

Automated modeling of leaf mangrove by optimizing convolutional neural networks

Paranita Asnur¹, Rifki Kosasih², Sarifuddin Madenda³, Dewi Agushinta R.⁴

¹Department of Agrotechnology, Faculty of Industrial Engineering, Universitas Gunadarma, Jakarta, Indonesia

²Department of Informatics, Faculty of Computer Science and Information Technology, Universitas Gunadarma, Jakarta, Indonesia

³Department of Information Technology, Universitas Gunadarma, Jakarta, Indonesia

⁴Department of Information System, Faculty of Computer Science and Information Technology, Universitas Gunadarma, Jakarta, Indonesia

Article Info

Article history:

Received Jan 21, 2025

Revised Jul 19, 2026

Accepted Aug 12, 2026

Keywords:

Computational ecology
Convolutional neural networks
Hyperparameter optimization
Leaf image-based classification
Mangrove species identification

ABSTRACT

Accurate mangrove species identification is fundamental to biodiversity conservation, ecological monitoring, and climate change mitigation because mangrove ecosystems provide essential ecological services and function as significant carbon sinks. This study proposes a systematic optimization framework for mangrove species identification by jointly investigating dataset size, convolutional depth, and hyperparameter configuration within a convolutional neural network (CNN). Leaf images of seven mangrove species collected in Kolaka Regency, Southeast Sulawesi, were augmented, resized to 128×128 pixels, and processed using the NVIDIA DGX A100 supercomputer. The framework systematically optimized the number of convolutional layers, learning rate (LR), batch size, number of epochs, kernel size, activation function (AF), and optimizer, followed by a comprehensive evaluation of their combined effects on classification performance. The optimized CNN achieved 98.93% testing accuracy, 98.71% precision, 98.71% recall, and a 98.86% F1-score. The results demonstrate that the integrated optimization of CNN architecture, dataset size, and hyperparameters substantially improves model robustness and generalization over conventional fixed CNN configurations, providing a practical deep learning framework for automated mangrove monitoring and biodiversity assessment.

This is an open access article under the [CC BY-SA](#) license.



Corresponding Author:

Paranita Asnur

Department of Agrotechnology, Faculty of Industrial Engineering, Universitas Gunadarma
Jakarta, Indonesia

Email: paranita@staff.gunadarma.ac.id

1. INTRODUCTION

Mangrove ecosystems play an important role in coastal protection [1], biodiversity conservation [2]–[5], and carbon storage [5]–[7]. They provide essential ecosystem services by reducing coastal erosion, supporting diverse flora and fauna, and functioning as one of the most effective natural carbon sinks for climate change mitigation. Consequently, the sustainable management and conservation of mangrove ecosystems require accurate species identification to support biodiversity assessment, ecological monitoring, and evidence-based conservation planning.

Viodor *et al.* [8] and Xia *et al.* [9] conducted preliminary research on deep learning that shows how convolutional neural networks (CNN) might be able to solve the problems with current mangrove identification methods. CNN's innovation has the potential to improve the accuracy of species identification,

including the classification of mangrove species, through complex image analysis, thereby promoting a shift towards more automated and precise identification methods. This is supported by studies conducted by Faza *et al.* [10] and Wan *et al.* [11].

Previous studies have shown that deep learning with CNN models makes a significant contribution to conservation efforts. In the aspect of identification and early detection of plant diseases, Gardie *et al.* [12] have proven the effectiveness of CNN in identifying diseases on tomato plant leaves with an impressive accuracy of 98.3%. Other studies [13], [14] developed a deep convolutional neural network (DCNN) model with data augmentation and hyperparameter optimization, suggesting that optimizing the CNN model's automation system can enhance its effectiveness in identifying plant diseases. By exploring the integration of evolutionary optimization techniques in neural networks, deep learning can provide benefits and make significant contributions to plant health monitoring [15].

The rapid advancement of deep learning has demonstrated strong capabilities in addressing complex pattern recognition problems. However, its application to mangrove species identification remains technically underdeveloped, particularly in terms of model optimization. Although recent studies have demonstrated that systematic hyperparameter tuning and architectural optimization can substantially improve CNN performance in image classification tasks [15]–[17], these optimization strategies have not yet been comprehensively applied to mangrove leaf classification. Existing mangrove-related studies primarily focus on developing CNN-based classification models [8], [10], [11] without systematically investigating the combined effects of network depth, dataset size, and hyperparameter configurations on classification performance under high inter-species morphological similarity. Consequently, the role of structured hyperparameter optimization in improving the robustness and generalization capability of CNN-based mangrove species identification remains an open research challenge.

This research aims to optimize mangrove species identification by analyzing leaf morphological characteristics using CNNs. Unlike previous studies that generally adopted fixed CNN architectures, this study systematically investigates the combined effects of dataset size, convolutional depth, and hyperparameter configuration to establish an optimal CNN framework for mangrove leaf classification. This study presents four main contributions. First, it proposes an automated CNN-based framework for mangrove species identification through the systematic optimization of the number of convolutional layers to improve feature extraction from leaf morphology. Second, it evaluates the influence of different dataset sizes on model learning and generalization, providing empirical evidence for selecting an appropriate training dataset in ecological image classification. Third, it performs comprehensive hyperparameter optimization by jointly analyzing the effects of learning rate (LR), batch size, number of epochs, kernel size, activation function (AF), and optimizer on classification performance. Finally, it systematically evaluates the combined impact of architectural and hyperparameter configurations to identify the most robust CNN model for mangrove species identification, thereby providing a practical deep learning framework that supports biodiversity assessment, environmental monitoring, and coastal ecosystem conservation.

2. METHOD

2.1. Data collection and dataset preparation

Data collection was conducted in the mangrove forest of Kolaka Regency, Southeast Sulawesi, Indonesia, using transects measuring 10×10 meters arranged perpendicular to the coastline. Mangrove leaf samples were collected by photographing individual leaves with a 48 MP smartphone camera from various angles and distances under natural lighting conditions, using a white paper background to enhance visual contrast. The images were then subjected to initial classification and coding prior to dataset categorization and systematically stored in directories according to leaf type. This acquisition procedure was designed to preserve key morphological features while ensuring consistency and reliability of image inputs for CNN training. Following the procedure proposed by Pandian *et al.* [13], all images were resized to a uniform resolution of 128×128 pixels and augmented using rotation (up to 90°), scaling, and horizontal and vertical flipping. These augmentation techniques were applied only to the training dataset to increase sample diversity while preserving the essential morphological characteristics of mangrove leaves. The resulting augmented dataset enabled the CNN model to learn more robust feature representations and improved its ability to classify mangrove species under varying image conditions.

