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Multi-Class Mangrove Classification Using Transfer Learning with MobileNet-V3 on Multi-Organ Images

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Abstract

Mangrove ecosystems are important for coastal protection, biodiversity conservation, and climate change mitigation. However, the accurate identification of mangrove species is very challenging due to the morphological similarities between different species, especially when the species are analyzed based on limited plant organs like leaves or stems. Manual identification methods have traditionally been time-consuming, error-prone, and require expert knowledge. Addressing these issues, this research suggests an automatic classification system based on Deep Learning techniques by leveraging the MobileNet-V3 architecture. The system is based on images of three different plant organs—leaves, stems, and seeds—of five mangrove species: Avicennia marina, Avicennia officinalis, Avicennia rumphiana, Rhizophora mucronata, and Sonneratia alba. Data augmentation techniques such as rotation, shifting, and flipping, as well as sharpness enhancement, were applied in the preprocessing step to enhance data variability and ease model generalization. The model was trained with a carefully selected set of hyperparameters and extensively validated through training and testing steps. The experiment results demonstrated outstanding performance with a training accuracy of 99.88% and perfect precision, recall, and F1-score values of 100%. Furthermore, testing with unseen data confirmed the robustness of the model since all test samples were correctly identified. This research concludes that the MobileNet-V3 architecture offers an effective approach to mangrove species classification and suggests that future work should involve larger and more varied datasets, real-world field environments, and the investigation of ensemble models to further extend the adaptability and scalability of mangrove monitoring systems.

Keywords : *Convolutional Neural Networks, Deep Learning, Mangrove Species, MobileNet-V3, Transfer Learning.*

1. INTRODUCTION

Mangrove ecosystems are an essential part in preserving the ecological balance of coastal areas [1], [2]. They act as natural barriers, save the coast from being washed away, provide a living environment for a great number of marine and terrestrial species, and a very big part of the carbon sequestration of the earth [3]. To keep mangroves and their forests and to be alert then the forests should be preserved and monitored. The problem is that the climate is changing a lot and also anthropogenic factors are becoming more intense, so that the minute we are now in such a hurry to save and monitor the mangrove forests and their destruction that we should open our eyes and start taking action [4], [5]. Regular ecological survey methods are still in use, but they have a number of restrictions such as time or financial limits as well as the necessity for expertise in botany. The undeniable consequence of this is that in an age of technological revolution, people are still faithful to the traditional approach. This is because many ecologists consider digital imaging and automated analysis as the next level of technology that would assist ecological professionals in monitoring these habitats effectively [6], [7]. With these

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improvements in system, the identification speed and the accuracy of the database will be enhanced. They can be used to draw rational decisions on natural resource management and on the restoration of these habitats and for making conservation laws for the protection of these ecosystems[8].

However, despite these advances in technology, the task of accurately classifying mangrove species remains fraught with complications [9]. Mangrove flora possess high morphological similarities among various species, with very subtle variations in stem, seed, and leaf morphology that are occasionally difficult to distinguish, even for veteran specialists [9]. Ecological influences, such as light, salinity of water, and soil composition, may also alter the visual appearance of mangrove specimens, rendering classification complicated [10], [11]. Furthermore, the inherent variability of growth within one species introduces an additional complexity, thereby rendering it difficult for the utilization of observations that are based on a single characteristic. Manual classification, although accurate when done by specialists, does not have the scalability that is necessary for expansive coastal zones and needs considerable time and effort [12], [13], [14].

Several related studies have touched on the proposed methods with their respective approaches, and each carries its own drawbacks. As in the study [9], a CNN model was developed for mangrove species classification based on leaf, stem, and seed images. They employed the K-Folds Cross Validation technique to enhance model accuracy and stability, achieving a remarkable accuracy of up to 99.78%. However, the limitation lies in the dataset used, which had uniform image resolution and a relatively small number of classes, potentially reducing the model's robustness when applied to more complex datasets or real-world field images with varying lighting conditions and morphological diversities.

