11 (1) 2025 13-28
Register: *Jurnal Ilmiah Teknologi Sistem Informasi*

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)

Contents lists available at www.journal.unipdu.ac.id

Register

Journal Page is available to www.journal.unipdu.ac.id/index.php/register

Research article

Classification of Betel Leaf Diseases Using Convolutional Neural Networks for Improved Disease Management

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ARTICLE INFO

Article history:
Received May 30th, 2024
Revised September 15th, 2024
Accepted May 4th, 2025
Available online May 17th, 2025

Keywords:
Betel Leaf Diseases
Image Classification
Deep Learning
InceptionResNetV2

Please cite this article in IEEE style as:
R. T. Wahyuningrum, I. H. Ayani, A. Bauravindah, I. A. Siradjuddin, and I. S. Faradisa, "Classification of Betel Leaf Diseases Using Convolutional Neural Networks for Improved Disease Management," *Register: Jurnal Ilmiah Teknologi Sistem Informasi*, vol. 11, no. 1, pp. 13-28, 2025.

ABSTRACT

The practice of traditional medicine utilizing plants, such as betel leaves, is deeply rooted in many cultures and remains significant for treating various ailments. However, diseases affecting betel leaves (Piper Betle L.) pose a critical challenge, as even localized damage to the leaves—typically the most affected part of the plant—can result in significant reductions in both the quality and quantity of yield. Such damage impacts not only the economic value of the crop but also the livelihoods of farmers who depend on its production. This study focuses on enhancing the detection and classification of diseases affecting betel leaves, employing a dataset of 4,000 images divided into four categories: healthy green leaves, anthracnose-infected green leaves, bacterial spot-infected green leaves, and healthy red leaves. Convolutional neural networks (CNN) were used for disease classification, with five architectures—DenseNet201, EfficientNetB3V2, InceptionResNetV2, MobileNetV2, and XceptionResNet50V2—implemented and evaluated. Among these, the InceptionResNetV2 model demonstrated the best performance, achieving 86.0% accuracy, 0.3880 loss, and a 98.0% ROC score, while the other models exhibited limitations due to overfitting and underfitting. This study provides a robust, AI-driven approach tailored to local conditions in Indonesia, supporting farmers with accurate disease detection and timely intervention strategies to reduce yield losses and enhance agricultural productivity.

1. Introduction

In recent years, there has been a resurgence in the use of traditional, complementary, and alternative medicine (TCAM) worldwide [1]. This trend is prevalent not only among ethnic minority populations but also in regions such as Sub-Saharan Africa [2]. The reasons for this shift are multifaceted, with one of the key drivers being the perceived safety and natural properties of traditional medicine [1]. For instance, in the fight against malaria, traditional medicine is being considered as a first-line treatment [3]. This approach could potentially delay the development of resistance in Plasmodium to modern anti-malarials [3]. Similarly, in Pakistan, the growing popularity of complementary and alternative medicine (CAM) further indicates a global shift towards traditional medicine [4].

One commonly used traditional medicine is the betel leaf (*Piper Betle L.*), which is often employed to treat mouth ulcers and vaginal discharge [5]. It is also frequently utilized as a mouthwash or antiseptic [5]. Betel is a natural ingredient that is easily obtainable and does not incur high costs associated with antibiotics [6], [7]. The increasing popularity of betel leaf in traditional medicinal

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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practices highlights the growing demand for natural remedies, especially in regions where access to modern healthcare is limited.

The cultural and medicinal significance of betel leaf (Piper Betle L.) is deeply rooted in various regions around the world, where it is used both traditional medicine and cultural rituals [8]. Traditionally, betel leaf has been valued for its antiseptic, anti-inflammatory, and antimicrobial properties, making it a common ingredient in natural remedies to treating a variety of ailments [9]. Its consumption, whether raw or as part of medicinal preparations, is widespread in many cultures, contributing to its high demand [8].

Beyond its medicinal uses, the cultivation and sale of betel leaf provide a significant source of income for millions of people, particularly in India and Southeast Asia, where it plays an important role in local economies [10], [11]. In Indonesia, betel leaf holds both cultural and economic importance, serving not only as a medicinal herb but also as a raw material for various industries. Studies indicate that in regions like Sidorejo Lor, Salatiga, betel leaf cultivation is a major driver of economic empowerment. A local women's group, Kelompok Wanita Kreatif (KWK) Seroja, has successfully developed betel-based products such as betel chips and betel mojito, highlighting its economic potential [12].

Similarly, in Tangerang, Indonesia, the Betel Leaf Empowerment Hub, an initiative by PT Pertamina Patra Niaga SHAFTHI, has transformed betel leaf into a catalyst for community development. This program engages local communities, including unemployed youth, informal workers, and women, in developing high-value betel-based products such as batik ecoprint, herbal teas (Teh SIJALE), skincare items like betel soap, and even organic pesticides [13]. These efforts demonstrate how betel leaf not only preserves traditional practices but also supports economic resilience through innovation and entrepreneurship.

Surveys indicate that nearly 25 million individuals in India derive their income from activities related to betel leaves, including cultivation, export, import, and management [14], [15]. In Indonesia, particularly in Manjalling, Gowa Regency, betel leaf cultivation contributes significantly to household income. Research shows that betel leaf farming accounts for between 32.43% and 88.88% of a household's total income in certain regions [16]. The relatively low-cost of betel cultivation, combined with increasing market demand, makes it a lucrative agricultural commodity. Farmers in Indonesia often adopt sustainable small-scale farming techniques, such as growing betel in polybags, to enhance yield stability and ensure high-quality production [13].

Over the past decade, the recorded productivity of betel in India has averaged around 1.9 million leaves per hectare [17]. These leaves play a significant role in both local consumption and export markets, contributing substantially to national economic growth. The annual turnover from betel leaf in India is estimated at around USD 120 million , with exports accounting for a major portion of this revenue [18]. Likewise, Indonesia's betel leaf industry demonstrates the country's agricultural diversity and the resilience of local farmers. Despite various challenges, including market fluctuations and farming constraints, they continue to maintain an impressive productivity rate, supporting both livelihoods and national economic development.

