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THRESHOLD IMPROVEMENT USING THE OTSU METHOD WITH HISTOGRAM ON PADDY IMAGES

Lukman Hakim[1]*, Hadhrami Ab Ghani[2], Hadi Santoso[3]

[1]Faculty of Computer Science, Universitas Mercu Buana, Indonesia
lukman_hakim@mercubuana.ac.id https://orcid.org/0000-0002-7325-826X
[2]Faculty of Data and Computing Sciences, Universiti Malaysia Kelantan, Malaysia
hadhrami.ag@umk.edu.my https://orcid.org/0000-0002-7648-8108
[3]Faculty of Computer Science, Universitas Mercu Buana, Indonesia
hadi.santoso@mercubuana.ac.id https://orcid.org/0000-0002-1288-4267
*Corresponding Author

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Abstract:

Accurate image segmentation methods play a very important role in improving paddy grain classification performance. One of the segmentation stages is determining the threshold, usually using classic Otsu. This method is widely used in the segmentation process, and the instability of the threshold in classic Otsu in uneven lighting and complex histogram distribution. This study proposes an improvement to the Otsu-based segmentation method by combining histogram normalization and trigonometric variance modulation, namely Otsu with normalization, Otsu Sine, and Otsu Tangent. The proposed methods were evaluated using Random Forest as a classifier and texture features with GLCM. Experimental results show that the Otsu Sine method achieves the best performance among the other methods, with an accuracy of 0.92, precision of 0.93, recall of 0.93, and F1 score of 0.93. Five-fold cross-validation yields superior results for Otsu-Sine, with the highest average accuracy (94.83%) among all methods. Further pairwise tests showed that the improvement in performance compared to classic Otsu was statistically significant (p = 0.04). Threshold stability analysis showed that Otsu-Sine maintained low variance while adapting effectively to changes in intensity distribution, whereas Otsu-Tangent showed high instability.

Keyword:

Image Segmentation; Otsu Method; Paddy Grain Classification.

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Introduction

President Prabowo, through the government's development agenda, has emphasized the importance of achieving national food self-sufficiency(Kantor Staf Presiden, 2025). Food independence is closely related to food sovereignty(Kantor Staf Presiden, 2025), in which rice serves as the main staple food for the Indonesian population. The sustainability of a country is strongly influenced by the development of its economic and agricultural sectors(Mamoriska, 2024). An imbalance in the agricultural sector can potentially lead to food shortages and large-scale hunger. Globally, food insecurity is estimated to affect approximately 2.4 billion people(Otekunrin, 2024). By 2050, food security challenges are expected to intensify due to rapid population growth, a declining agricultural workforce, climate change, and increasing fuel costs.

As a member of the World Trade Organization (WTO), Indonesia is required to comply with international regulations concerning the management of strategic food reserves, including rice(Mamoriska, 2024). Based on Law No. 7 of 1994, Indonesia must align its rice management policies with WTO provisions to maintain balance between national rice supply and consumption. In the 2020–2024 National Medium-Term Development Plan (RPJMN), the government targeted rice production of 39.2 million tons in 2020, increasing to 46.8 million tons in 2024. However, actual production has not fully met these targets due to reductions in harvested areas and declining productivity(Dahiri & Tineke, 2021). Rice production is influenced primarily by two factors: harvested area and productivity.

Each region has its own characteristics in terms of which crops are suitable and produce different yields. Agricultural land cultivation must be adjusted to the quality of the seeds to be planted, which affects production levels. Indonesia has a variety of rice varieties that have advantages in each region, such as Ciherang, Mekongga, and INPARI 32. Each rice variety has unique characteristics in terms of texture, aroma, taste, and antioxidant content (Suarti, 2024). One way to detect rice grain varieties is to use an image-based classification system, such as those found in various digital image processing techniques(Sadhana & Mangalwede, 2020). Rice grains can be distinguished based on grain size, grain shape, grain texture, grain color, and other visual features. These features can be obtained through image processing approaches. The Gray Co-occurrence Matrix A will be an efficient method in texture analysis. The Gray Co-occurrence Matrix is a method of spatial texture mapping(Setiawan et al., 2023).