Research [15], a CNN-based deep learning approach was developed to identify mangrove species in Bali using leaf images from 11 different species. Achieving an average validation accuracy of 98.86%, this method shows strong potential for leaf-based species identification. Nonetheless, the drawback of this research is its focus solely on a single plant organ—leaves—without accounting for variations in stems or seeds. This narrow focus could compromise classification performance when leaves are damaged, incomplete, or during certain growth stages where leaf features are less prominent.

Research [16] discusses the development of MCCUNet, a modified version of DeepLabV3+, for mangrove community classification using multispectral imagery obtained via UAVs. They tested three transfer learning strategies and found that fine-tuned transfer learning (Ft-TL) achieved the highest accuracy of 97.24%. Despite these promising results, the drawback is that the study concentrated on community-level classification rather than species-specific identification and relied on multispectral imagery, which requires specialized UAV equipment and sensors.

Therefore, despite the significant progress achieved by these studies, there remains a clear gap in the development of a robust and scalable classification framework that can accurately distinguish mangrove species using multiple plant organs—such as stems, leaves, and seeds—under varying natural conditions with only standard RGB imagery. This study aims to address these limitations by proposing a multi-organ image-based mangrove species classification system using a lightweight transfer learning model, MobileNet-V3, to achieve high accuracy while ensuring practical deployment in real-world coastal monitoring scenarios

2. METHOD

The suggested plan for the mangrove species classification system consists of two phases, which are the training phase and the testing phase. The process starts with data collection in the form of images representing mangrove stems, leaves, and seeds. Also, the acquired data undergoes a pre-processing phase to enhance the quality and integrity of the dataset, such as resizing, normalization, and augmentation processes. The dataset is then split into two portions, with 80% used for training and 20%

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for testing. During model training, the data training process is conducted by modifying the structure of the CNN based on MobileNet-V3. Apart from that, training parameters like learning rate, batch size, and optimization function are adjusted in order to accomplish the best performance in training.

For evaluating the process, it tests the trained model by employing 20% of the test data which had been segregated. The aim of the data validation process is to test the generalization ability of the model in predicting new samples. The classification result is examined with the help of a confusion matrix, which tells us about the accuracy, precision, recall, and classification performance. From this examination, the system can identify the classification result class of every test image. The flow of proposed scheme can be seen in Figure 1.