However, betel plants are vulnerable to diseases caused by fungi, bacteria, and viruses, which can impact both yield and quality [19]. In Indonesia, farmers have increasingly turned to modern disease prevention methods, such as organic cultivation and improved farming practices, to ensure the sustainability of betel production. Additionally, the integration of technology, particularly artificial intelligence and deep learning, offers promising advancements in disease detection and classification [20]. These technologies can enhance disease monitoring, enabling rapid diagnosis and timely intervention, ultimately resulting in higher crop yields and better quality control.

The field of agriculture is very influential, and artificial intelligence technology is often used in this field [21], [22], [23]. One extensively studied area is the ability to recognize objects using images [24], [25]. Deep learning has positioned itself at the center of machine learning development [26]. Its applications can be implemented in various jobs, such as, predicting possibilities and events, recognizing objects, diagnosing diseases on plant leaves [27], [28], [29], [30]. The purpose of image processing is to enable rapid and accurate identification or classification of diseases in plant leaves and

http://doi.org/10.26594/register.v11i1.4653

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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the processing of large amounts of data at the same time.

Deep learning models have been extensively used for leaf disease detection due to their ability to learn complex patterns and structures from large datasets. For instance, a study conducted by Elfatimi, et al. demonstrated the effectiveness of MobileNet for bean leaf disease detection, achieving over 92% accuracy across three datasets [31]. Similarly, Alam et al. compared nine widely used pre-trained models with a custom CNN for leaf disease detection [32]. Despite the sophisticated architectures and extensive pre-training of the pre-trained models, the custom CNN performed comparably and demonstrated superior efficiency in terms of training speed and memory requirements.

In the context of betel leaf disease detection, Kusuma and Jothi utilized a Vision Transformer alongside deep learning algorithms [19]. They evaluated four deep learning models—VGG19, DenseNet201, ResNet152V2, and the Vision Transformer model. The DenseNet201 model performed best, achieving a testing accuracy of 98.77%, while both the ResNet152V2 and Vision Transformer models also attained high levels of accuracy.

Mannamperumal et al. conducted a study using a Convolutional Neural Network (CNN) for IoT applications [33]. They developed an automated disease detection system that monitors changes in the disease status of the betel plant leaves using the Internet of Things (IoT). Another study by Hridoy et al. employed the EfficientNet B5 model for betel leaf disease detection, achieving a recognition accuracy of 98.84% with a dataset of 10,662 betel leaf images [20].

In conclusion, deep learning models have shown promising results in detecting leaf diseases, including those affecting betel leaf. However, further research is needed to explore additional deep learning models for betel leaf disease detection and to enhance the performance of existing models.

Despite the promising results of various deep learning models for plant disease detection, most studies have been conducted using datasets from different geographical regions, which may not fully reflect the conditions of betel leaf cultivation in Indonesia. The climatic conditions, agricultural practices, and specific disease patterns in Indonesia can differ significantly from those in other countries, potentially affecting the accuracy and reliability of pre-trained models.

Additionally, publicly available datasets for betel leaf disease detection are limited, especially for Southeast Asian regions. This lack of localized data hinders the development of context-specific solutions that could effectively support local farmers in identifying and managing betel leaf diseases.

To address this gap, this study uses a primary dataset collected from betel leaf farms in Indonesia, representing four disease categories commonly found in the region. By applying deep learning models to a locally sourced dataset, this research aims to develop a more accurate and contextually relevant solution for detecting diseases on betel leaves. The findings will provide a foundation for implementing automated disease detection systems that can be effectively used in Indonesia's agricultural environment.

The study implements and evaluates five different CNN architectures—InceptionResNetV2, DenseNet201, EfficientNetB3V2, MobileNetV2, and XceptionResnet50V2—to compare their performance in classifying betel leaf diseases. By leveraging deep learning techniques on a localized dataset, this research not only advances AI applications in agriculture but also provides a practical tool to help farmers in Indonesia take timely measures to prevent the spread of diseases, ultimately enhancing betel leaf production.

The organization of this research is as follows: Section 1 introduces plant diseases and current methods for classifying them, describes the problem statement, and provides solutions as as contributions to research. Section 2 discusses the research methods and dataset. Section 3 presents the experimental results and performance comparisons. Finally, Section 4 describes the conclusions of this research.

2. Materials and Methods

This study considered five CNN architectures, such as InceptionResNetV2 [34], DenseNet201 [35], EfficientNetB3V2 [36], MobileNetV2 [37], and XceptionResnet50V2 [38], to classify betel leaf diseases.

Fig. 1 presents a diagram illustrating the research flow, which involves several stages, including data collection, data preprocessing, data splitting, model building and training, and model analysis and evaluation.

http://doi.org/10.26594/register.v11i1.4653

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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The research process begins with **data collection**, during which images of betel leaves are captured using a Samsung Galaxy A52s smartphone. This ensures high-resolution image acquisition under consistent lighting conditions, which is essential for maintaining dataset quality. After data collection, the images undergo a **pre-processing** stage, where they are resized to 224×224 pixels to standardize input dimensions for deep learning models. Additionally, normalization is applied to scale pixel values, enhancing model convergence and reducing computational complexity.

Once pre-processing is completed, the **dataset is split** into training and testing sets using an 80:20 ratio. The larger training portion enables the model to learn diverse patterns from the data, while the test set is reserved to evaluate model performance on unseen images. The next step involves **modeling and training**, where various Convolutional Neural Network (CNN) architectures, including InceptionResNetV2 and DenseNet201, are implemented. These models are trained on the processed dataset to recognize and classify different types of betel leaf disease.

After training, **the models undergo evaluation** using the testing data, where key performance metrics such as accuracy and the Receiver Operating Characteristic (ROC) Area Under the Curve (AUC) score are assessed. This step ensures that the models generalize well and are effective in classifying leaves as Green health, Green Anthracnose, Green Bacterial Leaf-spot, or Red Healthy leaves. The final stage of the workflow is **performance analysis**, which involves a comparative study of the trained models. This includes examining their strengths, weaknesses, and any potential overfitting or underfitting issues to determine the most suitable architecture for betel leaf disease classification. The research concludes with insights that contribute to improving AI-driven plant disease detection, ultimately aiding farmers manage crop health more efficiently.

