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Real-Time Rice Leaf Disease Diagnosis: A Mobile CNN Application with Firebase Integration

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Abstract

Rice, the staple food for the majority of Indonesia's population, faces significant production threats from leaf diseases, which can decrease yields and jeopardize national food security. Traditional manual identification of these diseases is a major challenge for farmers, as it is often subjective, prone to misdiagnosis leading to incorrect treatments, time-consuming, demands specialized expertise, and is difficult to implement widely for effective real-time early prevention, allowing diseases to spread and significantly impact crop yields. This research addresses these challenges by developing an automated and easily accessible rice leaf disease diagnosis system. The system is manifested as a mobile application that integrates a Convolutional Neural Network (CNN) model, specifically utilizing the EfficientNetB0 architecture, for the classification of rice leaf images and leverages key Firebase services such as its Realtime Database for data synchronization and Cloud Storage for image management to ensure a scalable and responsive backend. The methodology involved several key stages. Firstly, the CNN model was developed by employing a transfer learning approach on the pre-trained EfficientNetB0 architecture. Secondly, the model underwent comprehensive testing using a dataset of 1,000 new rice leaf images, which were independently validated by agricultural experts. The results demonstrated that the developed CNN model achieved a global accuracy of 85.9%, with an average precision of 86.1% and recall of 85.9% (macro-average) in the expert validation testing phase with the 1,000 new images. However, the study also identified variations in the model's performance across different disease classes, highlighting areas that require further optimization to enhance detection effectiveness for specific types of rice leaf diseases. The primary benefit of this research is the provision of a practical rice leaf disease diagnosis tool that is readily accessible to farmers via a mobile application, empowering them with timely and accurate information for effective crop management. This can lead to reduced crop losses, improved yield quality, and contribute significantly to national food security. Furthermore, this research contributes to the field of applied machine learning and mobile computing in resource-constrained agricultural environments, offering valuable insights for the development of impactful informatics solutions.

Keywords : *Agricultural Technology, Convolutional Neural Network, Mobile Application, Mobile Integration, Rice Leaf Disease Detection.*

1. INTRODUCTION

Rice is a vital agricultural commodity in Southeast Asia, serving as a staple food [1] and an economic pillar [2], [3]. As the primary food crop for more than half of the global population, its production is crucial for food security and economic stability [4], [5]. In Southeast Asia, rice cultivation supports families and millions of farmers, influencing trade policies, national economies, and cultural practices [6]. Rice farming faces challenges from diseases such as Bacterial Leaf Streak, Dead Heart, Hispa, Bacterial Leaf Blight, Blast, Brown Spot, Downy Mildew, Bacterial Panicle Blight, and Tungro,

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which reduce crop yields and lower quality, thereby causing economic problems for farmers and consumers [7], [8]. These diseases lead to significant crop losses, impacting food availability and increasing global rice prices [9]. Such crop losses exacerbate food insecurity, especially in rice-dependent countries. Therefore, understanding and addressing these diseases are crucial for sustainable rice production and food security [10], [11].

The utilization of Convolutional Neural Networks (CNNs) in mobile applications offers a solution for real-time plant disease detection that is accessible to farmers [12], [13]. Using mobile devices, farmers can analyze plant images with a CNN model and receive instant feedback for timely disease management [14], [15]. This application helps farmers make better decisions despite limited technical knowledge, enhances diagnostic efficiency, and allows for early problem identification to reduce crop losses [16], [17]. Furthermore, mobile applications can facilitate continuous data collection from farmers to refine CNN models [18], and encourage collaboration and knowledge sharing, which can improve model performance over time [19], [20].

A major constraint is the lack of easy-to-use, real-time disease detection tools, while conventional methods like visual inspection are subjective and often delay identification [21], [22]. This delay risks significant crop losses, especially with rapidly spreading diseases. Innovative, technology-based solutions like CNNs are urgently needed. CNNs are effective in analyzing and recognizing visual patterns in plant disease images [23] and have proven superior to traditional methods in speed and detection accuracy [24], [25], [26]. Integrating CNNs into mobile applications makes these advanced detection capabilities accessible to farmers, empowering them to manage crops more effectively through real-time analysis and immediate feedback [24].

While several studies have explored CNNs for plant disease detection, including rice diseases, and some have proposed mobile applications, several gaps remain. Many existing solutions may focus on limited disease sets [27], rely on datasets captured under controlled laboratory conditions which may not generalize well to diverse field environments [28], or lack rigorous validation with new, unseen field data assessed by agricultural experts [15]. Furthermore, some applications might not be optimized for usability by farmers with varying technical literacy or may lack a robust backend for data management and potential future scalability [12]. This highlights the need for a mobile diagnostic tool that is not only accurate, leveraging advanced CNN architectures, but also validated under realistic field conditions, user-friendly for the target agricultural community, and built upon a scalable backend infrastructure.