The complete dataset was then divided into training and testing subsets to enable robust model development and unbiased performance evaluation. Consistent with a widely adopted supervised deep learning strategy, 80% of the dataset was allocated for training and 20% for independent testing. Furthermore, the training subset was partitioned into 80% for model training and 20% for validation

to facilitate hyperparameter optimization, reduce the risk of overfitting, and improve the model's generalization capability.

2.2. Model design and training

The model design and training process was conducted by varying the dataset size and the number of convolutional layers using the NVIDIA DGX A100 supercomputer. The initial CNN configuration consisted of a dropout rate of 0.25, 2×2 max pooling, two fully connected layers, a LR of 1×10^{-3} , 50 training epochs, a batch size of 64, kernel sizes of 3×3 , 5×5 , 3×3 , and 3×3 , and the rectified linear unit (ReLU) AF as shown in Figure 1. Figure 1 showing the sequence of convolutional, pooling, dropout, fully connected, and output layers used for feature extraction and classification. The best-performing configuration identified during this stage was subsequently selected for further hyperparameter tuning to improve the model's classification performance.

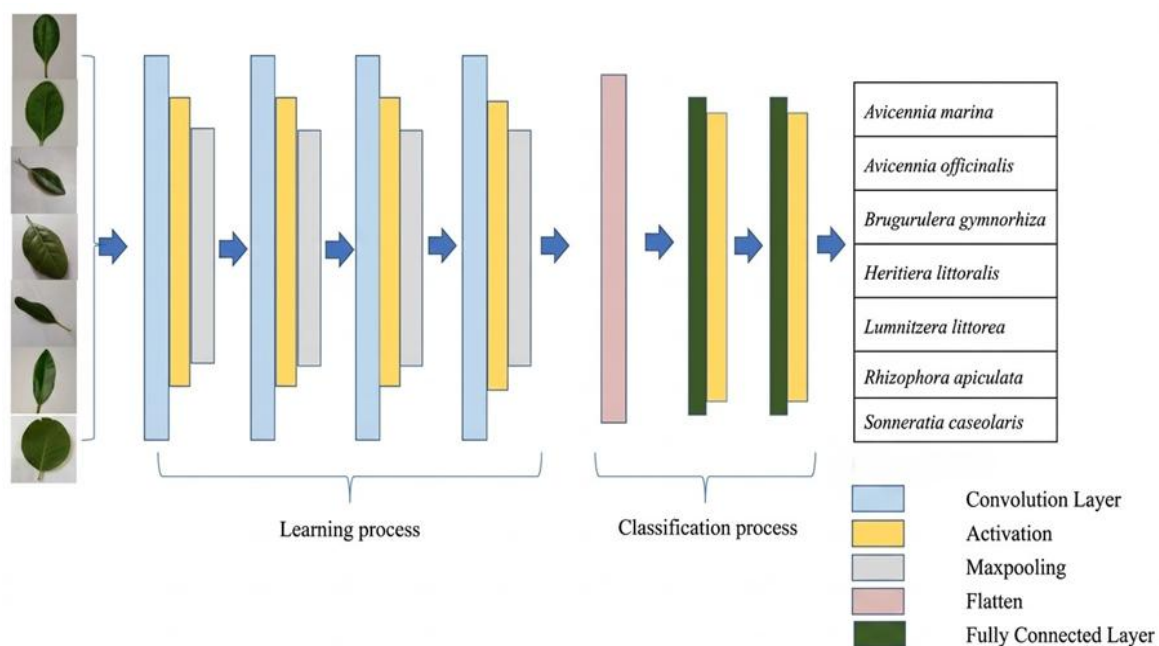


Figure 1. Proposed CNN architecture for mangrove species identification

All architectural configurations, training parameters, and computational settings were explicitly defined to ensure the reproducibility of the proposed CNN framework. This comprehensive specification enables other researchers to replicate the experimental procedures and objectively validate the reported results. Furthermore, it enhances the transparency and reliability of the proposed approach, facilitating future studies on deep learning-based mangrove species classification.

2.3. Hyperparameter tuning

Hyperparameter tuning was performed by systematically adjusting the LR, batch size, number of epochs, kernel size, AF, and optimization algorithm, as illustrated in Figure 2. Each hyperparameter was evaluated to determine its influence on the training process and the classification performance of the CNN model. This optimization procedure aimed to identify the most effective parameter combination for improving the accuracy and robustness of mangrove species identification.

2.4. Model evaluation

This study evaluated the optimized CNN model using the independent test dataset to assess its generalization capability on unseen data. The evaluation was conducted using a confusion matrix, from which accuracy, precision, recall, and F1-score were calculated to provide a comprehensive assessment of classification performance. These evaluation metrics enabled a detailed analysis of the model's effectiveness in distinguishing among different mangrove species and verified the robustness of the proposed optimization strategy.

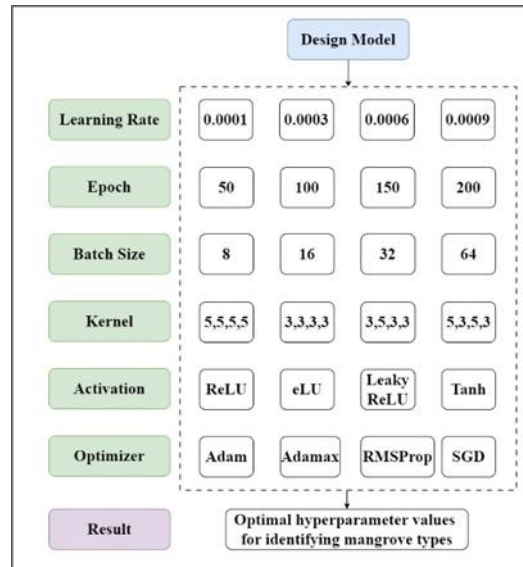


Figure 2. Workflow of CNN hyperparameter tuning for optimizing LR, batch size, epochs, kernel size, AF, and optimizer

3. RESULTS AND DISCUSSION

3.1. Image acquisition results

Figure 3 presents representative leaf images of the seven mangrove species used in this study, all standardized to a resolution of 128×128 pixels. These images constitute the dataset used for CNN training, validation, and testing. The standardized image resolution and species representation provide consistent input for feature extraction and enable a reliable evaluation of the proposed classification framework.