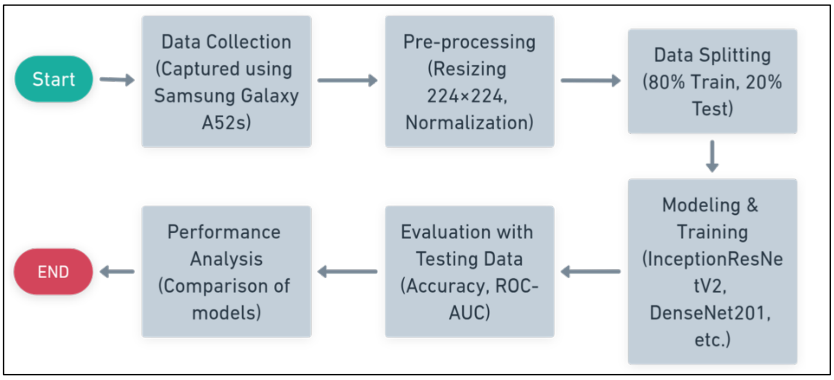

Fig. 1. Flowchart of Research Method

2.1. Dataset

In the process of classifying diseases on betel leaves, a suitable dataset is required, specifically, an image dataset of both disease and healthy betel plants. This datasetis divided into four classes, namely, healthy green betel leaves, anthracnose green betel leaves, bacterial leaf spot betel leaves, and healthy red betel leaves. The dataset is obtained by picking betel leaves and placing them on white paper, then photographing each betel leaves one by one by rotating the betel leaves, until 1000 images are obtained for each class.

The dataset comprises betel leaf images captured using the main camera of a Samsung Galaxy A52s smartphone, which produces images with dimensions of 9248×6936 pixels. The images were taken from a distance of approximately 15 cm, over several days between 09.00and 17.00 local time. A total of 1000 images were obtained, featuring 25 different objects, with 40 different photo angles or poses taken for each object. This dataset includes 4000 images in total.

Incorporating smartphones into agricultural research is well-supported by recent studies demonstrating their effectiveness in plant disease detection and data collection. For instance, a 2021 study developed a mobile application utilizing deep learning to detect and classify plant diseases directly on smartphones, achieving an accuracy of 97.9% on grape disease images without the need for server connectivity [39].

http://doi.org/10.26594/register.v11i1.4653

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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Additionally, a 2022 evaluation of various plant disease detection mobile applications highlighted the current state of artificial intelligence in agriculture. The study identified significant gaps in quality and reliability, emphasizing the need for further development and rigorous testing to achieve practical, field-ready solutions [40].

The collected dataset was then validated by the relevant parties, namely the Agriculture Office of Food Crops, Horticulture and Plantations of Bangkalan Regency at Jl. Soekarno Hatta No. 20 Bangkalan, on February 24, 2023. The following diagram presents the distribution and samples of the dataset, as shown in Fig. 2 and Fig. 3

Fig. 2. Distribution of dataset

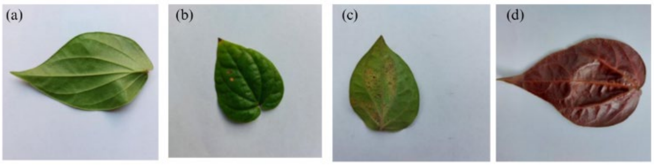

Fig. 3. Betel leaf disease: (a) Green health; (b) Green Anthracnose; (c) Green Bacterial Leaf-spot; (d) Red health

2.2. InceptionResNetV2

InceptionResNetV2 is a deep learning architecture designed to enhance the performance of image classification tasks by combining the strengths of two influential neural network designs: Inception modules and Residual connections [41]. This architecture was introduced by Szegedy et al. (2016). It builds upon earlier Inception versions by incorporating residual connections, which help reduce training time, stabilize the learning process, and enhance accuracy, especially in very deep networks.

The Inception modules enable the model to process input images using different filter sizes simultaneously (e.g., 1x1, 3x3, and 5x5 convolutions). This allows the network to capture both fine details and broader features in the images, making it well-suited for tasks such as distinguishing healthy leaves from diseased ones in betel leaf images. The addition of Residual connections helps the network avoid common issues such as vanishing gradients by creating shortcut paths that allow information to bypass certain layers, ensuring important features from earlier layers are preserved as the data progresses through the network.

Fig. 4 (a) illustrates the overall architecture of the InceptionResNetV2 model. The network starts with a stem block, shown in Fig. 4 (b), which processes the input image (size 299x299x3) and extracts basic features. The image is then passes through several layers, including Inception-ResNet blocks (A, B, and C) and Reduction blocks (A and B), which gradually refine the extracted features to make them more suitable for classification.

The InceptionResNetV2 architecture includes three main types of Inception-ResNet blocks, as shown in Fig. 5: Block A (Fig. 5a) focuses on capturing fine-grained details in the image, such as small spots or discolorations that indicate disease. Block B (Fig. 5b) captures medium-sized patterns and combines smaller and larger filters to detect more complex features. Block C (Fig. 5c) focuses on broader patterns to capture the overall structure of the leaf.

