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Comparison of YOLOv5 for Classifying Mangrove Leaf Species using CNN-Based

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ABSTRACT

Indonesia has many species of mangrove plants scattered throughout the coast to the river's edge. Species of mangrove plants can be distinguished based on root type, stem size, leaf shape, flower color, and fruit. Although each type of mangrove plant has different characteristics, several types look similar, especially on the leaves. Therefore, a model was needed to classify mangrove plant species by applying current technology to make it easier to recognize the type of mangrove plant. This research aims to implement the Convolutional Neural Network (CNN) method in classifying mangrove plant species. The algorithm used is the 5th version of You Only Look Once (YOLO) with 3 different variants (YOLOv5s, YOLOv5m, and YOLOv5l). The three variants have various processing times and numbers of layers. This study uses mangrove leaf images with a total image dataset of 400 images consisting of 4 types of mangrove plants: Avicennia alba, Bruguiera gymnorhiza, Rhizopora apiculata, and Sonneratia alba. The model performance achieved 82.50%, 88.75%, and 93.75% accuracy using YOLOv5s, YOLOv5m, and YOLOv5l, respectively.

1. INTRODUCTION

A significant extent of mangrove distribution characterizes Southeast Asia, which hosts a high species diversity. Southeast Asia contains one-third of the global mangrove population, attributable to its tropical climate. Indonesia possesses the largest mangrove ecosystem globally, comprising over 80% of this region. In tidal ecosystems, specific plant species thrive and are referred to as mangroves [2]. They represent an authentic woodland influenced by tidal changes [1]. Mangroves are often submerged at high tide and revealed at low tide. Eight different plant families comprise mangroves [3].

The discipline of plant morphology comprises two subfields: external morphology, also called morphology, and internal morphology, commonly known as plant anatomy [4]. In addition to stems, roots, flowers, leaves, and fruits, mangrove plants possess several other vital components. A prevalent method for distinguishing several species of mangrove plants is examining their fruits and flowers. Nonetheless, leaves are significant in plant taxonomy, with leaf texture as a common criterion [5]. Classifying mangrove species based on foliar characteristics is challenging due to the variety of species and their resemblance in leaf attributes. Computational recognition systems depend on leaf characteristics, including size, color, and shape [6]. A classification method is necessary to differentiate mangrove species based on their leaves for community and farmer identification. Technology enables the execution of precise analysis with significantly reduced potential for human error [7]. Traditional species identification typically relies on

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expert knowledge and manual examination of plant morphology, such as fruit, flower, or leaf characteristics. Yet, leaves are often the most accessible and widely used feature for plant taxonomy. The subtle differences in leaf shape, size, and texture necessitate the use of technology to enhance accuracy and reduce human error in species classification.

Extensive prior research has been conducted on leaf classification across several plant species. Ten attributes were evaluated in the classification of herbal leaves. K-Nearest Neighbor (KNN) and Naïve Bayes are widely utilized classification methods. The Naïve Bayes Classifier is the most rapid and straightforward among all Bayesian Learning techniques. KNN rapidly classifies data objects based on their minimal distance. Subsequent to the trials, the Naïve Bayes Classifier demonstrated an accuracy of 75%, while the K-Nearest Neighbor technique exhibited an accuracy of 70.83%. The Naïve Bayes Classifier algorithm surpasses the KNN approach [8]. Image segmentation techniques were employed on rice leaf datasets to convert the images into an analyzable format, while a CNN utilizing the VGG16 model was implemented to categorize diseases impacting rice leaves. The study used data on rice leaf disease, which was classified into three classes: Bacterial leaf blight, Brown spot, and Leaf smut. Consequently, thresholding and k-means clustering are the two techniques employed for segmentation. Subsequently, data augmentation was executed for the extensive and varied make dataset. The VGG16 model was trained using the RMSProp optimizer with a learning rate of 0.001, yielding an accuracy of 91.66% for the k-means dataset scenarios [9].

