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Identification of mangrove tree species using deep learning method

Paranita Asnur[1], Rifki Kosasih[2], Sarifuddin Madenda[3], Dewi A. Rahayu[4]
[1]Department of Computer Science, Gunadarma University, West Java, Indonesia
[2]Department of Informatics Engineering, Faculty of Industrial Technology, Gunadarma University, West Java, Indonesia
[3]Professor of Computer Science, Gunadarma University, West Java, Indonesia
[4]Department of Information Systems, Faculty of Computer Science and Information Technology, Gunadarma University, West Java, Indonesia

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ABSTRACT

Artificial intelligence can help classify plants to make identification easier for everyone. This technology can be used to classify mangrove trees. The degradation of mangrove forests has resulted in a 20% loss of biodiversity, an 80% loss of microbial decomposers, reduced C-organic soil, and fish spawning grounds, resulting in estimated losses in the ecological and economic fields for up to IDR 39 billion. The identification of different mangrove species is the first step in ensuring the preservation of these forests. Therefore, this research aimed to develop algorithms and a convolutional neural network (CNN) architectureto classify mangrove tree species with the highest possible accuracy using Python software. The architecture selection for this model includes a batch size of 32, an input image size of 128x128 pixels, four classes, four convolutionlayers, four rectified linear unit (ReLU) layers, 2x2 max-pooling, and two fully connected layers (FCL). The finding showed that the resulting accuracy from the test was 97.50%, while the validation test was 81.25%, applied to four types of mangrove leaves, including *Avicenia marina, Avicenia officialis, Rizophora apiculata,* and *Soneratia caseolaris*.

Corresponding Author:

Dewi A. Rahayu
Department of Information Systems, Faculty of Computer Science and Information Technology
Gunadarma University
Jl. Margonda Raya No. 100, Pondok Cina, Depok 16424, West Java, Indonesia
Email: dewiar@staff.gunadarma.ac.id

1. INTRODUCTION

The economic value of mangrove resources has been estimated to be IDR 39 billion [1]. Furthermore, mangroves play an important role in conserving the environment by storing carbon, estimated to be 70 t/ha to 666 t/ha [2]. It should be noted that the loss of mangrove forests due to clearing areas for residential homes, tourism, ponds, and other uses causes a decline in their function. Therefore, conservation activities aim to protect biodiversity, mitigate climate change, and promote sustainable development [3].

The degradation of Indonesia's mangroves is a cause for concern, as only 48% of the total area is classified as being in good condition [4]. The loss of mangrove forests significantly impacts environmental balance. For instance, the degradation of these forests has resulted in a 20% loss of biodiversity, an 80% loss of microbial decomposers, reduced C-organic soil, fish spawning grounds, and many other ecological and economic losses [5]. The destruction of mangrove forests through conversion to other land uses is a significant problem, as it puts many species at risk of extinction.

Taxonomists are no longer interested in manual species introduction because it is time-consuming and resource-intensive. However, as technology advances and is accessible, machine learning is becoming more popular in various fields. For instance, this technology makes species identification easier, more efficient, and more accurate. Introducing or identifying species using a technological approach can significantly advance human performance in various fields. The deep learning method has been applied in various research areas to ease human work, including in the medical field [6]–[8], economy [9], farm [10], history [11], [12], language [13], and animals fields [14].

Tree species identification using morphological features assisted by artificial intelligence has become popular. The human expertise is duplicated into a computer algorithm system allowing all users, including non-experts, to identify plant species with ease. Many algorithms have been developed to identify plant species using leaf shape features. Furthermore, various methods have been applied in research on plant species classification, including herbal plants [15]–[18], Shorea type [19], tropical trees [20], and types of fruit [21], [22].

The convolutional neural network (CNN) is the most commonly used part of the deep learning method compared to other neural networks. The advantage of this method is that it can automatically identify an object without first performing feature extraction. This is because the CNN structure resembles the neurons in the brains of humans and animals, particularly cats, which allows it to identify patterns more effectively [23].

Identifying a species requires a lengthy process, which begins with field survey activities, cataloging mangrove species, taking leaf samples as specimens, introducing the species to experts, and finally using the developed algorithm to identify the species. Research on the identification of mangrove species using image processing requires various features, including tree morphology with a web-based CNN algorithm. Previous research into mangroves has primarily been limited to seedlings. However, this research explores the damaged tree saplings, using all parts of the mangroves. This includes requiring samples, cost, and time [24]. Other researches were high-resolution satellite images [25] and leaf-shape features in three species of mangroves only [26]. The results using the CNN algorithm are expected to show a consistent accuracy level of more than 93.6% [8], [21], [27]–[34]. As a result, a CNN architecture that can adjust the number of layers to classify mangrove tree species will be implemented. It is anticipated that this will result in a high degree of accuracy. Experiments will be conducted to determine the parameter values that yield the best outcome, as well as the accuracy values for the mangrove species classification system as a whole.