http://doi.org/10.26594/register.v11i1.4653

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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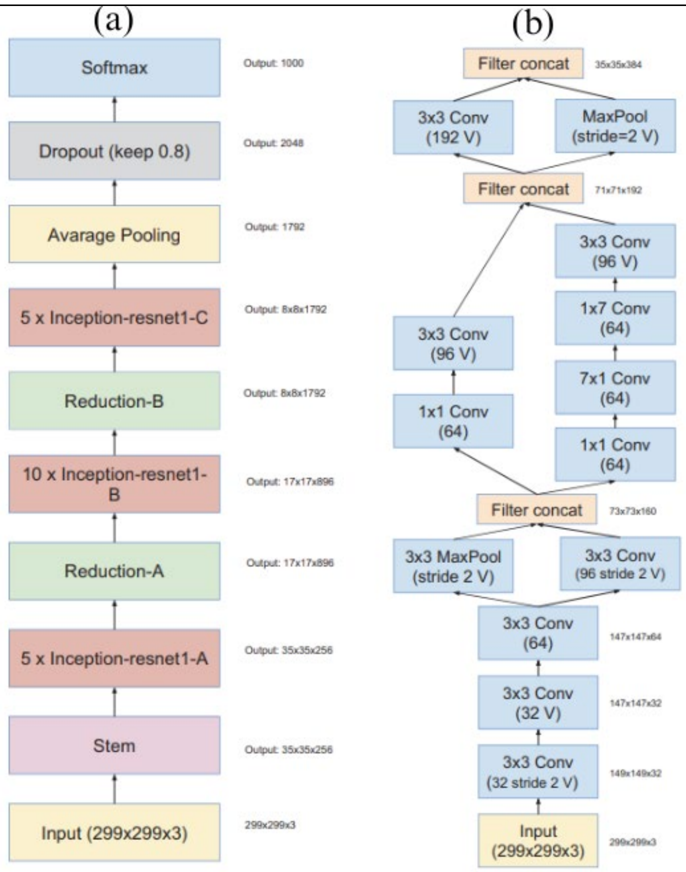

Fig. 4. Architecture of: (a) InceptionResNetV2; (b) steam block [34]

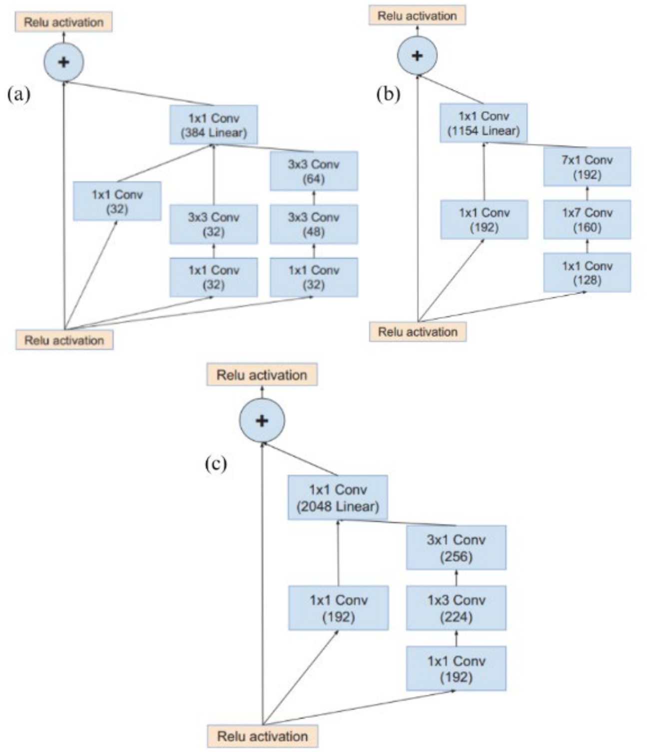

Fig. 5 InceptionResnet: (a) block-A; (b) block-B; (c) block-C [34]

To further reduce the size of the feature maps and improve efficiency, two Reduction blocks (A and B) are used, as shown in Fig. 6. These blocks perform downsampling operations that reduce the dimensions of the feature maps while retaining important information. Reduction block A focuses on reducing the image from 35x35 to 17x17 dimensions, while Reduction block B further reduces it to 8x8 dimensions.

http://doi.org/10.26594/register.v11i1.4653

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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The final layers of the network include average pooling, dropout, and a softmax layer for classification into predefined classes, such as healthy or diseased betel leaves. The use of dropout with a keep rate of 0.8 helps prevent overfitting, ensuring that the model generalizes well to unseen data.

By leveraging the combination of Inception modules and residual connections, InceptionResNetV2 provides a robust solution for automating the detection of betel leaf diseases, helping farmers identify problems early and apply the necessary treatments to prevent crop loss.

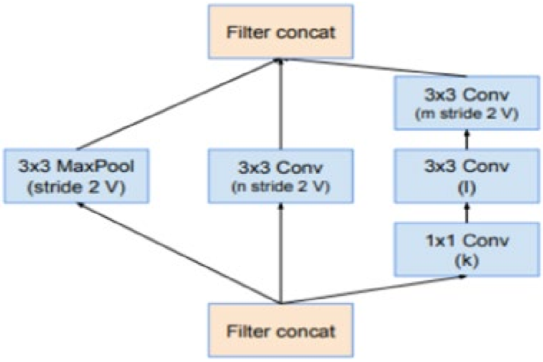

Fig. 6 (a) Reduction block-A [34]

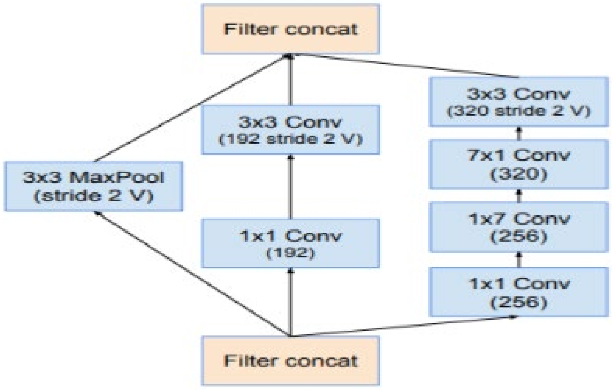

Fig. 6 (b) Reduction block-B [34]

2.3. Evaluation Metrics

The performance of a classification model can be assessed using various evaluation metrics to determine how well the model predicts the desired output. In this study, two primary evaluation metrics were used: accuracy and Receiver Operating Characteristic (ROC) Area Under the Curve (AUC). These metrics help to comprehensively evaluate the model's ability to correctly classify betel leaf diseases and distinguish between the different disease categories.

