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Note **Special Issue**

Mangrove species identification using Convolutional Neural Network

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ABSTRACT: Mangroves are unique coastal ecosystems that are rich in biodiversity and have significant ecological value. Identifying mangrove species is important for many applications, such as biodiversity, restoration, and monitoring. As traditional methods are complicated and time-consuming, non-experts need an approach to identify mangroves in a timely and cost-effective manner. In this study, we created a deep learning approach for mangrove species identification based on leaf image recognition. We used digital images of mangrove leaves to identify mangrove species by applying Convolutional Neural Networks (CNN). A dataset of leaf images from 11 'true' mangrove species found in Bali, Indonesia, was developed and divided into 80% for training and 20% for test datasets. About 20% of the training dataset was used for validation. Our results showed an accuracy of 98.86% on validation and 97.16% on a test set of images, promising possibilities for mangrove species identification. The finding indicates that the model effectively identifies mangrove species that are high in diversity and have morphological similarities.

KEY WORDS: Bali, Convolutional Neural Networks, deep learning, Indonesia, mangroves, plant identification.

INTRODUCTION

Nowadays, plant identification has been advanced by incorporating artificial intelligence into plant identification technology (Asnur *et al*., 2023). For mangrove ecosystems, this application is essential not only for biodiversity purposes but also for mangrove management and restoration. Mangrove ecosystems, found in tropical and subtropical coastlines worldwide, play a pivotal role in coastal protection, fishery resources, biodiversity, and livelihood (Barbier *et al*., 2011). Mangroves comprise a diverse group of plants, which can be classified into three groups: major mangrove species, minor mangrove species and mangrove associates (Tomlinson, 1994). The biodiversity of mangroves is considered relatively low compared with terrestrial plants, as several studies claimed that the number of mangrove species ranges from 65 species (Kathiresan and Bingham, 2001) to 70 species (Polidoro *et al*., 2010); however, their distinct distributional ranges in association with local conditions create morphological specialisation that leads to complexity of the ecosystem (Duke *et al*, 1998, Lugo 1974). The major mangrove species, so called 'true' mangroves, are found restricted in intertidal zones and well known for their morphological and physical adaptations with harsh environments, characterised by high salinity and tidal inundation (Kathiresan and Bingham, 2001). Other vegetation, defined as mangrove associates, can resemble 'true' mangroves but not exclusively inhabit the intertidal zones (Lugo and Snedaker, 1974).

The unique characteristics of mangroves create diverse morphology of this kind of plant that needs to be identified using traditional keys. The identification of mangrove species can rely on the examination of fruit and flower morphology (Kamruzzaman *et al*., 2019), but these components are only accessible at specific periods due to their seasonal pattern. Therefore, the leaf is most likely the primary option for mangrove identification due to its easy accessibility and availability at all times, and it can be utilised for specific identification based on distinct leaf features, such as shape, texture, size, colour, and other specific properties (Lucena *et al*., 2011; Nascimento *et al*., 2021). However, distinguishing visual differences in leaf characteristics between different species of mangroves may prove challenging for individuals lacking experience in this field (Dissanayake and Kumara, 2021; Viodor *et al*., 2022). In addition to morphological diversity among mangrove species, hybridisation between species can also result in taxonomy problems, such as difficulty in identification (Kathiresan and Bingham, 2001).

While identifying mangrove species with traditional methods might be difficult for non-experts, a deep-learning approach can provide excellent performance identification derived from expert knowledge (Alias *et al*., 2020; Azad *et al*., 2020). To date, the morphological attributes of plant leaves have been utilised as a promising dataset for the development of deep learning algorithms

Table 1. 'True' mangrove species used in this study and the number of samples (images) per species in the dataset.

Family /Species	Number of Sample Dataset	
	Real	Augmented
Acanthaceae		
Avicennia alba	500	1000
Avicennia marina	500	1000
Avicennia officinalis	500	1000
Combretaceae		
Lumnitzera recemosa	500	1000
Lythraceae		
Sonneratia alba	500	1000
Meliaceae		
Xylocarpus granatum	500	1000
Rhizophoraceae		
Bruguiera gymnorrhiza	500	1000
Ceriops decandra	500	1000
Rhizophora mucronata	500	1000
Rhizophora apiculata	500	1000
Rhizophora stylosa	500	1000
Total	5500	11000

in the identification of multiple species. Wan *et al.* (2019) proposed a compact patch-based Convolutional Neural Network (CNN) on GoogleLeNet structure to exploit the benefits of CNN in feature analysis on six mangrove species. This approach aimed to address the limitation of fixed and huge input sizes that restricted the use of CNNs in fringe mangrove forests. This method significantly decreased the role of down-sampling technology to create a more complex network with smaller input. Their model demonstrated superior classification accuracy at 98.8%. Another work on mangrove identification was conducted by Asnur *et al.* (2023) using a CNN structure to accurately classify four mangrove species. The model's architecture consisted of a batch size of 32, input images of size 128x128 pixels, four classes, four convolution layers, four rectified linear unit (ReLU) layers, 2x2 max-pooling, and two fully connected layers (FCL), giving the test with an accuracy rate of 97.50%. Inspired by technological advancements, Viodor *et al.* (2022) explored deep neural network-based deep learning applications for plant identification intended for handheld devices using a dataset of five mangrove species. The study also carried out experimental validation using deep learning and the suggested cutting-edge architecture. Their findings demonstrated the practicality of utilising MobileNetV3Small for mangrove species identification, with an accuracy of up to 97.07%. Another study by Viodor *et al* (2023) used a balanced dataset consisting of 5000 images from five mangrove species and demonstrated a model accuracy of up to 98.4%. Using a smartphone, this study integrated the trained model into a mobile application that can capture and identify the mangrove species through leaf images.

