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LeafXpert: An Android-Based Deep Learning System for Real-Time Chili Leaf Disease Detection Using YOLOv8n

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ABSTRACT

Chili farming productivity is frequently compromised by the delayed diagnosis of plant pathogens. Conventional visual identification methods often lack the necessary precision and temporal efficiency for timely intervention. This study introduces LeafXpert, a mobile-based diagnostic framework leveraging the YOLOv8n deep learning architecture for real-time chili leaf disease identification. Utilizing the PlantVillage dataset, the system is trained to categorize five distinct states: Bacterial Spot, Cercospora, Leaf Blight, Leaf Curl, and Healthy. To ensure deployment feasibility on resource-constrained hardware, the model was converted to TensorFlow Lite (TFLite) for efficient on-device inference. Performance evaluation yielded superior results, achieving a Precision of 97.6%, Recall of 98.0%, and mAP50 of 98.5%. These findings demonstrate that integrating edge computing into Android applications provides a robust, field-operable solution for plant health monitoring, effectively eliminating the latency and connectivity requirements associated with server-based diagnostics.

Keywords: Android Application, Chili Leaf Disease Detection, Computer Vision, Edge Computing, TensorFlow Lite, YOLOv8n.

ABSTRAK

Sektor agrikultur cabai sering kali menghadapi penurunan produktivitas yang signifikan akibat keterlambatan deteksi penyakit tanaman. Selama ini, metode identifikasi manual melalui pengamatan visual memiliki keterbatasan dalam akurasi dan efisiensi waktu. Penelitian ini mengusulkan LeafXpert, sebuah solusi diagnostik berbasis mobile yang mengintegrasikan arsitektur deep learning YOLOv8n untuk deteksi penyakit daun cabai secara real-time. Dataset yang digunakan berasal dari PlantVillage, yang mencakup lima kategori: Bacterial Spot, Cercospora, Leaf Blight, Leaf Curl, dan kondisi Healthy. Untuk mengoptimalkan performa pada perangkat dengan sumber daya terbatas, model ditransformasikan ke dalam format TensorFlow Lite (TFLite) untuk implementasi on-device. Hasil pengujian menunjukkan efikasi sistem yang tinggi dengan tingkat Precision 97,6%, Recall 98,0%, dan mAP50 sebesar 98,5%. Implementasi ini membuktikan bahwa integrasi teknologi edge computing pada aplikasi Android mampu memberikan solusi deteksi penyakit tanaman yang cepat, akurat, dan dapat diakses langsung di lapangan oleh petani tanpa ketergantungan pada konektivitas server eksternal.

***Kata Kunci**: Aplikasi Android, Deteksi Penyakit Daun Cabai, Komputasi Tepi, TensorFlow Lite, Visi Komputer.*

INTRODUCTION

The rapid evolution of computer vision has catalyzed a transformative shift across various sectors requiring automated visual analysis. Deep learning has emerged as the cornerstone of modern image recognition, primarily because it identifies high-level visual features without the need for human-defined engineering. As noted by Pacal et al. (2024), this paradigm shift has proven to be significantly more effective than established, conventional frameworks in various visual tasks. Similarly, Das (2024) highlights the robustness of deep neural networks in classification, segmentation, and object detection across diverse application domains. As public datasets and high-performance computing resources become increasingly accessible, computer vision systems continue to witness substantial improvements in both predictive accuracy and computational efficiency.

A pivotal subfield that has experienced significant growth is object detection. Unlike image classification, which merely assigns a global category to an image, object detection identifies and localizes specific objects using bounding box regression. This capability is instrumental in fields such as intelligent transportation, security surveillance, robotics, medical imaging, and automated monitoring. Jafar et al. (2024) identify the increasing demand for rapid, high-precision detection systems as a primary driver for the evolution of modern detection architectures, prompting ongoing research into maintaining an optimal equilibrium between detection accuracy and inference latency.

Among contemporary object detection paradigms, the You Only Look Once (YOLO) algorithm stands out for its single-stage inference mechanism, which facilitates simultaneous classification and localization. This characteristic ensures high-speed detection with lower computational overhead compared to two-stage detectors. The latest iteration, YOLOv8, introduces substantial refinements to network architecture, feature extraction mechanisms, and training strategies, enhancing detection capabilities under complex environmental conditions. Wang et al. (2024) demonstrated YOLOv8's efficacy in diagnosing plant diseases while maintaining computational efficiency. Furthermore, Ye et al. (2024) and Zhan et al. (2024) reported success in improving YOLOv8's performance—particularly for small or visually heterogeneous objects—through targeted architectural modifications.