2.3.1 Accuracy

Accuracy is one of the most commonly used evaluation metrics for classification tasks. It measures the proportion of correct predictions made by the model out of the total number of predictions. In other words, it indicates how often the model makes the correct decision. The formula for calculating accuracy is shown in equation (1).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \tag{1}$$

Where: True Positives (TP): The number of correctly predicted cases where the model identifies a diseased betel leaf category correctly (e.g., correctly classifying a "Green Anthracnose" leaf as "Green Anthracnose"). True Negatives (TN): The number of correctly predicted cases where the model identifies a healthy betel leaf correctly as "Green health" or another non-target class correctly. False Positives (FP): The number of incorrectly predicted cases where the model misclassifies a healthy leaf or another disease type as a different disease (e.g., classifying a "Green health" leaf as "Green Bacterial Leaf-spot"). False Negatives (FN): The number of incorrectly predicted cases where the model fails to detect a diseased leaf, classifying it incorrectly as healthy or as another disease type (e.g., misclassifying a "Red health" leaf as "Green health").

In this study, accuracy was used to compare the performance of different CNN architectures in classifying betel leaf diseases. While accuracy is a useful metric, it has limitations when dealing with imbalanced datasets, where one class may dominate the data. In such cases, accuracy alone may not provide a complete picture of the model's performance.

2.3.2 Receiver Operating Characteristic (ROC) Curve and Area Under the Curve (AUC)

The ROC curve is a graphical representation that shows the model's ability to distinguish between different classes by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold levels. It provides a visual method to evaluate how well the model can separate the different classes.

True Positive Rate (TPR)

Also known as sensitivity or recall, the TPR measures the proportion of actual positives that the model correctly identifies. It is calculated as follows equation (2).

http://doi.org/10.26594/register.v11i1.4653

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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$$\mathrm{TPR} = \frac{TP}{TP+FN} \tag{2}$$

Where:
TP = True Positives
FN = False Negatives

In the context of betel leaf disease classification, the TPR indicates how many diseased leaves were correctly classified as diseased by the model.

False Positive Rate (FPR)

The FPR measures the proportion of actual negatives that are incorrectly identified as positives by the model. In this case, FPR represents how often healthy leaves were misclassified as diseased. It is calculated as follows equation (3).

$$\mathrm{FPR} = \frac{FP}{FP+TN} \tag{3}$$

Where:
FP = False Positives
TN = True Negatives

Area Under the Curve (AUC)

The AUC score is a single numerical value that represents the area under the ROC curve. It provides a summary of the model's performance across all possible threshold values. The AUC score ranges from 0 to 1, where: AUC = 1.0 indicates a perfect classifier and AUC = 0.5 indicates a random classifier (similar to flipping a coin).

A higher AUC value indicates better model performance. In this study, a high AUC demonstrates the model's ability to distinguish between different betel leaf disease categories. For example, A model with an AUC of 0.98 can distinguish between healthy and diseased leaves with 98% accuracy across all possible thresholds.

The ROC curve and AUC are particularly important when dealing with imbalanced datasets because they provide a more comprehensive view of the model's performance beyond what accuracy alone can show.

3. Results and Discussion

Our experimental research was conducted on Google Colaboratory Pro using a GPU Tesla A100 40GB. The research was run on Python, utilizing Tensorflow and Keras libraries as the backend for the InceptionResNetV2, DenseNet201, EfficientNetB3V2, MobileNetV2 and XceptionResnet50V2 models.

Determining hyperparameters for training the model is a crucial work. We utilized Adam as the optimizer with a learning rate of 0.01. Another parameter is the epoch, which we set at 50. We tracked the error rate and accuracy using categorical cross-entropy as the loss function. The batch size was set to 32. During preprocessing, the image dataset was resized to 224×224 pixels to reduce image resolution. In addition, the dataset was split into 80:20 ratio for training and testing, with the training data used for K-fold cross-validation (K=5)

Evaluation metrics for this research utilize accuracy and the ROC AUC score. Accuracy compares the predictions of the precise model with the entire dataset [42]. The ROC (Receiver Operating Characteristic) curve is an evaluative metric that demonstrates the model's ability to distinguish different classes [43]. It plots the TPR (True Positive Rate) on the y-axis versus FPR (False Positive Rate) on the x-axis. AUC (Area Under Curve) represents the value corresponding to the area under the ROC curve, where a higher AUC value signifies a more superior model.

3.1. Training and Validation

This section presents a comprehensive analysis of the performance of five Convolutional Neural Network (CNN) architectures: InceptionResNetV2, XceptionResNet50V2, DenseNet201, MobileNetV2, and EfficientNetV2B3. The models were evaluated using five-fold cross-validation on a dataset of betel leaf images. Key evaluation metrics include training accuracy, validation accuracy, and training time for each fold. The analysis identifies performance trends and highlights challenges such as overfitting and underfitting observed in certain models. This discussion also provides insights into potential strategies for improving model performance.

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3.1.1. InceptionResNetV2

The InceptionResNetV2 model demonstrated the best overall performance across all folds. The highest validation accuracy, 83.7%, was achieved on fold-5, with a corresponding training accuracy of 94.4%. The model maintained stable performance across the other folds, with validation accuracies ranging from 43.8% to 83.7%. This indicate that while the model generalizes well, it remains sensitive to certain subsets of the data.

Table 1. Train performance of InceptionResNetV2.

InceptionResNetV2			
Fold	**Accuracy**	**Val Accuracy**	**Train Time (m)**
1	0.928	0.698	10.624
2	0.945	0.778	10.335
3	0.936	0.747	10.411
4	0.835	0.438	10.470
5	0.944	0.837	10.500

The steady performance of InceptionResNetV2 across most folds suggests that its architecture is well-suited for the classification task, effectively balancing training and validation accuracy. However, fold-4 presented a significant drop in validation accuracy, suggesting that certain data subsets may pose challenges for model generalization. Future work could focus on applying data augmentation techniques to address these challenges and further enhance model robustness.

3.1.2. XceptionResnet50V2

The XceptionResNet50V2 model showed moderate performance, achieving a peak validation accuracy of 79.2% on fold-3, with a corresponding training accuracy of 88.0%. The model's average training time was 9.855 minutes, which is slightly shorter than that of InceptionResNetV2 model.

Table 2. Train performance of XceptionResnet50V2.