This paper aims to provide an understanding of the approach of mangrove identification using CNN, focusing on transfer learning on a dataset of leaf images of 11 'true' mangrove species from 5 different mangrove families. In the present study, mangrove leaves were utilised as the primary database object for performing training on object recognition. The dataset was conducted on the training model based on the confusion matrix and classification report. This model, namely *e-mangrove* model, will be incorporated into *MonMang* application, a mangrove monitoring tool for optimising field activities, including research surveys and monitoring of mangrove rehabilitation/restoration.

MATERIALS AND METHODS

Dataset Collection

The dataset was built for mangrove leaves of 11 'true' mangrove species that were collected in December 2023 from mangrove forests in Jembrana, Bali, Indonesia (Table 1), where a preliminary study of mangrove biodiversity has been carried out since 2010. Using information from the area we are familiar with, we aimed to build a knowledge base for the creation of mangrove databases in Indonesia.

Given the complexity of mangrove tree structure and radically different heights within species, the height of the canopy at which we collected the leaves was not taken into account (Camargo Maia & Coutinho, 2012). Due to time constraints, only one or two individuals from each species were collected, and they were promptly photographed to prevent colour fading.

A white background was used to photograph the leaves image on both the upper and lower sides, with 250 leaves per species. In order to improve the image composition, the image was taken in balanced format with a 1x1 ratio on an Android smartphone with the resolution of 2992x2992 pixels (Figure 1). This is a default resolution of image captured from the smartphone that will retain detailed features, allowing flexibility in preprocessing and potential future analyses that may require finer details or different input sizes. Image preparation was carried out on the dataset before model training in data processing.

We started by setting up a dataset and renaming it with "lab-image sequence". All images were resized to 600×600 pixels using Microsoft Picture Manager in order to encounter challenges in running the model. The dataset was split into three sections: training, validation, and testing set. From a total dataset of 5500 images, the training dataset made up 80% of the dataset, which contained 4400 total images then 20% of the training dataset (880 images) were designated as validation datasets, which were used to adjust hyperparameters and track the model's performance during training. The testing dataset comprised 20% of the dataset (1100 images) toevaluate the final performance of the trained model (Sidik *et al.*, 2023). In this work, we employed a balanced

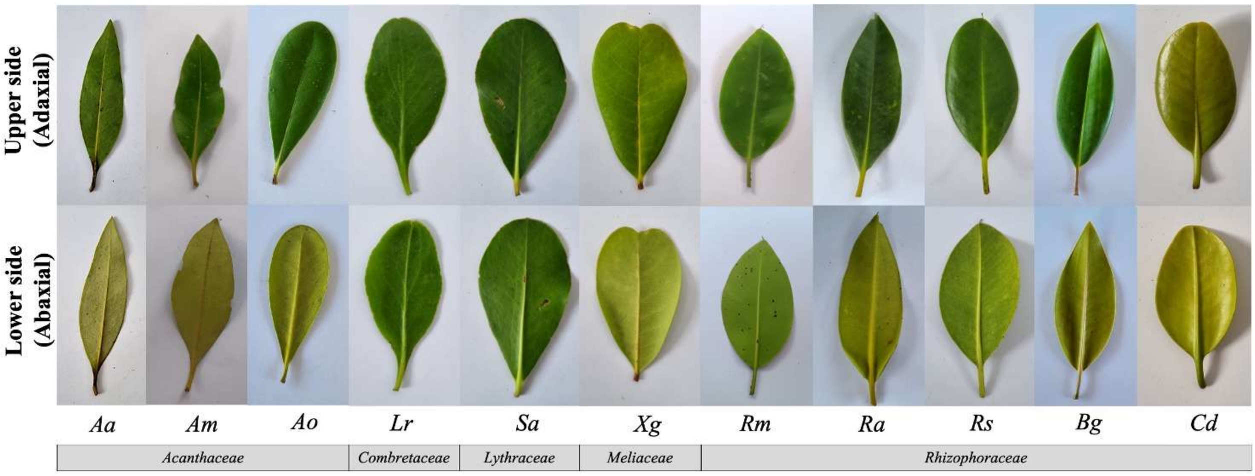

Fig. 1. Leaf images of eleven 'true' mangrove species used white background (upper and lower side): *Avicennia alba* (**Aa**), *Avicennia marina* (**Am**), *Avicennia officinalis* (**Ao**), *Bruguiera gymnorrhiza* (**Bg**), *Ceriops decandra* (**Cd**), *Lumnitzera racemosa* (**Lr**), *Rhizophora mucronata* (**Rm**), *Rhizophora apiculata* (**Ra**), *Rhizophora stylosa* (**Rs**), *Sonneratia alba* (**Sa**), and *Xylocarpus granatum* (**Xg**)

dataset, which provides an equal number of images for each class. In many applications, using a balanced dataset for deep learning training is the preferable method since it can enhance generalisation, boost model performance, and yield more precise assessment metrics (Bengar *et al*., 2022).

Each dataset was numbered and stored in a different folder to ensure that no imaging faults appeared twice in the training or testing datasets. To evaluate the model's generalisability and robustness, we trained the model on an augmented dataset of 11000 images, of which 80% (8800 images) were used for training, and 20% of the training dataset (1760 images) were used for validation. The remaining 20% (2200 images) were used for testing.