Although the images were standardized to a relatively low resolution of 128×128 pixels, they preserved the essential morphological characteristics of mangrove leaves, including the leaf apex, margin, and base, which are important for species discrimination. As shown in Figure 3, the leaf images were captured using a smartphone camera with a white background to enhance visual contrast and improve the visibility of morphological features required for CNN-based classification. The dataset consists of seven mangrove species, namely *Avicennia marina* (Am), *Avicennia officinalis* (Ao), *Bruguiera gymnorhiza* (Bg), *Heritiera littoralis* (Hl), *Lumnitzera littorea* (Lt), *Rhizophora apiculata* (Ra), and *Sonneratia caseolaris* (Sa), whose variations in leaf morphology provide discriminative features for automated mangrove species identification.



Figure 3. Representative mangrove leaf images acquired using a smartphone camera and resized to 128×128 pixels for CNN training, illustrating the morphological characteristics of the seven mangrove species included in the dataset

3.2. Model design and training results

The results of the CNN model design and training demonstrate that the optimal network architecture depends on the size of the training dataset. As the dataset size increases, a greater number of convolutional layers are required to effectively extract complex feature representations and improve classification performance. This finding indicates that the relationship between dataset size and convolutional depth should be optimized jointly rather than being determined independently. Table 1 summarizes the training and testing results obtained from different combinations of dataset sizes and convolutional layer configurations.

Table 1. Training and testing performance of CNN models with different dataset sizes and numbers of convolutional layers executed on the NVIDIA DGX A100 platform

Number of data	Number of convolutions	Training		Testing	
		Loss	Accuracy	Loss	Accuracy
1,418	1	0.0724	0.9797	0.2138	0.9329
	2	0.0268	0.9982	0.2186	0.9399
	3	0.0378	0.9912	0.2312	0.9258
	4	0.0724	0.9797	0.3521	0.8869
1,750	1	0.0714	0.9814	1.0612	0.6886
	2	0.0334	0.9950	0.3491	0.8771
	3	0.0303	0.9950	1.1502	0.6257
	4	0.0964	0.9714	0.6138	0.8229
	5	0.1219	0.9607	0.3729	0.8714
7,000	1	0.0548	0.9805	0.2282	0.9293
	2	0.0376	0.9873	0.2894	0.9071
	3	0.0339	0.9889	0.2217	0.9193
	4	0.0375	0.9893	0.1674	0.9521
	5	0.0486	0.9848	0.1579	0.9493

With 1,418 images, the one-layer CNN achieved 93.29% accuracy, indicating that performance depends on both network depth and model configuration. This finding is consistent with recent evidence that hyperparameter tuning and architectural choices influence CNN performance in agricultural image classification [18]. These results suggest that a simpler model could be optimal for smaller datasets and does not require many convolutional layers to achieve high accuracy. Testing accuracy varies as the number of convolutional layers increases. For example, a model with two convolutional layers and 1,750 images achieved a test accuracy of 87.71%, which is higher than that of more complex models. This finding is consistent with previous evidence that CNN performance can vary substantially with network depth and architectural configuration, indicating that increasing model depth does not necessarily lead to improved classification performance [19].

Dataset size and architectural configuration jointly affected testing accuracy, with the four-layer CNN achieving 95.21% accuracy on the 7,000-image dataset. This finding is consistent with recent research showing that architectural depth and hyperparameter settings influence CNN performance and generalization in agricultural image classification [18]. In larger datasets, the importance of careful CNN hyperparameter tuning becomes very clear. The model with four convolutional layers achieved a test accuracy of 95.21% on 7,000 images, which is the same as the results from Pacal *et al.* [20], who show that CNNs can be used in many areas, such as agriculture and species recognition. This level of accuracy underscores the need for meticulous hyperparameter tuning to achieve optimal results in complex image recognition tasks. Overall, these results indicate that the optimal CNN architecture is determined by the interaction between dataset size and convolutional depth rather than by increasing model complexity alone. Figure 4 illustrates the training and validation performance of the proposed CNN model with four convolutional layers throughout the learning process. As shown in Figure 4(a), the training accuracy rapidly approaches a high value, while the validation accuracy exhibits greater fluctuations, indicating that the model learns the training data effectively but generalizes poorly to unseen samples. Similarly, Figure 4(b) shows that although the training loss decreases steadily, the validation loss fluctuates across epochs, suggesting mild overfitting and highlighting the need for careful hyperparameter optimization to improve model stability and generalization. These observations further justify the subsequent hyperparameter optimization stage, which aims to improve convergence stability and reduce the performance gap between training and validation datasets.

According to the study by Pacal *et al.* [20], changes in validation accuracy and loss values show how challenging it is for deep learning models to regularize and generalize. Although the model is efficient in learning from the training data, its results on the validation set show a lack of consistency. This reflects the

model's tendency to overfit the training data, which reinforces the argument for the need to adjust hyperparameters to improve the model's generalization capability. Sakib *et al.* [21] demonstrated that training CNNs with different convolutional layer configurations makes test accuracy better. This shows how important it is to try out different model structures to get the best results. In this study, the experimental results indicate that a four-convolution-layer architecture provides the best trade-off between feature extraction capability and generalization performance when combined with the largest dataset, forming the basis for the subsequent hyperparameter optimization experiments.