Deep learning algorithm has made the automatic recognition of rice varieties easy and feasible in images. Image segmentation is critical in this process (Yu et al., 2023), because it directly affects the accuracy of recognition. Typically, segmentation is done by the conventional Otsu thresholding method; however, this has many restrictions.

The Otsu method is commonly used for two-level thresholding, but it assumes a bimodal histogram distribution and uniform illumination. Histogram distribution of images varies across rice grains as a result of varying illumination, reflective surfaces, textures between different varieties. Conventional Otsu algorithm could yield unstable threshold values in low-contrast images. Therefore, inaccurate separation of the object and background might occur. Existing methods to improve upon this problem typically center on entropy optimization or using metaheuristics. However, few studies look at how nonlinear manipulation of between class variance can stabilize thresholds for agricultural image datasets, and one might affect practically imperfect outcomes. The use of trigonometric modulation in this study, based on image processing or deep learning on Otsu's variance, to overcome gaps in the segmentation stage.

Based on these considerations, an improved segmentation method is commonly employed. On rice grain images, we have built a shiny new comprehensive/ exhaustive method to pursue this tradition. This can flesh out the Otsu method for rice grain images with digital signal processing techniques that have been typically used on seismic signals.

1. Introducing the Otsu thresholding framework by modulating variance using trigonometric functions (sine and tangent).
2. This paper demonstrates improved threshold stability under uneven lighting conditions.
3. In this way, a computationally efficient segmentation method for agricultural image data is finally achieved without requiring connectivity.
4. This paper suggests that this system still has broad potential: This technology may be applicable for general purposes not listed here, such as grain-based object recognition systems or other agricultural needs.

Literature Review

Several studies have used GLCM (Gray Level Co-occurrence Matrix) to improve texture feature extraction capabilities. GLCM has four features, namely contrast, homogeneity, energy, and disparity, which contribute significantly to image recognition (Setiawan et al., 2023)(Nugroho et al., 2024)(Jing & Tang, 2024).

Many studies related to image processing and segmentation face challenges such as image noise, lighting, low contrast, and intensity variations. These challenges must be resolved in order to achieve high classification accuracy in image classification, namely by improving the classic Otsu thresholding method with a combination of Chan Vese and Bayesian probability approaches. This study has achieved segmentation results that are superior to the classic Otsu method(Jing & Tang, 2024).

Image segmentation has also gained increasing attention as a critical stage in feature extraction. Various segmentation techniques have been explored using color, texture, and pixel intensity features, including applications in satellite imagery. Comparative studies have evaluated multiple segmentation approaches, such as threshold-based, region-based, edge-based, clustering-based, watershed-based, and artificial neural network (ANN)–based segmentation. Among these, ANN-based segmentation demonstrated superior accuracy, particularly for real-time applications(Meinam et al., 2025).

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Furthermore, studies on multi-threshold image segmentation have proposed enhanced Otsu-based methods incorporating entropy measures and greedy optimization strategies. One approach introduced a multi-level thresholding technique that combines the Otsu method with ant colony optimization to determine optimal threshold values. The combination of Otsu's thresholding improved segmentation results in image data while maintaining computational efficiency(Sang et al., 2024).

Other related research has focused on refining the original Otsu method by considering image brightness characteristics. In this approach, the optimal threshold is determined by aligning it more closely with the foreground region of the image. A threshold-weighted Otsu (TW-OTSU) method was introduced, where both the threshold weight and gray-level values are adjusted based on the peak distribution of foreground intensities. The results demonstrated that the TW-OTSU method effectively addressed poor segmentation performance and achieved higher segmentation accuracy compared to the conventional Otsu approach(Xu et al., 2025).

Proposed Methodology

Figure 1 illustrates the pre-processing stages in image processing as part of the data transformation process. This study consists of several stages, beginning with the manual acquisition of grain images using a mobile phone camera. The pre-processing stage includes image resizing, noise reduction, thresholding using the Otsu method, and the extraction of shape, size, and texture features based on GLCM. In addition, this study proposes an enhancement to the conventional Otsu method to improve segmentation performance.