Network Architecture

In this study, we explored MobileNetV2, a Convolutional Neural Network (CNN), as a deep-learning model for identifying mangrove species. MobileNetV2 is a compact neural network structure created for effective processing on mobile gadgets (Michele *et al*., 2019). This CNN offers efficient power consumption and computational capabilities, making it suitable for low-cost and compact mobile phone models (Howard *et al*., 2017) by drastically reducing the amount of memory and processes required while maintaining the same level of accuracy (Sandler *et al*., 2018). The technique divides ordinary convolution operations into two separate stages: depthwise convolution and pointwise convolution (Lu *et al*., 2022; Tu *et al*., 2020). A depthwise separable convolution is utilised to decrease the quantity of parameters and computational workload, enhancing efficiency in terms of both size and speed. Therefore, MobileNetV2 applies depthwise separable convolution and a bottleneck block architecture to attain high efficiency. MobileNetV2 utilises ReLU as an activation function to bring non-linearity into the model, enabling it to learn intricate patterns.

MobileNetV2 is frequently trained and run in Google Colab, which is a resourceful tool for creating and training deep learning models (Carneiro *et al*., 2018). Google Colab is often used for image recognition and classification projects due to its efficiency in terms of model size and computational efficiency, as well as the fact that it offers free access to a powerful GPU or TPU (Praveen Gujjar *et al*., 2021). Users can use MobileNetV2 in Google Colab to effectively manage picture recognition tasks without straining computing resources (Xie *et al*., 2022).

CNN architecture utilised in this study for the Deep Neural Network, together with transfer learning, is shown in Figure 2. Transfer learning was implemented by using a MobileNet-based model as the basis model, where the classification layer was removed and initialised with ImageNet weights. We improved it with the addition of Conv2D, MaxPooling2D, Flatten, Dense, Rescaling, RandomFlip, RandomZoom, and RandomRotation layers for a specific use case or dataset. The output was passed to the batch normalisation layer, which normalised the input for the following layer and enhanced network speed and convergence. Subsequently, we implemented the Rectified Linear Unit (ReLU) activation function in MobileNetV2 with the formula as follows:

$$ReLu(x) = \max(0, x)$$

where (x) represents the input from the specific neuron or layer. A dropout layer was included to mitigate overfitting and enhance the model's generalisation capabilities (Wani *et al*., 2020).

Environment and setting

The model's data processing and training were set in the Jupyter Notebook and the Google Colab environment. Utilising a Precision 3470 machine with a 12th generation Intel® Corei5-1250P that was primarily utilised during the research for pre-processing the dataset, including

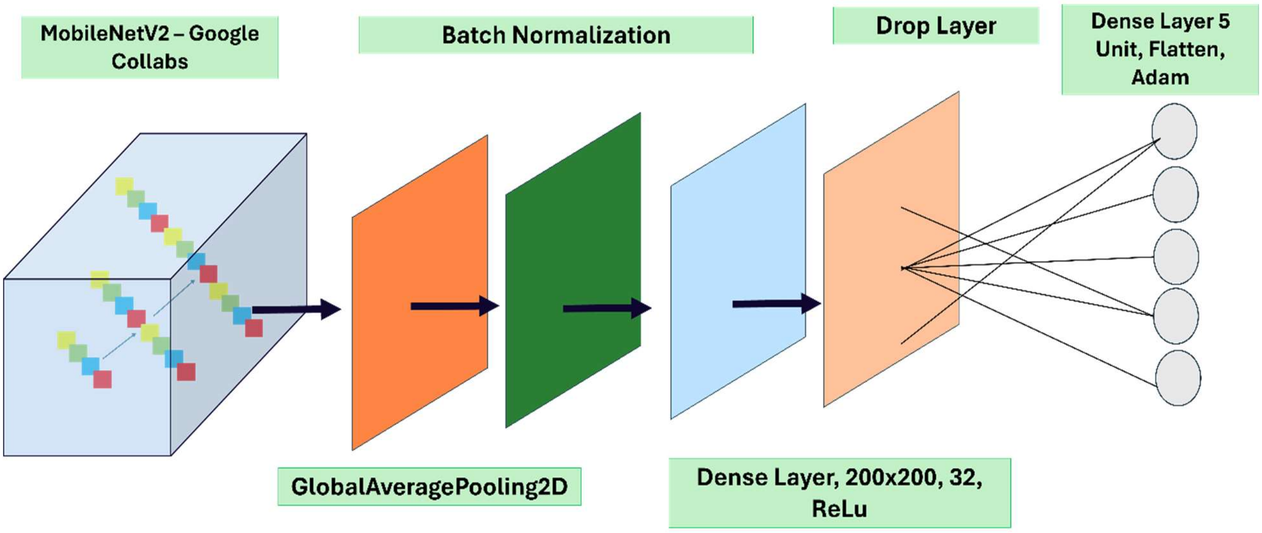

Fig. 2. MobileNetV2 architecture.

Table 2. *e-mangrove* model parameters for large model and small model.

No	Layer Type	Large Model		Small Model	
		Output Shape	Parameter	Output Shape	Parameter
1	random_flip (RandomFlip)	200, 200, 3	0	200, 200, 3	0
2	random_zoom (RandomZoom)	200, 200, 3	0	200, 200, 3	0
3	random_rotation (RandomRotation)	200, 200, 3	0	200, 200, 3	0
4	rescaling_1 (Rescaling)	200, 200, 3	0	200, 200, 3	0
5	conv2d (Conv2D)	200, 200,16	448	200, 200,8	224
6	max_pooling2d (MaxPooling2D)	100, 100, 16	0	100, 100, 8	0
7	conv2d_1 (Conv2D)	100, 100, 32	4640	100, 100, 16	1168
8	max_pooling2d_1 (MaxPooling 2D)	50, 50, 32	0	50, 50, 16	0
9	conv2d_2 (Conv2D)	50, 50, 64	18496	50, 50, 32	4640
10	max_pooling2d_2(MaxPooling2D)	25, 25, 64	0	25, 25, 32	0
11	dropout (Dropout)	25, 25, 64	0	25, 25, 32	0
12	flatten (Flatten)	40000	0	20000	0
13	dense (Dense)	128	5120128	128	1280064
14	dense_1 (Dense)	13	1677	13	845
	Total Parameters	5145389 (19.63 MB)		1286941 (4.91MB)	
	Trainable parameters	5145389 (19.63MB)		1286941(4.91MB	
	Non-trainable parameters	0			0

organising, cleaning, and augmenting image data. These tasks, though less computationally intensive than model training, require a reliable machine with sufficient processing power and memory to handle a large volume of high-resolution images efficiently. For deep learning training, the use of Google Colab was essential, as its powerful GPU resources were leveraged to significantly accelerate the model training process. This setup enabled the efficient handling of computationally intensive tasks, including the training of the model on large dataset and the fine-tuning performed using transfer learning.