The CNN Squeezenet and AlexNet models were compared to classify the leaf disease. The network employed stochastic gradient descent with momentum (SGDM) for optimization. The dataset utilized in this investigation comprised 3,852 photos categorized into four classifications: healthy, blight, spot, and rust. It was acquired from PlantVillage. Three categories of data are recognized: training, validation, and testing. Eight percent was allocated for training and validation, while the remainder was designated for testing. Cross-validation training achieves an accuracy of 100% for both Squeezenet and AlexNet. Furthermore, the model retains the appropriate weights and biases for the classification of testing data. The recognition results achieved an accuracy of 97.69% with AlexNet. Squeezenet achieves an accuracy of 44.49%. This experimental setting revealed that AlexNet outperformed Squeezenet in classifying maize leaf diseases [10]. The CNN model, a product of deep learning, achieved a test accuracy of 99.40% in the automatic classification of diverse trees based on their leaves. The trees comprise Lemon, Ashoka, Curry, Sheesham, Neem, Hibiscus, Guava, and Henna. This study used a locally sourced dataset, including 10,000 leaf photographs, with 1,000 images allocated to each tree species. The results indicate that the proposed approach provides a dependable classification model for tree identification based on leaf features [11].

This research employs the YOLO algorithm version 5, which remains underutilized for classification purposes. YOLO version 5 is a neural network commonly utilized for visual data processing and represents an upgrade of CNN [8], [9]. YOLO version 5 is applicable for object identification and recognition within a picture. This technology detects structural deterioration via unmanned aerial vehicles [10]. Furthermore, research on leaf-based tree identification employs the CNN methodology [11]. The data for this research were compiled using four mangrove species: Rhizophora apiculata, Sonneratia alba, Bruguiera gymnorrhiza, and Avicennia alba. The YOLO version 5 classification model employs these four mangrove species as its categories. This study addresses this gap by evaluating the performance of three YOLOv5 variants—YOLOv5s, YOLOv5m, and YOLOv5l—for classifying mangrove leaf species based on image data. The objective is to determine which YOLOv5 model offers the best trade-off between accuracy and computational efficiency. The findings contribute to the development of accessible tools for mangrove monitoring, especially for non-expert users such as local communities and field practitioners.

2. METHOD

The CNN is a method for image classification [12], [13]. It is an enhanced iteration of the Multi-Layer Perceptron (MLP) designed to analyze and manage two-dimensional data [14]. CNN is distinctive among artificial neural networks since it can extract features and represent data at many levels of abstraction, utilizing signals and pictures [15]. The YOLO algorithm is among the numerous algorithms that employ CNN techniques. This approach aims to identify items [16]. Technology has progressed to the fifth edition of YOLO, which offers enhanced accuracy compared to earlier versions.

YOLOv5 variants (s, m, l) were trained under identical conditions to ensure fair comparison, equipped with nine pre-trained models, can optimize the utilization of available hardware resources to adapt

to any system due to its speed, modular architecture, and proven real-time performance. YOLOv5n represents the nano variant, YOLOv5s denotes the small variant, YOLOv5m signifies the medium variant, YOLOv5l indicates the large variant, and YOLOv5x refers to the extra-large variant. This categorization relies on model size; larger models yield superior results, although they need more time to process an individual image [10]. Adaptive anchor computation, adaptive picture scaling, and mosaic data enhancement are among the technologies employed in the input of YOLO version 5. The "Backbone" component encompasses the Focus and Common Spatial Pattern sections [17]. The FPN+PAN structure is integrated into the 'Neck' segment. The GIoU_Loss was used instead of the traditional IoU computation method for prediction. Although YOLO 5's performance does not match its predecessor, YOLO 4, it offers advantages in model utilization due to its speed and agility. Each stage of the experimental pipeline—data acquisition (image dataset), pre-processing, training, and testing—is described explicitly. Figure 1 illustrates the proposed approach for the classification of mangrove leaves.