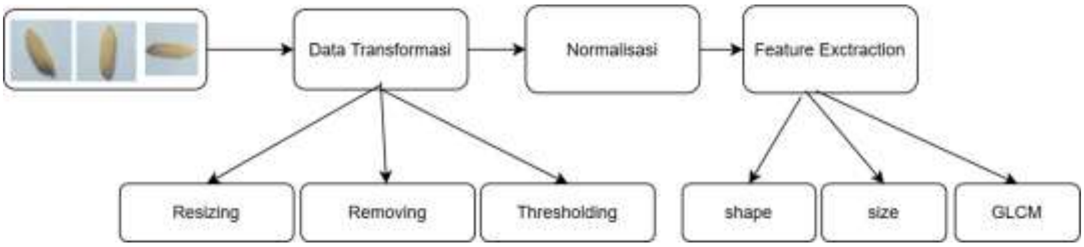

Figure 1: Pre-Processing Stage

Dataset

A total of 2,500 paddy grain images were collected, representing five Indonesian rice varieties: PandanWangi, Ciherang, IR64, Rojolele, and Inpari. Each paddy grain variety consists of 500 images taken using a mobile phone camera at a consistent distance of 10 cm under controlled indoor lighting conditions. The images were resized to 300 × 300 pixels to ensure uniform input dimensions. Each rice grain was captured at two angles (0° and 90°) to increase texture variation. The dataset was divided using an 80:20 train-test split, where 80% of the data were used for training and 20% for testing. No data augmentation was applied to preserve original histogram characteristics. Figure 2 presents sample images of each paddy grain variety**.**

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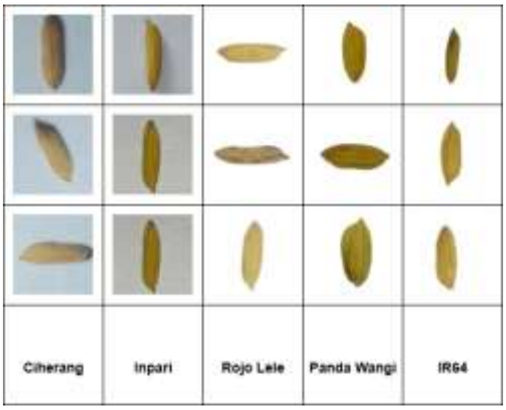

Figure 2: Paddy Grain Dataset

Problems in Threshold Enhancement

Image processing is highly dependent on the data transformation or pre-processing stage, in which image segmentation plays a crucial role in determining precision through adjustments of threshold values. These threshold values subsequently influence the results of image classification or detection based on histogram analysis(Sang et al., 2024)(Xu et al., 2025).

Otsu Thresholding Method

Otsu's method is widely used for image segmentation by determining an optimal threshold value. This method divides an image into two classes, namely the background and the foreground, based on the selected threshold (Xu et al., 2025)(Jing & Tang, 2024)(Kalyani et al., 2021)(B et al., 2023). The image is partitioned into two groups, W_1 and W_2, at a gray-level threshold T, such that W1 = {0, 1, 2, ..., T} and W2 = {T+1, T+2, ..., L-1}, where L is the total number of gray levels in the image. Suppose the number of pixels at gray level i is n_i, and N is the total number of pixels in the image.
The probability of occurrence of gray level i is defined in Equation 1(Unajan et al., 2019).

$$i = \frac{n_i}{N}, P_i \geq 0, \sum_{i=0}^{L-1} P_i = 1 \qquad (1)$$

The equations for W_1 and W_2 correspond to the object of interest and the background. The probabilities of the two classes are shown in Equation 2.

$$P_{w1} = \sum_{i=0}^{T} and\ P_{w2} = \sum_{P_i} = 1 - P_{w1} \qquad (2)$$

For classes W_1 and W_2, the calculations can be performed as shown in Equations 3 and 4.

$$\mu_{w1} = \sum_{i=0}^{T} \frac{i * P_i}{P_{w1}} \qquad (3)$$

W_1=lower class probability
W_2=upper class probability

$$\mu_{w2} = \sum_{i=T+1}^{T} \frac{i * P_i}{P_{w2}} \qquad (4)$$

Equation 5 is a derivative formula based on equations 3 and 4:

$$\sigma^2(T) = P_{w1}P_{w2}(\mu_{w1} - \mu_{w2})^2 \qquad (5)$$

The optimal threshold value T* can be obtained by maximizing the within-class variance.

$$T^* = Arg \max_{0<T<L-1} \sigma^2(T) \qquad (6)$$

The standard Otsu method is widely used for thresholding in image segmentation. This method is widely applied in image processing or data transformation stages to produce better image quality.