The model was trained using inputs resized to 600x600 pixels, with a size of 19.63 MB for the large model and 4.91 MB for the small model. The training process then divided the data into three sets: a training set that contained 80% of the complete data, a validation set that contained 20% of the training set, and a testing set that had 20% of the entire data. The training dataset only includes single-leaf images from a carefully chosen collection of leaf shots. Before using MobileNetV2 to train the deep learning model, hyperparameters were specified to improve the model's performance on fresh data. Each model was configured to utilise input images with a 200x200 pixel resolution. After using the Adam optimiser to fine-tune the models to a batch size of 32, the models were assembled using the Categorical Cross-Entropy loss function and made ready for training. As indicated in Table 2, we used these hyperparameters consistently in all testing to ensure a fair and comparable comparison of results. To guarantee accurate results and remove bias in both the training and validation phases, three-fold cross-validation was carried out.

Table 3. Comparison of e-mangrove large and small model based on their training performance.

Small model										
Epoch		**10**		**20**		**30**		**40**		**50**
Dataset	**Real**	**Augmented**	**Real**	**Augmented**	**Real**	**Augmented**	**Real**	**Augmented**	**Real**	**Augmented**
Accuracy	81.02	84.89	89.89	90.22	92.52	89.72	96.07	91.68	96.73	93.83
ValAccuracy	88.30	83.69	84.89	91.70	90.80	93.92	96.14	93.07	98.64	95.51
Precision	0.73	0.78	0.80	0.82	0.82	0.80	0.90	0.84	0.85	0.86
Recall	0.72	0.76	0.77	0.82	0.78	0.79	0.90	0.84	0.85	0.84
Average Time (s/epoch)	56s 402ms /step	84s 303ms/step	52s 371ms/ step	84s 305ms/step	51s 371ms/ step	111s 404ms/step	49s 354ms/ step	97s 353ms/step	49s 352ms/ step	107s 388ms/step
Large Model										
Epoch		**10**		**20**		**30**		**40**		**50**
Dataset	**Real**	**Augmented**	**Real**	**Augmented**	**Real**	**Augmented**	**Real**	**Augmented**	**Real**	**Augmented**
Accuracy	85.98	85.16	92.89	94.35	92.75	95.50	96.07	96.99	97.16	96.49
ValAccuracy	89.77	85.68	94.20	94.83	96.82	96.88	97.27	99.09	98.86	96.99
Precision	0.76	0.88	0.59	0.84	0.84	0.87	0.88	0.92	0.90	0.87
Recall	0.76	0.86	0.59	0.82	0.85	0.87	0.87	0.92	0.89	0.87
Average Time (s/epoch)	85s 613ms /step	236s 858ms/step	132s 951ms/ step	144s 523ms/step	72s 518ms/ step	159s 577ms/step	105s 756ms/ step	151s 549ms/step	73s 525ms/ step	233s 846ms/step

Evaluation matrix

We assessed the model's performance using a particular test set that included scores for accuracy, precision, and recall. Accuracy is the ratio of correct forecasts to total predictions. Precision evaluates the accuracy of positive predictions produced by the model. Recall is the proportion of true positives to the total number of genuine positive cases in the dataset.

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

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

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

True Positive (TP) is the count of instances accurately identified as positive by a model. Conversely, True Negative (TN) represents the occurrences accurately identified by a model as negative. False Positive (FP) is the count of occurrences where a model inaccurately predicts a positive outcome. False Negative (FN) occurs when a model wrongly forecasts instances as negative.

RESULTS AND DISCUSSION

Table 3 compares the training performance of multiple MobileNetV2 iterations, with particular emphasis on cross-validation outcomes, computation time, and epoch size prior to and during optimisation. The SM10, SM20, SM30, SM40, and SM50 models were small models in the sense of size and number of epochs. These models used less processing power and fewer iterations, yet they exhibited an ideal variance in validation accuracy. Compared to the large models (models LM10, LM20, LM30, LM40, and LM50), the small models were more portable and ideal for use on mobile devices for plant species identification.

Our work yielded the greatest results as a preliminary e-mangrove model at 50 epochs of the large model on a real dataset, with 97.16% training accuracy and 98.86% validation accuracy. Our findings are consistent with a recent study conducted by Viodor *et al.*, (2023), which involves creating a mobile application using the deep learning model MobileNetV3 for the identification of mangrove species. This program also included a feature for recording and analysing the variety of these species. In Viodor *et al* (2023), a dataset of 5,000 photos of five prevalent mangrove species in Clarin, Bohol was gathered, and a deep-learning model was developed utilising transfer learning techniques. The MobileNetV3Large model demonstrated a high accuracy rate of 98.4% when tested on a collection of photos, suggesting its proficiency in accurately identifying different mangrove species. The proficient model was incorporated into a mobile application capable of capturing and classifying mangrove leaves using a smartphone camera. The application's intuitive interface, live data recording, and cloud-based structure make it well-suited for extensive biodiversity monitoring and management, facilitating expedited and more effective data collecting and analysis (Atsumi *et al.*, 2024; Urbano *et al.*, 2024).