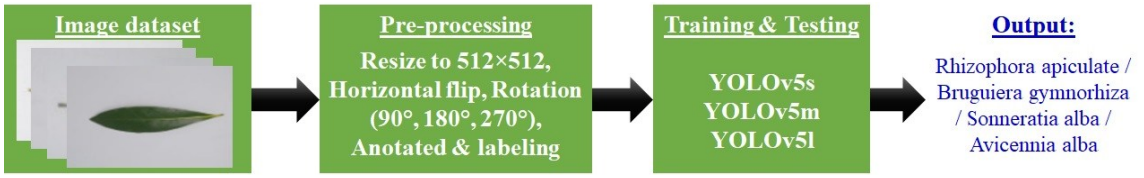

Figure 1. The proposed model for mangrove leaf classification

2.1. Image Dataset

The dataset for this study was acquired through the picture acquisition technique. The data collection has multiple stages: observation, sampling, and recording leaf images. The observation phase entails direct observation within the Tarakan City Mangrove Conservation Area, followed by the classification of mangrove species by research requirements [18]. This study encompasses four species of mangrove plants: Rhizophora apiculata, Bruguiera gymnorhiza, Sonneratia alba, and Avicennia alba. The leaf photos were obtained using a digital camera integrated into a smartphone [19]. A comprehensive picture of data is presented in Table 1.

Table 1. Detailed information regarding the image dataset

Image	Information
Format	JPEG
Resolution	3456 × 3456 pixel (ratio 1:1)
File size	2 Mb – 3 Mb
Object distance	20 cm
Focus distance	4,88 mm
Total images	400 images

2.2. Pre-processing

The objective of this method is to highlight the most essential elements of the image pertinent to the current operation. In the pre-processing phase, the input data is downscaled from 3456 × 3456 pixels to 512 × 512 pixels. Subsequently, it was utilized via an augmentation procedure that included horizontal flipping and rotations of 90°, 180°, and 270°. Consequently, 1590 photos were generated in the dataset upon completing the augmentation phase. Figure 2 illustrates an example of the enhancement outcome.

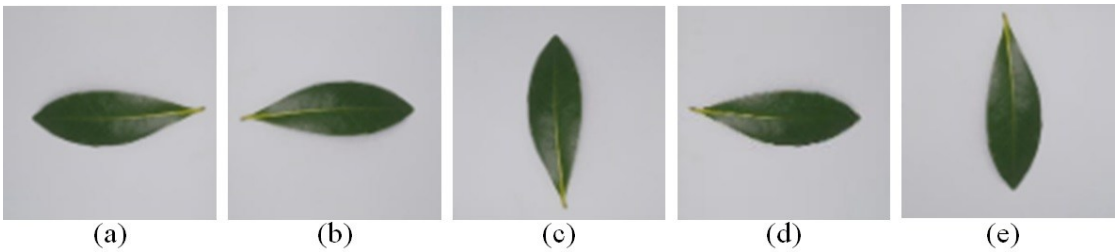

Figure 2. The illustration of augmentation results: (a) original image, (b) horizontally flipped, (c) rotated 90°, (d) rotated 180°, and (e) rotated 270°

2.3. Training and Testing

The dataset was partitioned into three subsets: training, validation, and test, at a ratio of 90%:5%:5%. During the training phase, various iterations of YOLO version 5 are utilized, including YOLOv5s with 149 layers, YOLOv5m with 212 layers, and YOLOv5l with 275 layers. Filters were modified on each layer to extract characteristics from training photos. The model was directed to traverse each layer sequentially and retain the extracted features. Using the classification process, the features were subsequently employed to compare and categorize input photos. Figure 3 illustrates the outcomes of the training and testing procedures.