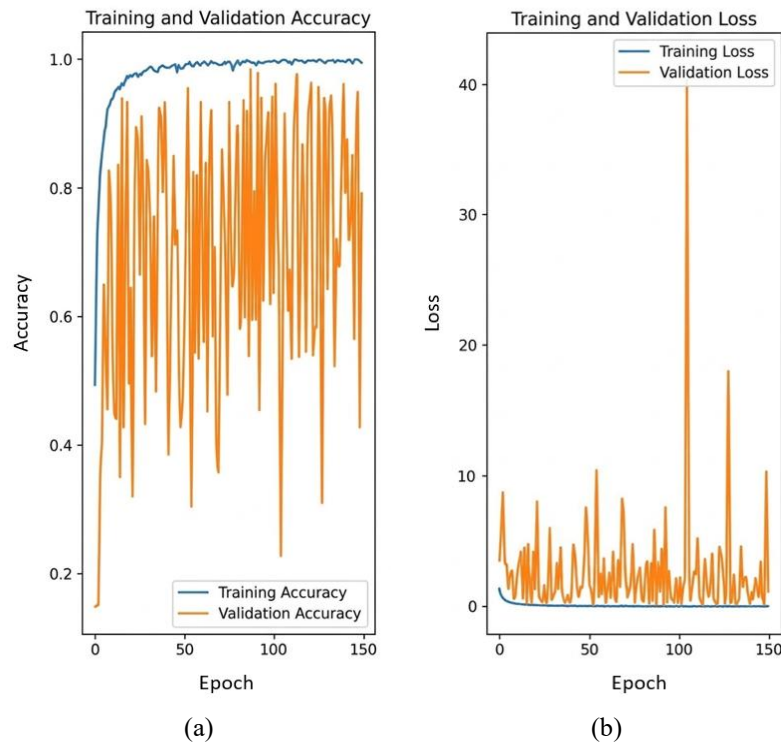


Figure 4. Training and validation performance of the proposed CNN model during the learning process of (a) training and validation accuracy across epochs and (b) training and validation loss across epochs

3.3. Hyperparameter tuning

Table 2 presents the effects of hyperparameter tuning, including LR, number of epochs, batch size, kernel size, AF, and optimizer, on the training and testing performance of the proposed CNN model. The experimental results demonstrate that different hyperparameter configurations produce noticeable variations in classification accuracy and loss, confirming that model performance is highly sensitive to parameter selection. This observation is consistent with previous studies, which reported that systematic optimization of LR, batch size, optimizer, and network architecture is essential for improving CNN convergence, robustness, and classification accuracy in plant image analysis and other complex image recognition tasks [16], [22]. Unlike previous studies that optimized these parameters individually, this study systematically evaluates their combined effects within the optimized CNN architecture obtained from the previous stage. This integrated evaluation enables the identification of the most robust parameter combination for mangrove species classification under high inter-species morphological similarity.

Buthelezi *et al.* [23] and Wu *et al.* [24] highlighted the critical role of LR in achieving stable model convergence, demonstrating that an appropriate LR effectively balances training stability and generalization performance. More recently, Davies and Sivakumari [16] further confirmed that systematic hyperparameter optimization, particularly the selection of an appropriate LR in conjunction with batch size and optimization algorithms, substantially improves CNN classification performance in plant leaf image analysis. In the present study, a LR of 3.00×10^{-4} achieved an optimal balance between training and testing accuracy while minimizing prediction loss. This result demonstrates the effectiveness of the proposed hyperparameter optimization strategy in improving CNN convergence and generalization. Compared with both lower

(1.00×10^{-4}) and higher (6.00×10^{-4} and 9.00×10^{-4}) LR, the selected value produced more stable convergence and consistently superior testing performance. The finding is consistent with previous studies showing that carefully optimized LR enhance model stability and classification accuracy in deep learning-based image recognition [8], [25].

Table 2 demonstrates that the number of training epochs substantially influences both classification accuracy and model loss. Increasing the training duration to 150 epochs improved the testing accuracy by 0.22% while reducing the loss by 1.36%, indicating that sufficient training iterations enable the CNN to learn more discriminative feature representations. This finding is consistent with Anchitaalagammai *et al.* [26], who reported that an appropriate number of training epochs is essential for improving classification performance, although excessively long training may increase computational cost without proportional performance gains. Furthermore, Igiri *et al.* [27] emphasized that efficient hyperparameter optimization should balance predictive accuracy with computational efficiency. The results indicate that extending training beyond 150 epochs did not produce additional performance gains, suggesting that this configuration provides an effective balance between model accuracy and computational cost.

Table 2. Performance comparison of different hyperparameter configurations, including LR, number of epochs, batch size, kernel size, AF, and optimizer for CNN-based mangrove species classification

No	LR	Epoch	BS	Kernel	AF	Optimizer	Training		Training		Time (H:M:S)	Testing		
							Loss	Accuracy	Loss	Accuracy		Loss	Accuracy	Time (ms)
1	0.0001	50	64	3, 5, 3, 3	ReLU	Adam	0.0414	0.9855	4.8822	0.4929	00:16:32	0.0799	0.9771	644
2	0.0003	50	64	3, 5, 3, 3	ReLU	Adam	0.0414	0.9855	4.8822	0.4929	00:16:22	0.0799	0.9771	644
3	0.0006	50	64	3, 5, 3, 3	ReLU	Adam	0.0315	0.9873	0.9542	0.7879	00:16:18	0.1605	0.9579	648
4	0.0009	50	64	3, 5, 3, 3	ReLU	Adam	0.0263	0.9927	1.7597	0.7443	00:16:36	0.1592	0.9500	632
5	0.0003	50	64	3, 5, 3, 3	ReLU	Adam	0.0570	0.9805	0.5435	0.8329	00:16:38	0.0780	0.9771	694
6	0.0003	100	64	3, 5, 3, 3	ReLU	Adam	0.1007	0.9682	1.1892	0.7014	00:32:08	0.1410	0.9543	658
7	0.0003	150	64	3, 5, 3, 3	ReLU	Adam	0.0113	0.9968	1.1797	0.7986	00:49:14	0.1390	0.9795	646
8	0.0003	200	64	3, 5, 3, 3	ReLU	Adam	0.0635	0.9782	0.4638	0.8607	01:03:55	0.0960	0.9764	710
9	0.0003	150	8	3, 5, 3, 3	ReLU	Adam	0.0042	0.9984	0.8399	0.8364	00:49:20	0.0950	0.9729	638
10	0.0003	150	16	3, 5, 3, 3	ReLU	Adam	0.0109	0.9968	0.3122	0.9157	00:48:11	0.0860	0.9800	658
11	0.0003	150	32	3, 5, 3, 3	ReLU	Adam	0.0182	0.9932	1.0659	0.7907	00:49:15	0.0490	0.9893	647
12	0.0003	150	64	3, 5, 3, 3	ReLU	Adam	0.0113	0.9968	1.1797	0.7986	00:48:13	0.0640	0.9793	646
13	0.0003	150	32	5, 5, 5, 5	ReLU	Adam	0.0121	0.9962	4.8162	0.9293	00:47:50	0.0713	0.9714	697
14	0.0003	150	32	3, 3, 3, 3	ReLU	Adam	0.0066	0.9975	0.3708	0.8886	00:48:31	0.1775	0.9443	794
15	0.0003	150	32	3, 5, 3, 3	ReLU	Adam	0.0182	0.9932	1.0659	0.7907	00:49:15	0.0491	0.9893	647
16	0.0003	150	32	5, 3, 5, 3	ReLU	Adam	0.0119	0.9962	0.3171	0.9300	00:48:57	0.1041	0.9686	677
17	0.0003	150	32	3, 5, 3, 3	ReLU	Adam	0.0182	0.9932	1.0659	0.7907	00:49:15	0.0491	0.9893	647
18	0.0003	150	32	3, 5, 3, 3	Leaky ReLU	Adam	0.0117	0.9964	0.5678	0.8786	00:48:46	0.1156	0.9750	971
19	0.0003	150	32	3, 5, 3, 3	eLU	Adam	0.0120	0.9962	1.8289	0.6964	00:48:06	0.1190	0.9679	782
20	0.0003	150	32	3, 5, 3, 3	Tanh	Adam	0.6143	0.9904	1.5878	0.4964	00:49:25	0.6600	0.9564	693
21	0.0003	150	32	3, 5, 3, 3	ReLU	Adam	0.0182	0.9932	1.0659	0.7907	00:49:15	0.0491	0.9893	647
22	0.0003	150	32	3, 5, 3, 3	ReLU	Adamax	0.0029	0.9995	0.2994	0.9350	00:48:34	0.0839	0.9764	650
23	0.0003	150	32	3, 5, 3, 3	ReLU	RMSprop	0.0059	0.9980	1.5891	0.7386	00:48:35	0.0986	0.9729	641
24	0.0003	150	32	3, 5, 3, 3	ReLU	SGD	0.4907	0.8229	1.2611	0.5486	00:48:46	1.1064	0.6093	642