This research aims to address these gaps by introducing a mobile application designed for farmers in the Indonesian context to diagnose rice leaf diseases using a CNN model, specifically EfficientNetB0 known for its balance of accuracy and computational efficiency suitable for mobile deployment. The goal is to improve detection accessibility, efficiency, and accuracy. Given the importance of rice farming, technology-based disease management is vital for enhancing productivity. This application offers a user-friendly, real-time tool for field use, supported by a CNN model for image classification. For its functionality, the application integrates Firebase cloud services. Firebase was chosen for its robust suite of tools tailored for mobile application development, including its Realtime Database for efficient data synchronization of diagnostic results and image metadata, Firebase Cloud Storage for scalable storage of rice leaf images, and its inherent scalability to handle a growing user base and data volume. This backend choice facilitates rapid diagnosis, timely action by farmers, and historical data tracking, while the application prioritizes a simple and easy-to-operate user interface (UI) for farmers with varying technical skills.

The main objectives of this research are: (1) To develop a mobile application integrating an EfficientNetB0-based CNN model for the accurate diagnosis of common rice leaf diseases. (2) To rigorously evaluate the model's performance and generalization capability using a new dataset of rice leaf images collected from diverse field conditions and independently validated by agricultural experts.

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(3) To implement a user-friendly mobile interface coupled with a scalable Firebase backend to provide a practical and accessible diagnostic tool for farmers. The key contributions of this work include: (a) a validated mobile-based diagnostic tool specifically for rice leaf diseases prevalent in regions like Indonesia; (b) empirical evidence on the performance of the EfficientNetB0 architecture on real-world, expert-annotated field images of rice diseases; and (c) a practical system architecture leveraging mobile and cloud technologies that can be adapted for other agricultural diagnostic applications.

2. RESEARCH METHODOLOGY

The research methodology is illustrated in Figure 1, which provides an overview of the stages involved in the research conducted by the researchers:

Figure 1. Research Flow Diagram

2.1. System Architecture Design

This research developed a mobile-based platform for efficient, real-time diagnosis of rice leaf diseases. The system combines a Convolutional Neural Network (CNN) for image analysis with a backend infrastructure for request processing and data management, as detailed in Figure 2. The operational flow begins when a farmer captures a rice leaf image via the mobile application. This image is sent as a request to a Virtual Private Server (VPS), which then forwards it to an Application Programming Interface (API). The API, built with Bun.js (request handling) and Python (processing logic), bridges the mobile application and the EfficientNetB0 CNN model. The API relays the image to the CNN model, which analyzes it and returns a disease prediction. The API then sends this diagnostic result back to the mobile application, either via the VPS or directly (see Figure 2 for data paths). For data persistence, the API logs diagnostic information (image reference, results) into a PostgreSQL database. The mobile application can also directly query this database for user diagnostic history. This architecture provides a responsive, cloud-based solution to aid farmers in rapid crop health management.

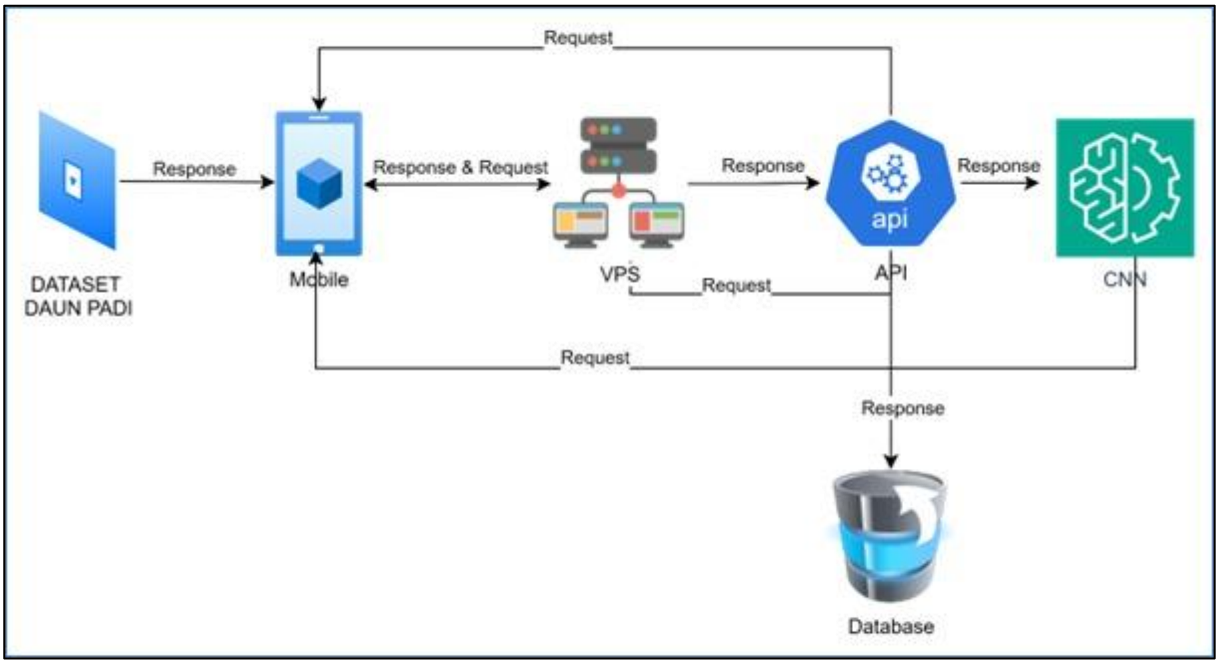

Figure 2. Architecture of Rice Leaf Disease Detection Mobile Application

2.2. Data Collection and Pre-processing

Two distinct datasets were employed for model development and evaluation. First, a public Kaggle dataset (https://www.kaggle.com/datasets/subhauiioo/rice-disease-detection) containing 10,407 images of rice leaves, categorized by various diseases (e.g., Bacterial Leaf Blight, Rice Blast, Brown Spot) and healthy states, served as the primary data for model training. This dataset was divided into 80% for training, 15% for validation (for hyperparameter tuning and preventing overfitting), and 5% for initial testing to ensure a fair evaluation of generalization, with detailed counts provided in Table 1.