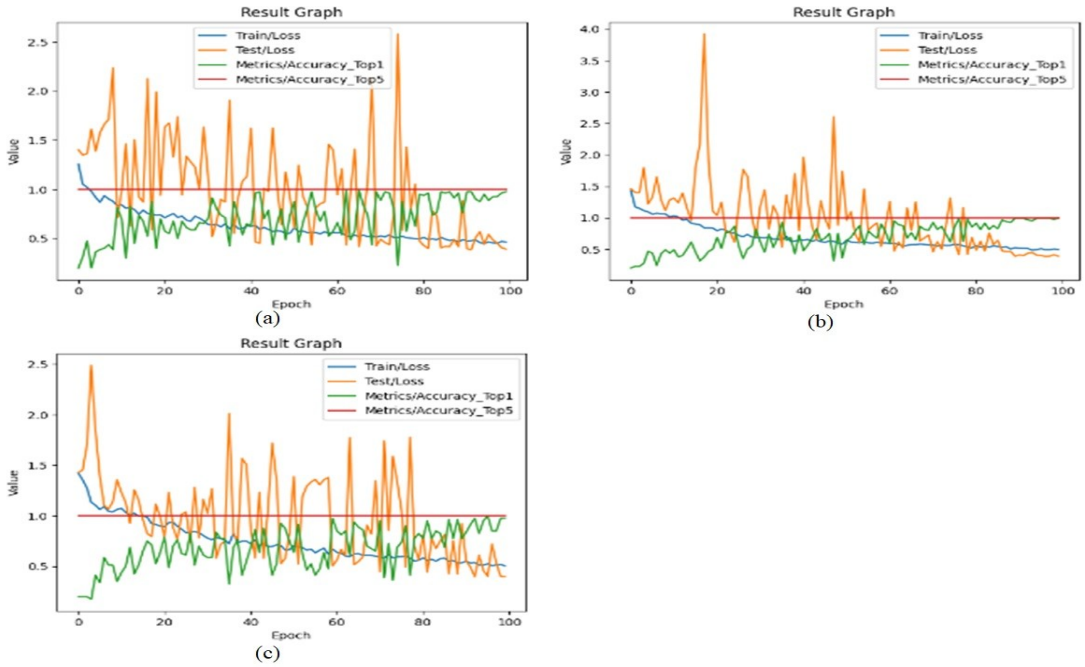

Figure 3. The training and testing results using YOLO: (a) YOLOv5s, (b) YOLOv5m, and (c) YOLOv5l

2.4. Model Evaluation

A multi-class confusion matrix was employed to evaluate the performance of the trained variations of the YOLO version 5 model: YOLOv5s, YOLOv5m, and YOLOv5l at this stage [20], [21]. The accuracy, precision, and recall metrics were derived from the multi-class confusion matrix generated for each variant. These parameters evaluate the efficacy of the YOLO version 5 model in identifying mangrove plant species from leaf photos. Accuracy refers to the extent to which a model's projected results align with the observed outcomes [22]. The precision of a test denotes the quantity of pertinent outcomes identified, whereas recall reflects the extent to which the test can categorize data. The assessment criteria were established utilizing Equations 1 to 3 [23], [24]. Figure 4 illustrates the multi-class confusion matrix for this investigation.

$$Precision = \frac{X_{ii}}{\sum_{k=1}^{n} X_{ji}} \times 100, \quad (1)$$

$$Recall = \frac{X_{ii}}{\sum_{k=1}^{n} X_{ij}} \times 100, \quad (2)$$

$$Accuracy = \frac{\sum_{i=1}^{n} X_{ii}}{\sum_{i=1}^{n} \sum_{j=1}^{n} X_{ij}} \times 100. \quad (3)$$

Figure 4. The confusion matrix for the mangrove leaves classification with four classes

X_{ii} represents the number of images correctly identified as L_i using the suggested model. X_{ij} is the count of images that the suggested approach incorrectly labels as L_i, whereas they really should be labeled as L_j. The number of images that should be classified as L_j but are instead identified as L_i utilizing the suggested approach is represented by $X_{ij,}$ otherwise. The values of these parameters varied between zero and one hundred. The proposed model was deemed robust and dependable if the number was close to 100.

3. RESULTS AND DISCUSSION

A total of 200 images were used to evaluate the classification performance of YOLOv5s, YOLOv5m, and YOLOv5l in identifying four mangrove species: Avicennia alba (AA), Bruguiera gymnorhiza (BG), Rhizophora apiculata (RA), and Sonneratia alba (SA). The evaluation employed standard classification metrics including precision, recall, and overall accuracy. The results, presented in Table 2, show that the YOLOv5l variant outperformed the others with an accuracy of 93.75%, followed by YOLOv5m at 88.75%, and YOLOv5s at 82.50%.