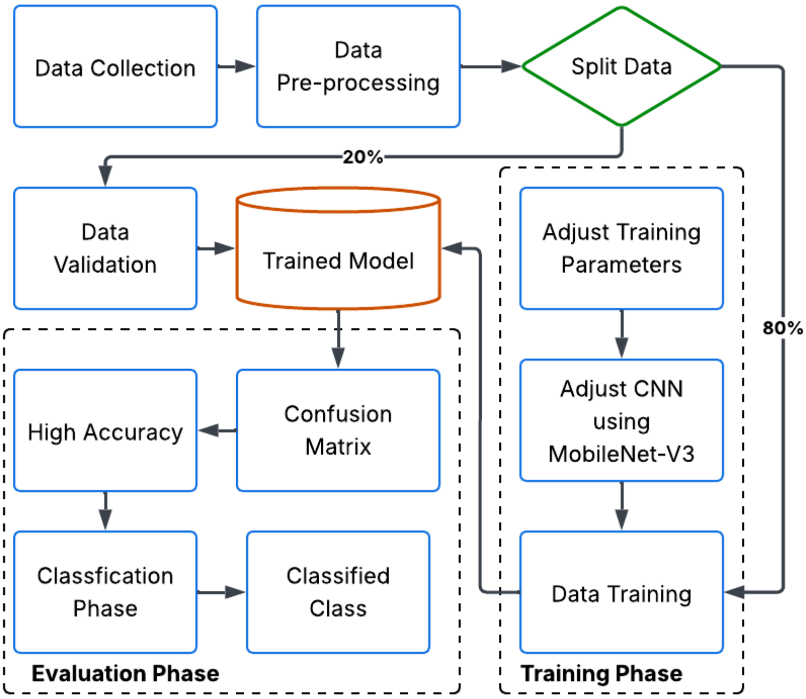

Figure 1. Flow of Proposed Scheme

As a note, the stages in the proposed workflow will be explained sequentially in the following sub-chapters, starting from 2.1 Data Collection, 2.2 Data Pre-processing, 2.3 Training Preparation, 2.4 CNN-based MobileNet-V3, and 2.5 Confusion Matrix. Each process will be described systematically to provide a structured overview of the research methodology. The evaluation results of the model, including analysis of classification performance and accuracy, will be presented in more detail in the next chapter.

2.1. Data Collection

The data collection process in this study used a public dataset obtained from research [9]. This dataset consists of five classes of mangrove species, namely Avicennia Marina, Avicennia Officinalis, Avicennia Rumphiana, Rhizophora Mucronata, and Sonneratia Alba. Each class includes images of various plant parts, namely stems, leaves, and mangrove seeds, thus enriching the variety of visual features that can be used for classification. All images in the dataset have been resized to 256 × 256 pixels with three color channels (RGB) to ensure input consistency in the model training process. The dataset has also been balanced with 150 images for each class, so that a total of 750 images are ready to

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be used in the pre-processing and model training stages. Sample of dataset each class can be seen in Figure 2.

(a) Avicennia Marina Class

(b) Avicennia Officinalis Class

(c) Avicennia Rumphiana Class

(d) Rhizophora Mucronata Class

(e) Sonneratia Alba Class

Figure 2. Sample Public Datasets Each Class

2.2. Data Pre-processing

During the pre-processing stage, data augmentation and enrichment are of particular concern in order to enrich the amount of training data and avoid overfitting of the model. Data augmentation is achieved by techniques such as rotation of images, shifting of images, and flipping of images [17], [18], [19]. Rotation of images is conducted at arbitrary angles to create variations in the direction of images, whereas image shifting is done to move the objects' positions in the image [20]. Horizontal flip is used to create reflection images that possess the capability to increase data diversity. Augmentation process helps the model learn to detect objects under various different conditions even with limited data exposure[21]. Apart from augmentation, the improvement stage is also used to improve image quality such that the model can detect important features more clearly. The image is rotated by a random angle within a certain range, for example, rotating the image between -30° and +30° as seen in (1).

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} cos(\theta) & -sin(\theta) \\ sin(\theta) & cos(\theta) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (1)$$

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Where θ is the rotation angle, and (x, y) are the pixel coordinates before rotation, while (x', y') are the pixel coordinates after rotation. Image shifting simulates a change in the object's position in the image. It is typically done in the horizontal and vertical directions as seen in (2).

$$ShiftedImage(x', y') = Image(x - dx, y - dy) \quad (2)$$

Where dx and dy are the shift values in the horizontal and vertical directions. Image flipping produces a reflection of the image. It can be done either horizontally (left-right) or vertically (top-bottom) as seen in (3).

$$Flipped\ Image(x', y') = ShiftedImage(w - x, y) \quad (3)$$

Where w is the width of the image, and x is the pixel position in the horizontal direction. On the other hand, enhancement technique used is image sharpening enhancement that is to accentuate the details and edges of objects in the image. Sharpening is attained using a convolution technique that enhances the sharpening of the image such that the model is able to spot key details in the image effortlessly. Mathematically, sharpening enhancement can be seen in (4).

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad (4)$$

Where G_x and G_y are the Sobel kernels for detecting horizontal and vertical edges. The result of the convolution produces a sharper image.