GLCM Feature

The use of GLCM enhances the processing results at the data transformation stage, which involves diverse grain images and textures. Grains possess various textures that require high accuracy in recognition. GLCM is capable of extracting features such as energy, entropy, contrast, and homogeneity, which improve image processing results during the pre-processing stage.

Evaluation Metrics

Measuring the performance of a model in deep learning is carried out using accuracy, precision, recall, and F1-score(Chang et al., 2024)(Bhupendra, Kriz Moses, Ankur Miglani, 2022)(Faurina et al., 2024). Accuracy, based on the confusion matrix, measures how correctly the model classifies or predicts the types of rice varieties. Precision represents the degree of correctness in the model's class predictions, while recall measures how accurately the model identifies samples belonging to the actual class. The confusion matrix is a tool used to evaluate the performance of a model in Deep Learning or Machine Learning for classification tasks, containing both the predicted and actual values(Rajalakshmi et al., 2024).

Two levels of evaluation were conducted in this study:

Segmentation Accuracy (Pixel-Level Accuracy)

Segmentation accuracy is defined as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} x100 \qquad (7)$$

$$Precision = \frac{TP}{TP + FP} x100 \qquad (8)$$

$$Recall = \frac{TP}{TP + FN} x\ 100 \qquad (9)$$

$$F1 - Score = \frac{2x\ Precision\ x\ Recall}{Precision + Recall} x\ 100 \qquad (10)$$

where:
TP = correctly segmented foreground pixels
TN = correctly segmented background pixels

FP = false foreground pixels
FN = missed foreground pixels

Classification Performance

Classification accuracy is defined as:

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \quad (11)$$

Additional performance metrics include:

- Precision
- Recall
- F1-score

Derived from the confusion matrix to provide a comprehensive evaluation.

Proposed Otsu Variants

Otsu with Histogram Normalization (Otsu-N)

The Otsu method is used for image segmentation and for determining the threshold value T that optimally separates an image into two classes. Increasing the intensity probability helps in determining a more optimal threshold value. Histogram integration enhances the standard Otsu method through peak analysis and histogram distribution.
The normalized histogram $P_{(i)}$ is calculated from the pixel intensities as follows:

$$P(i) = \frac{n_i}{N}, \quad i=0,1,2,\ldots, L-1 \quad (12)$$

Where:
L = the number of gray levels (usually 256)
n_i = the number of pixels with intensity *i*
N = the total number of pixels in the image

Histogram normalization improves intensity distribution stability prior to threshold optimization.

Otsu Sine Method

The classical between-class variance is defined as:

$$\sigma^2 b = w_1 w_2 (\mu_1 - \mu_2)^2$$

Proposes the Otsu sine method combined with the histogram; the sine method formula is as follows:

$$\sigma^2 b, sine = Pw_1 . Pw_2 (P\mu_1 - P\mu_2)^2 . \sin(\theta) \quad (13)$$

The value of θ is used to increase sensitivity to differences between classes and stabilise the histogram, with this formula being more adaptive to the variance of the intensity distribution

Otsu Tan Method

Proposes for the Otsu Tangent Method with histogram combination, the Otsu Tangent Method formula is as follows:

$$\sigma^2 b, tan = Pw_1 . Pw_2 (P\mu_1 - P\mu_2)^2 . \tan(\theta) \quad (14)$$

The tangent module increases the response variance of small mean differences and makes the objective function more sensitive to histogram changes.

Algorithm Modified Otsu with Random Forest for Paddy Grain Classification

Input: RGB paddy grain images
Output: paddy grain variety classification

1: Read image
2: Apply color normalization (optional)
3: Convert to grayscale
4: Compute histogram
5: Determine threshold using modified Otsu
6: Segment image using threshold
7: Extract texture features using GLCM
8: Extract shape and size features
9: Fuse all features
10: Normalize features
11: Classify using Random Forest
12: Evaluate classification performance

Results and Discussion

Comparison of the Modified Otsu Method

Based on the experimental results using various rice images with different backgrounds, the Otsu method was enhanced by integrating histogram-based color normalization(Al-Johania & Elrefaei, 2019), Otsu-sine, and Otsu-tangent approaches, without employing GLCM features. The modified Otsu method demonstrated improved threshold stability and segmentation accuracy in deep learning applications. This enhancement allowed the method to effectively separate objects from their backgrounds and reduce noise in rice images. As shown in Figure 3, several sample images with different backgrounds were tested randomly. The implementation of the improved Otsu method was carried out using the Python programming language.