Table 2. The performance of the mangrove leaf classification model in various YOLO versions

YOLO's version	Class	Evaluation Parameters		
		Precision (%)	Recall (%)	Accuracy (%)
YOLOv5s	AA	90	69.23	82.50
	BG	75	83.33	
	RA	80	94.12	
	SA	85	89.47	
YOLOv5m	AA	95	79.17	88.75
	BG	85	89.47	
	RA	90	100	
	SA	85	89.47	
YOLOv5l	AA	100	90.91	93.75
	BG	90	94.74	
	RA	95	100	
	SA	90	90	

Table 2 shows the suggested model's performance variations. YOLO variants were used to construct the model for optimal performance. Only YOLOv5l had an accuracy value of 90%, while the other kernels approached 80%. It prevented different versions from reaching the highest accuracy. The weakest performer was YOLOv5s, with 82.50% accuracy. Based on accuracy, YOLOv5s had the lowest accuracy at 82.50%, followed by 88.75% and 93.75%. The improved performance of YOLOv5l can be attributed to its deeper architecture, which enables better feature extraction and classification capability. These findings align with previous studies where deeper CNN models like VGG16 and AlexNet outperformed shallower networks in leaf disease detection and classification tasks [9], [11]. Specifically, the precision and recall metrics for YOLOv5l remained consistently high across all classes, suggesting the model's robustness in distinguishing visually similar mangrove species. Figures 5(a)–(c) demonstrate the dataset's classification results using YOLOv5s, YOLOv5m, and YOLOv5l.

In Figure 5(a), the highest misclassification occurred in class BG, with three images (two misclassified as classes AA and RA and one as class SA). Simultaneously, the SA class exhibited the fewest errors. Two images were erroneously classed as class BG. Figure 5(b) indicates that the predominant errors arise in the RA and BG classes. Three images were misclassified. Nonetheless, a singular mistake transpired in class SA, which was categorized as class BG. Moreover, Figure 5(c)

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illustrates that all images in class SA are accurately classified; however, one image is erroneously labeled as class RA in class AA. Meanwhile, two classes were inaccurately categorized as BG and RA classes.

Class		Target Class			
		AA	BG	RA	SA
Predicted Class	AA	16	0	1	3
	BG	1	15	1	3
	RA	0	1	17	2
	SA	0	2	0	18

(a)

Class		Target Class			
		AA	BG	RA	SA
Predicted Class	AA	18	0	1	1
	BG	0	17	1	2
	RA	0	1	17	2
	SA	0	1	0	19

(b)

Class		Target Class			
		AA	BG	RA	SA
Predicted Class	AA	19	0	1	0
	BG	0	18	1	1
	RA	0	1	18	1
	SA	0	0	0	20

(c)

Figure 5. The confusion matrix for the classification result of mangrove leaf using: (a) YOLOv5s, (b) YOLOv5m, and (c) YOLOv5l

The confusion matrix analysis further revealed that the most common misclassifications occurred in the BG and AA classes for YOLOv5s and YOLOv5m, likely due to overlapping leaf morphology. In contrast, YOLOv5l demonstrated fewer misclassifications and better balance across all categories. This result supports our initial hypothesis that increasing the depth and complexity of the mo del would yield better classification performance, particularly in datasets with subtle inter-class differences.

Overall, the study demonstrates that YOLOv5, especially the 'l' variant, is a viable deep learning architecture for classifying mangrove leaf species. The findings have broader implications for ecological monitoring and species identification, suggesting that object detection frameworks can serve as powerful tools for automated environmental assessments in the field.

4. CONCLUSION

This research demonstrates the feasibility and effectiveness of using YOLOv5, a deep learning-based object detection model, for classifying mangrove leaf species. Among the three YOLOv5 variants evaluated—YOLOv5s, YOLOv5m, and YOLOv5l—the YOLOv5l model exhibited the highest accuracy (93.75%), indicating that larger models with more parameters are better suited for handling fine-grained classification tasks in ecological datasets. The findings underscore the potential of modern computer vision tools in addressing practical environmental challenges. By offering a fast, accurate, and scalable method for species identification, the model can support community-led conservation, environmental monitoring, and digital biodiversity mapping. For the broader research field, this study provides a foundational framework for integrating object detection architectures into plant taxonomy tasks. For practitioners and stakeholders, the outcome presents an opportunity to reduce dependency on taxonomic experts, particularly in remote areas where such expertise may be limited. Future work should explore deploying this model into mobile or drone-based systems to enable real-time classification in natural environments. Expanding the dataset to include more species and testing the model across different geographic regions will also help validate the model's robustness and generalizability.

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