Batch size also plays a crucial role in determining training stability and model generalization. Consistent with the recommendation of Lin [28], the experimental results indicate that a batch size of 32 produced the highest testing accuracy while maintaining a relatively low loss value. Similar observations were reported by Davies and Sivakumari [16], who demonstrated that the joint optimization of batch size, LR, and optimization algorithms significantly enhances CNN performance for plant leaf image classification by improving convergence stability and reducing prediction errors. This finding indicates that excessively small or large batch sizes reduce generalization performance, whereas an intermediate batch size provides a better balance between optimization stability and classification accuracy.

Kernel size determines the receptive field of convolutional filters and directly affects the model's capability to capture spatial features. Ding *et al.* [29] demonstrated that larger kernels can improve feature extraction by incorporating broader contextual information. In the present study, although a uniform 5×5 kernel produced competitive results, the hybrid configuration of 3×3 , 5×5 , 3×3 , and 3×3 achieved the best overall performance, suggesting that combining different receptive fields provides a more effective representation of mangrove leaf morphology. This result demonstrates that heterogeneous kernel configurations capture complementary morphological characteristics more effectively than uniform kernel designs.

The experimental results also confirm the effectiveness of the ReLU AF in CNN-based image classification. Hao *et al.* [30] showed that ReLU improves computational efficiency while mitigating the vanishing gradient problem during network training. Moreover, the superior performance of the Adam optimizer observed in this study is consistent with Wang *et al.* [22], who demonstrated that adaptive optimization strategies improve convergence by dynamically adjusting parameter updates. More recently, Davies and Sivakumari [16] further reported that the integration of optimized LR, batch sizes, and adaptive optimization algorithms substantially enhances CNN robustness and predictive performance in plant image classification tasks. Overall, the optimal CNN model was obtained through the combined configuration of four convolutional layers, a LR of 3.00×10^{-4} , 150 training epochs, a batch size of 32, a hybrid kernel configuration (3×3 , 5×5 , 3×3 , and 3×3), the ReLU AF, and the Adam optimizer. This integrated optimization strategy constitutes the main technical contribution of this study because it demonstrates that CNN performance for mangrove species identification is governed by the interaction among architectural design, dataset size, and hyperparameter configuration rather than by optimizing individual parameters independently. Collectively, these findings highlight that systematic hyperparameter optimization is fundamental to developing reliable deep learning models for ecological monitoring and automated mangrove species identification.

3.4. Model testing and evaluation

The performance of the model resulting from hyperparameter tuning analysis is illustrated through the presented data as shown in Figure 5. The model successfully achieved high precision, recall, and F1-scores in classifying various mangrove species, with an overall accuracy rate approaching 0.99. This success confirms the effectiveness of hyperparameter tuning in CNNs and aligns with the literature that emphasizes the importance of a carefully calibrated LR and the tuning of other hyperparameters for optimizing CNNs. The works of Buthelezi *et al.* [23] and Wu *et al.* [24] support this. Unlike previous studies that primarily reported final classification accuracy, the present study demonstrates that high performance is achieved through the systematic integration of dataset size optimization, convolutional depth selection, and hyperparameter tuning rather than through architectural complexity alone. This finding indicates that the interaction among these optimization components plays a decisive role in improving CNN generalization for mangrove leaf classification.