2.3. Training Preparation

For the training preparation stage, the computing device used consists of an AMD Ryzen 5 5600X processor combined with an NVIDIA GeForce RTX 3070 Ti graphics card, as well as 32 GB of RAM and 1 TB of internal storage (ROM). This hardware configuration allows the model training process to be time efficient and can handle large data volumes. In addition to hardware, the hyperparameter settings used in model training are also very important to ensure optimal performance. Further details regarding the hyperparameter values used can be seen in Table 1.

Table 1. Training hyperparameter

Hyperparameter	Value
Learning Rate	0.0001
Batch Size	32
Max Epochs	20
Optimizer	Adam
Momentum	0.9
Dropout Rate	0.5
Loss Function	Categorical Crossentropy

As seen in Table 1, hyperparameters used for model training include a learning rate of 0.001, a batch size of 32, and 50 epochs. The Adam optimizer with a momentum of 0.9 was chosen, and a dropout rate of 0.5 was applied to prevent overfitting. The categorical crossentropy loss function was utilized for the multi-class classification task. These hyperparameters were selected to optimize the performance of the MobileNet-V3 model based on the dataset and experimental setup.

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2.4. CNN-based MobileNet-V3

The MobileNet-V3 model that is based on CNN is used for the classification task due to its capability to process large data with high accuracy efficiently [22], [23]. MobileNet-V3 is used with depthwise separable convolutions that reduce the number of parameters and computational cost compared to traditional CNN models [24], [25], [26]. The model is particularly optimal for use in mobile and embedded systems, as it achieves a good balance between speed and performance. MobileNet-V3 layers can be seen in Figure 3.

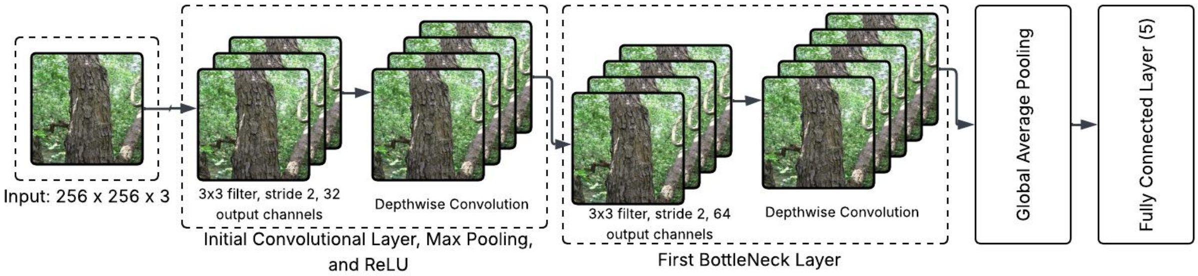

Figure 3. Layers of MobileNet-V3

Based on Figure 3, the model consists of several convolutional layers followed by fully connected layers, utilizing ReLU activations to introduce non-linearity. The output layer uses a softmax activation function to classify the input images into one of the five mangrove species classes. The MobileNet-V3 architecture starts with an input layer that accepts images of size 256x256x3, representing RGB images resized for the model. The first layer is a convolution layer with a 3x3 kernel and 32 filters with a stride of 2, followed by batch normalization and ReLU6 activation to introduce non-linearity. This is followed by several depthwise separable convolution blocks, where each depthwise convolution is applied to individual input channels, significantly reducing computational cost. A pointwise convolution (1x1) is then applied to combine the depthwise outputs.

The core of MobileNet-V3 is the bottleneck layer, which is repeated three times, with the number of filters gradually increasing at each stage to capture progressively higher-level features. In the first bottleneck block, the network uses 32 filters, followed by 64 filters in the second, 128 filters in the third, and 256 filters in the final stage. Each bottleneck consists of depthwise separable convolutions with increasing filter sizes to capture fine-grained details at different scales. After passing through the bottleneck layers, the model undergoes global average pooling, which reduces the output feature map into a single value per channel. Finally, the output is passed through a fully connected (dense) layer with 5 units, corresponding to the 5 species classes, followed by a softmax activation to provide class probabilities, enabling the classification of input images into one of the five mangrove species.