The training and validation accuracy graphs for e-mangrove models using real datasets are shown in Figure 3, while the corresponding graphs for e-mangrove models utilising augmented datasets are shown in Figure 4. The figures show that, with a small variation in the other model, the large model has the highest accuracy. Due to its outstanding cross-validation performance, this model has the lowest loss.

The classification performance of the model was evaluated using both the real and augmented datasets, with the results demonstrating varying levels of accuracy across species. In the real dataset (Figure 5a), the model achieved high confidence levels for species such as

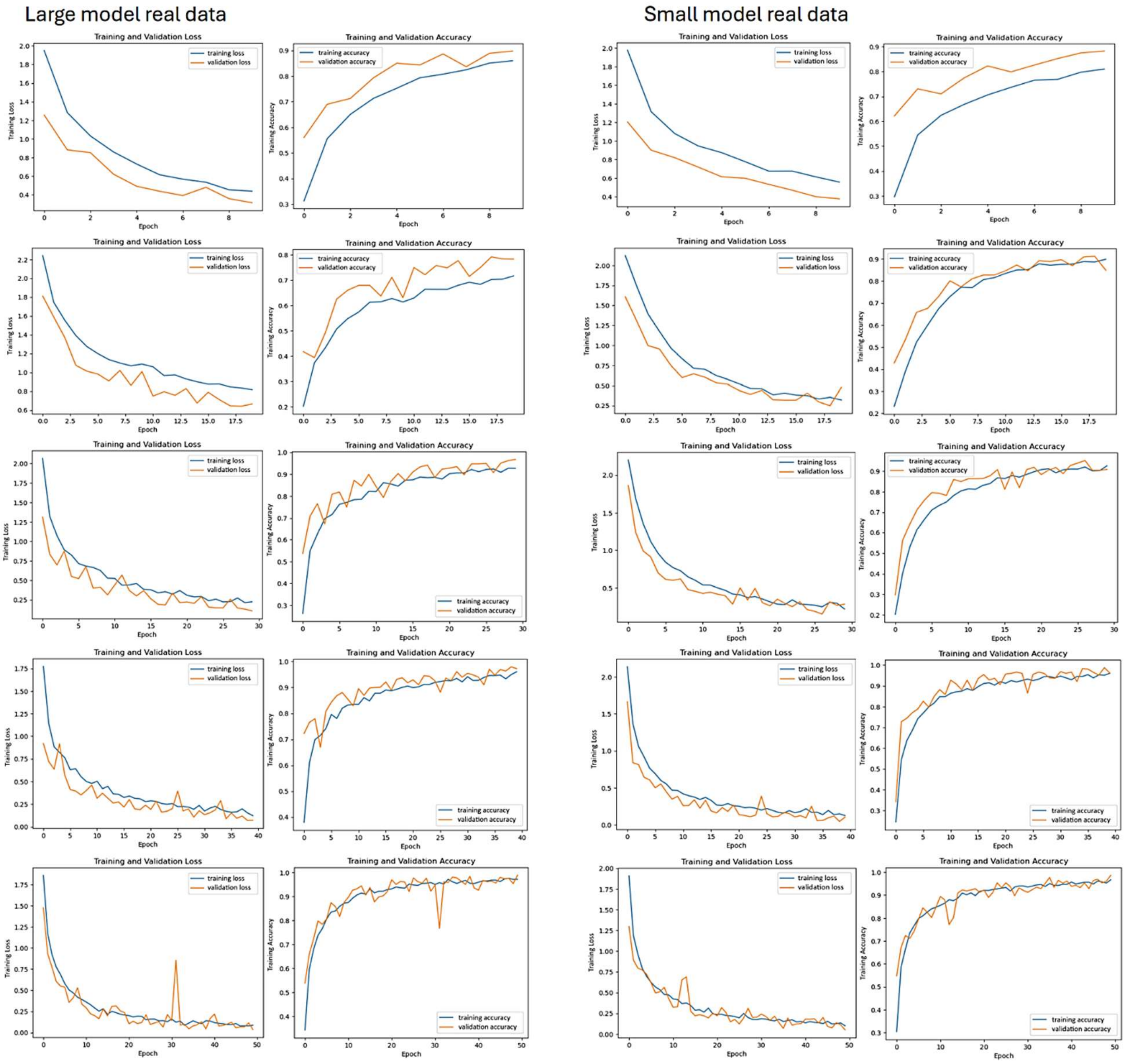

Fig. 3. Training and validation history for large and small models at epoch 10, epoch 20, epoch 30, epoch 40, and epoch 50 using real dataset

Avicennia alba (100%) and *Ceriops decandra* (99.81%), while certain species, including *Sonneratia alba* (47.29%) and *Rhizophora apiculata* (61.30%), showed lower confidence. Similarly, in the augmented dataset (Figure 5b), the model generally performed better, with high confidence scores for species of *Bruguiera gymnorrhiza* (99.98%) and *Rhizophora stylosa* (99.54%). However, some samples, such as *Ceriops decandra* (36.20%), remained challenging.

Large numbers on the diagonal part of the confusion matrices (Figure 6 and Figure 7) indicated an accurate prediction for both training and validation datasets in the real data and forecasts produced by each model. In the testing dataset, the trained models accurately predicted the majority of the classes as well, however, misclassifications were still found. For instance, the model misclassified *Xylocarpus granatum* as *Rhizophora mucronata* and *Sonneratia alba, Avicennia officinalis* as *Rhizophora apiculata* and *Bruguiera gymnorrhiza,* and *Ceriops decandra* as *Rhizophora stylosa*. It implies that in return for greater model size and longer computing times, large models can provide greater accuracy than small models. However, more research is required to provide a higher-quality dataset that could increase classification accuracy.