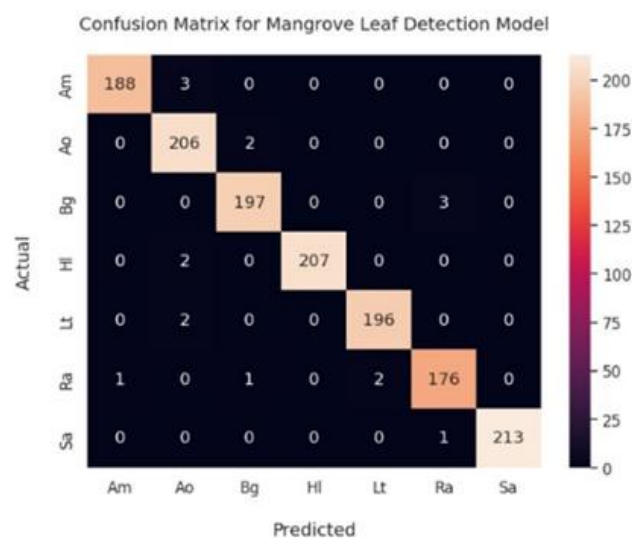


Figure 5. Confusion matrix of the optimized CNN model, illustrating the classification performance of the seven mangrove species after hyperparameter tuning

The confusion matrix provides deeper insights into the model's precision in classifying various mangrove species, showing very low inter-class errors. This indicates that the model with the latest configuration successfully identified the distinctive features important for each species, which is essential for accurate classification. This success is a significant step forward in the efforts of biodiversity conservation and environmental management. The optimized parameters show strong support in

identifying mangrove species using the CNN model. This study uses images with a resolution of 128×128 pixels, seven classes, four convolutional layers, a dropout rate of 0.25, max pooling, a LR of $3.E-04$, 150 epochs, a batch size of 32, ReLU activation, and optimization through Adam. This configuration represents the optimal combination identified through systematic experimentation, demonstrating that robust classification performance can be achieved without increasing input image resolution or employing deeper pre-trained architectures. This model is more accurate as in Table 3 than models used in earlier research that had different architectures and datasets [8], [25]. This finding highlights the importance of using a balanced dataset and properly tuned hyperparameters to achieve robust mangrove species classification. The ReLU AF was suggested by Hao *et al.* [30], and the Adam optimizer was suggested by Wang *et al.* [31]. Both of these have been shown to improve complex classification by incorporating effective model optimization strategies.

This study demonstrates the effectiveness of an adapted CNN model for mangrove species identification through comparative evaluation with recent deep learning approaches. Using a balanced dataset comprising seven mangrove species and a standardized image resolution of 128×128 pixels, the proposed model achieved a classification accuracy of 98.93%. This performance is comparable to results reported for mobile network version 3 (MobileNetV3) architectures with higher input resolutions, which achieved accuracies of 97.03% and 98.4% for the small and large variants, respectively [8], [25]. More importantly, the proposed CNN achieved superior classification accuracy despite using substantially lower-resolution images (128×128 versus 224×224 pixels) and a larger number of species classes. These results suggest that systematic optimization of CNN architecture and hyperparameters can compensate for lower image resolution while improving model generalization. Moreover, consistently high precision, recall, and F1-scores indicate that the proposed CNN configuration provides robust and reliable species discrimination, supporting its applicability in ecological research and mangrove conservation initiatives. This comparative evaluation highlights the primary novelty of the proposed framework, namely that a carefully optimized lightweight CNN can achieve state-of-the-art performance without relying on deeper transfer-learning architectures or higher-resolution inputs, thereby reducing computational requirements while maintaining high predictive accuracy.

Through the development of an optimized CNN model for the high-accuracy identification of mangrove species, this research holds enormous potential for application in the conservation of mangrove ecosystems. The practical applications can include real-time species identification in the field using mobile devices, integration into camera- or drone-based monitoring systems, and support in mangrove ecosystem rehabilitation programs. Thus, this research can make an important contribution to accelerating and improving the accuracy of monitoring and conserving mangroves, which are key ecosystems in climate change mitigation and biodiversity preservation. The relatively lightweight architecture and low image-resolution requirement also improves the feasibility of deploying the proposed model on edge devices and mobile platforms for real-time ecological monitoring.

This study has several limitations that should be acknowledged. First, the proposed model was trained using relatively low-resolution images (128×128 pixels), which may limit its ability to capture subtle morphological differences among closely related mangrove species. Second, the dataset included only seven mangrove species, potentially restricting the model's generalization capability when applied to more diverse mangrove ecosystems. In addition, the relatively limited dataset may increase the risk of overfitting despite the implementation of data augmentation and hyperparameter optimization. Furthermore, practical deployment in real-world environments requires additional optimization to ensure reliable performance on resource-constrained devices with limited computational capabilities. Future research should therefore investigate higher-resolution imagery, larger and more diverse datasets, advanced regularization techniques, and systematic hyperparameter optimization to further improve the robustness, scalability, and generalization capability of CNN-based mangrove species identification models, as highlighted by recent studies [16], [32], [33]. Future work should also investigate the transferability of the optimized hyperparameter configuration to other mangrove ecosystems, additional species, and lightweight deployment frameworks to validate the general applicability of the proposed optimization strategy.

Table 3. Comparison of the proposed CNN model with previous deep learning approaches for mangrove species identification using different network architectures and datasets

Researcher	Model architecture	Dataset	Accuracy (%)
Viodor <i>et al.</i> [8]	MobileNetV3Large accuracy	224×224 pixels, balanced dataset, 5 types	98.4
Viodor <i>et al.</i> [25]	MobileNetV3Small accuracy	224×224 pixels, imbalanced dataset, 5 types	97.03
This study	CNN mangrove	128×128 pixels, balanced dataset, 7 types	98.93

4. CONCLUSION

This study demonstrated that systematic optimization of CNN configurations can substantially improve mangrove leaf classification performance. Among the evaluated configurations, the optimal model achieved a testing accuracy of 98.93%, demonstrating that appropriate selection of dataset size, convolutional depth, and training hyperparameters can improve classification performance while maintaining computational efficiency. The optimized CNN provides a practical foundation for automated mangrove species identification and can support AI-assisted ecological monitoring and biodiversity assessment. Although the results demonstrate strong classification performance, further validation using larger and more geographically diverse datasets is needed to assess model transferability across different mangrove environments. Future research should therefore focus on expanding field-based datasets and evaluating the optimized model under diverse environmental conditions.

ACKNOWLEDGMENTS

The authors gratefully acknowledge Universitas Gunadarma for providing access to the NVIDIA DGX A100 supercomputer facility. The high-performance computing infrastructure substantially accelerated the training, hyperparameter optimization, and experimental evaluation of the CNN models, enabling efficient large-scale image processing and performance validation in this study.