2. RESEARCH METHOD

The steps required to classify mangrove species based on leaves are shown in Figure 1. The research starts with data collection by taking leaf samples for the dataset, image acquisition using a smartphone camera, species identification, and a mangrove classification system design using the CNN algorithm. A pre-processing of the image will be carried out before carrying out the training process.

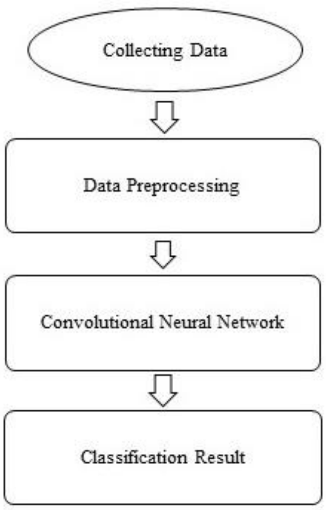


Figure 1. Research stages

2.1. Dataset

The digital image acquisition process must consider the camera type or other acquisition tool, the resolution, lighting technique, desired magnification or zooming, distance from the subject, and angle of capture. The next step is pre-processing the image to prepare it for further processing. The digital image is cropped and resized in this step to facilitate further processing.

Mangrove leaves were collected for image acquisition by cutting off four-leaf stalks. Leaves with quality characteristics were selected based on clear color and intact shape criteria. Images were captured using a cellphone camera with a resolution of 48 MP, placed at an angle of 1,800 and 25 cm from the object. Lights were used for lighting, while the white paper provided a background for the leaves, as shown in Figure 2. The acquired leaves were stored in each folder by type and renamed according to the specified code. 80% of the obtained images were used for training, while 20% was reserved for test data.

This research used four types of mangrove leaves measuring 128x128 pixels, as shown in Figure 3. The types of mangrove leaves classified included *Avicenia marina* as shown in Figure 3(a), *Avicenia officialis* as shown in Figure 3(b), *Rizophora piculate* as shown in Figure 3(c), and *Soneratia caseolaris* as shown in Figure 3(d).

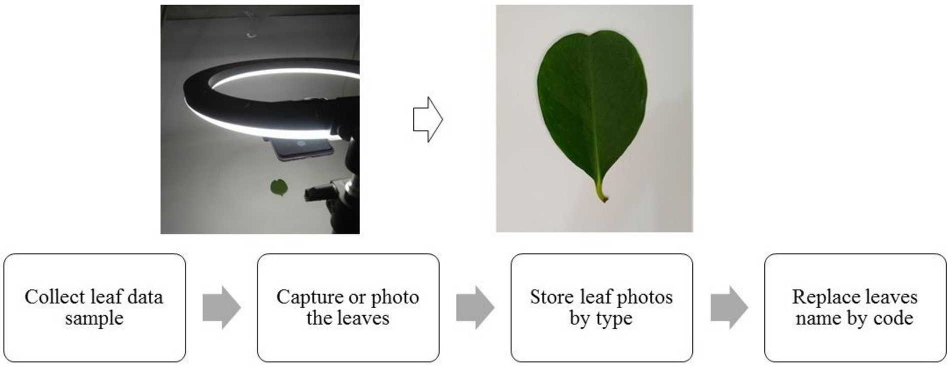


Figure 2. Leaf image capture process

(a) (b) (c) (d)

Figure 3. Mangrove leaves of (a) *Avicennia marina* (Am), (b) *Avicenia officialis* (Ao), (c) *Rhizophora apiculata* (Ra), and (d) *Sonneratia caseolaris* (Sa)

2.2. Convolutional neural network (CNN) method

CNN can emulate the human brain in recognizing shapes and figures. For instance, it can easily distinguish between a dog and a cat and categorize them into separate classes. However, type recognition is better if more hidden layers are used as much as this process makes data analysis challenging.

CNN is the development of multilayer perceptron (MLP), designed to process two-dimensional data. It is included in the type of deep neural network due to its high network depth and is widely applied to image data. In image classification, MLP is unsuitable because it does not store spatial information from image data, causing poor results. CNN, on the other hand, has three layers, including convolutional, pooling, and fully- connected layers, making it more effective in this instance.

