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Comparison of MobileNet and VGG16 CNN Architectures for Web-based Starfish Species Identification System

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Abstract

Bunaken Marine Park (BMP) is famous for its rich marine biodiversity. BMP is an asset for the marine tourism industry of the Manado city government, and the North Sulawesi Province of Indonesia needs to be strengthened. This research aims to build a web-based intelligent system using a convolutional neural network (CNN) to identify starfish species to initiate developing a media center marine biota identification system of BMP. Two CNN architectures, namely MobileNet and VGG16, were conducted to produce identification models. The first stage carried out a training process on 1800 starfish image data and then evaluated using the 5-fold cross-validation technique. Validation results show that MobileNet is superior to the VGG16 architecture by achieving validation accuracy of 100% for each fold while VGG16 produces validation accuracy in the range of 94% to 100%. On the other hand, in the second stage of model testing, it was found that VGG16 worked better than MobileNet in identifying 200 new data. The Best Model produced by VGG16 achieved testing accuracy of 100% while MobileNet produced 99.5%. However, stability analysis of the identification models produced by both architectures shows that MobileNet has relatively small loss values ranging from 0.00069325 to 0.00214802 as well as smaller standard deviation values of 0.27 compared to 0.61 produced by VGG16. These findings indicate MobileNet is more stable in carrying out identification work compared to VGG16 of, thus the best model provided by MobileNet is taken to deploy in the web platform which is created using the Python flask framework. The proposed system can be used to strengthen the marine tourism industry as a media center of educational marine biota using deep learning approaches.

Keywords: Mobilenet, VGG16, Starfish, Cross-Validation, CNN, Bunaken

1. Introduction

Bunaken Marine Park (BMP) is renowned for its abundant marine biodiversity. BMP is a valuable asset for the marine tourism industry of the Manado City Government and the North Sulawesi Province of Indonesia that needs to be reinforced. This research aims to develop an intelligent web-based system utilizing a convolutional neural network (CNN) for the identification of starfish species, as a preliminary step toward creating a marine biota identification media center for BMP.

North Sulawesi is one of the regions in Indonesia that is famous for its marine biodiversity [1]. This diversity is crucial for maintaining the balance of marine ecosystems, in addition to having high economic and scientific value. However, many starfish species in the region are threatened with extinction due to human activities such as habitat destruction, overfishing, and marine pollution. Therefore, in-depth on starfish species in North Sulawesi has become urgent to support conservation efforts[2] . Research on marine ecosystems that uses the CNN algorithm is very limited, some studies that use the CNN algorithm such as that conducted by research [3] related to the classification of images of leaf

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disease types using CNN algorithms and MobileNet architecture with feature extraction showing excellent accuracy. Research [4] human activity recognition based on webcam capture using CNN method with mobilenet architecture. Research [5] identified types of wood using convolutional neural networks with mobilnet architecture resulting in training accuracy of 98%, testing of 93.3% and presentation of mobilenet Architecture of 28% and 93% for its accuracy.

Research [6] related to the classification of images of tomato seed cultivars using the CNN model and the MobileNet-BiLSTM approach showed excellent results. In the first scenario, MobileNetv2 achieved an accuracy of 93.44%. In the second scenery, the feature of Mobile Netv2 was used in the BiL STM network, increasing the accuracy to 96.09%. This study proved the effectiveness of the in-depth learning method to distinguish tomato Seed cultivators. Research [7] on the classification of parcel box images using CNN MobileNet showed good results. Out of 4882 images collected, MobileNet achieved an accuracy of 84.6%, recall 82%, and specificity of 88.54%. MobileNet proved faster than VGG16 and ResNet50, showing its potential to identify damaged parcel boxes in underground logistics systems.However, specific research using the MobileNet architecture on the CNN algorithm to identify types of marine stars in North Sulawesi is still very limited. MobileNet is a variant of CNN designed for devices with low computing power, making it ideal for use in fields with limited resources [8], [9], [10]. Given the advantages of MobileNet in terms of efficiency and speed, this research is important to test how well this architecture can identify and classify different types of marine stars in North Sulawesi with high accuracy. With this research, it is expected to make a significant contribution to efforts to preserve marine biodiversity in North Sulawesi as well as paving the way for the application of similar technologies to other biodiversity research in the future.

Research [11] on Modification of VGG16 Architecture for Digital Image Classification of Spices in Indonesia. This research shows the best value results with accuracy reaching an average of 81%, recall value of 76%, and precision value of 81% for the training phase and for the validation phase, accuracy of 85%, recall value of 80%, and precision value of 84%. Research [12] on the classification of salak fruit quality using the VGG16 transfer learning architecture shows research from the effectiveness of transfer learning in classifying the quality of salak fruit with very good accuracy results. With the highest accuracy result of 95.83%, achieving 97.2% precision and 94.6% recall. Research [13] using the extraction approach is transfer learning VGG16. CNN combined with the transfer learning approach outperforms all manual feature extraction methods such as local binary patterns, Color Channel Statistics, Color Histograms, Haralick Texture, Hu Moments, and Zernike Moments. CNN combined with the transfer learning approach yielded accuracies of 73.05%, 93.41%, and 90.60%, using OverFeat, Inception-v3, and Xception architectures, respectively, as feature extractors in the FLOW-ERS102 dataset.

Just like MobileNet, the other CNN architecture VGG16 is also rarely used to identify starfish. VGG16 has accuracy and feature extraction capabilities that make it suitable for classifying complex things. This research aims to analyze and compare the performance of two famous CNN architectures MobileNet and VGG16 in identifying starfish and then deploy the best model on a web platform so it can be used by tourism in real time. This research can significantly contribute to the conservation of marine biodiversity in North Sulawesi and pave the way for the application of similar technology in other biodiversity research in the future.

The restricted use of convolutional neural networks (CNNs), more especially the MobileNet and VGG16 designs, in detecting starfish species in marine environments is the issue this study attempts to solve. CNN is still rarely employed in marine biodiversity research, especially for starfish identification, although being frequently used in other fields including categorizing wood types, human activities, and leaf disease types. Furthermore, MobileNet has not been thoroughly evaluated for the identification of marine species, despite being well-known for its effectiveness on devices with constrained processing capability.

In order to identify and categorize starfish species in North Sulawesi, this study suggests creating a web-based intelligent system that uses two CNN architectures, MobileNet and VGG16. The goal of the study is to compare the performance of the two architectures and apply the most accurate and reliable model to a real-time web platform. While earlier research has shown that CNN, including MobileNet, is excellent in a variety of picture classification tasks, this study is unusual in that it applies these architectures to starfish species, which has not received enough attention.