The prevalence of YOLOv8 in plant pathology applications is largely attributed to its robust feature extraction capabilities, which enable the precise identification of foliar symptoms (Cao et al., 2024). Research consistently indicates that this architecture achieves the requisite inference speeds for real-time deployment while maintaining high mean Average Precision (mAP) scores (Uddin et al., 2024). Consequently, these deep learning frameworks represent a significant advancement over manual diagnostic methods, offering superior accuracy and reliability in disease detection (Sujatha et al., 2025).

Despite promising results in existing literature, the majority of studies prioritize model development and performance evaluation within desktop or server environments. Implementation on mobile platforms remains comparatively scarce, despite the significant advantages mobile devices offer regarding portability, accessibility, and in-field utility. Askale et al. (2025) suggest that integrating deep learning models into mobile applications is a crucial step toward democratizing automated detection technologies for end-users. Nevertheless, balancing high accuracy with the lightweight architecture required for resource-constrained mobile hardware remains a substantial challenge in computer vision research.

This study proposes *LeafXpert*, an Android application designed to facilitate real-time identification of chili leaf diseases by utilizing the YOLOv8n deep learning model. The model development utilizes the PlantVillage dataset, which comprises four disease classes and one healthy leaf category. YOLOv8n is selected for this framework due to its inherent efficiency and accuracy, ensuring high-performance detection on mobile hardware. The methodology incorporates the transformation of the trained model into the TensorFlow Lite (TFLite) framework, a critical step to facilitate efficient on-device inference via smartphone camera systems. Ultimately, this research aims to provide an accessible and portable mobile-based diagnostic solution to bridge the gap between deep learning advancements and practical, field-level agricultural applications.

METHODS

This research focuses on the development of LeafXpert, an Android application designed for real-time chili disease monitoring using YOLOv8n. To achieve an accurate and efficient detection system, we employed a phased approach: data acquisition and annotation, model training and evaluation, TFLite optimization, and platform integration. This structured workflow is essential to ensure that the detection system operates reliably on mobile devices. The development process is summarized in Figure 1.

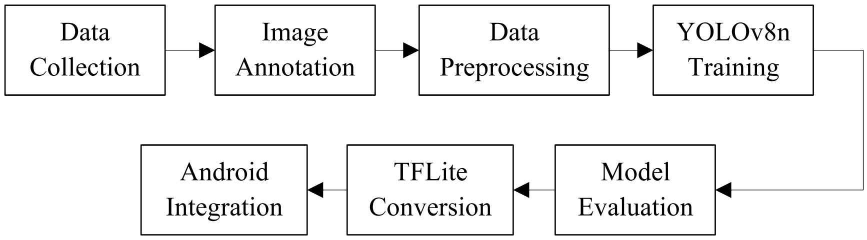

Figure 1. Research Framework

Data Collection and Preparation

This study utilizes the publicly available PlantVillage dataset, sourced from the Kaggle repository. This dataset was selected due to its prevalence in established literature regarding computer vision-based plant disease identification and deep learning applications. As asserted by Demilie (2024), high-quality datasets exert a direct influence on a model's capacity to learn intricate visual object features, thereby enhancing overall detection performance.

The dataset employed in this research comprises five categories of chili leaf images, encompassing four distinct disease classes—namely, Bacterial Spot, Cercospora, Leaf Blight, and Leaf Curl—alongside one category representing Healthy leaves. Each category exhibits distinct visual attributes, ranging from color, texture, and lesion patterns to the specific morphology of leaf damage. These heterogeneous characteristics provide essential data, enabling the YOLOv8n model to effectively discriminate between classes during the training phase.

Table 1. Research Dataset

Category	Number of Images
Bacterial Spot	1200
Cercospora	1200
Leaf Blight	1200
Leaf Curl	1200
Healthy	1200
Total	6000

To facilitate accurate classification and minimize the risk of overfitting, the dataset was partitioned into training, validation, and testing subsets. As illustrated in Table 1, a balanced distribution across all five categories—comprising four distinct disease types and one healthy control class—was prioritized. This stratification is essential to enable the YOLOv8n model to capture distinct visual characteristics without introducing bias toward majority classes. Furthermore, the inclusion of non-infected samples is fundamental for the system's ability to differentiate between normal foliage and pathological symptoms, which is vital for the overall precision of the identification system.