The convolutional layer generates a feature map, highlighting the original figure's unique properties. The number of convolutional layers will determine the number of feature maps. For example, if there are four convolutional layers, the feature map will also be four. 2-dimensional matrices are typically used and can be either 5x5 or 3x3. However, 1x1 matrics are also becoming more common. The filter is obtained from the dataset training process [35].

2.3. Convolution operation

Convolution operations are useful for image processing tasks such as filtering, masking, and transformation. This operation can only be performed between two vectors or matrices of the same size, which is typically an odd number. It is not a vector/matrix multiplication; the result is a scalar value expressed as an asterisk symbol "*." Mathematically, convolution is defined as the product sum of each corresponding element [36]. The convolution process is formulated as in (1) [23].

$$h^k = f(W^k * x + b^k) \tag{1}$$

The architecture of the CNN in Figure 4 is divided into two major parts, the feature extraction layer and the fully-connected layer (MLP).

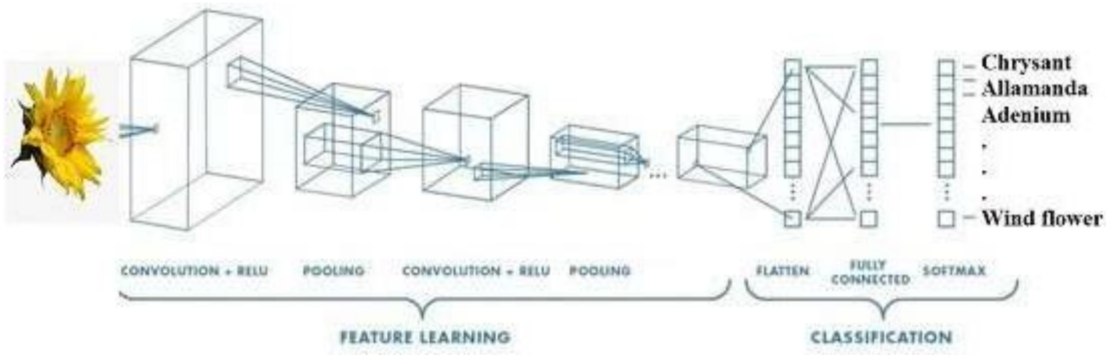


Figure 4. CNN architecture [37]

2.4. Training process

The training was conducted to develop a CNN algorithm that could be used to classify different mangrove tree species. The algorithm was developed using four convolution layers, as shown in Figure 5.

The architecture comprises 17 layers, including input and output layers, four convolution layers measuring 3x3 and 5x5 with dimensions of 64, 128, 512, and 512, respectively, four ReLU layers, four max-pooling layers measuring 2, two fully connected layers (FCL) as well as a layer softmax.

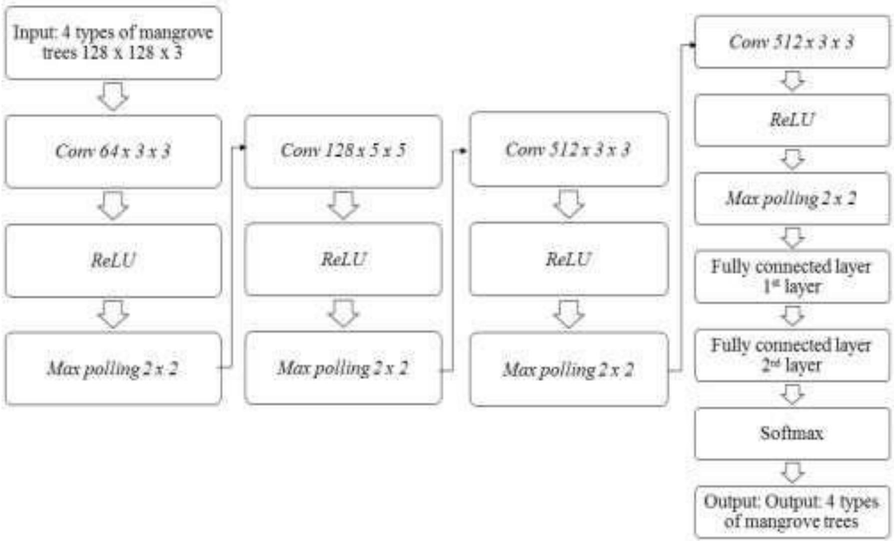


Figure 5. CNN architecture model

3. RESULTS AND DISCUSSION

3.1. Training data and test data

The data training used is 80% of the dataset provided, or 40 leaf images for each type of leaf, as shown in Table 1. The use of training data is more important than the use of test data. This is because the learning algorithm developed can form the best model. The model that has been formed can then be tested using test data. This process continues until the optimum level of accuracy is achieved.