Table 1. Rice Leaf Disease Dataset from Kaggle (Source: [13])

No	Disease Name	Number of Original Dataset	Number of Testing Dataset	Number of Training Dataset	Number of Validation Dataset
1	Normal	1764	89	1411	264
2	Bacterial leaf blight	479	25	383	71
3	Bacterial leaf streak	380	19	304	57
4	Bacterial panicle blight	337	18	269	50
5	Blast	1738	88	1390	260
6	Brown spot	965	49	772	144
7	Dead hearth	1442	73	1153	216
8	Downy mildew	620	31	496	93
9	Hispa	1594	80	1275	239
10	Tungro	1088	55	870	163
	Total Number of Disease = 10	Original Dataset = 10.407	Testing Dataset = 527	Training Dataset = 8323	Validation Dataset = 1557

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Second, to assess real-world performance, a field dataset of 1,000 rice leaf images was collected directly from paddy fields under diverse weather and plant conditions. This dataset, comprising 100 images for each of the 10 disease/healthy classes (detailed in Table 2), was exclusively used for expert validation of the trained model's ability to identify diseases in more varied and unstructured environments.

Table 2. Rice Leaf Disease Dataset Collected Directly from Paddy Fields

No	Disease Name	Number of Data
1	Normal	100
2	Bacterial leaf blight	100
3	Bacterial leaf streak	100
4	Bacterial panicle blight	100
5	Blast	100
6	Brown spot	100
7	Dead hearth	100
8	Downy mildew	100
9	Hispa	100
10	Tungro	100
	Number of Disease = 10	Dataset = 1000

Prior to CNN model input, images underwent preprocessing to standardize data and enhance model performance. Key steps included resizing all images to a consistent dimension (e.g., 256x256 pixels) and normalizing pixel values to a 0-1 range. To improve model robustness against field condition variability (e.g., lighting, camera angles, orientation), reduce overfitting, and increase the effective size of the training data, augmentation techniques such as random rotations, flips, and color adjustments were applied. These preprocessing and augmentation steps are crucial for developing a model that can accurately classify rice leaf diseases under diverse real-world conditions.

2.3. CNN Model Development & Training

The CNN model architecture implemented in this research is designed to classify diseases in rice leaf images, utilizing EfficientNetB0, known for its balance of high accuracy and computational efficiency. The conceptual workflow, illustrated in Figure 3, encompasses image input, feature extraction, and classification stages.

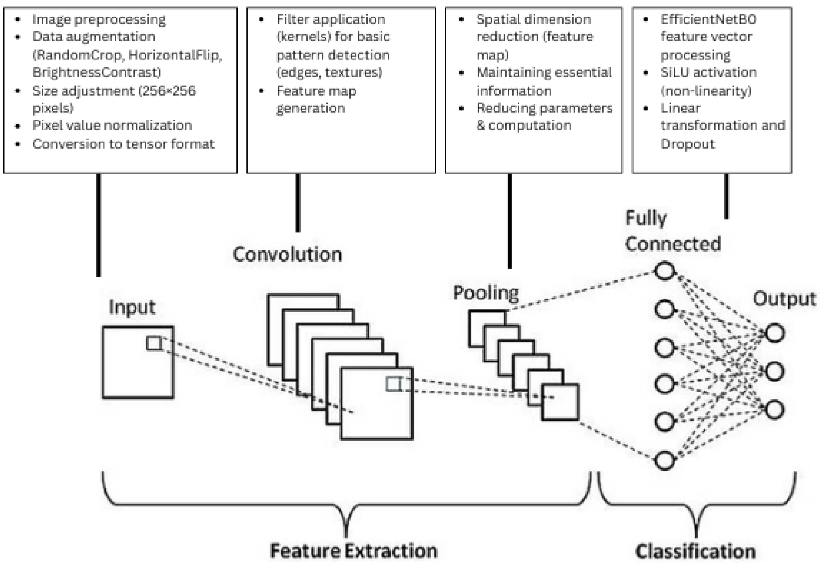

Figure 3. CNN Architecture (Adapted from: [29])

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The process begins with input images, preprocessed as detailed in Section 2.2 (including augmentation, resizing to 256x256 pixels, normalization, and tensor conversion). This tensor data is then fed to the model in batches using torch.utils.data.DataLoader. The core of the model performs feature extraction using the pre-trained EfficientNetB0 base. EfficientNetB0, initially trained on ImageNet, excels at identifying diverse visual features through its sophisticated architecture comprising numerous convolutional layers (including depthwise separable convolutions), pooling layers, and squeeze-and-excitation blocks. This stage transforms the input image into a 1000-dimension feature vector. This feature vector subsequently enters the classification stage. As depicted by the Fully Connected layers in Figure 3, this stage maps extracted features to the 10 target disease classes (including healthy leaves). The custom classifier head consists of a dropout layer (probability 0.25) applied to the 1000-dimension feature vector, followed by a fully connected layer (fc1) reducing dimensionality to 128. A SiLU (Sigmoid Linear Unit) activation function introduces non-linearity. Another dropout layer (probability 0.5) is applied for further regularization before a final fully connected layer (fc2) maps the 128-dimension vector to 10 output neurons. These output logits are converted to a logarithmic probability distribution using a log_softmax activation function, yielding the model's final predictions.