The findings of this study will enhance the use of CNN in marine research while also aiding in the conservation of marine biodiversity. Following extensive training and testing, the top-performing model will be implemented on a web-based platform, allowing for its useful application in marine tourism and educational programs. Moreover, this study sets the path for future applications of CNN in other biodiversity research fields, highlighting the promise of deep learning in environmental conservation efforts

Deep learning method was used in similar previous research to identify starfish. Research [14] used MobileNetV2 and VGG19's CNN architectures to identify Crown of Thorn Starfish (COTS). MobileNet received 82.0% validation accuracy, whilst VGG19 obtained a satisfactory 87.01%. Additionally, the accuracy of the VGG19 model was successfully improved by 92.6% with the use of a self-attention algorithm. Research [15] conducted You Only Look Once version-5 (YOLOv5) to detect the COTS. A good performance model was obtained shown by 93%, 77%, and 84% values of Precision, Recall, and F1-score, respectively. Another study [16] has classified three species of starfish Pisaster ochraceus, Pycnopodia helianthiodes and Solaster dawsonii using RESNET architecture of CNN. A good accuracy of 97.91 was achieved with 4% misclassified on Pisaster ochraceus class, 1% on Pycnopodia helianthiodes, and 2% of Solaster dawsonii. [17] reports the object detection model of YOLOv5 outperforms compared with YOLO-X, Detectron2, Faster RCNN, and Retina Net in detecting COTS using the Kaggle video dataset of the Great Barrier Reef of Australia. Their result shows that YOLOv5 achieved a 0.628 F2-score higher than the other model.

Similar studies mentioned above have initiated the issue of artificial intelligence-based marine biodiversity conservation but have not considered the educational aspect, which is one of the important targets of our research. Our research initiated the development of the Bunaken Marine Park as a marine biodiversity conservation center equipped with educational facilities so that, apart from recreational purposes, tourists gain knowledge about the abundant diversity of marine biodiversity in the Bunaken Marine Park.

2. Research Method

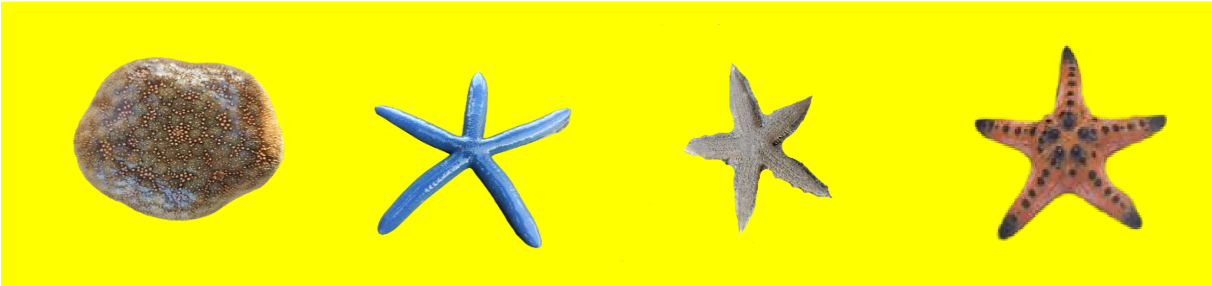
Several studies use a one-shot learning approach [18], [19], [20] due to limited data. However, this study employs training models through classical supervised learning because of the substantial training data set of 1800 photos, which enables CNNs to learn from numerous examples to increase classification accuracy. This research starts by collecting starfish image data from some locations in the coastal area of North Sulawesi, especially from the coastal region of Bunaken Marine Park, which included Bunaken Island, Siladen Island, and Manado Tua Island, and then pre-processing them to ensure consistent quality and size. Next, the MobileNet and VGG16 architectures were implemented and trained on a dataset of pre-processed starfish images using 5-fold cross-validation techniques. The trained model was evaluated using accuracy, precision, and gain metrics on a separate test dataset. The evaluation results are analyzed to determine the effectiveness of the MobileNet and the VGG16 architectures in identifying starfish species. The last step is to deploy the best model in the web platform so that can be used in real time

2.1. Research Data

This study used 200 original images of starfish from four species: Luidia foliolata, Linckia laevigata, Culcita novaeguineae, and Protoreaster nodosus, with each species having 50 images per class. To increase the amount of dataset, augmentation is carried out [21] so that the total image data becomes 2000. These images are divided into training, validation, and testing datasets, as shown in table 1. Figure 1 displays examples of the four types of starfish, which are categorized as classification classes in this study

Table 1. Starfish Data Distribution

No	Species	Data Distribution			Total
		Training	Validation	Test	
1	Culcita Novaeguineae	360	90	50	500
2	Linckia laevigata	360	90	50	500
3	Luidia foliolata	360	90	50	500
4	Protoreaster nodosus	360	90	50	500
	Total	1440	360	200	2000



Culcita novaeguineae Linckia laevigata Luidia foliolata Protoreaster nodosus

Figure 1. Four classification classes of starfish species

Data augmentation techniques were used to make sure the dataset was reliable and representative of various environmental situations. By artificially increasing the dataset's variability through random rotations, flips, zooms, and lighting modifications, these strategies assist avoid overfitting and enhance the model's capacity to generalize to new data. In order to replicate real-world circumstances where starfish may appear in various orientations, lighting, or partial occlusion, the photos were enhanced. This made the identification procedure more difficult and realistic.

2.2. Research Stages

This research is divided into 3 stages of development, testing, and deployment. The augmentation process is performed to increase the amount of data to avoid underfitting in the training process. The next process is training and validation with 5-fold cross-validation so that five models are derived and then the evaluation process is carried out on them. In the testing stage, the evaluation process is again conducted on testing data that was not used in the previous stage. The best model that has been evaluated will be used for deployment in the next stage. These three processes are shown in figure 2.