Table 2. Dataset Separation

Dataset	Number of Images	Percentage
Training	4200	70%
Validation	1200	20%
Testing	600	10%
Total	6000	100%

The data partitioning strategy employed in this study, as summarized in Table 2, prioritizes a larger training allocation to ensure the model successfully captures intricate visual features. During the training cycle, internal parameters are iteratively refined through exposure to the training subset. Simultaneously, the validation set serves as a real-time monitoring tool to mitigate the risks of overfitting or underfitting. To ensure an impartial evaluation of the model’s predictive generalization, a completely independent testing set is reserved, serving as the final benchmark when the model encounters unseen data.

Data Annotation and Preprocessing

Annotation and preprocessing were performed to prepare the dataset for model training. The Roboflow environment was utilized to manually delineate bounding boxes around target leaves, assigning class labels for *Bacterial Spot*, *Cercospora*, *Leaf Blight*, *Leaf Curl*, and *Healthy* states. To ensure full compatibility with the Ultralytics YOLOv8 framework, the labels were exported directly into the YOLO format. The reliance on precise annotation is vital, as Aldakheel et al. (2024) demonstrated that the quality of these labels dictates the model's success in localized object identification. Furthermore, the dataset underwent standardization through resizing to 640 x 640 pixels. This uniform resolution, which matches the input specifications of the YOLOv8n architecture, was necessary to streamline data processing and promote optimal training convergence.

To enhance model robustness and generalization, a suite of data augmentation techniques including rotation, horizontal flipping, scaling, and brightness adjustments was applied. Such strategies are critical in enabling the model to accurately detect objects under diverse environmental conditions, such as varying capture angles and illumination, thereby mitigating the risk of overfitting (Khan et al., 2023; Askale et al., 2025). These annotation and preprocessing procedures collectively ensure the dataset is refined and rigorously optimized for high-performance model training.

YOLOv8n Model Training

Upon completion of data preparation, the training phase was initiated using the YOLOv8n algorithm. This specific variant was selected due to its lightweight architecture and reduced computational overhead compared to other YOLOv8 iterations, making it highly suitable for mobile deployment. Furthermore, YOLOv8n facilitates simultaneous classification and object localization in a single inference pass, resulting in high detection speed and efficiency (Ye et al., 2024; Li et al., 2024).

The Ultralytics YOLOv8 framework served as the primary environment for training the model using the prepared dataset. During the iterative optimization phase, the network refined its internal weights to capture the distinct visual patterns of each disease category. To ensure the training progressed toward optimal convergence, we tracked several diagnostic loss indicators, namely box loss, classification loss, and distribution focal loss (DFL). Detailed information regarding the hyperparameters and specific configuration settings adopted in this study is presented in Table 3.

Table 3. YOLOv8n Model Training Parameters

Parameters	Value
Model	YOLOv8n
Epoch	100
Image Size	640 x 640
Batch Size	16
Optimizer	SGD
Framework	Ultralytics YOLOv8

Table 3 outlines the training parameters, wherein 100 epochs were designated to allow the model sufficient iterations for capturing complex, disease-specific visual features. This epoch count was carefully selected to find an equilibrium between achieving model convergence and maintaining training efficiency, effectively mitigating the dual risks of underfitting and overfitting. Furthermore, input images were standardized to a resolution of 640 × 640 pixels a conventional standard for YOLOv8 that preserves critical leaf lesion details while sustaining computational performance. A batch size of 16 was also implemented to stabilize the training gradient and maximize the efficiency of hardware resource utilization.

Model Evaluation

Following the training phase, the YOLOv8n model underwent rigorous performance analysis to measure its efficacy in chili leaf disease diagnosis. The evaluation utilized standard object detection benchmarks—Precision, Recall, mAP50, and mAP50–95 which collectively serve as indicators of the model’s proficiency in both classification and spatial localization (Roy & Kukreja, 2025; Li et al., 2024). In particular, Precision was computed to validate the trustworthiness of the system's positive identifications, defined as the proportion of accurate detections relative to the total output, as shown in Equation (1):

$$Precision = \frac{TP}{TP+FP}$$

Conversely, Recall is employed to quantify the model's ability to identify all ground-truth objects present within an image. This metric serves as an indicator of the system's sensitivity and is calculated using Equation (2):