2.5. Model Evaluation using Confusion Matrix

the confusion matrix is used to evaluate the performance of the MobileNet-V3 model in classifying the five mangrove species: Avicennia Marina, Avicennia Officinalis, Avicennia Rumphiana, Rhizophora Mucronata, and Sonneratia Alba. The matrix helps identify the species that the model classifies well and the species for which misclassifications occur [27], [28]. These insights are essential for fine-tuning the model and improving its ability to generalize, as well as for identifying potential biases in the dataset. The overall performance of the model is quantified by calculating metrics such as accuracy, which is derived from the diagonal elements, and other metrics like precision, recall, and F1-score for a more detailed evaluation of the classification results [29], [30]. These metrics provide a

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comprehensive evaluation of the model's classification performance. The equations for each metric can be seen in (5) to (8).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision \times Recall} \tag{8}$$

Where TP (True Positives) refers to the number of instances that are correctly predicted as positive, TN (True Negatives) represents the number of instances correctly predicted as negative, FP (False Positives) is the count of instances incorrectly predicted as positive, and FN (False Negatives) is the count of instances incorrectly predicted as negative.

3. RESULT

In this chapter, an evaluation test is conducted as outlined in the research methodology, which encompasses both the training phase and the testing phase. As described in the proposed method, the training phase involves the model being trained on a dataset of mangrove species images, with appropriate data augmentation and enhancement techniques applied to improve model generalization. During the testing phase, the trained model is evaluated using unseen data to assess its performance. The evaluation is based on key performance metrics such as accuracy, precision, recall, and F1-score, which provide a comprehensive understanding of how well the model can classify mangrove species. These results are discussed in detail to assess the model's strengths and potential areas for improvement.

As a note, Section 3.1 discusses the training phase, where the model undergoes training using the specified hyperparameters and architecture. Section 3.2 presents the testing phase, where the model is evaluated using unseen data to assess its classification performance and generalization ability.

3.1. Training Phase

The training phase was conducted using the hyperparameters listed in Table 1, which include learning rate, batch size, and optimizer settings. The model architecture, as discussed in the previous section, is based on MobileNet-V3, with several convolutional layers, including the bottleneck blocks, designed to capture progressively higher-level features. During training, the model underwent multiple epochs, with the training accuracy and loss being monitored to assess its learning process. As shown in Figure 4(a), the training accuracy converges rapidly within the first epoch, indicating the model's ability to learn effectively from the dataset. Meanwhile, Figure 4(b) illustrates the training loss curve, which tracks the decrease in error as the model adjusts its weights, aligning with the accuracy curve in Figure 4(a). These results demonstrate the model's capacity to learn and optimize its parameters during the training phase.

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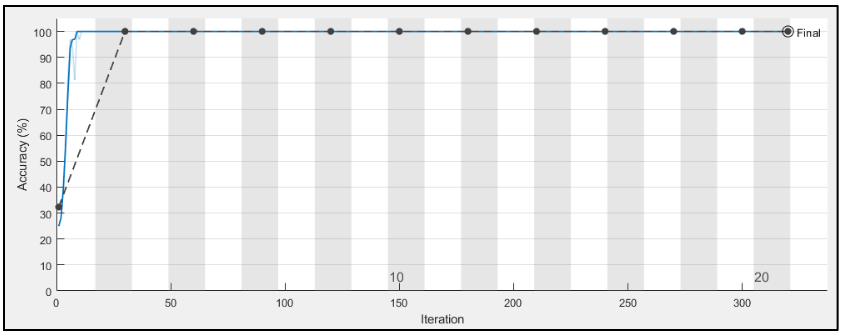
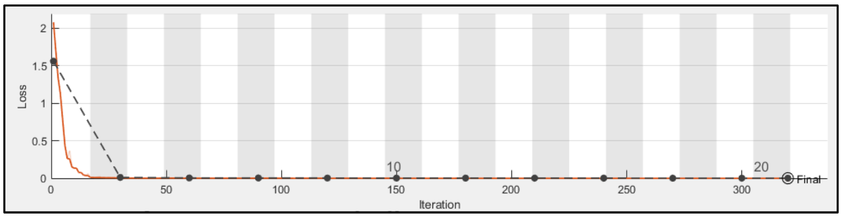