CONCLUSION

In this study, we developed the e-mangrove model, a deep learning system for mangrove species identification,

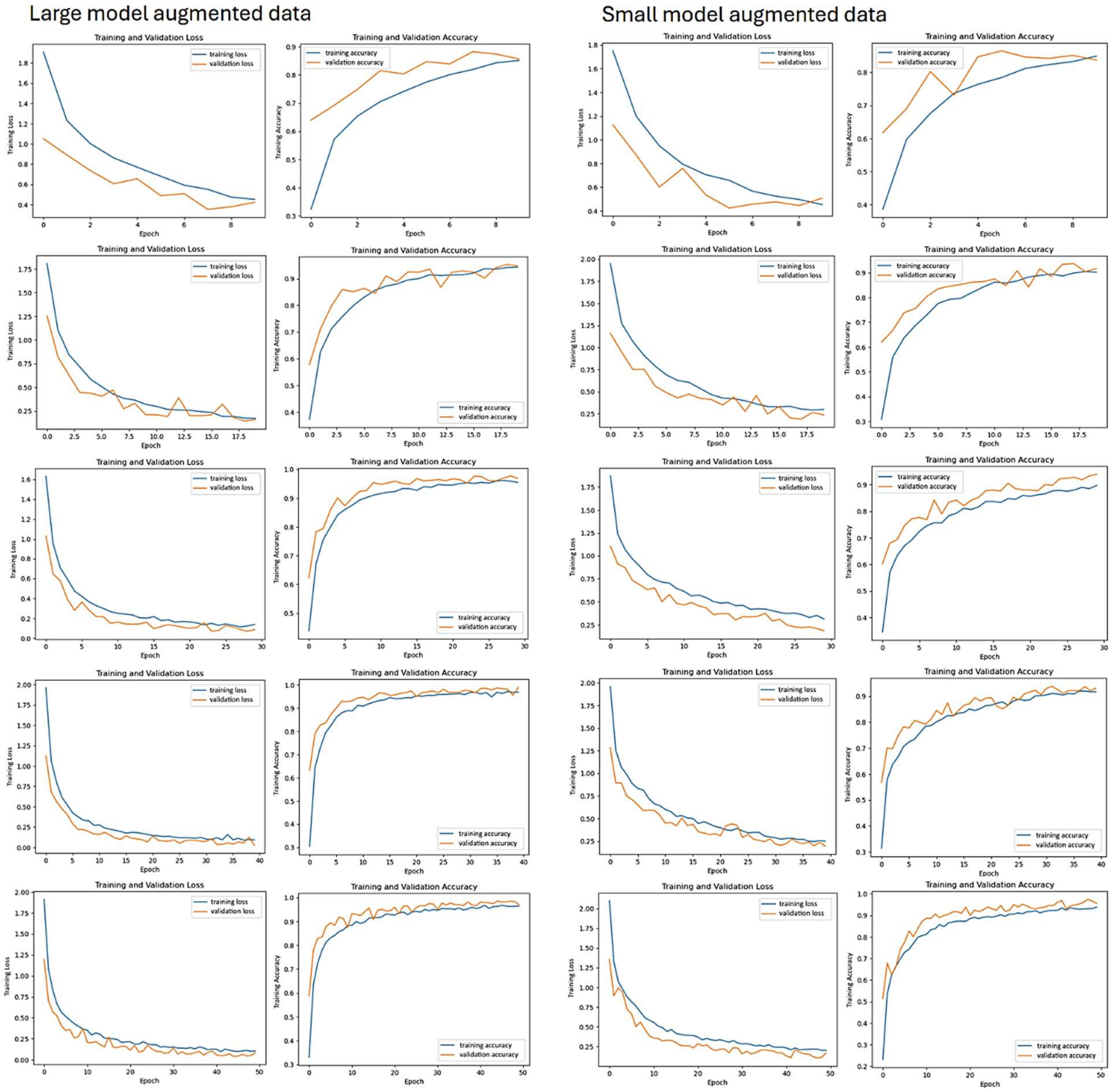

Fig. 4. Training and validation history for large and small models at epoch 10, epoch 20, epoch 30, epoch 40, and epoch 50 using augmented dataset

using deep convolutional neural networks. The model was trained on a balanced dataset of 5500 images representing 11 "true" mangrove species, achieving an accuracy of 97.16% on the test data. Additionally, we trained the model on an augmented dataset of 11000 images—double the original size—to enhance its generalizability and robustness, resulting in an accuracy of 96.49 % on the test data. These findings suggest that the model could serve as an effective tool for agile mangrove identification.

AUTHOR CONTRIBUTIONS

FS, EK, ARN, NW, RW, and IWED conceived and planned the study. ARN wrote the manuscript with support from FS, EK, NW and NBSD. ARN, NW, NMNBSD, SN, DSA, and ANA performed computation and data analysis. EK verified the analytical methods. FS, NW, INS, and NMNBSD contributed to dataset preparation. FS, RW, and IWED assisted supervise the project.