XceptionResnet50V2			
Fold	**Accuracy**	**Val Accuracy**	**Train Time (m)**
1	0.928	0.698	10.624
2	0.945	0.778	10.335
3	0.936	0.747	10.411
4	0.835	0.438	10.470
5	0.944	0.837	10.500

While the XceptionResNet50V2 model performed well in terms of training accuracy, its validation accuracy indicates that there is room for improvement in generalization. The model may benefit from additional regularization techniques to reduce overfitting and enhance its performance on unseen data.

3.1.3. DenseNet201

DenseNet201 achieved the highest overall validation accuracy of 86.7% on fold-3, with a corresponding training accuracy of 97.6%. However, it also recorded the longest average training time of 11.649 minutes, indicating a trade-off between model accuracy and computational efficiency.

Table 3. Train performance of DenseNet201.

DenseNet201			
Fold	**Accuracy**	**Val Accuracy**	**Train Time (m)**
1	0.928	0.698	10.624
2	0.945	0.778	10.335
3	0.936	0.747	10.411
4	0.835	0.438	10.470
5	0.944	0.837	10.500

DenseNet201's high validation accuracy highlights its capability to learn complex patterns from the image data. However, its longer training time may pose challenges for real-time applications or resource-constrained environments. Future research could focus on optimizing the model's architecture to reduce training time while maintaining its accuracy.

3.1.4. MobileNetV2

MobileNetV2 experienced significant overfitting across all folds, with an average training accuracy of 94.1% but a validation accuracy of only 25.1%. The model's training time was notably shorter, averaging of 3.429 minutes, making it a lightweight option.

http://doi.org/10.26594/register.v11i1.4653

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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Table 4. Train performance of MobileNetV2.

	MobileNetV2		
Fold	Accuracy	Val Accuracy	Train Time (m)
1	0.928	0.698	10.624
2	0.945	0.778	10.335
3	0.936	0.747	10.411
4	0.835	0.438	10.470
5	0.944	0.837	10.500

The overfitting observed in MobileNetV2 suggests that the model struggles to generalize beyond the training data. Incorporating techniques such as data augmentation, early stopping, and transfer learning could potentially improve its performance.

3.1.5. EfficientNetV2B3

EfficientNetV2B3 displayed a combination of underfitting and overfitting across different folds. The model achieved an average validation accuracy of 25.6% and a training accuracy of 94.9%, with an average training time of 7.094 minutes.

Table 5. Train performance of EfficientNetV2B3.

	EfficientNetV2B3		
Fold	Accuracy	Val Accuracy	Train Time (m)
1	0.928	0.698	10.624
2	0.945	0.778	10.335
3	0.936	0.747	10.411
4	0.835	0.438	10.470
5	0.944	0.837	10.500

EfficientNetV2B3's inconsistent performance indicates that it requires further hyperparameter tuning and possibly additional regularization to enhance its generalization capabilities. Exploring with different learning rates and batch sizes could help optimize its performance.

A comparison of the five models reveals that InceptionResNetV2 and DenseNet201 outperformed the others in terms of validation accuracy and generalization. MobileNetV2 and EfficientNetV2B3, on the other hand, faced significant challenges with overfitting and underfitting, respectively. The InceptionResNetV2 model emerged as the most reliable architecture for betel leaf disease classification, offering strong validation accuracy and reasonable training time. DenseNet201 also showed excellent results but with a higher computational cost. Conversely, MobileNetV2 and EfficientNetV2B3 require further optimization to address their overfitting and underfitting tendencies. Overall, this comprehensive analysis highlights the importance of model selection and optimization in achieving robust performance for plant disease detection tasks.

Fig. 7 shows the accuracy and loss of the InceptionResNetV2 model during training on fold-5. The X-axis of the accuracy graph represents the number of training epochs, while the Y-axis shows the accuracy or loss rate. The results indicate that accuracy steadily increases, although some epochs still exhibit fluctuations. In the loss graph, the first epoch and epoch-9 exhibit high error values, reaching up to 118928.3906. However, the error value starts to decrease in the subsequent epochs, and the model eventually converges.

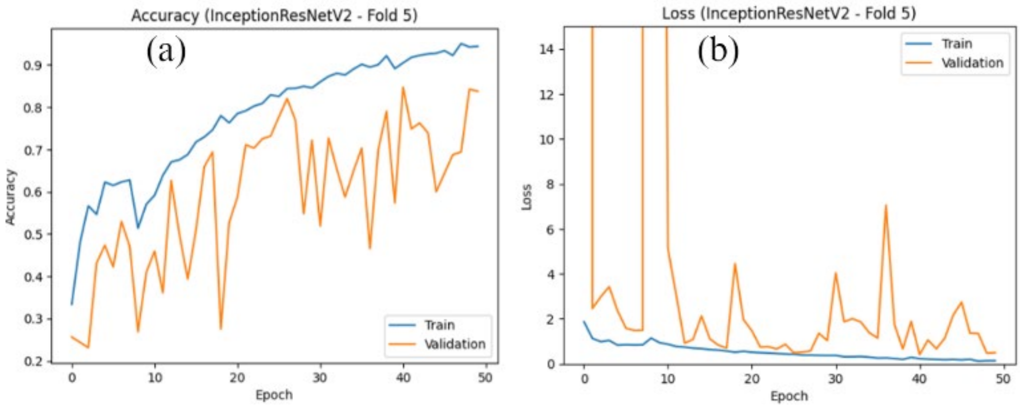

Fig. 7. History training of InceptionResNetV2 at fold-5: (a) Accuracy; (b) Loss

http://doi.org/10.26594/register.v11i1.4653

 ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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3.2. Testing

The testing results show that the InceptionResNetV2 model achieved the best performance, with an accuracy of 86.0%, a ROC score of 98.0%, and a relatively low loss of 0.3880. In contrast, the MobileNetV2 model performed the worst, with an accuracy of only 25.1%, a ROC score of 51.0%, and a significant loss of 142.1048, indicating severe overfitting and poor generalization.

Table 6 and Table 7 provide a summary of the training and testing performances based on the best fold for each model.

Table 6. Training performance all models based on best fold.