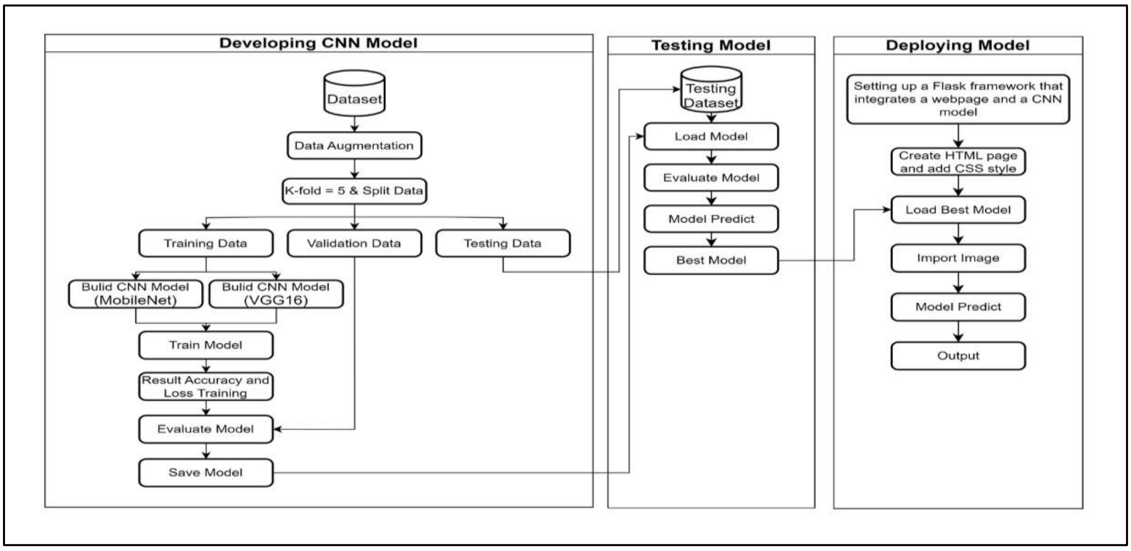


Figure 2. Research stages of starfish identification

2.3. Cross Validation

Cross-validation [22], [23], [24] is a technique used in machine learning to evaluate the classification model. The data was divided into training and validation data. In this research, the value of k is taken equal to 5, which means it will create 5 different models with different training and validation data. Shown in figure 3 is the division of training and validation data in each fold. It is shown that the training data is marked in yellow and the validation data is marked in blue. The remaining 200 data from a total of 2000 data were used for the testing process in the testing stage.

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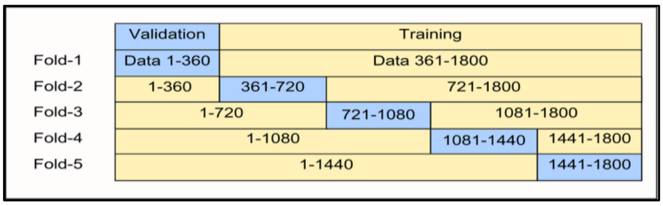


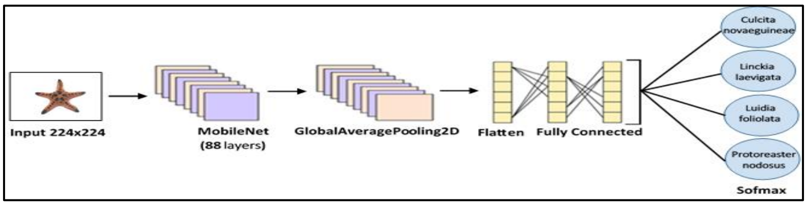
Figure 3. 5-Fold Cross-Validation of training and validation data

2.4. Convolutional Neural Network

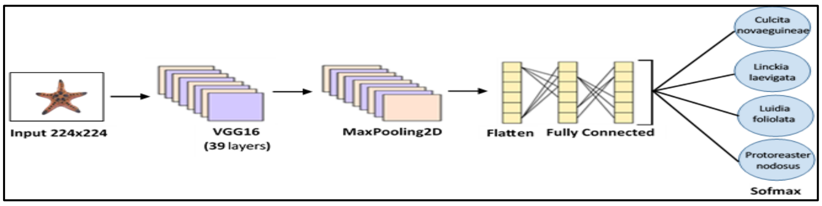
CNN [25], [26] is a type of artificial neural network used widely in image recognition and visual processing. The MobileNet and VGG16 are two famous architectures of CNN that are used widely on image data.

This research performs MobileNet and VGG16 to identify the species of starfish based on its images. The inputs image is processed by MobileNet which consists of 88 layers while VGG16 used 39 input layer. Average Pooling layer was setup for MobileNet and MaxPooling2D for VGG16. Both architecture used softmax to generate classification probabilities. The final classification consists of four classes: Luidia foliolata (LF), Linckia laevigata (LL), Culcita novaeguineae (CN), and Protoreaster nodosus (PN). Figure 4 shows CNN model architecture of MobileNet (a) and VGG16 (b) used in this study.

MobileNet and VGG16 were chosen for this study because of their unique benefits in terms of simplicity, efficiency, and feature extraction, which make them appropriate for recognizing species of starfish in an environment with limited resources. With its lightweight yet robust architecture, MobileNet is especially made for devices with low processing power. It is perfect for real-time applications like web-based platforms that identify marine biodiversity. Despite being more computationally intensive, VGG16 is good in capturing intricate patterns in photos like starfish because of its deep layers, which are excellent at feature extraction. Even though architectures like ResNet or Inception provide more complicated methods and deeper networks, including residual connections, they are frequently more computationally demanding and can add needless complexity to the particular task of classifying starfish. Through the selection of MobileNet and VGG16, this study strikes a compromise between computational effectiveness and robust feature recognition capabilities, guaranteeing a workable solution for real-time deployment while preserving high accuracy.



(a)



(b)

Figure 4. CNN Model Architecture of MobileNet (a) and VGG16 (b)

2.5. Confusion Matrix

Confusion matrix [27], [28], [29] is a technique used to evaluate the performance of classification algorithms. It provides a complete picture of how the model predictions compare to the actual values of the test data. Table 2 shows the confusion matrix of starfish classification system with four classes of LF, LL, CN, PN. T and F characters denotes true and false prediction respectively. Accuracy can be calculated

Table 2. Confusion matrix of starfish with 4 classes

		Actual Values			
		LF	**LL**	**CN**	**PN**
Predicted Values	LF	T	F	F	F
	LL	F	T	F	F
	CN	F	F	T	F
	PN	F	F	F	T

Accuracy rate of the model can be calculated using eq. (1)

$$\text{Accuracy} = \frac{\text{total T}}{\text{total data}} * 100\% \tag{1}$$

3. Result and Discussion

3.1. Training and Validation Result

3.1.1. MobileNet Architecture

The training process through learning rate = 0.001, epoch = 10, batch size = 8, and 5 fold cross-validation. Figure 5 shows plotting graph of loss and accuracy of each fold in the training process, while figure 6 shows plotting graph of loss and accuracy of the best model (a) and the worst (b) in validation process. Table 3 summarizes the MobilNet architecture validation results for each fold, including loss, accuracy, precision, recall, and F1-score.