The model's training commenced with initialization by loading weights from a previously saved checkpoint (model_best.pth.tar). For the fine-tuning strategy, based on the provided code, at least the final classifier layer of the base EfficientNetB0 (efficient_net.classifier.1) and the custom fully connected layers (fc1, fc2) were set to be trainable. Stochastic Gradient Descent (SGD) was employed as the optimizer, configured with an initial learning rate of 1x10-5, momentum of 0.9, and weight decay of 1x10-5. The optimizer's state was also loaded from the checkpoint. The CrossEntropyLoss function was utilized to compute the difference between predicted and actual labels. Training was conducted for a total of 100 epochs, resuming from epoch 10 as indicated by the training loop (range(10, EPOCHS)), with a batch size of 128. The learning rate was managed through two mechanisms: a step decay function (lr = initial_lr * (0.1 ** (epoch // 30))) applied at the start of each epoch, and a CosineAnnealingLR scheduler (with T_max=10, eta_min=1e-6) whose step() method was invoked after each validation phase based on validation loss. Throughout the training, after each epoch, the model's performance was evaluated on the validation set. A checkpoint, including the model state, optimizer state, and the best validation accuracy achieved so far, was saved if the current epoch's validation accuracy (acc1) surpassed the previous best. The entire training process was conducted using PyTorch on a system equipped with a GPU.

2.4. Mobile Application Development

The mobile application for rice leaf disease diagnosis was developed using the Flutter cross-platform framework, chosen for its ability to create responsive, high-performance applications compatible with both Android and iOS, thereby ensuring broad accessibility for farmers with varying device capabilities. The primary design focus was to simplify disease detection and management through an intuitive user interface (UI), particularly for image capture and receiving diagnostic results, while ensuring efficient data handling and minimal device resource consumption. This application utilizes a hybrid backend architecture to leverage the distinct advantages of different cloud services. Firebase handles user authentication and related functionalities. The core image processing and diagnostic data management are handled by a custom backend consisting of a Virtual Private Server (VPS) running a Bun.js and Python-based API, with PostgreSQL as the primary database. This hybrid approach combines Firebase's ease of use for user-facing services with the control and flexibility of a custom VPS setup for intensive computations and structured data storage.

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The application usage flow, illustrated in the updated Figure 4, begins with user authentication via Firebase. Once authenticated, the farmer can access disease information or capture an image of a suspect rice leaf. This image is then securely transmitted to the VPS, where the API processes the request and forwards the image to the pre-trained CNN model (detailed in Section 2.3) for analysis. The diagnostic result from the CNN is returned via the API to the mobile application for display to the user. The expert validation workflow is also integrated: experts can review diagnoses through the app, and their validated labels (correct or corrected) are submitted via the API and stored in the PostgreSQL database, facilitating continuous model improvement.

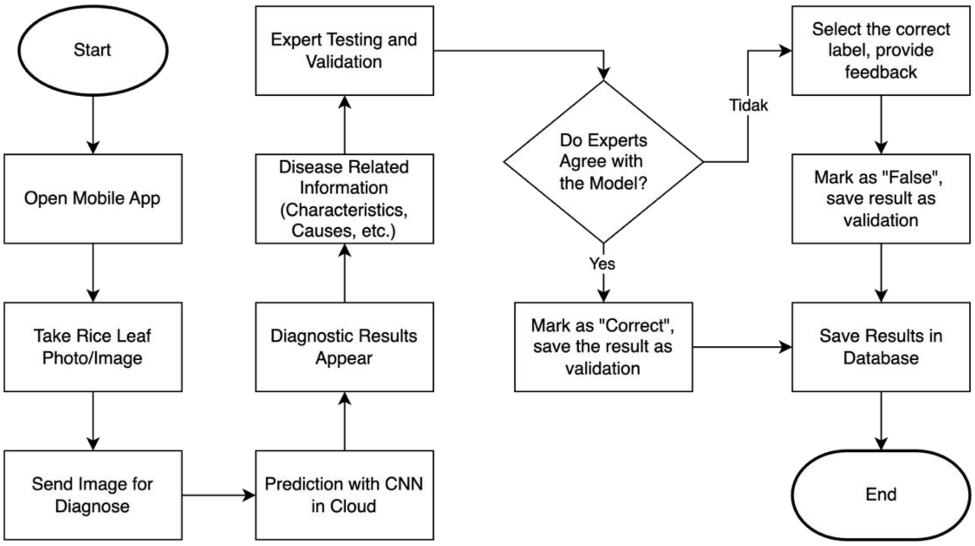

Figure 4. Application Usage Flow Diagram

Data management is distributed across the hybrid backend. The PostgreSQL database, managed via the VPS-hosted API, serves as the primary repository for diagnostic results, image metadata (references/paths, upload timestamps), expert validation data, and potentially anonymized geographical or plant condition data. Each uploaded image and its associated diagnosis are linked to ensure traceability. Firebase Firestore (or Realtime Database) may be used to store user profile information linked via Firebase Authentication UIDs and potentially application settings or pointers to results for quick user access, while image files themselves might be temporarily stored or directly processed by the VPS. The application's UI is designed with simplicity and intuitiveness as core principles, ensuring ease of operation for farmers with diverse technical backgrounds. Clear navigation, appropriately sized interactive elements, and a streamlined workflow for image submission and result retrieval minimize user confusion. Diagnostic results are presented clearly, often with actionable advice. This user-centric design, combined with the robust and flexible hybrid backend, aims to provide an effective and accessible tool for farmers to manage rice crop health more efficiently.