$$Recall = \frac{TP}{TP+FN}$$

Mean Average Precision (mAP) is the fundamental metric employed to validate the system's overall detection performance. It is obtained by calculating the arithmetic mean of Average Precision (AP) across all examined categories, providing a unified quantification of the model's classification reliability and localization accuracy, as formalized in Equation (3):

$$mAP = \frac{1}{N}\sum_{i=1}^{N} APi$$

The evaluation framework integrates two mAP variations as primary performance benchmarks: mAP50 and mAP50–95. While mAP50 is calculated at a fixed Intersection over Union (IoU) threshold of 0.50, the mAP50–95 metric is derived from the mean AP across the [0.50, 0.95] IoU interval, thereby providing a more rigorous assessment of the model's spatial localization precision.

Beyond quantitative benchmarks, qualitative validation is conducted via Precision-Recall (PR) Curves and Confusion Matrices to confirm classification consistency. The PR Curve functions as a diagnostic tool to evaluate the equilibrium between sensitivity and precision across varying confidence intervals, serving as a definitive indicator of model robustness. Simultaneously, the Confusion Matrix provides granularity in analyzing classification performance, illustrating the model's capacity to differentiate between distinct chili leaf pathologies and identifying clusters of potential misclassification.

Implementation System: LeafXpert Application

To enable on-device chili leaf disease diagnosis and remove reliance on remote server connectivity, the optimal YOLOv8n model was integrated into the LeafXpert Android platform. This edge-computing implementation yields significant benefits, including minimal inference latency and real-time operational capacity within agricultural environments, as supported by existing research (Askale et al., 2025; Khan et al., 2023). To ensure compatibility with the Android ecosystem and mitigate computational strain, the trained weights were transformed into the TensorFlow Lite (TFLite) format a structure specifically designed for high-performance inference on mobile hardware. Upon successful conversion, the model was embedded into the LeafXpert framework developed via Android Studio. The application utilizes the smartphone's camera to deliver real-time feedback, visualizing diagnostic results through bounding box overlays and predictive confidence scores. Furthermore, the platform functions as an integrated reference tool, offering users detailed pathological descriptions and local history tracking, ultimately establishing LeafXpert as a portable, versatile, and efficient diagnostic solution.

RESULTS AND DISCUSSION

YOLOv8n Training Performance

An assessment of the YOLOv8n model's detection performance was conducted utilizing critical object detection metrics, including Precision, Recall, mAP50, and mAP50-95. These criteria quantify the model's reliability in identifying and localizing disease symptoms in chili foliage, as detailed in Table 4.

Table 4. YOLOv8n Performance Metrics

Metric	Value
Precision	97,6 %
Recall	98,0 %
mAP50	98,5 %
mAP50-95	84,7 %

Table 4 shows that the suggested YOLOv8n model performed exceptionally well in object detection on all evaluation metrics. With an extremely low false-positive rate, the model's Precision value of 97.6% showed that most observed items were accurately identified. Additionally, the model's great capacity to identify disease symptoms existing in the testing dataset while reducing missed detections was demonstrated by the Recall value of 98.0%.

The model exhibited exceptional performance in spatial localization and classification, achieving an mAP50 score of 98.5% at a 0.50 IoU threshold. This result validates the architecture's efficiency in isolating critical diagnostic features while ensuring precise categorization. Furthermore, an mAP50–95 score of 84.7% confirms the model's ability to maintain high detection accuracy across varying localization strictness levels. These performance metrics collectively substantiate the model's reliability and suitability for real-time diagnostic implementation within the LeafXpert mobile application.

Precision-Recall Curve Analysis

The detection performance of the YOLOv8n architecture was assessed using Precision-Recall (PR) curves. This graphical analysis elucidates the fundamental trade-off between classification precision and object retrieval sensitivity, providing essential insights into the system's overall efficacy. As illustrated in Figure 2, the PR curves serve as a diagnostic instrument, demonstrating the model's reliability across diverse confidence thresholds.