(a) Training accuracy



(b) Training Loss

Figure 4. Results of Deep Learning MobileNet-V3

After obtaining the training accuracy and loss graphs as shown in Figure 4, the model's performance was further evaluated through the confusion matrix, presented in Figure 5. The results from the confusion matrix reveal that the model achieved perfect classification, with all instances being correctly predicted as True Positives (TP) for each of the five mangrove species classes. There were no False Positives (FP) or False Negatives (FN), indicating that the model performed flawlessly during the testing phase without any misclassifications.

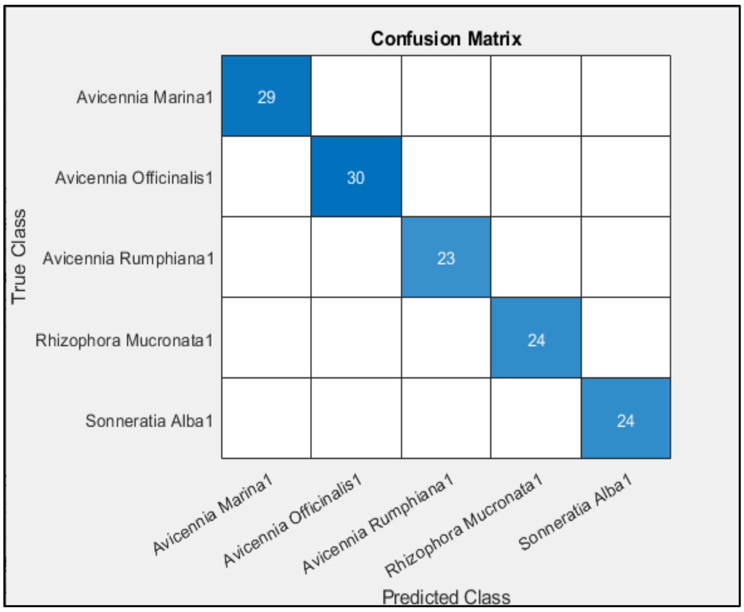


Figure 5. Table of Confusion Matrix

Following the near-perfect classification results from the confusion matrix, the model's performance metrics, including accuracy, precision, recall, and F1-score, are summarized in Table 2.

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With an accuracy of 99.88% and 100% precision, recall, and F1-score, the model demonstrates exceptional performance in classifying the five mangrove species classes. The accuracy reflects the overall correctness of the model's predictions, while the perfect precision, recall, and F1-score indicate flawless classification for each class, with no false positives or false negatives.

3.2. Testing Phase

Table 3. Single testing prediction

Input Testing Data	Actual Class	Predicted Class	Conclusion
Avicennia Marina1.jpg	Avicennia Marina	Avicennia Marina	TP
Avicennia Marina7.jpg	Avicennia Marina	Avicennia Marina	TP
Avicennia Officinalis2.jpg	Avicennia Officinalis	Avicennia Officinalis	TP
Avicennia Officinalis9.jpg	Avicennia Officinalis	Avicennia Officinalis	TP
Avicennia Rumphiana1.jpg	Avicennia Rumphiana	Avicennia Rumphiana	TP
Avicennia Rumphiana3.jpg	Avicennia Rumphiana	Avicennia Rumphiana	TP
Rhizophora Mucronata4.jpg	Rhizophora Mucronata	Rhizophora Mucronata	TP
Rhizophora Mucronata8.jpg	Rhizophora Mucronata	Rhizophora Mucronata	TP
Sonneratia Alba1.jpg	Sonneratia Alba	Sonneratia Alba	TP
Sonneratia Alba5.jpg	Sonneratia Alba	Sonneratia Alba	TP