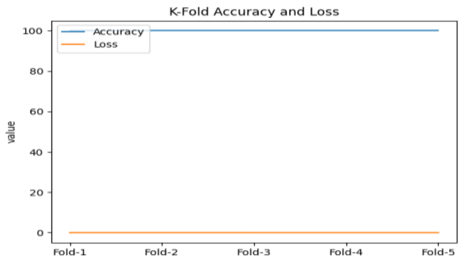
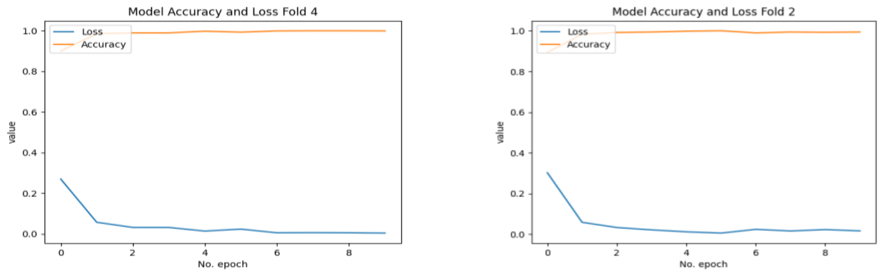


Figure 5. The graph of loss and accuracy for each fold of MobileNet



(a) (b)

Figure 6. Graphs of loss and accuracy of the best (a) and the worst (b) model of MobileNet

Table 3. MobileNet validation results

Fold	Loss	Accuracy	Precision	Recall	F1-score
1	0.00099739	1.0	1.0	1.0	1.0
2	0.00214802	1.0	1.0	1.0	1.0
3	0.00202902	1.0	1.0	1.0	1.0
4	0.00069325	1.0	1.0	1.0	1.0
5	0.00162640	1.0	1.0	1.0	1.0

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Notably, all folds achieved perfect validation accuracy (1.0), precision (1.0), recall (1.0), and F1-score (1.0). Fold 4, however, achieved the lowest validation loss (0.00069325), suggesting it might be the best-performing model in terms of minimizing loss. Figure 7 shows the confusion matrix for folds 1 to 5, show that all models successfully predict the validation data accurately. This indicates that the models are proficient in recognizing image patterns and can effectively identify new, previously unseen data

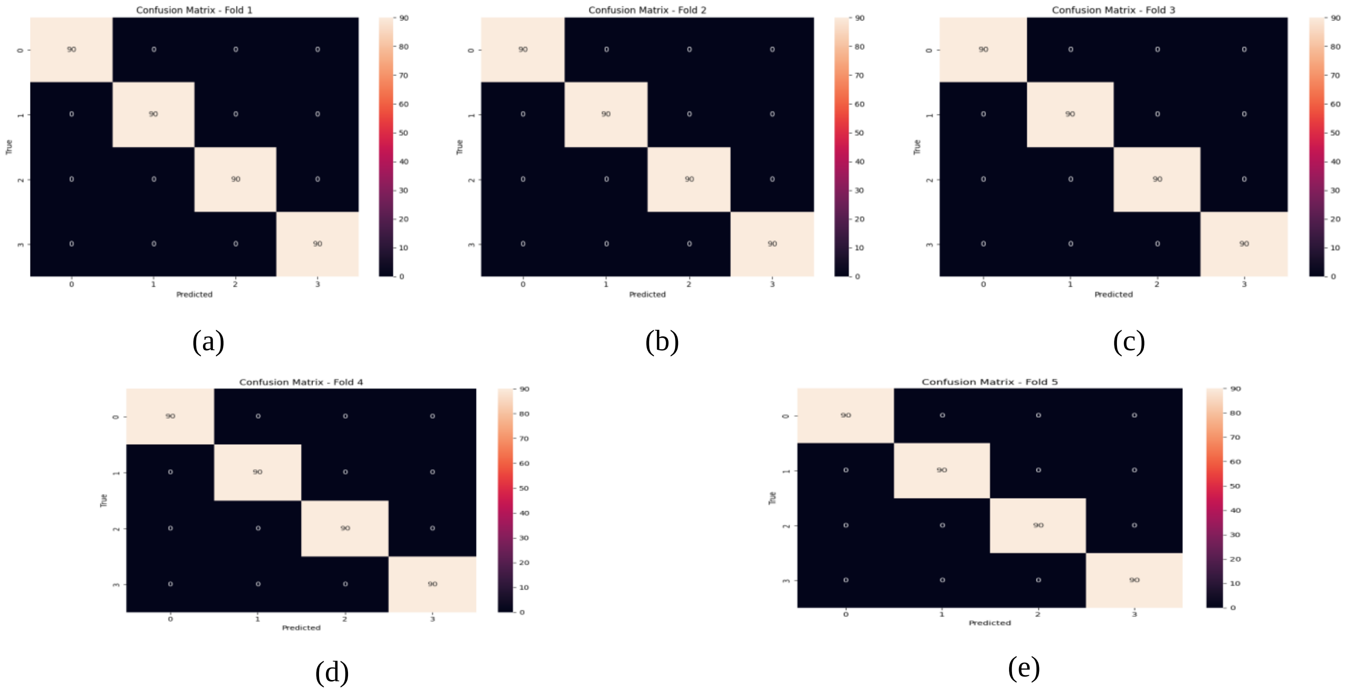

Figure 7. Confusion Matrix of Validation Result of each fold using MobileNet Architecture

The 100% accuracy attained after training raises the possibility of overfitting, in which the model may have learned specific patterns by heart instead of broad ones. Regularization strategies including data augmentation and dropout techniques were used to stop this. In order to assist the model learn more robust features, augmentation rotated, flipped, and otherwise changed photos, intentionally increasing data variability. Additionally, dropout could be utilized to randomly promote generalization by deactivating neurons during training. These methods are essential for guaranteeing that, even with great training accuracy, the model functions properly on unknown data.

This research applied regularization techniques of data augmentation as described in the research data section as well as the dropout technique to avoid overfitting during the training process. To ensure that overfitting does not occur, we test all the obtained calcification models with new data, which is explained in the testing results section.

3.1.2. VGG16 Architecture

The training process of VGG16 using hyper parameters of learning rate=0.001, epoch = 10 and batch size = 8. Fivefold cross-validation was also use to evaluate the stability of the classification models. Figure 8 shows accuracy and loss graphic of each folds while figure 9 shows the graph of accuracy and loss of the best model (a) and the worst (b) from fold-5 and fold-4, respectively. Table 4 summarizes the validation loss and accuracy of each fold.