Table 1. Typestyles training data and test data

Type	Code	Training Data	Test Data	Total
Avicenia marina	Am	40	10	50
Avicenia officialis	Ao	40	10	50
Rizophora apiculata	Ra	40	10	50
Soneratia caseolaris	Sa	40	10	50

3.2. Research parameters

After preparing and pre-processing the data, the next step is determining the number of layers to be applied. Various modifications have been made to the CNN architecture since 1989, and in the last 10 years, researchers have focused on the depths of neural networks [23]. In this research, four convolution layers were used as modifications to the CNN architecture. Table 2 shows the parameters used.

Table 2. Parameter model

Parameter	Total
Batch size	32
Input image size	128 x 128
Number of classes	Four classes
Number of Layers	4 Layers
ReLU	4 Layers
Max-pooling 2D	2 x 2
FCL	2 Layers

3.3. Determining the number of epochs

There is no provision for the exact epochs number to form a good model because it is experimental. Therefore the analysis is carried out using an epoch value of 0-50 to obtain the optimal model. Table 3 shows the results of the experimental epoch values in the mangrove dataset.

Table 3. Accuracy of test data and training data for mangrove tree species

Number of epochs	Time (s)	Training Loss	Validation Loss	Training Accuracy	Validation Accuracy
1	122	1.5813	1.4036	0.4125	0.5000
5	80	0.4778	1.6886	0.8063	0.5000
10	72	0.2758	5.4593	0.9125	0.5000
15	74	0.1972	1.0068	0.9250	0.5938
20	74	0.2187	5.6441	0.9188	0.8125
25	75	0.1695	0.7708	0.9313	0.8125
30	72	0.1313	6.5833	0.9375	0.8125
35	75	0.1140	0.7971	0.9625	0.8125
40	72	0.0876	7.3051	0.9750	0.8125
45	78	0.0898	0.9348	0.9750	0.8125
50	76	0.0751	6.9598	0.9750	0.8125

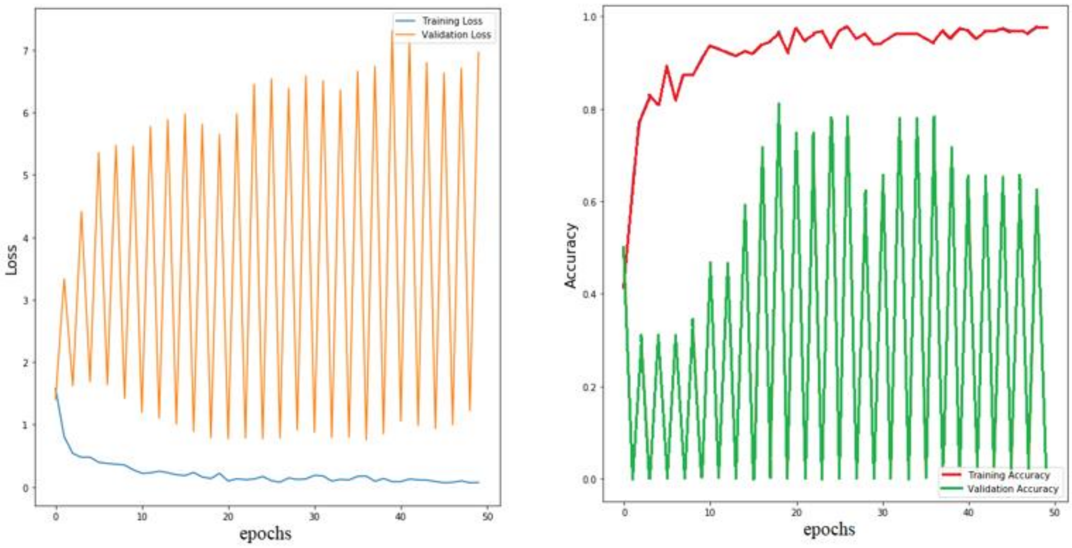
The number of training epochs has a direct impact on the accuracy of the training and testing process. Testing the training and test data using a range of epochs in multiples of five showed that the training data's accuracy value increases to a maximum value of 97.50% and training loss of 0.07511 at the 50^{th} epoch. The required computation time is 76 seconds, with an average of 15 seconds per step.