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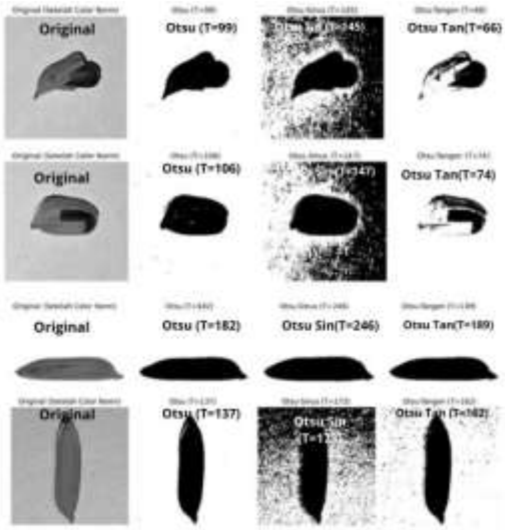

Figure 3: Paddy Grain Dataset

Figure 4 presents the thresholding results of Otsu's test with GLCM, excluding histogram color normalization.

Figure 4: Testing Without Histogram Color Normalization on Otsu

Figure 5. Evaluation of the proposed Otsu method combined with GLCM feature extraction on grain images. The segmentation results demonstrate improved separation between the grain and background, accompanied by noticeable variations and enhanced stability in the selected threshold values (T).

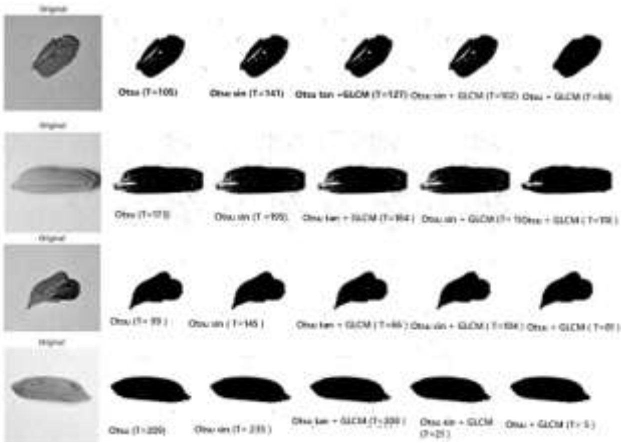

Figure 5: Testing Of the Proposed Otsu Method and The Use Of GLCM

Table 1: presents a comparison of segmentation results using shape, size and GLCM features and the standard Otsu method and its modified variants.

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Table 1: Comparison Proposed Model

Method	Accuracy	Precision	Recall	F1-Score
Otsu	0.90	0.89	0.90	0.89
Otsu Normalization	0.91	0.91	0.92	0.91
Otsu sine	0.92	0.93	0.93	0.93
Otsu tan	0.89	0.89	0.90	0.88

The performance comparison indicates that the Otsu-Sinus method achieved the best overall results, with the highest accuracy (0.92), precision (0.93), recall (0.93), and F1-score (0.93). The Otsu with normalization shows balanced performance improvements over classical Otsu, while Otsu-Tangent yields the lowest overall performance, particularly in F1-score (0.88). These results confirm that sine-based variance modulation enhances segmentation quality and classification reliability more effectively than the other evaluated variants.

Statistical Validation and Stability Analysis

Cross-Validation Analysis

Cross-validation testing to ensure segmentation reliability using 5-fold cross-validation, testing on a random dataset by dividing it into 5 equal subsets, each iteration of testing using 4 subsets for training and 1 subset for validation. Table 2 shows the cross-validation results in the form of the average accuracy and standard deviation of all folds.