Training Best Fold			
Model	**Fold**	**Val Accuracy**	**Training Time (m)**
InceptionResNetV2	5	83.7%	10.500
XceptionResnet50V2	3	79.20%	9.855
DenseNet201	3	86.7%	11.649
MobileNetV2	1-5	Overfitting	3.429
EfficientNetV2B3	1-5	Underfitting, Overfitting	7.094

Table 7. Testing performance all models based on best fold.

Testing Best Fold				
Model	**Fold**	**Accuracy**	**ROC Score**	**Training Time (m)**
InceptionResNetV2	5	86.0%	98.0%	0.3880
XceptionResnet50V2	3	76.6%	92.8%	1.1035
DenseNet201	3	82.5%	96.5%	0.6034
MobileNetV2	1	25.1%	51.0%	142.1048
EfficientNetV2B3	1	66.3%	85.4%	1.7728

This study evaluated multiple deep learning architectures for betel leaf disease classification, focusing on their accuracy, computational efficiency, and generalization ability. Among the models tested, InceptionResNetV2 demonstrated the highest testing accuracy and ROC score, confirming its effectiveness in classifying betel leaf diseases. Its combination of inception modules and residual connections enabled it to capture both fine-grained details and broader patterns, ensuring superior generalization. The model maintained a reasonable training time of 10.5 minutes, making it a viable option for real-world applications.

DenseNet201 emerged as another strong performer, achieving the highest validation accuracy during training (86.7%) and an impressive testing accuracy of 82.5%, with a ROC score of 96.5%. Its densely connected layers helped mitigate the vanishing gradient problem and promoted better feature reuse, enhancing overall performance. However, it required the longest training time (11.649 minutes), reflecting its higher computational cost. Despite this, DenseNet201 remains a strong contender for practical deployment, as supported by Kusuma and Jothi (2024), who reported it achieving 98.77% accuracy in early betel leaf disease detection [19]. Similarly, Alam et al. (2024) found DenseNet201 to outperform MobileNetV2 and exhibit strong generalization across plant disease datasets, reinforcing our findings [32].

On the other hand, XceptionResNet50V2 performed moderately well, achieving a testing accuracy of 76.6% and a ROC score of 92.8%. Its depthwise separable convolutions allowed efficient learning, but signs of overfitting in certain folds suggest that additional regularization techniques could further enhance its generalization performance.

MobileNetV2, however, suffered from severe overfitting, achieving high training accuracy (94.1%) but extremely low testing accuracy (25.1%). This suggests that its lightweight architecture, while computationally efficient, struggled to capture the complex textures of betel leaf diseases. These results aligns with findings from Alam et al. (2024) but contrast with Elfatimi et al. (2024), who reported over 92% accuracy using MobileNet on bean leaf datasets [31], [32]. This discrepancy highlights the importance of dataset-dependent model selection.

Lastly, EfficientNetV2B3 exhibited inconsistent performance, showing signs of both underfitting and overfitting across different folds. It achieved a testing accuracy of 66.3% and a ROC score of 85.4%, indicating that further hyperparameter tuning is needed to stabilize the model. This result differs from

 http://doi.org/10.26594/register.v11i1.4653

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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Hridoy et al. (2022) [20], where EfficientNetB5 achieved a 98.84% recognition accuracy, suggesting that EfficientNet's performance is highly dependent on dataset properties and optimization strategies.

The results highlight the trade-offs between accuracy, training time, and generalization capabilities among different CNN architectures. The superior performance of InceptionResNetV2 and DenseNet201 indicates their suitability for real-time disease detection applications. However, MobileNetV2's poor performance underscores the importance of balancing model complexity with robustness.

For practical deployment in agricultural settings, models must not only achieve high accuracy but also be computationally efficient. InceptionResNetV2 strikes this balance, making it a recommended choice for farmers and agricultural stakeholders seeking automated disease detection solutions.

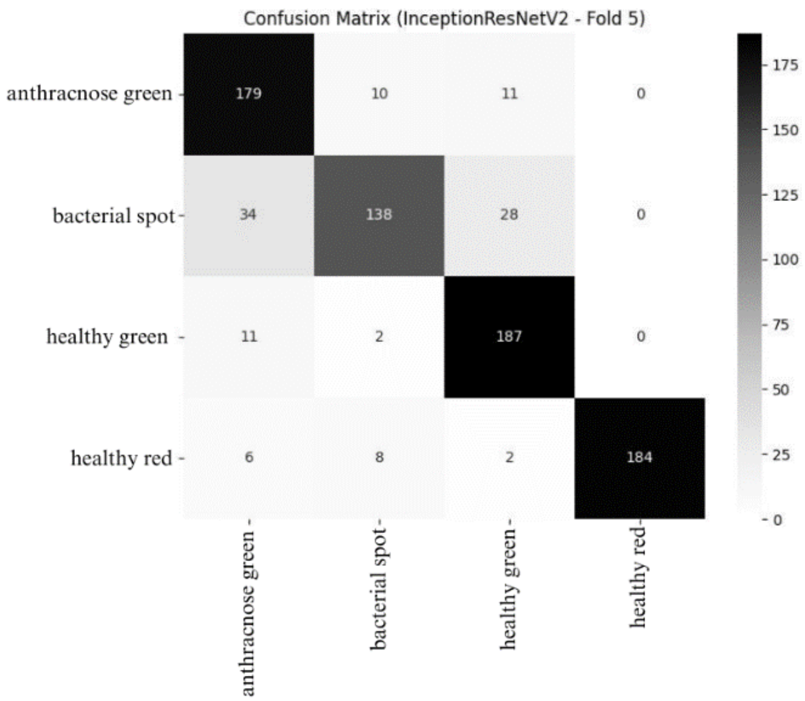

Fig. 8. Confusion Matrix InceptionResNetV2 fold-5

The performance of the InceptionResNetV2 model can be further analyzed using its confusion matrix and ROC curves. Fig. 8 shows the confusion matrix for InceptionResNetV2 on fold 5, providing a detailed breakdown of the classification results across four classes: anthracnose green, bacterial spot, healthy green, and healthy red. The confusion matrix highlights that the model achieved high accuracy in classifying each class, with minimal misclassifications. The highest number of correct predictions was observed in the healthy green class, with 187 correctly identified samples. However, some confusion is observed between the anthracnose green and bacterial spot classes, where a few samples were misclassified. This suggests that these two disease types share similar visual features, which the model may find difficult to distinguish.