The test data showed a steadily increasing trend, reaching a peak value of 81.25% at the 25th epoch. The loss remained at a constant level of 0.7708 until the 50th epoch. This indicates that the effectiveness of determining the epoch value is too high [38], as the optimum value was obtained on the 25 images.

The minimum error in training loss was seen at epoch 50, with a loss of 0.0751. The corresponding validation loss at epoch 45 was 0.7539. As seen in Table 3, the accuracy of the training and test data seemed to reach an optimum value before the total number of images was tested and trained as a whole. The minimum error in training loss was observed at epoch 50, where the loss was 0.0751. The validation loss at epoch 45 was 0.7539. In Table 3, it can be seen that the accuracy of both the training and test data was at the optimum value before all images were used for training and testing.

3.4. Data analysis

Once the best model has been determined, it must be tested using test data to validate it. Figure 6 displays a graph of data loss and accuracy. Figure 6(a) demonstrates that the value of training loss steadily decreases over time, starting at 1.5 and eventually dipping at 0.07. The training results show that the learning is effective in classifying mangrove species. The loss value, in this case, is different from the validation loss case, which typically increases from the beginning to the end. The shape of the leaves may be a distinguishing factor between *Avicenia marina, Avicenia officialis, Rizophora apiculata* species, as all three have elliptical leaves. According to [25], accuracy cannot be 100% because *Avicennia alba* and *Rizophora apiculata* have a needle like shape. As can be seen in Figure 6(b), the training accuracy value steadily increases from the beginning to the end. This is higher than the accuracy seen in the test data, indicating overfitting in the training process.



(a) (b)

Figure 6. Developed CNN architectures are (a) data lost chart and (b) graph data accuracy

4. CONCLUSION

The research showed that the choice of architecture with the model parameters including batch size 32, input image size 128x128 pixels, four classes, four layers, four ReLU, 2D max-pooling 2x2, and two FCL layers is the most effective. Based on the parameter model, the accuracy of the training data was 97.50%, and the accuracy of the test data was 81.25%. This shows that the algorithm developed can be used to classify mangrove trees. This research is expected to help taxonomists identify species more effectively and efficiently. Future research should investigate the way datasets are collected and test the reliability of the developed architecture.

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BIOGRAPHIES OF AUTHORS

Paranita Asnur is received a B.S in Forestry Department (University of North Sumatera), Indonesia, in 2009, M.Si in Tropical Silviculture (IPB University) in 2013, and she currently studying Ph.D. in Information Technology, Gunadarma University, Indonesia. She has worked as a lecturer at the Department of Agrotechnology, Faculty of Industrial Technology, Gunadarma University, Depok, Indonesia. Her research interests are agriculture and forestry, image processing, object recognition, and deep learning. She can be contacted via email: paranita@staff.gunadarma.ac.id.

Rifki Kosasih He received a B.S degree in Mathematics (Indonesia University), Indonesia, in 2009, the M.S degree in Mathematics (Indonesia University) in 2012, and the Ph.D. degree (Gunadarma University), Indonesia, in 2015. He has worked as a lecturer in the Department of Informatics, Industrial Technology Faculty, Gunadarma University, Depok, Indonesia. His research interests are manifold learning, 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 post-doctoral program of Information Technology, at Gunadarma University. He received his Bachelor's degree in Physics Instrumentation, from the University of Indonesia in 1989, a master's in Integrated Device Electronics, from INSA de Lyon in 1992, and Ph.D. in Electronics and Image Processing, from Universite de Bourgogne, France in 1995. His research interests are Image and Video Processing, Multimedia data compression, Content-based image and video retrieval, Steganography: Encryption, Decryption, Coding and Decoding of multimedia secret documents, and Real-time system architecture (FPGA and ASIC design). He can be contacted at email: sarif@staff.gunadarma.ac.id.

Dewi A. Rahayu is an associate professor of Information Technology in the post-doctoral program of Information Technology, at Gunadarma University. She had her Bachelor's degree in 1993 and Doctoral degree from Gunadarma University in 2007. Her Master's degree was from the Asian Institute of Technology in Bangkok, Thailand. She is giving some lectures in the Department of Information Systems at the Faculty of Computer Science and Information Technology. Her research interest is in Human-Computer Interaction, Image Processing, and Information Technology. She can be contacted at email: dewiar@staff.gunadarma.ac.id or dewiar@gmail.com.