Table 2: Cross-Validation Performance Comparison

Method	Mean Accuracy(%)	Std.Deviation
Otsu	92.45	1.79
Otsu Normalization	91.81	1.45
Otsu sine	94.83	2.57
Otsu tan	89.65	2.43

Based on cross-validation testing on Otsu variance, the highest accuracy result was 94.83% for Otsu Sine, while for classic Otsu it was 92.45%, Otsu with normalization was 91.81%, and Otsu Tangent had the lowest accuracy at 89.65%. Otsu Sine had the highest standard deviation among the Otsu variants, with increased accuracy indicating better segmentation robustness. For the Otsu Tangent method, the accuracy results were low and sensitive to histogram fluctuations.

Statistical Significance Test

Statistical significance test on the Otsu sin method with classical Otsu, with this paired t-test confirming the performance of the method.
Based on the results of the null hypothesis (Ho) comparing the two methods, the results are as follows:
T-value = -2.99

- P-value = 0.04

A comparison of statistical significance tests between the Otsu-Sine and classic Otsu methods shows a t-value of −2.99 and a p-value of 0.04. If the p-value is below the threshold of <0.05, this indicates that the increase in accuracy achieved by the Otsu-Sine method is statistically significant.

Threshold Stability Analysis

Threshold stability testing, the mean deviation against 4 Otsu variants was calculated based on 100 randomly selected images. This test measures how consistent the threshold values are.

Table 3: Threshold Stability Comparison

Method	Mean Threshold	Std.Deviation
Otsu	87.82	2.75
Otsu Normalization	87.74	2.71
Otsu sine	117.94	2.81
Otsu tan	93.2	29.6

Test results on each Otsu variant show threshold stability for the classic Otsu and normalised Otsu methods with average threshold values (87.82 and 87.74) with relatively low standard deviations, the results of both variants being stable and conservative. The threshold stability results for the Otsu Sine method were higher on average (117.94) while maintaining a standard deviation (2.81), indicating effective adaptation to shifts in intensity distribution without causing instability. The Otsu Tangent method produced a higher standard deviation (29.6) than the Otsu Sine method. In this method, the sensitivity level is high to histogram fluctuations, and the threshold consistency is less consistent between images.

Computational Complexity and Runtime Analysis

Computational complexity testing to determine the extent to which computational resources are used efficiently or inefficiently in processing time for each image, using the Otsu method combined with trigonometry, for the classical Otsu computational complexity $O(L)$, where L represents the number of grey levels. The complexity results are as follows:
$O(L + c)$ where c represents constant trigonometric computation.

Runtime evaluation was conducted on an Intel i7-12700 processor (8GB RAM).

Table 4: Average Runtime Per Image

Method	Mean Threshold
Otsu	0.051
Otsu Normalization	0.279
Otsu sine	0.053
Otsu tan	0.054

Based on execution time testing on each Otsu variant, the execution results for classic Otsu (0.051 seconds), Otsu Sine (0.053 seconds), and Otsu Tangent (0.054 seconds) on each grain image. Trigonometric modulation does not significantly increase the computational cost. For

Otsu Tangent, the execution time is longer (0.279 seconds). The final results of the Otsu Sine method maintain computational efficiency and improve segmentation performance.

Conclusion

This study shows that the proposed Otsu-Sine method is a powerful and effective improvement over the traditional Otsu thresholding technique in rice grain image segmentation. The experimental results show that Otsu Sine performs better in classification and is more reliable, which has been verified through cross-validation and statistical significance testing. Threshold stability analysis shows that Otsu-Sine is able to handle brightness changes well and maintain consistent results, while Otsu Tangent struggles to remain stable under similar conditions. Computational analysis shows that the proposed method maintains the same level of efficiency and runs quickly without slowing down. Otsu-Sine provides a lightweight and reliable method for separating different parts of an image, making it a good choice for real-world use in analysing agricultural images.

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Conflict of Interest Statement:	The authors declare no conflict of interest.
Ethics Statement:	This study did not involve any human participants, animals, or sensitive data requiring ethical approval. The authors confirm that the research was conducted in accordance with accepted academic integrity and ethical publishing standards.
Author Contribution Statement:	Lukman Hakim conceptualization and methodology; Hadhrami Ab Ghani supervision and validation; Hadi Santoso data analysis and implementation.

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