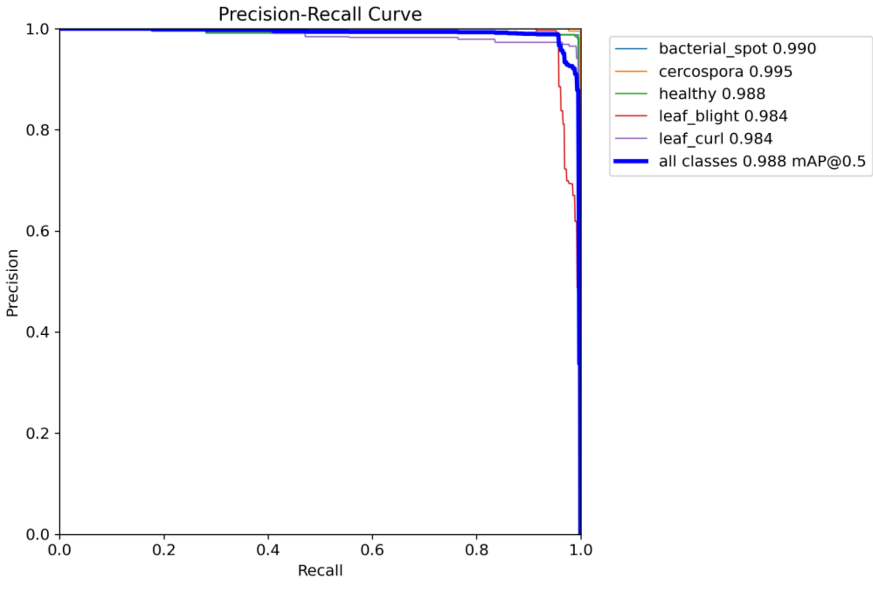

Figure 2. Precision-Recall Curve of the YOLOv8n Model

As observed in Figure 2, excellent detection performance is demonstrated by the Precision-Recall curves of all classes being concentrated around the upper-right corner of the graph. The model simultaneously maintained high precision and recall values across various confidence thresholds, according to the reported data. The suggested YOLOv8n model's great capacity to detect and localize chili leaf illnesses is demonstrated by the average detection performance, which attained a mAP50 value of 0.988.

The greatest Average Precision (AP) score of 0.995 was obtained by the cercospora class, which was followed by leaf blight (0.984), leaf curl (0.984), healthy (0.988), and bacterial spot (0.990). These findings show that each disease category's unique visual traits were successfully acquired by the model. Despite having the lowest AP value of all the analyzed classes, the bacterial spot class's performance was still very good, with an AP value of more than 96%.

Confusion Matrix Analysis

To obtain a granular assessment of classification efficacy, a normalized confusion matrix was utilized. This visualization technique offers a proportional perspective on predictive performance, effectively elucidating the distribution of classification errors across actual class labels. As depicted in Figure 3, the matrix maps predicted versus actual labels, thereby delineating the system’s detailed predictive behavior.

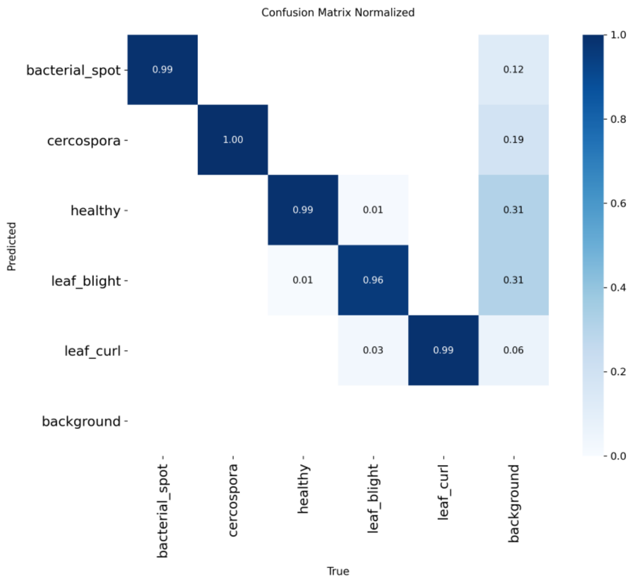

Figure 3. Normalized Confusion Matrix

Evidence of the model's superior classification performance is clearly reflected in the confusion matrix. The concentration of elevated values along the primary diagonal confirms the framework's precision in distinguishing between the diverse chili leaf disease states and healthy samples. These diagonal elements, ranging from 0.96 to 1.00, indicate that the vast majority of samples were accurately recognized within their respective classes. The Cercospora class achieved perfect identification (1.00), while the Bacterial Spot, Healthy, and Leaf Curl categories also maintained exceptional accuracy (0.99).