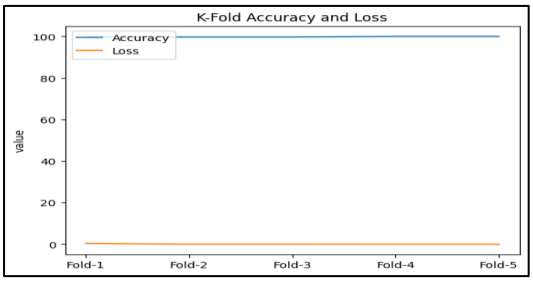

Figure 8. The graph of loss and accuracy for each fold of VGG16

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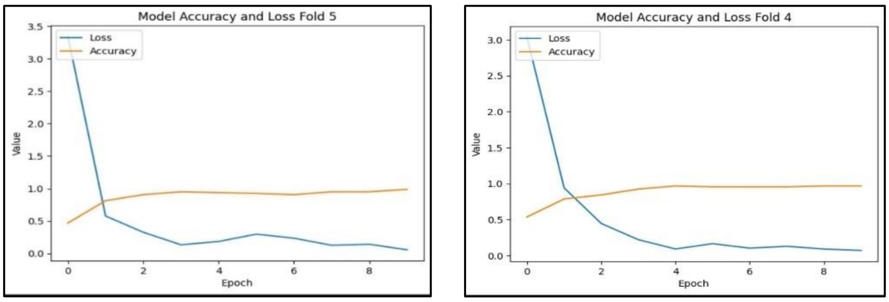


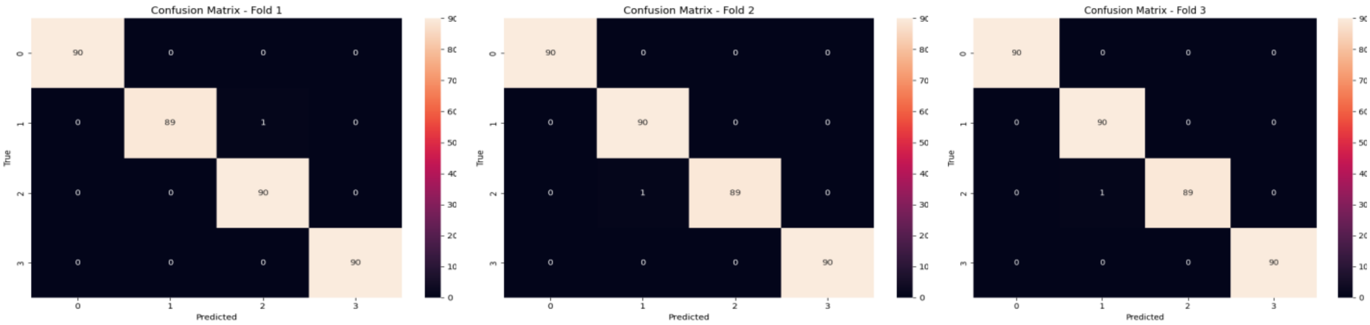
(a) (b)

Figure 9. Graphs of loss and accuracy of the best (a) and the worst (b) model of VGG16

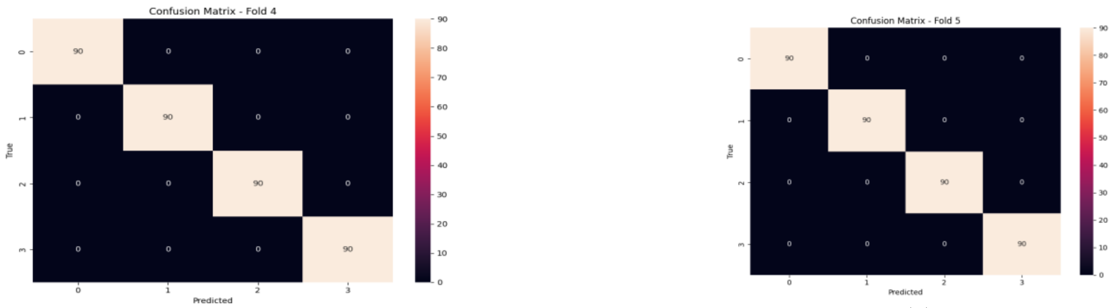
Table 4. VGG16 validation results

Fold	Loss	Accuracy	Precision	Recall	F1-score
1	0.04560389	0.975	0.9775	0.975	0.975
2	0.06407831	0.975	0.9775	0.975	0.975
3	0.00912648	1.0	1.0	1.0	1.0
4	0.05964056	0.94999	0.96	0.95	0.95
5	0.00318821	1.0	1.0	1.0	1.0

The best model was obtained from fold-5 and the worst from fold-4. Compare to MobileNet as shown in table 3, MobileNet architecture is leading for each folds. Figure 10 shows the confusion matrix of validation results of folds 1 through 5, revealing the different models' varying degrees of success in predicting the accuracy of the validation data. Confusion matrix of fold 4 and 5, as shown in Figure 10 (d) and Figure 10(e), stand out as the only ones that achieve perfect prediction for all 360 validation images. In contrast, Figure 10(a), (b) and (c), each shows one mispredicted validation image. This indicates only two models are capable of demonstrating proficiency in recognizing image patterns and effectively identifying new, previously unseen data



(a) (b) (c)



(d) (e)

Figure 10. Confusion matrix of validation results of each fold usingVGG16

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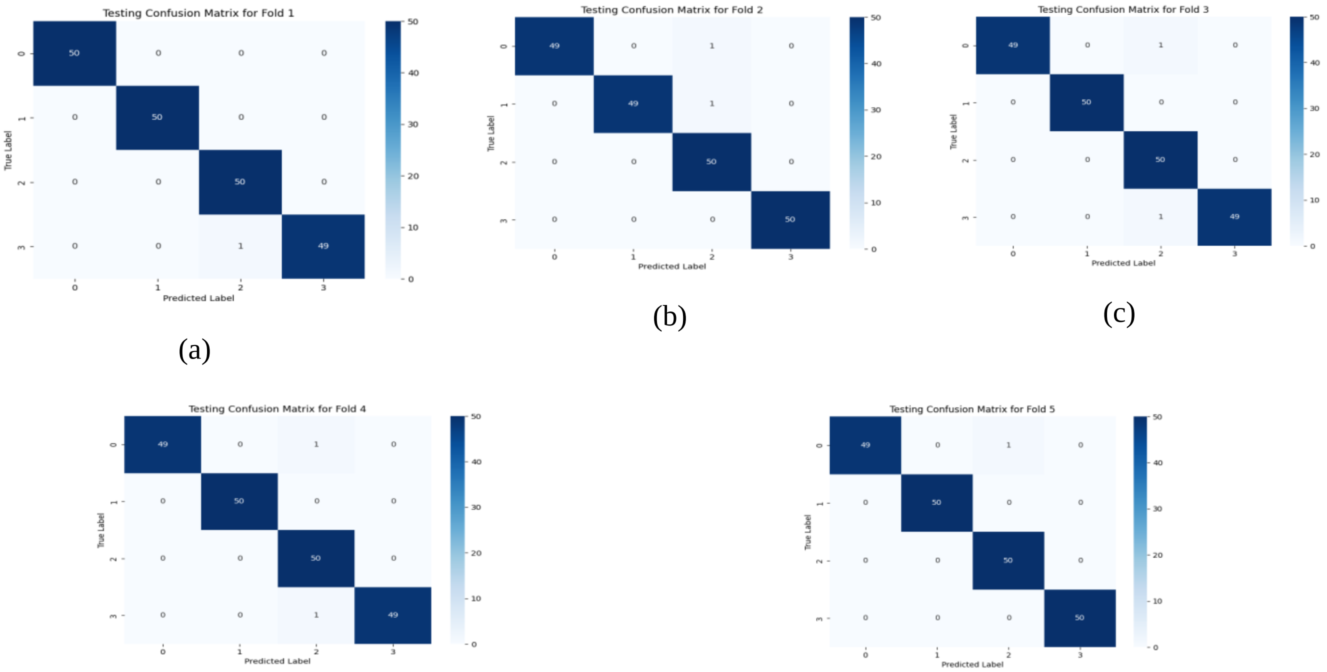
3.2. Testing Result