FUNDING INFORMATION

This research received no external funding or research grant.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Paranita Asnur	✓	✓			✓	✓		✓	✓	✓		✓	✓	
Rifki Kosasih		✓	✓	✓	✓				✓		✓			
Sarifuddin Madenda	✓	✓		✓	✓		✓			✓		✓	✓	
Dewi Agushinta R.		✓				✓	✓			✓	✓			

C : Conceptualization	I : Investigation	Vi : Visualization
M : Methodology	R : Resources	Su : Supervision
So : Software	D : Data Curation	P : Project administration
Va : Validation	O : Writing - Original Draft	Fu : Funding acquisition
Fo : Formal analysis	E : Writing - Review & Editing	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in the Mendeley Data repository at <https://doi.org/10.17632/fc5sm4x88c.1> (Dataset ID: fc5sm4x88c.1).

REFERENCES

[1] B. Blankespoor, S. Dasgupta, and G. M. Lange, “Mangroves as a protection from storm surges in a changing climate,” *Ambio*, vol. 46, no. 4, pp. 478–491, May 2017, doi: 10.1007/s13280-016-0838-x.

[2] Rahman *et al.*, “A review on the biodiversity and conservation of mangrove ecosystems in Indonesia,” *Biodiversity and Conservation*, vol. 33, no. 3, pp. 875–903, 2024, doi: 10.1007/s10531-023-02767-9.

[3] Wiryanto, Sunarto, and S. M. Rahayu, “Biodiversity of mangrove aquatic fauna in Purworejo, Central Java, Indonesia,” *Biodiversitas*, vol. 18, no. 4, pp. 1344–1352, 2017, doi: 10.13057/BIODIV/D180409.

[4] J. Zhao *et al.*, “Distribution pattern of mangrove fish communities in China,” *Biology*, vol. 11, no. 12, 2022, doi: 10.3390/biology11121696.

[5] K. Analuddin *et al.*, “Aboveground biomass, productivity and carbon sequestration in *Rhizophora stylosa* mangrove forest of Southeast Sulawesi, Indonesia,” *Biodiversitas*, vol. 21, no. 4, pp. 1316–1325, 2020, doi: 10.13057/biodiv/d210407.

- [6] D. Murdiyarso, H. Krisnawati, W. C. Adinugroho, and S. D. Sasmito, "Deriving emission factors for mangrove blue carbon ecosystem in Indonesia," *Carbon Balance and Management*, vol. 18, no. 1, 2023, doi: 10.1186/s13021-023-00233-1.
- [7] M. A. Kusumaningtyas *et al.*, "Carbon sequestration potential in the rehabilitated mangroves in Indonesia," *Ecological Research*, vol. 37, no. 1, pp. 80–91, Jan. 2022, doi: 10.1111/1440-1703.12279.
- [8] A. C. C. Viodor, C. J. G. Aliac, and L. T. S.-Feliscuzo, "Identifying mangrove species using deep learning model and recording for diversity analysis: a mobile approach," in *2023 IEEE Open Conference of Electrical, Electronic and Information Sciences, eStream 2023-Proceedings*, 2023, pp. 1–6, doi: 10.1109/eStream59056.2023.10134992.
- [9] J. Xia, N. Yokoya, and T. D. Pham, "Probabilistic mangrove species mapping with multiple-source remote-sensing datasets using label distribution learning in Xuan Thuy National Park, Vietnam," *Remote Sensing*, vol. 12, no. 22, pp. 1–17, Nov. 2020, doi: 10.3390/rs12223834.
- [10] S. Faza, E. B. Nababan, S. Efendi, M. Basyuni, and R. F. Rahmat, "An initial study of deep learning for mangrove classification," in *IOP Conference Series: Materials Science and Engineering*, Oct. 2018, vol. 420, no. 1, doi: 10.1088/1757-899X/420/1/012093.
- [11] L. Wan, H. Zhang, G. Lin, and H. Lin, "A small-patched convolutional neural network for mangrove mapping at species level using high-resolution remote-sensing image," *Annals of GIS*, vol. 25, no. 1, pp. 45–55, Jan. 2019, doi: 10.1080/19475683.2018.1564791.
- [12] B. Gardie, K. Azezew, and S. Asemie, "Image-based tomato disease identification using convolutional neural network," *Indian Journal of Science and Technology*, vol. 14, no. 42, pp. 3126–3132, 2021, doi: 10.17485/ijst/v14i42.1164.
- [13] J. A. Pandian *et al.*, "A five convolutional layer deep convolutional neural network for plant leaf disease detection," *Electronics*, vol. 11, no. 8, pp. 1–15, 2022, doi: 10.3390/electronics11081266.
- [14] X. Chao, G. Sun, H. Zhao, M. Li, and D. He, "Identification of apple tree leaf diseases based on deep learning models," *Symmetry*, vol. 12, no. 7, pp. 1–17, 2020, doi: 10.3390/sym12071065.
- [15] J. S. H. Al-bayati and B. B. Üstündağ, "Hybrid intelligent technology for plant health using the fusion of evolutionary optimization and deep neural networks," *Expert Systems*, vol. 40, no. 4, May 2023, doi: 10.1111/exsy.12756.
- [16] J. Davies and S. Sivakumari, "Median interacted pigeon optimization-based hyperparameter tuning of CNN for paddy leaf disease prediction," *Chemical and Biological Technologies in Agriculture*, vol. 12, no. 1, 2025, doi: 10.1186/s40538-025-00785-z.
- [17] C. Coppola, L. Papa, M. Boresta, I. Amerini, and L. Palagi, "Tuning parameters of deep neural network training algorithms pays off: a computational study," *Top*, vol. 32, no. 3, pp. 579–620, 2024, doi: 10.1007/s11750-024-00683-x.
- [18] J. Mendes, J. Lima, L. Costa, E. M. T. Hendrix, and A. I. Pereira, "Impact of hyper-parameter tuning on CNN accuracy in agricultural image classification," *Smart Agricultural Technology*, vol. 11, Aug. 2025, doi: 10.1016/j.atech.2025.101016.
- [19] M. Chhabra, B. Sharan, M. Elbarachi, and M. Kumar, "Intelligent waste classification approach based on improved multi-layered convolutional neural network," *Multimedia Tools and Applications*, vol. 83, no. 36, pp. 84095–84120, 2024, doi: 10.1007/s11042-024-18939-w.
- [20] I. Pacal *et al.*, "A systematic review of deep learning techniques for plant diseases," *Artificial Intelligence Review*, vol. 57, no. 11, 2024, doi: 10.1007/s10462-024-10944-7.
- [21] S. Sakib, Z. Ashrafi, and M. A. B. Siddique, "Implementation of fruits recognition classifier using convolutional neural network algorithm for observation of accuracies for various hidden layers," 2019, *arXiv: 1904.00783*.
- [22] C. Wang, P. Du, H. Wu, J. Li, C. Zhao, and H. Zhu, "A cucumber leaf disease severity classification method based on the fusion of DeepLabV3+ and U-Net," *Computers and Electronics in Agriculture*, vol. 189, 2021, doi: 10.1016/j.compag.2021.106373.
- [23] S. B. Buthelezi, S. Reddy, and B. Twala, "Learning rate optimisation of an image processing deep convolutional neural network," in *Proceedings of 2020 IEEE International Conference on Power, Instrumentation, Control and Computing, PICC 2020*, 2020, doi: 10.1109/PICC51425.2020.9362351.
- [24] Y. Wu *et al.*, "Demystifying learning rate policies for high accuracy training of deep neural networks," in *Proceedings-2019 IEEE International Conference on Big Data, Big Data 2019*, 2019, pp. 1971–1980, doi: 10.1109/BigData47090.2019.9006104.
- [25] A. C. C. Viodor, C. J. G. Aliac, and L. T. S.-Feliscuzo, "Mangrove species identification using deep neural network," in *Proceeding-6th International Conference on Information Technology, Information Systems and Electrical Engineering: Applying Data Sciences and Artificial Intelligence Technologies for Environmental Sustainability, ICITISEE 2022*, 2022, pp. 1–6, doi: 10.1109/ICITISEE57756.2022.10057793.
- [26] J. V. Anchitaalagammai, S. L. J. S. Revathy, S. Kavitha, and S. Murali, "Factors influencing the use of deep learning for medicinal plants recognition," in *Journal of Physics: Conference Series*, 2021, vol. 2089, no. 1, doi: 10.1088/1742-6596/2089/1/012055.
- [27] C. P. Igeri, O. U. Anyama, and A. I. Silas, "Effect of learning rate on artificial neural network in machine learning," *International Journal of Engineering Research*, vol. 4, no. 2, pp. 359–363, 2021, doi: 10.17577/IJERTCONV6IS17007.
- [28] R. Lin, "Analysis on the selection of the appropriate batch size in CNN neural network," in *Proceedings-2022 International Conference on Machine Learning and Knowledge Engineering, MLKE 2022*, 2022, pp. 106–109, doi: 10.1109/MLKE55170.2022.00026.
- [29] X. Ding, X. Zhang, J. Han, and G. Ding, "Scaling up your kernels to 31×31 : revisiting large kernel design in CNNs," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2022, pp. 11953–11965, doi: 10.1109/CVPR52688.2022.01166.
- [30] W. Hao, W. Yizhou, L. Yaqin, and S. Zhili, "The role of activation function in CNN," in *Proceedings-2020 2nd International Conference on Information Technology and Computer Application, ITCA 2020*, 2020, pp. 429–432, doi: 10.1109/ITCA52113.2020.00096.
- [31] Y. Wang, Z. Xiao, and G. Cao, "A convolutional neural network method based on Adam optimizer with power-exponential learning rate for bearing fault diagnosis," *Journal of Vibroengineering*, vol. 24, no. 4, pp. 666–678, 2022, doi: 10.21595/jve.2022.22271.
- [32] M. Iftikhar, I. A. Kandhro, N. Kausar, A. Kehar, M. Uddin, and A. Dandoush, "Plant disease management: a fine-tuned enhanced CNN approach with mobile app integration for early detection and classification," *Artificial Intelligence Review*, vol. 57, no. 7, 2024, doi: 10.1007/s10462-024-10809-z.
- [33] L. Kujur, V. Gupta, and A. Singhal, "A hybrid multi-optimizer approach using CNN and GB for accurate prediction of citrus fruit diseases," *Discover Applied Sciences*, vol. 7, no. 3, 2025, doi: 10.1007/s42452-025-06593-2.

