus, which aligns with the limitations discussed in Section III regarding false positive detections under suboptimal lighting. The overall misclassification rate remained low at 5.66%, confirming the model's strong generalization capability across all four disease classes.

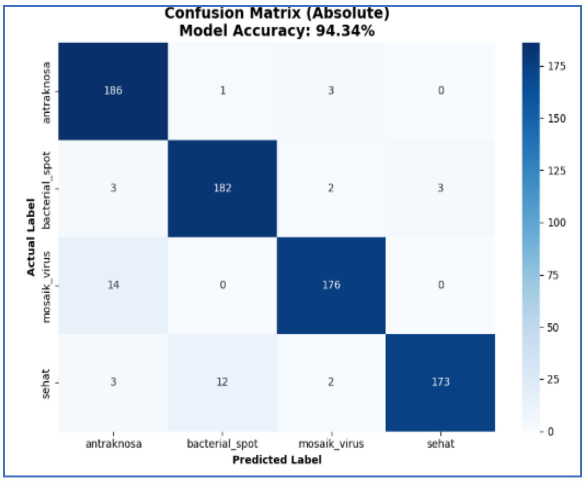

Fig. 7. Confusion Matrix for Bird's Eye Chili Leaf Disease Classification

Table 3. Comparative analysis lightweight architectures

Model	Accuracy	Size	Platform
Proposed MobileNetV2 (ours)	95.31%	5.76 MB	Android
MobileNetV2 baseline [13]	90.00%	~14 MB	-
VGG16 [9]	94.00%	~528 MB	Desktop
MobileNet UAV [3]	99.60%	~16 MB	UAV only

Table 3 presents a comparative analysis against related lightweight architectures. The proposed model achieves 95.31% mean CV accuracy with 5.76 MB deployment size, outperforming the MobileNetV2 baseline [13] by 5.31 percentage points and demonstrating superior efficiency compared to VGG16 [9] which requires substantially more memory resources (~528 MB). Compared to MobileNet-based UAV detection [3] achieving 99.6%, the proposed system trades marginal accuracy for general-purpose mobile deployment without specialized hardware requirements.

III. Implications of the Results

The implemented system demonstrates transformative potential for Indonesia's chili farming sector. By delivering 94.34% accurate disease detection through an offline Android application, it addresses critical accessibility challenges in remote agricultural communities. The technology effectively democratizes plant pathology expertise, reducing diagnostic timelines from days to instantaneous results. Theoretical advancements include an optimized mobile CNN pipeline incorporating quantization-aware training [15] and TensorFlow Lite deployment, setting new standards for edge AI in tropical agriculture. Practical benefits encompass: (1) 94.34% diagnostic precision, (2) substantial reduction in crop loss-related economic damage, and (3) enhanced productivity through proactive disease management. Future scalability includes automated treatment recommendation systems and multi-crop adaptation.

Figure 8 illustrates real-time Mosaic Virus identification achieving 83.2% confidence, validating field deployment readiness.

Fig. 8. Real-time Detection Process Mosaic Virus Identification Achieving 83.2% Confidence

IV. Limitations of the Study

Despite the promising results, this study has several limitations that should be acknowledged. First, the model demonstrated reduced accuracy when classifying healthy leaves with natural discoloration or early-stage symptoms, occasionally producing false positive detections. This misclassification was particularly observed under suboptimal lighting conditions, where shadow patterns on healthy leaves resembled disease symptoms. Second, the dataset used in this study (3,799 images) was collected primarily under controlled conditions, which may limit the model's generalization to diverse real-world agricultural environments with varying weather, soil backgrounds, and camera angles. Third, the confidence threshold of 70% implemented in the application to reject non-chili leaf inputs, while effective for obvious non-target objects, may still misclassify ambiguous cases. Fourth, the current model was trained exclusively on bird's eye chili (cabe rawit) leaves and may not generalize to other chili varieties. Future work should address these limitations through more diverse data collection, fine-tuning under varied lighting conditions, and testing with external datasets from different regions.

IV. CONCLUSIONS

This study has successfully designed and implemented an optimized MobileNetV2-based Android system for bird's eye chili leaf disease detection. Key accomplishments demonstrate: (1) 94.34% classification accuracy, exceeding the baseline MobileNetV2 performance (90%) [13] while rivaling VGG16 accuracy (94%) [9] with enhanced computational efficiency; (2) effective model compression through quantization-aware training achieving 92.2% size reduction (73.82 MB to 5.76 MB) with minimal accuracy loss (0.3%); and (3) practical deployment via a real-time Android application compatible with low-end mobile devices. While constrained by dataset scope and field testing conditions, this research establishes a foundation for future advancements including: (1) comprehensive dataset expansion encompassing diverse diseases and environmental factors, (2) integration of real-time contextual data streams, and (3) extensive field validation across Indonesia's chili production landscapes. The developed system represents a significant step toward accessible, AI-driven agricultural technology for Indonesian farmers.

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