3.2.1. MobileNet Architecture

Based on validation process results, it was observed that the model in fold 4 exhibited the best performance among the five models, achieving an accuracy of 100%. However, during the testing phase, as shown in figure 11(d), the fold 4 model misclassified two images out of a total of 200 new images data. These findings mean that the model still performs marvelously even when detecting new data never used in the training and validation process. This indicates that the model guarantees good performance when used in the real world.

In line with its performance during training and validation, the fold 2 model also misclassified two images in the testing set. Despite the misclassifications, the testing results of these five models show very good performance with accuracy equal to or above 99%, indicated that the classification model still able recognize the species of starfish based on its images



(a) (b) (c)

(d) (e)

Figure 11. Confusion matrix of testing results each fold using MobileNet architecture

Based on the confusion matrix shown in figure 11 and figure 12, and by using eq. (1), accuracy of testing result of both architectures are shown in table 5.

Table 5. Accuracy of testing results of MobileNet and VGG16

		Fold				
		1	**2**	**3**	**4**	**5**
MobileNet	Accuracy	99.5%	99%	99%	99%	99.5%
	Accuracy average = 99.2%					
	Standard Deviation =0.27					
VGG16	Accuracy	98.5%	99.5%	100%	99.5%	100%
	Accuracy average = 99.5%					
	Standard Deviation = 0.61					

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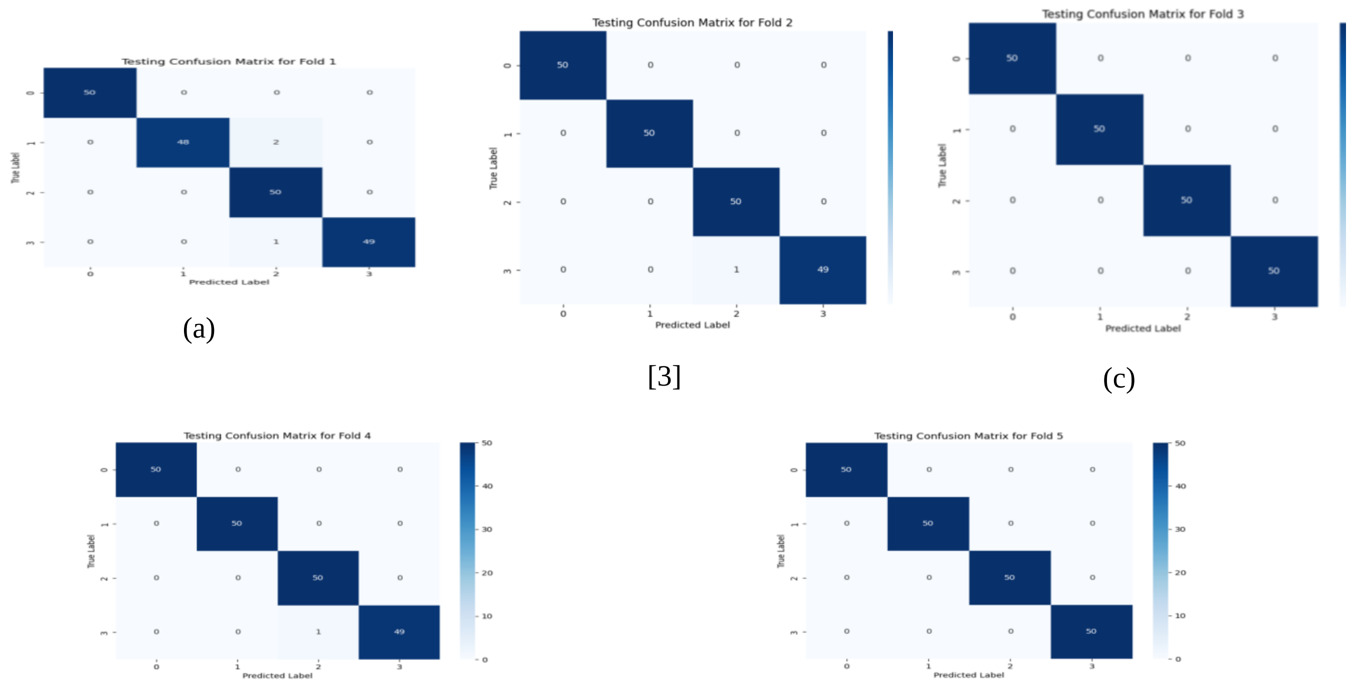
3.2.2. VGG16 Architecture

The testing results shows that the best model of fold 5 misclassified one image out of 200 new image data. The model achieved a sufficient accuracy of 99.5%, a little bit decrease compared to its validation result. All models obtained using VGG16 show excellent performance with accuracy equal to or above 99% as shown in figure 12 (a) to figure 12 (e).



(a) [3] (c)

(d) (e)

Figure 12. Confusion matrix of testing results of each fold usingVGG16 architecture

3.3. Architecture Comparison

Based on the validation and testing results shown in table 3, table 4, table 5, table 6, figure 11 and figure 12, it can be seen that both the architecture of MobileNet and VGG16 provided an excellent performance even for the worst model still shows a very good result. The MobileNet architecture produces a perfect validation accuracy of 100% for all folds while VGG16 produce validation accuracy in the range of 95% to 100%. On the contrary, VGG16 achieved the testing accuracy in the range of 98.5% to 100%, while MobileNet provided the testing accuracy in the range of 99% to 99,5%

Based on loss values produced by both architectures that shown in table 3 and table 4 where MobileNet have relatively small loss values ranging from 0.00069325 to 0.00214802 indicate MobileNet is better than VGG16. Besides that, the standard deviation value of 0.27 produced by the MobileNet architecture as shown in table 5 is smaller than the standard deviation value of 0.61 produced by VGG16 shown in table 6, indicating that MobileNet is relatively more stable compared to VGG16 in predicting new data. Based on comparison results, MobileNet showed slightly superior performance compared to VGG16 in terms of consistency in the task of classifying starfish species based on its images, thus the best classification model which provided from Fold 4 using CNN's MobileNet architecture was taken to deploy on the web platform so that can be used in real time.