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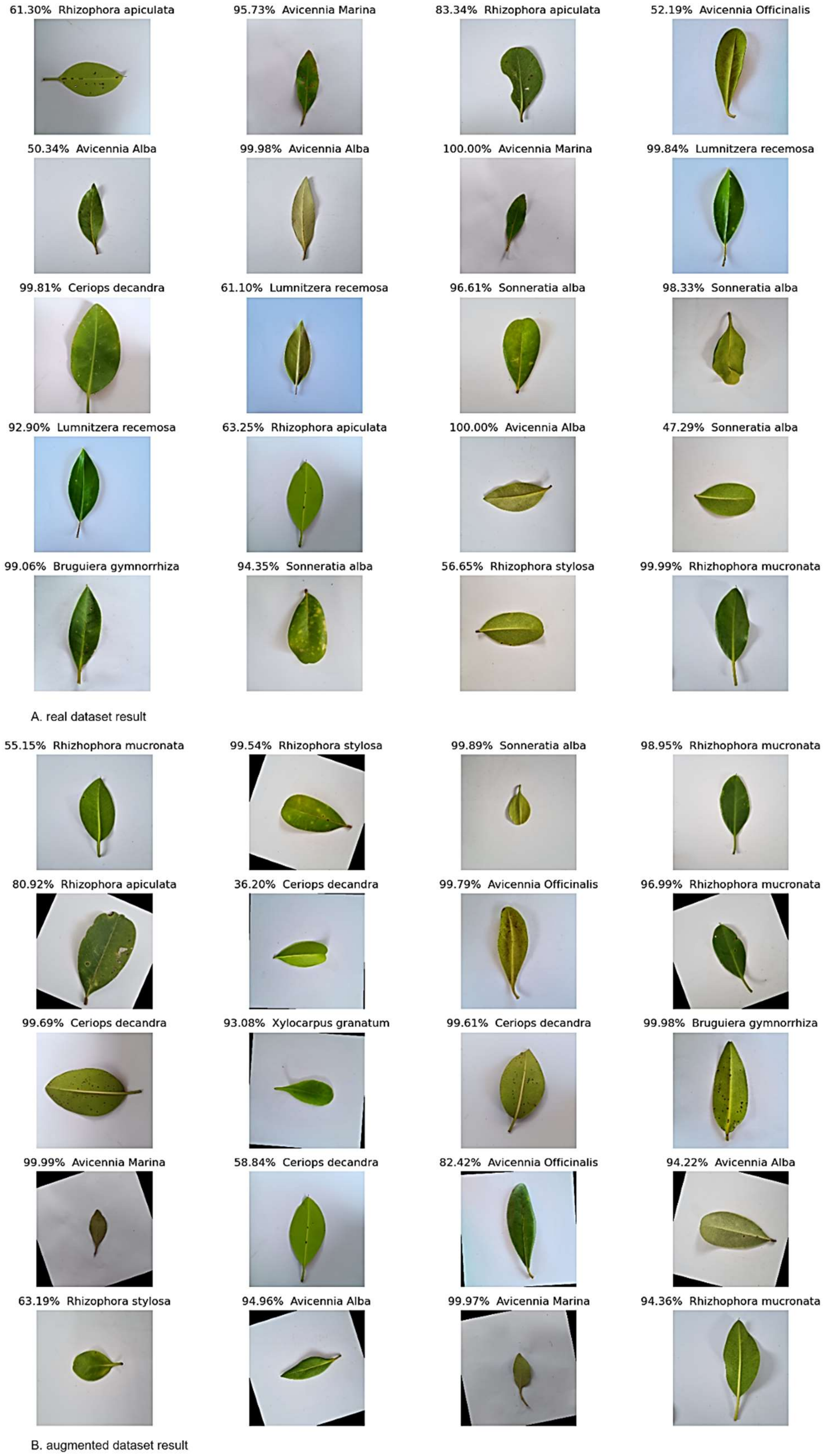

Fig. 5. Classification results for the real dataset (**A**) & augmented dataset (**B**) using the large model trained for 50 epochs..