The testing phase was conducted using a separate set of images that were not included in either the training or validation datasets. This approach ensures an unbiased evaluation of the model’s actual performance, as the model was never exposed to these particular images during its learning process. As shown in Table 3, the testing dataset consisted of a variety of images representing each of the five mangrove species. The model’s ability to correctly classify all test images as True Positives (TP) indicates that the model successfully generalized the features learned during training to accurately predict unseen data.

4. DISCUSSIONS

Based on Table 2, our study based on the MobileNet-V3 architecture, demonstrates superior performance in mangrove species classification, achieving an accuracy of 99.88% with perfect precision, recall, and F1-score of 100%. When compared to previous studies, such as the one by Research [9], which achieved an impressive accuracy of 99.78% using K-Folds cross-validation, our model outperforms the previous model in both accuracy and stability. The use of the MobileNet-V3 architecture, known for its efficiency in handling large-scale image datasets, coupled with data augmentation and enhancement techniques, contributed to the improved generalization of our model, allowing it to handle the diversity of mangrove species and their visual features more effectively.

Table 2. Performance of confusion matrix

Researcher	Model	Accuracy	Precision	Recall	F1-Score
[9]	CNN Based on K-Folds	99.78%	100%	100%	100%
[15]	CNN Based on Modified Layer	98.86%	92%	92%	N/A
Our Study	CNN Based on MobileNet-V3	99.88%	100%	100%	100%

However, like the study in Research [15], which focused on using leaf images alone for classification, our approach also uses specific plant organs—stem, seed, and leaf—making it more robust compared to leaf-only-based models. The accuracy of 98.86% achieved in Research [15] is commendable, but it was limited by its narrow focus on a single plant organ. Our method, by incorporating all three plant organs, provides a more comprehensive and versatile solution for mangrove species identification, particularly in real-world applications where leaves may be incomplete or

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damaged. Despite this, future work could benefit from testing the model in more diverse environmental conditions to further evaluate its robustness in real-world scenarios.

Furthermore, consistent success across all test samples indicates that the model did not overfit to the training or validation data, but instead learned robust and distinctive features of each mangrove species. By using a completely independent testing dataset, this study emphasizes the effectiveness of the proposed MobileNet-V3-based CNN model in real-world applications, where variability in samples is inevitable. This robust generalization performance is critical for practical applications, especially in environments where image conditions may differ from those seen during training.

5. CONCLUSION

This study successfully proposed and implemented a CNN-based classification model using the MobileNet-V3 architecture for the identification of five mangrove species, namely Avicennia Marina, Avicennia Officinalis, Avicennia Rumphiana, Rhizophora Mucronata, and Sonneratia Alba, based on images of leaves, stems, and seeds. Through a comprehensive training phase involving data augmentation (rotation, shifting, flipping) and enhancement (sharpness improvement), the model was trained to generalize better and minimize overfitting. The training was carried out using optimized hyperparameters, and the architecture design, discussed previously, was able to extract high-level features effectively from the input images.

The model's testing procedure proved satisfactory. The model's results revealed 99.88% overall training accuracy while precision, recall, and F1-score values reached 100% on all occasions, establishing perfect classification during the entire validation process. The confusion matrix confirmed that instances were correctly classified without any mismatched predictions. Additionally, the one-image testing based on a total set of unseen images provided a further endorsement of the model's stability as it made perfect predictions for all classes. The independent test confirmed that the model did not just learn the patterns of training but generalized successfully on new inputs. Future work might focus on enriching the dataset by including images observed under various environmental conditions as well as on examining more complex structures or ensemble methods for enhancing the model's flexibility and ability under more complex conditions.

CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

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