As demonstrated by a lower standard deviation value than VGG16, MobileNet offers a more consistent and dependable solution for classification tasks. Regarding to differences in accuracy and stability between both architectures, there are many factors that might contribute to this, one of which is the differences in their respective architectural models

The proposed system in this research shows superior performance compared to previous similar works in several aspects, as shown in table 6 where the abbreviation NR means Not Reported. The description of the detected starfish species as shown in figure 13 (b) initiates educational facilities. In the future, this facility could be expanded to allow relevant experts to enrich system knowledge about the detected marine biota.

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Table 6. Comparison with previous similar works

Study	Accuracy	Precision	Recall	F1-Score	F2-Score	Educational Feature
[14]	92.6%	NR	NR	NR	NR	Not Available
[15]	NR	93%	77%	84%	NR	Not Available
[16]	97.91%	NR	NR	NR	NR	Not Available
[17]	Not Report	NR	NR	NR	0.628	Not Available
This study	100% validation 99% testing	100%	100%	100%	NR	Available

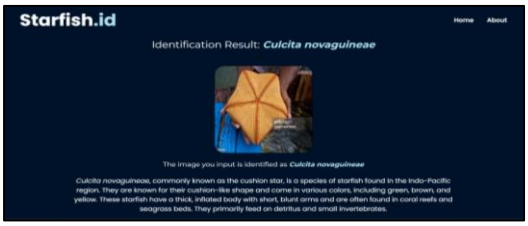
3.4. Deployment

The CNN model and Flask framework are combined in a web application to enable real-time predictions for starfish identification. Following the training, validation, testing, and evaluation processes covered in the preceding sections, the best model is saved in an appropriate format and loaded into the Flask application at server startup. RESTful APIs can be created with Flask, specifying endpoints where users can submit starfish photos for classification. When a picture of a starfish is received, Flask preprocesses it by scaling and normalizing the pixel values to satisfy the input specifications of the CNN model. After recognizing the species of starfish and generating confidence scores, the program uses the model to generate predictions. In order to provide the user with the prediction results, Flask creates a response, usually in JSON format, and provides an intuitive web interface for simple image uploads and result presentation. Because of this integration, advanced machine learning is now feasible and accessible for applications involving marine biodiversity.

The system proposed in this research can assess the initiation of the development of Bunaken Marine Park as a media center for the conservation and education of marine biota based on an artificial intelligence approach.

Figure 13 shows the main (a) that allow user input a starfish images to identify, (b) Page to display identification result and and (c) is the page that provides information about classification classes that discussed in this study. The web-based sytem was developed using Phyton Flask Framework.

(a)



(b)

(c)

Figure 13. Web-based system for identification starfish species: (a) main menu input starfish image, (b) Pages to display identification result and (c) page to display classification classes of starfish species.

There are a number of potential drawbacks to using a CNN model for starfish recognition in practical settings. The model's scalability is a major issue; when the quantity of photos or the number of starfish species rises, the model could need to be retrained to preserve accuracy. This can require a lot of resources and possibly a strong computational foundation. Furthermore, the model's performance is influenced by image quality, which is impacted by different lighting situations. Features can be obscured by dim lighting or shadows, which can result in inaccurate classifications.

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Identification attempts may be made more difficult by environmental factors like water turbidity or backdrop distractions in underwater photos. These situations may introduce noise that the model cannot interpret, resulting in conflicting predictions. Furthermore, connectivity issues may arise in the deployment environment (such as remote locations or mobile devices), which would restrict access to the model for real-time predictions. Addressing these constraints is critical for guaranteeing the identification system's reliability and efficacy in practical applications, particularly conservation and education initiatives.

4. Conclusion

The study was conducted using 200 starfish data, which were augmented to 2000 images, with 500 images per species of Luidia foliolata, Linckia laevigata, Culcita novaeguineae, and Protoreaster nodosus. In the MobileNet architecture, images were input into the network at a resolution of 224x224 pixels, processed through 88 layers of MobileNet, followed by a Global Average Pooling layer, and then a Flatten layer. In contrast, the VGG16 architecture processed images through 39 layers using the same pixel resolution, followed by a MaxPooling2D layer and a Flatten layer. Both architectures concluded by sending extracted features to fully connected layers, using softmax for classification probability results. Both architectures of MobileNet and VGG16 have shown effective classification capabilities in validation and testing processes, but MobileNet has demonstrated greater consistency across all folds, making it a more robust model in this study. Based on the comparative analysis, it is evident that the MobileNet architecture demonstrates superior consistency and lower loss values as well as standard deviation values compared to the VGG16 architecture meaning MobileNet architecture is superior and suitable for identifying the starfish species based on its images. Future research can explore the application using findings in this research to a wider range of marine species and incorporate environmental data to strengthen the marine tourism industry as a media center of educational marine biota using deep learning approaches.

5. Declarations

5.1. Author Contributions

Conceptualization: L.A.L., F.J.P., S., I.K., I.N.G.A.A., H.S.; Methodology: S.; Software: L.A.L.; Validation: L.A.L., S., and I.N.G.A.A.; Formal Analysis: L.A.L., S., and I.N.G.A.A.; Investigation: L.A.L.; Resources: S.; Data Curation: S.; Writing Original Draft Preparation: L.A.L., S., and H.S.; Writing Review and Editing: S., L.A.L., and H.S.; Visualization: L.A.L.; All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5.3. Funding

We are grateful to Sam Ratulangi University in Manado, Indonesia, for their essential assistance, funding, andsupport throughout this study project.

5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] K. von Rintelen, E. Arida, and C. Häuser, "A review of biodiversity-related issues and challenges in megadiverse Indonesia and other Southeast Asian countries," *Research Ideas and Outcomes*, vol. 3, no. 1, pp. 1-16, 2017.

[2] S. Supono, D. John, W. Lane, J. Putih, A. Timur, and J. Utara, "Echinoderm fauna of the Lembeh Strait, North Sulawesi: inventory and distribution review," *Marine Research in Indonesia*, vol. 39, no. 1, pp. 51-61, 2014.

[3] C. Sarkar, D. Gupta, U. Gupta, and B. B. Hazarika, "Leaf disease detection using machine learning and deep learning: Review and challenges," *Applied Soft Computing*, vol. 145,no. 1, pp. 110534-110546, 2023/09/01/ 2023.

[4] H. Kim, S. Lee, and H. Jung, "Human activity recognition by using convolutional neural network," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 9, no. 1, pp. 52-70, 2019.

[5] H. Hendriyana and Y. Maulana, "Identification of Types of Wood using Convolutional Neural Network with Mobilenet Architecture," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 4, no. 1, pp. 70-76, 2020.