2.5. System Testing and Expert Validation

The system's CNN model performance was rigorously evaluated through an expert testing and validation process using 1,000 new rice leaf images. This dataset was entirely independent of the model's training, development-phase validation, or initial testing sets, ensuring an objective assessment of generalization capability under real-world conditions. These images, encompassing various types of diseases and healthy leaf conditions, were initially unlabeled by the system. The CNN model first performed disease class predictions for each of the 1,000 images, and these initial predictions were recorded. Subsequently, agricultural experts from Jenderal Soedirman University conducted a thorough

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review using the developed mobile application. For each image, experts compared the original leaf photo with the model's prediction and its associated confidence score. If an expert deemed the model's prediction correct, it was validated as "Correct." Conversely, if an expert disagreed, they selected "Incorrect," provided the accurate disease label, and could include feedback regarding the discrepancy. This corrective feedback is crucial for future model refinement.

All expert feedback, including validations, corrections, and reasons for discrepancies, was systematically recorded. The database was subsequently updated with these expert-validated labels, creating an enriched dataset containing both the model's initial predictions and the final expert-verified labels. This validated dataset serves as a valuable asset for future retraining efforts, enabling continuous improvement of the model's accuracy. ollowing the complete review and validation of all 1,000 images, a comprehensive performance evaluation was conducted. Standard metrics, including accuracy, precision, recall, and F1-score, were calculated based on the expert validation results. These metrics are defined as follows, where TP (True Positives) are correctly identified positive instances, FP (False Positives) are negative instances incorrectly identified as positive, FN (False Negatives) are positive instances incorrectly identified as negative, and TN (True Negatives) are correctly identified negative instances. Precision is calculated as:

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

Recall (sensitivity) is calculated as

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

Specify is calculated as

$$Specify = \frac{TN}{TN+FP} \quad (3)$$

F1-Score is calculated as

$$2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

A confusion matrix was also generated to analyze the distribution of correct and incorrect predictions across each disease class. These analyses provide a deep understanding of the model's strengths and areas requiring further improvement.

3. RESULTS

3.1. CNN Model Performance Context and Initial Benchmarking

To establish a baseline and provide context for the CNN model developed in this study, performance metrics from a relevant previous study by the authors [30] are presented in Table 3. This earlier work, which also focused on rice leaf disease classification using a similar CNN approach, reported a global accuracy of 98.86% on its specific dataset and under its testing conditions. This included a micro-precision of 100% and a micro-recall of 99.42%. These prior results (Table 3) served as an internal benchmark and highlighted the potential of CNNs, thereby motivating the current research's focus on development and rigorous validation on an entirely new, field-collected dataset with expert oversight.

Table 3. CNN Model Performance in Previous Research (Source: [30])

Metric	Score
Accuracy	98,86%
Precision	100%
Recall	99,42%
F1-Score	99,70%

3.2. Mobile Application Interface for Diagnosis and Validation

The developed mobile application, built using Flutter, served as the primary platform for both potential farmer use and for conducting the expert validation process in this study. Key aspects of the application's user interface (UI) are illustrated in Figure 5. The "History" feature (Figure 5.a) allows users to track past diagnoses, providing details such as disease type, date, and thumbnail images. A detailed diagnostic view (Figure 5.b) presents images of infected leaves along with comprehensive disease descriptions, symptoms, potential causes, and comparative reference images. The application also features a dashboard (Figure 5.c) capable of displaying summary statistics; in this study, it was utilized to visualize aspects of the validation data.

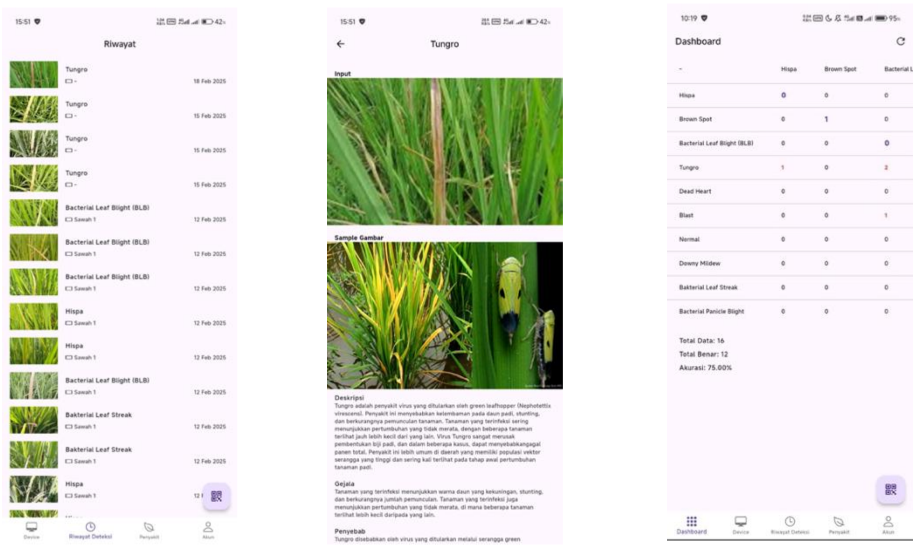

Figure 5. a) Application History Section, b) Detailed Disease Diagnosis View, c) Dashboard View