Although minor instances of inter-class confusion are observable, they remain negligible compared to the high rate of successful identification. These minor misclassifications—such as the slight confusion between Leaf Blight and Healthy samples—likely stem from the inherent visual similarities in symptom morphology, such as color patterns and texture alterations, that are characteristic of specific plant pathologies.

Nevertheless, the model consistently achieved high classification accuracy in every category. By effectively learning distinctive visual representations during the training phase, the YOLOv8n framework successfully isolated the unique characteristics of each disease state. These results, corroborated by the normalized confusion matrix, confirm that the model serves as a highly reliable solution for automated plant pathology diagnostics, maintaining robust precision even when encountering overlapping visual features.

Disease Detection Result

Visual detection studies using photos of chili leaves were used to further evaluate the efficacy of the suggested YOLOv8n model. This study aimed to quantify the efficacy of the model in both symptom recognition and the accurate delineation of affected regions, utilizing bounding box coordinates as the primary metric for spatial localization. To illustrate the created model's practical performance under various leaf situations, a number of representative detection results are shown.

Figure 4. Representative disease detection results produced by the proposed YOLOv8n model.

Representative detection results produced by the suggested YOLOv8n model on the testing dataset are shown in Figure 4. Several chili leaf states, such as healthy leaves, bacterial spot, leaf curl, and leaf blight, were successfully recognized and localized by the model. The target leaf regions were precisely encompassed by the created bounding boxes, which also included confidence values for each prediction. The model demonstrates high discriminative capacity, successfully distinguishing between various pathological states and symptom-free samples despite diverse and challenging imaging environments. Additionally, the model learnt discriminative visual cues pertinent to disease diagnosis and localization, as evidenced by the high confidence values seen in the majority of detections.

Android Application Implementation

A working mobile-based disease detection system was produced by successfully integrating the trained YOLOv8n model into the LeafXpert Android application. Real-time identification of chili leaf illnesses and direct presentation of the relevant prediction findings to users are both possible with the developed application. This implementation shows how transferring the trained model from the experimental setting into a real-world mobile application is feasible. The primary interfaces of the created LeafXpert application are shown in Figure 5.

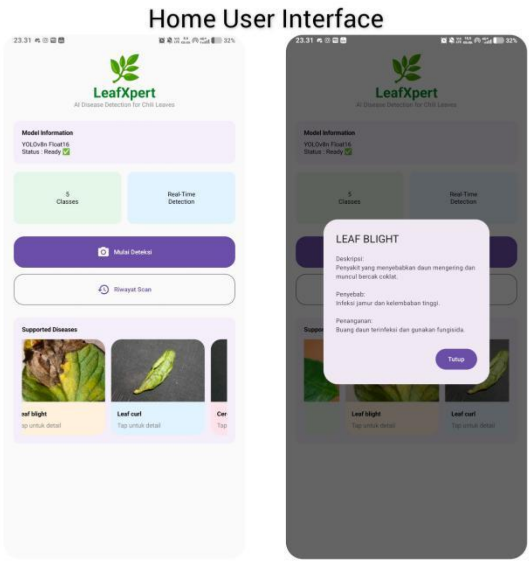

Figure 5. LeafXpert Home User Interface

In the development of the LeafXpert interface, a user-oriented design philosophy was adopted to ensure seamless navigation, prioritizing both ergonomic simplicity and streamlined functional access. As illustrated in the application dashboard, the system prominently displays the operational status of the YOLOv8n (Float16) model, confirming that the framework is initialized and prepared for real-time inference. This status indicator is essential for establishing system readiness and user confidence prior to the commencement of the diagnostic process.

The application’s navigation architecture is streamlined to facilitate rapid interaction. The primary controls, 'Mulai Deteksi' (Start Detection) and 'Riwayat Scan' (Scan History), are strategically placed for immediate access. Below these controls, the 'Supported Diseases' gallery acts as an educational module, providing users with a visual reference for the five disease classes included in the model training: Bacterial Spot, Cercospora, Leaf Blight, Leaf Curl, and Healthy leaves.