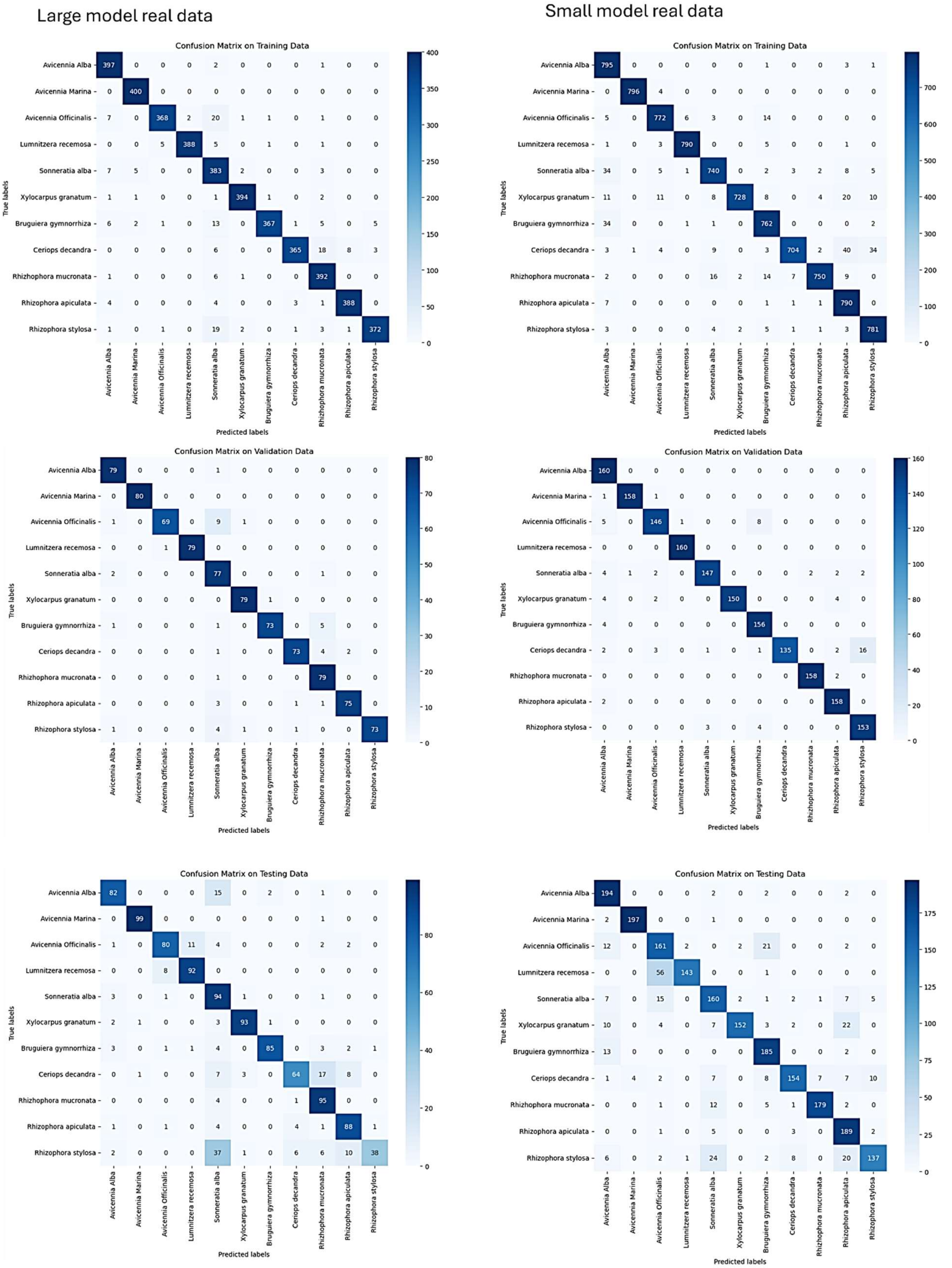

Fig. 6. Confusion matrix for large model (**Left**), small model (**Right**) at epoch 50 for training data, validation data, and testing data using real dataset

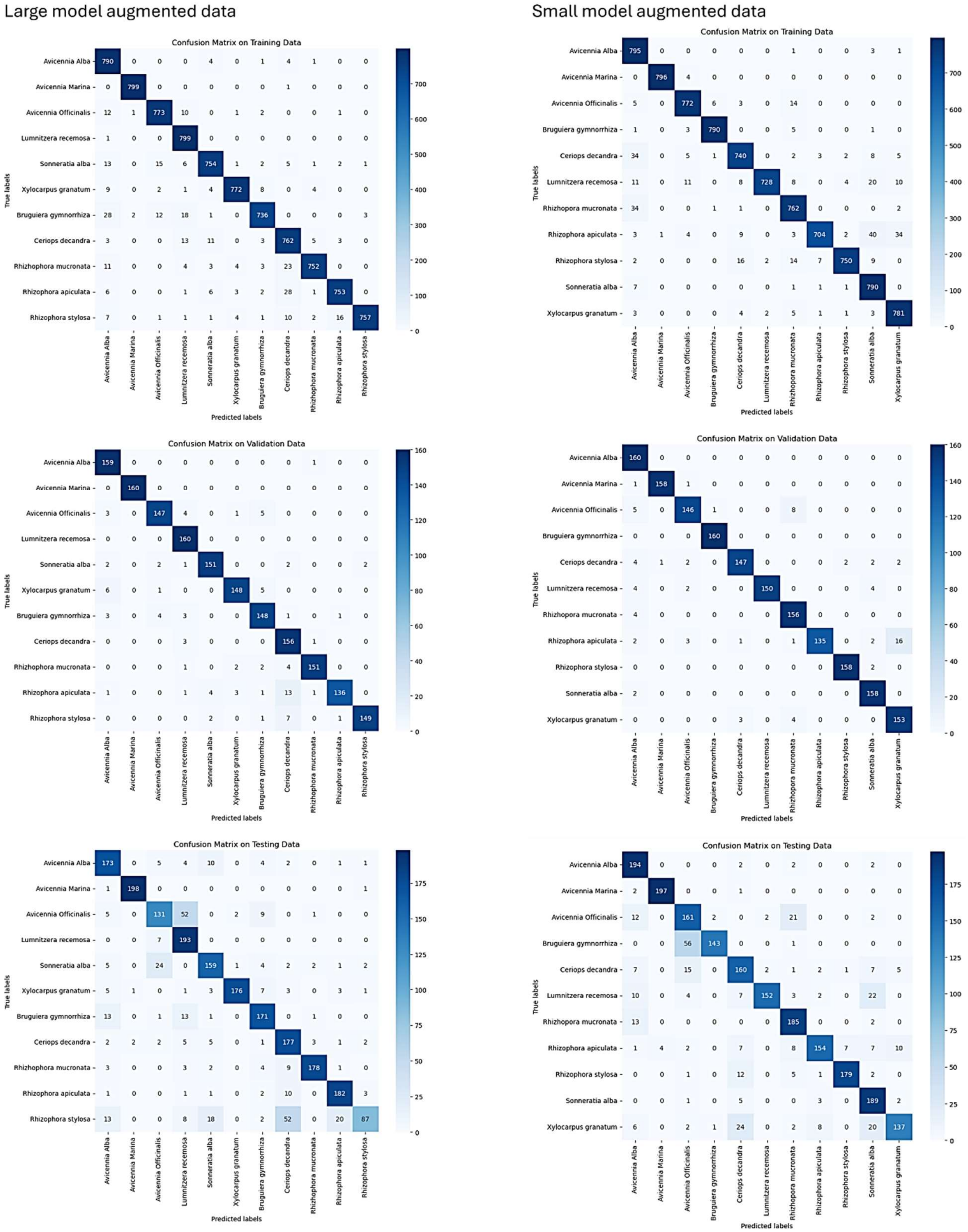

Fig. 7. Confusion matrix for large model (**Left**), small model (**Right**) at epoch 50 for training data, validation data, testing data using augmented dataset

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