[6] K. Sabanci, "Benchmarking of CNN Models and MobileNet-BiLSTM Approach to Classification of Tomato Seed Cultivars," *Sustainability*, vol. 15, no. 1, pp. 1-14, 2023.

[7] M. Kim, Y. Kwon, J. Kim, and Y. Kim, "Image Classification of Parcel Boxes under the Underground Logistics System Using CNN MobileNet," *Applied Sciences*, vol. 12, no. 3, pp. 1-12, 2022.

[8] L. Latumakulita, F. Mandagi, F. Paat, D. Tooy, S. Pakasi, S. Wantasen, D. Pioh, R. Mamarimbing, B. Polii, J. Pongoh, A. Pinaria, E. Tenda, and N. Islam, "Web-Based System for Medicinal Plants Identification Using Convolutional Neural Network," *Bulletin of Social Informatics Theory and Application*, vol. 6, no. 2, pp. 158-167, 2022.

[9] I. N. G. A. Astawa, I. G. N. B. Caturbawa, E. Rudiastari, M. L. Radhitya, and N. K. D. Hariyanti, "Convolutional Neural Network Method Implementation for License Plate Recognition in Android," in *2018 2nd East Indonesia Conference on Computer and Information Technology (EIConCIT)*, vol. 2018, no. 1, pp. 176-179, 2018.

[10] S. Bouguezzi, H. Fredj, T. Belabed, C. Valderrama Sakuyama, H. Faiedh, and C. Souani, "An Efficient FPGA-Based Convolutional Neural Network for Classification: Ad-MobileNet," *Electronics*, vol. 10, pp. 1-22, 2021.

[11] E. Tanuwijaya and A. Roseanne, "Classification of Indonesian Spices Digital Image using Modified VGG 16 Architecture," *Matrik: Jurnal Manajemen, Teknik Informatika, dan Rekayasa Komputer*, vol. 21, no. 12, pp. 189-196, 2021.

[12] R. Rismi and A. Luthfiarta, "VGG16 Transfer Learning Architecture for Salak Fruit Quality Classification," *Telematika*, vol. 18, no. 1, pp. 37-48, 2021.

[13] P. Hridayami, I. K. G. D. Putra, and K. S. Wibawa, "Fish Species Recognition Using VGG16 Deep Convolutional Neural Network," *Journal of Computing Science and Engineering*, vol. 13, no. 2, pp. 124-130, 2019.

[14] M. Heenaye- Mamode Khan, A. Makoonlall, N. Nazurally, and Z. Mungloo- Dilmohamud, "Identification of Crown of Thorns Starfish (COTS) using Convolutional Neural Network (CNN) and attention model," *PLOS ONE*, vol. 18, no. 6, pp. 1-10, 2023.

[15] Q. Nguyen, "Detrimental Starfish Detection on Embedded System: A Case Study of YOLOv5 Deep Learning Algorithm and TensorFlow Lite framework," *Journal of Computer Sciences Institute*, vol. 23, no. 5, pp. 105-111, 2022.

[16] H. Chege, *Prototyping Artificial Intelligent Classifiers using Deep Learning*, 2020.

[17] S. Sheth and D. J. Prajapati, "Recognition of Underwater Starfishes using Deep Learning," in *2022 Second International Conference on Next Generation Intelligent Systems (ICNGIS)*, vol. 2022, no. 1, pp. 1-5, 2022.

[18] N. O' Mahony, S. Campbell, A. Carvalho, L. Krpalkova, G. Velasco-Hernandez, S. Harapanahalli, D. Riordan, and J. Walsh, "One-Shot Learning for Custom Identification Tasks; A Review," *Procedia Manufacturing*, vol. 38, no. 1, pp. 186-193, 2019.

[19] L. Alzubaidi, J. Zhang, A. J. Humaidi, A. Al-Dujaili, Y. Duan, O. Al-Shamma, J. Santamaría, M. A. Fadhel, M. Al-Amidie, and L. Farhan, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *Journal of Big Data*, vol. 8, no. 1, pp. 1-74, 2021/03/31 2021.

[20] A. Puzanov, S. Zhang, and K. Cohen, "Deep reinforcement one-shot learning for artificially intelligent classification in expert aided systems," *Engineering Applications of Artificial Intelligence*, vol. 91, no. 1, pp. 1-21, 2020/05/01/ 2020.

[21] I. N. G. A. Astawa, I. K. G. D. Putra, M. Sudarma, and R. S. Hartati, "KomNET: Face Image Dataset from Various Media for Face Recognition," *Data in Brief*, vol. 31, no. 1, pp. 1-17, 2020/08/01/ 2020.

[22] M. Markatou, H. Tian, S. Biswas, and G. Hripcsak, "Analysis of Variance of Cross-Validation Estimators of the Generalization Error," *Journal of Machine Learning Research*, vol. 6, no. 4, pp. 1127--1168, 2005.

[23] D. Berrar, "Cross-Validation," in *Encyclopedia of Bioinformatics and Computational Biology*, M. G. Shoba Ranganathan, Kenta Nakai, Christian Schönbach, Ed., ed: Academic Press, 2018.

[24] L. Latumakulita, I. N. G. Astawa, V. Mairi, F. Purnama, A. Wibawa, N. Jabari, and N. Islam, "Combination of Feature Extractions for Classification of Coral Reef Fish Types Using Backpropagation Neural Network," *JOIV: International Journal on Informatics Visualization*, vol. 6, no. 4, pp. 643-649, 2022.

[25] J. Naranjo-Torres, M. Mora, R. Hernández-García, R. J. Barrientos, C. Fredes, and A. Valenzuela, "A Review of Convolutional Neural Network Applied to Fruit Image Processing," *Applied Sciences*, vol. 10, no. 2, pp. 1-31, 2020.

[26] Z. Yi, "Evaluation and Implementation of Convolutional Neural Networks in Image Recognition," *Journal of Physics: Conference Series*, vol. 1087, no. 3, pp. 1-4, 2018.

[27] D. Krstinic, M. Braović, L. Šerić, and D. Božić-Štulić, "Multi-label Classifier Performance Evaluation with Confusion Matrix," *Computer Science & Information Technology*, vol. 10, no. 1, pp. 01-14, 2020.

[28] L. Latumakulita and T. Usagawa, "Indonesia Scholarship Selection Model Using a Combination of Back-Propagation Neural Network and Fuzzy Inference System Approaches," *International Journal of Intelligent Engineering and Systems*, vol. 11, no. 1, pp. 79-90, 2018.

[29] L. A. Latumakulita and T. Usagawa, "A combination of backpropagation neural network on fuzzy inference system approach in Indonesia scholarship selection process: Case study: “Bidik misi” scholarship selection," in *2017 13th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)*, Guilin, China, vol. 2017, no. 1, pp. 1309-1314, 2017.