The expert validation workflow was directly integrated into the mobile application. Figure 6 shows the dedicated interface used by experts. It presented the input image alongside the model's prediction, a reference sample image, and supporting information about the predicted disease (Figure 6.a). Experts then used options to mark the diagnosis as "Valid Data" or "Invalid Data" (Figure 6.b). Validations were confirmed (Figure 6.c), while for invalid diagnoses, experts could provide the correct label and additional feedback, all of which was stored for subsequent analysis and model refinement

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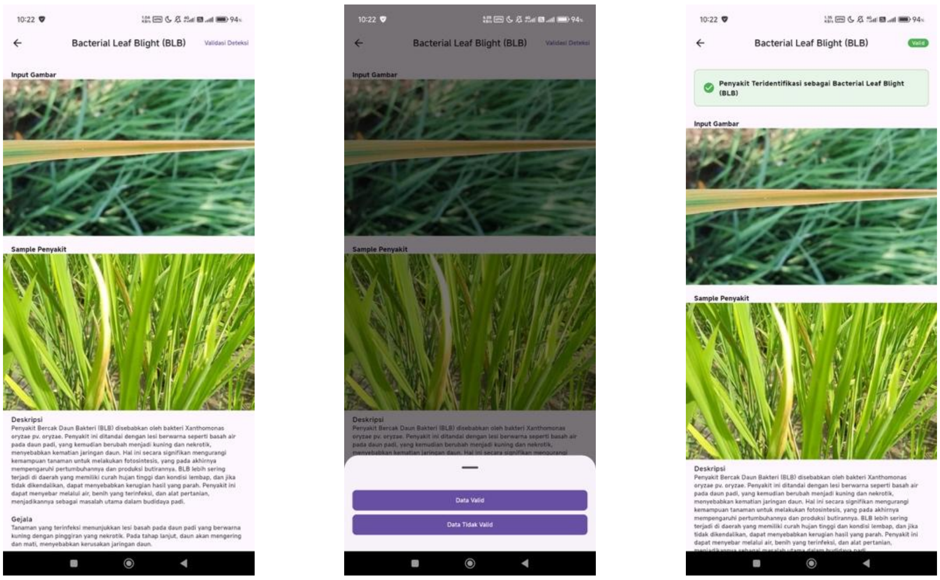

Figure 6. a) Initial Validation View, b) Validation Choices, c) Confirmation after Validation

3.3. Expert Validation of the Developed CNN Model

The core performance evaluation of the CNN model developed in this research was conducted through the expert validation process detailed in Section 2.5, utilizing the mobile application interface described above and the 1,000 new rice leaf test images. A confusion matrix, presented in Table 4, visually summarizes the model's prediction accuracy against the actual classes determined by the experts. The matrix rows represent the actual disease classes, while the columns indicate the predicted classes. Diagonal values denote correct classifications (True Positives, TP) for each class, and off-diagonal values represent misclassifications. With 100 samples for each of the 10 classes, Table 4 provides a comprehensive overview of prediction frequencies and error types.

Table 4. Confusion Matrix of Expert Validation Results

Class	Normal	Bacterial Leaf Streak	Dead Heart	Hispa	Bacterial Leaf Blight	Blast	Brown Spot	Downy Mildew	Bacterial Panicle Blight	Tungro	Total
Normal	85	5	2	3	1	1	2	0	0	1	100
Bacterial Leaf Streak	3	90	2	1	1	1	0	1	1	0	100
Dead Heart	2	3	84	4	2	1	1	2	0	1	100
Hispa	4	2	3	85	1	2	2	0	1	0	100
Bacterial Leaf Blight	3	4	2	2	79	2	1	3	1	3	100
Blast	2	1	1	3	1	89	2	0	1	0	100
Brown Spot	1	1	2	2	2	1	87	1	1	2	100
Downy Mildew	2	2	1	1	3	1	1	86	0	3	100
Bacterial Panicle Blight	3	1	1	2	2	1	1	0	88	1	100
Tungro	3	1	1	1	4	0	2	1	1	86	100

Detailed quantitative performance metrics, calculated based on the confusion matrix (Table 4) and defined in Section 2.5 (Eq. 1-4), were determined for each class. As an illustration, for the "Normal" class, with TP=85, FP=23, and FN=15 from Table 4, the Precision (Eq. 1) is 0.787, Recall (Eq. 2) is

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0.85, Specifity (Eq. 3) is 0.9744, and F1-Score (Eq. 4) is 0.8173. A similar calculation process was applied to all disease classes, with the comprehensive results presented in Table 5.