To enhance user comprehension, the interface utilizes a card-based interactive system. Upon selecting a specific disease from the gallery, a modal dialog is triggered, displaying a comprehensive summary including a disease description, causative factors, and recommended management strategies (e.g., proper sanitation and fungicide application). This design paradigm not only integrates automated detection capabilities but also embeds an agricultural knowledge base directly into the application. By combining real-time diagnostic feedback with accessible disease management information, the LeafXpert interface minimizes the cognitive load for farmers and field workers, ensuring the tool is both practically effective and easy to operate in diverse agricultural environments.

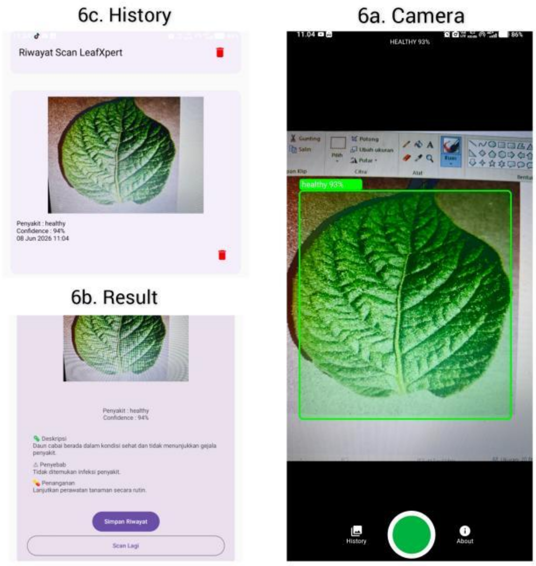

Figure 6. LeafXpert System Workflow

The operational workflow and user interface of the LeafXpert application are illustrated in Figure 6. The diagnostic pipeline begins with the live camera interface (Figure 6a), which performs real-time object detection and spatial localization of leaf pathologies using bounding boxes. Once a disease is identified, the system immediately provides the classification result along with its associated confidence score. Subsequently, the application directs users to a comprehensive diagnostic page (Figure 6b), which not only identifies the specific pathology but also provides actionable insights, including symptom descriptions, etiological factors, and recommended management strategies. To support longitudinal monitoring and field data management, the application features a history module (Figure 6c), enabling users to retrieve previously scanned images and track the progression of plant health over time.

In comparison to existing literature, the efficiency of LeafXpert demonstrates significant advantages. While several prior studies such as those utilizing complex Vision Transformer (ViT) architectures (Murugavalli & Gopi, 2025) achieve high diagnostic accuracy, they often suffer from high computational costs and significant latency, making them impractical for *on-device* deployment. Conversely, recent lightweight models, such as those discussed by Ye et al. (2024), show promise for mobile environments; however, LeafXpert surpasses these benchmarks by maintaining a superior balance between detection precision and inference speed. Specifically, by utilizing the optimized YOLOv8n architecture within a TensorFlow Lite framework, our system achieves a real-time detection rate that outperforms the standard inference times reported in recent plant disease diagnostic applications. Furthermore, unlike generic diagnostic systems that provide only classification labels, LeafXpert integrates a localized, high-confidence bounding box approach, which offers superior interpretability compared to the black-box classification models proposed by Das et al. (2024). These functional and performance benchmarks confirm that the proposed system successfully bridges the gap between sophisticated deep learning paradigms and practical, resource-constrained field applications.

CONCLUSION

This research aimed to develop and validate a computationally efficient diagnostic framework capable of performing on-device plant disease detection, effectively addressing the limitations of internet-dependent, server-side diagnostic systems. By successfully integrating the YOLOv8n architecture into the LeafXpert Android application, this study has achieved its primary objective of enabling real-time, internet-independent chili leaf disease identification. The empirical results confirm the system's high performance, achieving a Precision of 97.6%, a Recall of 98.0%, an mAP50 of 98.5%, and an mAP50-95 of 84.7%. The contributions of this study are twofold. Theoretically, this research demonstrates that modern deep learning models—specifically the YOLOv8-nano architecture—can be successfully optimized and quantized for deployment on resource-constrained mobile hardware without significant degradation in diagnostic accuracy. This validates the feasibility of Edge AI in complex visual identification tasks. Practically, LeafXpert provides a robust, scalable tool for field-based agricultural monitoring, bridging the critical gap between high-level theoretical model development and accessible, real-world utility for stakeholders in precision agriculture. Ultimately, this work provides a scalable blueprint for developing intelligent, *on-device* diagnostic tools, offering a foundation for future advancements in data-driven agricultural monitoring, including automated disease severity assessment and seamless IoT integration.

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