The ROC curves presented in Fig. 9 provide an additional perspective on the classification performance of InceptionResNetV2 across all five folds. These curves demonstrate the model's ability to differentiate between positive and negative cases at various threshold levels. The AUC values range from 0.75 to 0.98, indicating varying degrees of performance across the folds. The highest AUC score of 0.98 was achieved in fold 5, aligning with the highest testing accuracy observed. This suggests that the model's performance is relatively stable and reliable when tested on different subsets of the dataset.

The ROC curve analysis also highlights that InceptionResNetV2 consistently performs well across multiple folds, indicating strong generalization to unseen data. This robustness is a crucial factor for practical applications in agriculture, where the model must handle diverse data collected under varying environmental conditions. The comparison between folds shows that even in the lowest-performing fold (fold 4, with an AUC of 0.75), the model still maintained acceptable classification performance. This underscores its ability to handle dataset variations while maintaining high accuracy.

http://doi.org/10.26594/register.v11i1.4653

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ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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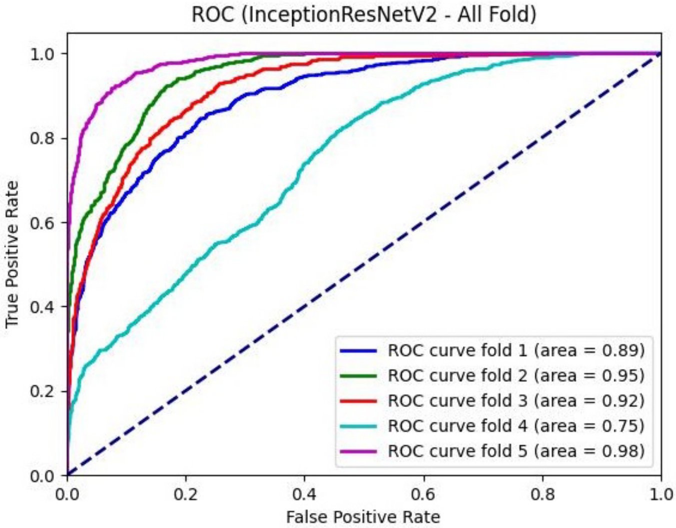

Fig. 9 ROC score InceptionResNetV2 all fold

4. Conclusion

This study has demonstrated the effectiveness of leveraging deep learning models to classify betel leaf diseases using a localized dataset from Indonesian farms. Among the five CNN architectures evaluated—InceptionResNetV2, DenseNet201, EfficientNetB3V2, MobileNetV2, and XceptionResNet50V2—InceptionResNetV2 emerged as the most robust, achieving a testing accuracy of 86.0% and an impressive ROC score of 98.0%, while DenseNet201 also performed well with a testing accuracy of 82.5% and a ROC score of 96.5%. However, MobileNetV2 and EfficientNetV2B3 struggled with overfitting and underfitting, respectively, highlighting the significance of balancing model complexity and robustness. The study also emphasizes the importance of localized datasets, such as the one used here, with 4,000 high-resolution images across four classes, which capture region-specific agricultural practices, climatic conditions, and disease patterns. These findings indicate the practical potential of models like InceptionResNetV2 and DenseNet201 for real-time disease detection systems, offering a balance between accuracy and computational efficiency to assist farmers in preventing crop losses and improving productivity.

Although this study presents a significant contribution to the classification of betel leaf diseases using deep learning models, several limitations should be acknowledged to provide a more comprehensive understanding of the results. First, the dataset used in this research consists of only four classes of betel leaf conditions: healthy green betel leaves, anthracnose green betel leaves, bacterial spot betel leaves, and healthy red betel leaves. While this dataset represents the most common types of betel leaf diseases found in the study area, it does not encompass a wider range of diseases or leaf conditions that may occur in different regions or under varying environmental conditions, potentially limiting the models's generalizability. In addition, the data collection process was constrained to a single device, the Samsung Galaxy A52s smartphone, under specific lighting and background conditions, which may affect the model's performance in more diverse and uncontrolled environments. Furthermore, this study did not incorporate advanced data augmentation techniques or ensemble learning methods, which could potentially enhance the model's accuracy and robustness by improving generalization across different datasets. Another limitation lies in the fact that the models were evaluated in a controlled experimental setting, without consideration of real-time deployment or mobile application integration. While the proposed models show promising performance in classification tasks, their practicality and effectiveness in real-world agricultural applications, such as in-field disease detection, remain to be validated.

To address these limitations, several future directions are proposed. Expanding the dataset to include a more diverse range of betel leaf diseases and capturing images under various environmental conditions would improve the model's generalizability across different regions and farming practices. Additionally, implementing advanced data augmentation techniques and ensemble learning methods could enhance the model's performance by reducing the risks of overfitting and underfitting observed in some of the tested models. Future research should also focus on deploying the classification model in real-time applications, such as mobile platforms or IoT devices, to provide farmers with instant disease detection and treatment recommendations in the field. Moreover, adapting the proposed deep learning approaches for cross-domain applications, such as detecting diseases in other plant species, would expand the scope of this research and contribute to the wider field of plant disease detection. Finally, incorporating Explainable AI (XAI) techniques would improve the interpretability of the model's predictions, providing users with insights into the rationale behind the classification decisions and thereby increasing trust and adoption of AI-based solutions in agriculture.

Acknowledgment

Thank you to the Bangkalan Agriculture Service for validating the betel leaf dataset for experimental methods in this research and the Institute for Research and Community Service (LPPM) of University of Trunojoyo Madura for providing National Collaborative Research funding with contract number 5895/UN46.4.1/PT.01.03 /2023.

Author Contributions

R. T. Wahyuningrum: Conceptualization, methodology, validation, and writing – review & editing. I. H. Ayani: Funding acquisition, resources, and visualization. A. Bauravindah: Data curation, software, and writing – original draft. I. A. Siradjuddin: Formal analysis, supervision, and writing – review & editing. I. S. Faradisa: Investigation, project administration, and writing – review & editing.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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