Table 5. Test Results on Mobile Application

Class	TP	FP	FN	TN	Support	Precision	Recall (Sensitivity)	Specificity	F1-Score
Normal	85	23	15	877	100	0.787	0.85	0.9744	0.8173
Bacterial Leaf Streak	90	20	10	880	100	0.8182	0.9	0.9778	0.8571
Dead Heart	84	15	16	885	100	0.8485	0.84	0.9833	0.8442
Hispa	85	19	15	881	100	0.8173	0.85	0.9789	0.8333
Bacterial Leaf Blight	79	17	21	883	100	0.8229	0.79	0.9811	0.8061
Blast	89	10	11	890	100	0.899	0.89	0.9889	0.8945
Brown Spot	87	12	13	888	100	0.8788	0.87	0.9867	0.8744
Downy Mildew	86	8	14	892	100	0.9149	0.86	0.9911	0.8866
Bacterial Panicle Blight	88	6	12	894	100	0.9362	0.88	0.9933	0.9072
Tungro	86	11	14	889	100	0.8866	0.86	0.9878	0.8731
Total	**859**	**141**	**141**	**8859**	**1000**				
Average						**0.86094**	**0.859**	**0.98433**	**0.8594**

The overall model performance, based on the expert validation of 1,000 test samples (Table 5), shows a global accuracy of 85.9% (859 correct predictions). The macro-average precision, recall, and F1-score were 0.8609, 0.8590, and 0.8594, respectively. The micro-average values for these metrics were 0.8590, consistent with the global accuracy. Analysis of per-class metrics in Table 5 indicates performance variation. The model demonstrated strong performance for classes such as Blast (Recall 0.89, Precision 0.899) and Bacterial Panicle Blight (Precision 0.9362, Recall 0.88). Good performance was also observed for Bacterial Leaf Streak (Recall 0.90). Other classes, including Dead Heart, Hispa, Brown Spot, Downy Mildew, and Tungro, showed fairly good performance, though with some instances of false positives or false negatives. This variability highlights areas for potential future model refinement. A detailed comparison with other state-of-the-art studies will be presented in the Discussion section.

4. DISCUSSION

This research focused on developing and evaluating a mobile-based system using a Convolutional Neural Network (CNN) model, specifically EfficientNetB0, for the diagnosis of rice leaf diseases. The model achieved a global accuracy of 85.9% when tested on 1,000 new images independently validated by agricultural experts, with macro-average precision, recall, and F1-score of 0.8609, 0.8590, and 0.8594, respectively. These results underscore the model's potential for practical field application and its generalization capability on real-world data. However, analysis of per-class metrics (Table 5) and the confusion matrix (Table 4) revealed performance variations. While the model demonstrated high effectiveness for diseases like Blast and Bacterial Panicle Blight, challenges were observed with others, such as Bacterial Leaf Blight, and some misclassifications occurred for the "Normal" (Healthy) class. This variability is likely attributable to visual similarities between certain disease symptoms or diverse disease manifestations not fully captured during training.

4.1. Comparison with Previous Studies

The 85.9% accuracy achieved in this study on expert-validated field data provides a realistic performance benchmark. This contrasts with our previous work [13], which reported 98.86% accuracy on a different dataset, highlighting the increased challenge and importance of validation on new, diverse field-collected images. The broader field of CNN-based rice disease detection has seen various

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approaches. For instance, [27] explored optimized CNNs combined with SVMs for six common rice diseases using a dataset of 6,330 images, aiming for enhanced detection. Research [28] implemented a pretrained VGG16 model with image segmentation for classifying rice leaf diseases, emphasizing CNNs' efficiency. Study [15] presented a real-time detection framework using Faster R-CNN for multiple rice diseases and pests, showcasing architectural adaptability. While these studies demonstrate the capabilities of different CNN architectures, direct performance comparison is nuanced due to variations in datasets, the number and types of diseases, and validation methodologies.

Several studies have also focused on mobile application development for plant diseases. Research [31] developed a mobile phone application leveraging deep learning for both rice disease and insect pest detection, illustrating the practical deployment of such technologies. Similarly, [12] created an Android application using DCNNs for identifying fall armyworms in maize, and [13] utilized CNNs in a mobile app for detecting Tuta Absoluta damage in tomatoes, both emphasizing accessibility for farmers. While not exclusively on rice, these works underscore the trend and utility of mobile-based diagnostic tools. Our research contributes to this area by not only developing a mobile interface (Figures 5 and 6) but also by rigorously validating the integrated CNN model's performance on new field data specific to rice diseases prevalent in the Indonesian context. The need for such validated, accessible tools is further supported by [32] who evaluated existing plant disease detection apps and stressed the necessity of ensuring quality and effectiveness to meet farmers' needs.

The challenges identified in our study, such as distinguishing diseases with similar symptoms, align with general findings in CNN-based plant disease detection research. Research [33] also noted gaps in previous rice disease detection research, including suboptimal accuracy and unbalanced datasets, issues that data augmentation strategies, as explored by [34], aim to mitigate. Our use of expert validation, as underscored by [35] regarding the necessity of integrating human expertise, adds a layer of robustness to our findings compared to studies relying solely on public dataset splits without field expert oversight.