BIOGRAPHIES OF AUTHORS



Paranita Asnur     received her B.S. degree in Forestry from the University of North Sumatra, Indonesia, in 2009, her M.S. degree in Tropical Silviculture from IPB University in 2013, and her Ph.D. degree in Information Technology from Gunadarma University, Indonesia. She is currently a lecturer in the Department of Agrotechnology, Faculty of Industrial Technology, Gunadarma University, Depok, Indonesia. Her research interests include agriculture, forestry, and agrotechnology informatics. She can be contacted at email: paranita@staff.gunadarma.ac.id.



Rifki Kosasih     received his B.S. degree in Mathematics from the University of Indonesia, Indonesia, in 2009, his M.S. degree in Mathematics from the University of Indonesia in 2012, and his Ph.D. degree from Gunadarma University, Indonesia, in 2015. He is currently a lecturer in the Department of Informatics, Faculty of Industrial Technology, Gunadarma University, Depok, Indonesia. His research interests include manifold learning, image segmentation, image processing, object recognition, and deep learning. He can be contacted at email: rifki_kosasih@staff.gunadarma.ac.id.



Sarifuddin Madenda     is a professor of Information Technology in the Doctoral Program of Information Technology at Gunadarma University, Indonesia. He received his B.Sc. degree in Physics Instrumentation from the University of Indonesia in 1989, his M.Sc. degree in Integrated Device Electronics from INSA de Lyon, France, in 1992, and his Ph.D. degree in Electronics and Image Processing from Université de Bourgogne, France, in 1995. His research interests include image and video processing, multimedia data compression, content-based image and video retrieval, steganography, and real-time system architectures such as FPGA and ASIC design. He can be contacted at email: sarif@staff.gunadarma.ac.id.



Dewi Agushinta R.     is an associate professor of Information Technology in the Doctoral Program of Information Technology at Gunadarma University, Indonesia. She received her B.Sc. degree in 1993 and her Ph.D. degree from Gunadarma University in 2007. She obtained her M.Sc. degree from the Asian Institute of Technology, Bangkok, Thailand. She currently teaches in the Department of Information Systems, Faculty of Computer Science and Information Technology, Gunadarma University. Her research interests include human-computer interaction, image processing, and information technology. She can be contacted at email: dewiar@staff.gunadarma.ac.id or dewiar@gmail.com.