4.2. Interpretation of Findings and Contributions to Computer Science

The selection of EfficientNetB0 proved suitable for balancing accuracy and computational efficiency, a critical consideration for mobile deployment. The transfer learning approach facilitated model development, particularly valuable when dealing with specialized agricultural datasets that may be limited compared to general image datasets like ImageNet [15]. This study's primary contribution lies in the development and rigorous field-data validation of a mobile-accessible diagnostic tool. From an informatics and computer science perspective, this research demonstrates a practical application of machine learning and mobile computing to address real-world agricultural challenges. It contributes to applied computer vision by tackling image-based classification in complex, uncontrolled field environments, which often present greater variability than laboratory conditions. Furthermore, it illustrates the design and potential of mobile decision support systems for delivering timely, data-driven insights to end-users like farmers in resource-constrained settings. The integration of an expert validation loop within the application (Figure 6) also highlights a pathway for human-AI collaboration, where expert knowledge refines AI models, a growing area of interest in applied AI. The performance variations across disease classes suggest that visual symptom similarity remains a challenge, pointing to the need for more sophisticated feature extraction techniques or multi-modal data integration in future iterations.

4.3. Limitations of the Study

Despite the promising results, this study has several limitations that should be acknowledged. The scope of the dataset, while including a new 1,000-image expert-validated field set, could be expanded;

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larger datasets encompassing greater geographical diversity, more rice varieties, varying growth stages, and multiple seasons might further enhance model robustness and generalization. The initial training relied on a public Kaggle dataset, which may carry inherent biases and not fully represent all local field conditions in Indonesia. Furthermore, evaluation of the mobile application's performance—such as image upload times across different network conditions, task success rates for farmers, and system resource consumption on various devices—was not conducted in this research phase. The current evaluation also did not include Receiver Operating Characteristic (ROC) curve or Area Under the Curve (AUC) analysis. Finally, the model's applicability is currently limited to the 10 specific rice leaf diseases (and healthy leaves) included in this study.

4.4. Future Research Directions

Building upon the current findings and addressing the identified limitations, future research will focus on several key areas. Model enhancement will be a priority, aiming to further improve accuracy and recall, especially for diseases that are currently harder to distinguish; this will involve exploring advanced data augmentation techniques, incorporating larger and more diverse training datasets from various Indonesian regions and seasons, and potentially investigating more sophisticated CNN architectures or ensemble methods. Another direction is to expand the disease and pest repertoire, extending the model's capability to identify a wider range of rice diseases and common pests to provide a more comprehensive diagnostic tool. The integration of IoT and environmental data also presents a promising avenue, where data from IoT sensors (e.g., monitoring weather conditions, soil moisture, temperature) could enable predictive analysis of disease outbreaks, serving as additional input to the model or triggering alerts for proactive crop management. Significant effort will also be directed towards enhancing the user interface and experience by conducting usability studies with farmers to gather feedback for refining the mobile application's interface, with a focus on accessibility for users with varying levels of digital literacy and incorporating features based on their practical needs. Finally, conducting rigorous quantitative application performance evaluation, including testing upload/processing times under different network conditions and task success rates, will be essential for assessing real-world viability.

5. CONCLUSION

This research successfully developed and validated a mobile-based system integrating an EfficientNetB0 model for rice leaf disease diagnosis, achieving a global accuracy of 85.9% on a challenging set of 1,000 new images independently validated by agricultural experts. While performance varied across disease classes, this result demonstrates a significant capability for practical field application. The key contributions of this study include: (1) the development of an accessible mobile diagnostic tool tailored for common rice leaf diseases; (2) the rigorous validation of the EfficientNetB0 model on a novel, expert-annotated field dataset, providing a realistic performance benchmark; and (3) the design of a system architecture (integrating mobile, cloud/server, and database technologies) that facilitates this diagnostic process. The application developed has the distinct potential to empower farmers, particularly in resource-constrained regions like Indonesia, by providing an easily accessible and rapid diagnostic tool. Such a system can lead to more timely and accurate disease identification, enabling targeted interventions, potentially reducing reliance on broad-spectrum pesticides, minimizing crop losses, and ultimately contributing to improved yields and sustainable rice farming practices. This work forms a basis for the continued modernization of agricultural practices through accessible technology.

From a computer science perspective, this research contributes significantly to the field of applied artificial intelligence in agriculture. It demonstrates the practical deployment of deep learning models

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(EfficientNetB0) on mobile platforms for complex image recognition tasks within challenging, real-world agricultural environments. Furthermore, the study underscores the importance of robust validation methodologies, including expert verification, for building trustworthy and effective AI systems. The development of the backend infrastructure also offers insights into creating scalable and maintainable solutions for agricultural data management and diagnostic delivery. This work showcases how mobile technology can bridge the gap between advanced AI capabilities and the practical needs of end-users in critical sectors such as food production, providing a foundation for further data-driven agricultural innovations. Future development will focus on enhancing model accuracy and recall, particularly for difficult-to-distinguish diseases, through advanced data augmentation, expanded and more diverse datasets, and potential architectural adjustments. Plans also include broadening the application's diagnostic scope to include a wider range of plant diseases and pests, integrating predictive analytics using environmental data from IoT sensors, and improving usability through formal farmer-led studies and offline functionality. These advancements are anticipated to maximize the system's impact on agricultural productivity and sustainable disease management.

CONFLICT OF INTEREST

The author declares that there is no conflict of interest between the author or the object of research in this study.

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